Movement coordination in a discrete multi-articular action from a dynamical systems perspective

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Abstract

Dynamical systems theory represents a prominent theoretical framework for the investigation of movement coordination and control in complex neurobiological systems. Central to this theory is the investigation of pattern formation in biological movement through application of tools from nonlinear dynamics. Movement patterns are regarded as attractors and changes in movement coordination can be described as phase transitions. Phase transitions typically exhibit certain key indicators like critical fluctuations, critical slowing down and hysteresis, which enable the formulation of hypotheses and experimental testing. An extensive body of literature exists which tested these characteristics and robustly supports the tenets of dynamical systems theory in the movement sciences. However, the majority of studies have tended to use a limited range of movement models for experimentation, mainly bimanual rhythmical movements, and at present it is not clear to what extent the results can be transferred to other domains such as discrete movements and/or multi-articular actions.

The present work investigated coordination and control of discrete, multi-articular actions as exemplified by a movement model from the sports domain: the basketball hook shot. Accordingly, the aims of the research programme were three-fold. First, identification of an appropriate movement model. Second, development of an analytical apparatus to enable the application of dynamical systems theory to new movement models. Third, to relate key principles of dynamical systems theory to investigations of this new movement model.

A summary of four related studies that were undertaken is as follows:

1. Based on a biomechanical analysis, the kinematics of the basketball hook shot in four participants of different skill levels were investigated. Participants were asked to throw from different shooting distances, which were varied in a systematic manner between 2m and 9m in two different conditions (with and without a defender present). There was a common significant trend for increasing throwing velocity paired with increasing wrist trajectory radii as shooting distance increased. Continuous angle kinematics showed high levels of inter- and intra-individual variability particularly related to throwing distance. Comparison of the kinematics when throwing with and without a defender present indicated differences for a novice performer, but not for more skilled individuals. In summary, the basketball hook shot is a suitable movement model for investigating the application of dynamical systems theory to a discrete, multi-articular movement model where throwing distance resembles a candidate control parameter.
2. Experimentation under the dynamical systems theoretical paradigm usually entails the systematic variation of a candidate control parameter in a scaling procedure. However there is no consensus regarding a suitable analysis procedure for discrete, multi-articular actions. Extending upon previous approaches, a cluster analysis method was developed which made the systematic identification of different movement patterns possible. The validity of the analysis method was demonstrated using distinct movement models: 1) bimanual, wrist movement, 2) three different basketball shots, 3) a basketball hook shot scaling experiment. In study 1, the results obtained from the cluster analysis approach matched results obtained by a traditional analysis using discrete relative phase. In study 2, the results from the method matched the a-priori known distinction into three different basketball techniques. Study 3 was designed specifically to facilitate a bimodal throwing pattern due to laboratory restrictions in throwing height. The cluster analysis again was able to identify the a-priori known distribution. Additionally, a hysteresis effect for throwing distance was identified further strengthening the validity of the chosen movement model.
3. Using eight participants, hook shot throwing distance was varied between 2m and 9m in both directions. Some distinct inter-individual differences were found in regards to movement patterning. For two subjects clear transitions between qualitatively distinct

different patterns could be established. However, no qualitative differences were apparent for the remaining participants where it was suggested that a single movement pattern was continually scaled according to the throwing distance. The data supported the concept of degeneracy in that once additional movement degrees of freedom are made available these can be exploited by actors. The underlying attractor dynamics for the basketball hook shot were quite distinct from the bistable regime typically observed in rhythmical bimanual movement models.

4. To provide further evidence in support of the view that observed changes in movement patterning during a hook shot represented a phase transition, a perturbation experiment with five participants was performed. Throwing distance was once again varied in a scaling manner between 2m and 9m. The participants wore a wristband which could be attached to a weight which served as a mechanical perturbation to the throwing movement. Investigation of relaxation time-scales did not provide any evidence for critical slowing down. The movements showed high variation between all subsequent trials and no systematic variation in relation to either the mechanical perturbation or the successive jumps in throwing distance was indicated by the data.

In summary, the results of the research programme highlighted some important differences between discrete multi-articular and bimanual rhythmical movement models. Based on these differences many of the findings ubiquitous in the domain of rhythmical movements may be specific to these and accordingly may not be readily generalized to movement models from other domains. This highlights the need for more research focussing on various movement models in order to broaden the scope of the dynamical systems framework and enhance further insight into movement coordination and control in complex neurobiological systems.

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1 Chapter One : Introduction

At its core, this thesis is concerned with gaining a better understanding of how movement coordination in biological organisms is achieved. How is it possible that we can walk from point A to point B? How are we able to pick up a cup and drink our tea? How can we jump over a fence without losing balance? How can we throw a ball towards a target? Whilst these questions are at some level of description relatively easy to answer: “Well, we just do it!”, they each deal with basal properties of biological organisms and the means of these organisms to interact with their environment. Examining these questions from a structural level and, therefore, referring to actual physiological structures, the answers to these questions become difficult (if possible to answer at all). However, they provide a first glimpse of the tremendous complexity involved in movement coordination. Accordingly, the aims of this thesis are tailored to current knowledge of movement coordination and control, and upon reading it, one will not encounter any definitive answers to these questions. However, the present programme of work attempts to make a small but worthwhile contribution to the great and mysterious puzzle of movement coordination in biological organisms, and perhaps one day we will be able to answer such questions.

A theoretical perspective with the potential to help us solve these problems on movement coordination in the future is provided by dynamical systems theory (DST). Routed in nonlinear physics, this framework has provided relatively simple but fascinating solutions for complex problems in movement coordination. Over the course of the last thirty years, DST has provided an established theoretical foundation for the investigation of problems in movement coordination in biological organisms. The present programme of work adopted this framework and accordingly much of the first part of the literature review in the second chapter will be devoted to the description and summary of the dynamical systems framework to movement coordination. Indeed, the starting point for this programme of work will be a definition of movement coordination developed by the Russian movement scientist Bernstein (1896-1966) which will provide a frame of reference maintained throughout the thesis. The first part of Chapter 2 will be concluded with an overview of the issues surrounding the dynamical systems framework. As discussed further in the second chapter, these ideas are concerned with: (i) relation of discrete and rhythmical movement models; (ii) biomechanical degrees of freedom; and (iii), degenerate vs. task determined movement models.

Accordingly, in the second part of Chapter 2, a movement model will be described which will enable experimental investigation of each of these issues: the basketball hook shot. Following previous investigations of ballistic throwing movements from a DST perspective, a review of the literature on basketball throwing will highlight the candidacy of the basketball hook shot as an appropriate movement model in order to address the three identified issues. In Chapter 3, the candidacy of the basketball hook shot is empirically examined in a study describing significant adaptations in movement patterning of the basketball hook shot movement due to changes in throwing distance. Since the basketball hook shot marks a considerable deviation from many previous applied movement models in the literature, results obtained during Chapter 3 will highlight some limitations regarding existing analysis methods. Accordingly, in Chapter 4 the literature will be revisited and several different analysis methods for studying coordination and control in discrete, multi-articular actions will be investigated. Based on the results from this overview, a new cluster analysis approach will be identified as a potential method to enable investigation of discrete multi-articular actions, such as the basketball hook shot, using the conceptual framework of DST.. In Chapter 5, the cluster analysis method will be formulated based on previous work from the literature and the feasibility will be examined with several validations studies.

The new movement model investigated in Chapter 3 and the analytical apparatus from Chapter 5 enabled the application of the conceptual framework of DST to the basketball hook shot, as an exemplar of discrete multi-articular actions, which will be the main aim of Chapter 6. The results obtained in Chapter 6 highlighted, for the basketball hook shot, some strong differences compared to more traditional movement models. Nevertheless, the results seem to support dynamical systems theory as a feasible theoretical framework able to incorporate various domains of biological movement coordination into a coherent programme. Based on the results from Chapter 6, in Chapter 7 a refinement of the experiment in Chapter 6 will be presented which will further highlight some key differences between the basketball hook shot and existing movement models typically encountered in studies of movement coordination in DST (e.g., the concept of critical slowing down). The last chapter of this thesis, the epilogue, will conclude with a summary of this programme of work and provide some propositions for future research.

2 Chapter Two : Literature Review

Part One - Theoretical Overview of Literature

Scientific studies investigating human movement coordination require the adoption of a theoretical framework to guide analysis and interpretation of collected data. One of the most prominent frameworks in recent times has been dynamical systems theory which presents the basis for the present work. Dynamical systems theory seeks to understand human coordination through the concepts of synergetics and nonlinear dynamics. However, in order to provide a basis of what is actually meant by movement coordination, a definition will be provided, which will serve as a common thread leading through the thesis.

Bernstein's Legacy: Defining coordination

Coordination

A central notion in the area of motor control is the so-called degrees of freedom problem, which was first appreciated and accordingly formulated by the Russian scientist Nicolai Aleksandrovich Bernstein (1896-1966) who investigated movement coordination. From his studies Bernstein derived the necessity for a sensory adjustment mechanism for goal-directed behaviour. In the early 20th century this insight went against commonly accepted standards which were based on pure reflex models of movement control (Bernstein, 2006a).

Bernstein's arguments stemmed from the notion that movements always take place in an environment under the influence of internally self-generated forces and external forces which together act upon the mover. External forces can be viewed as a gradient field in which the behaviour of the movement system unfolds. Since the force field can change in time in ways which cannot be completely predicted by the movement system the external forces experienced by the actor can continually change. Accordingly, for successful achievement of task-goals the movement system has to be able to adapt and to accommodate for these externalities and Bernstein pointed out that movement coordination demands therefore an adjustment mechanism within the movement system (Bernstein, 1967, 2006b).

Investigating the internal force production of the neuro-anatomical system the complexity of coordination is further increased. For example, the mere structural assembly of a muscle appears to be quite ill-suited for successful movement control. Muscle functioning always depends on the current and the past status of the muscle tissue resulting in highly nonlinear properties of the movement system. Hence during movement the functional relationship is constantly changing, making successful movement coordination a highly complex task (especially for a hierarchical control system which prescribes muscle commands in advance of movement initiation) (Bernstein, 1996). Therefore, the application of a specific signalling pattern to the muscle can lead to very different outcomes always depending on the current context the muscles resides in. Further, usually the same force can be produced by different combination of muscles depending on the current anatomical arrangement of the movement system which further complicates the task of coordination. These insights lead Bernstein to conclude that no strict signalling patterns can be stored by the central nervous system (Bernstein, 1967). Any simple signalling mechanism from the centre to the periphery would not be sufficient for successful behaviour, in other words univocality of the signal and the corresponding effect cannot exist. Accordingly, he termed this notion as *"functional non-univocality"* (Bernstein, 1967, p.105).

The different parameters which are necessary to define a specific movement in external space resulting from the force generated in the neuro-biological system and within the external force field can be seen together as the degrees of freedom of the system. Relating the necessary degrees of freedom of the actor in three dimensional space with those which underlie the degrees of movement generation it becomes obvious that the number of the latter is exponentially higher compared to the resulting movement degrees of freedom. Hence the system inherently possesses redundancy. The main problem posed to the movement system now lies in regulating these redundant degrees of freedom, representing the so-called 'degrees of freedom problem'. Accordingly, Bernstein formulated coordination as follows:

> *"The co-ordination of a movement is the process of mastering redundant degrees of freedom of the moving organ, in other words its conversion to a controllable system"* (Bernstein, 1996, p.127)

This definition of coordination enables movement scientists to investigate the degrees of freedom problem at several levels of observation. In studies of movement coordination the degrees of freedom are usually equated with the biomechanical degrees of freedom set by the body joints (Newell and Vaillancourt, 2001) which also represents the level mainly followed in this thesis.

Coordination as task-dependent integration

Investigating movement variability in highly trained movements Bernstein noticed that movements are not *"chains of details but structures which are differentiated into details"* and called them *"morphological structures"* (Bernstein, 1967, p.69). These morphological structures should not be seen as static entities but they develop in time and adapt to environmental demands. They were based on a hierarchy where the building blocks were formed by so-called synergies. Synergies were formulated as integrated body structures consisting of several units which work together in order to fulfil task demands. Applying changes to one part of the movement resulted in global reorganization of movement sometimes at far removed sites from the perturbing source highlighting interaction and coupling effects between the different components. Bernstein saw this integration of movements as one of the key features of coordination (Bernstein, 1967). The integration was achieved in a task dependent manner and served the present task goal which, according to Bernstein, is the most important constant in actually solving a particular movement problem. Bernstein postulated that it is the required solution (or the task outcome) which should be represented in the central nervous system (Bernstein, 1967).

Investigating the outcome of similar actions in several contexts Bernstein noticed qualitative similarities. He captured this fact through the notion of topological objects where qualitative properties are shared across different contexts as opposed to metric features. For example, participants are able to write the letter A with different effectors, e.g. with both hands, the feet, or the mouth, and the according outcome will easily be identifiable as the letter A (Bernstein, 1967). However, the actual metric specifics between outcomes will differ despite preservation of the qualitative peculiarities of the letter A (see Figure 2-1).

Figure 2-1: Topological class of letters A. Adapted from Bernstein (1967, p.43)

In conclusion, Bernstein's insights can be used as a general framework for some of the key issues in movement science. Bernstein's definition of coordination will underpin the discussion to follow and its implications (non-univocality, degrees of freedom, redundancy, morphological structures, and topological objects) provide a set of features that any theory explaining human movement behaviour should address. In the next section the application of dynamical systems theory to movement coordination will be introduced which will be subsequently linked to Bernstein's framework.

The Dynamical Systems Theory (DST) and Movement coordination

A possible solution for the degrees of freedom problem emerged when the application of synergetics, a theory of complex physical systems, found a correspondence in the study of human movement behaviour. Preceded by work from Kelso (e.g. Kelso, 1984), Haken, Kelso and Bunz (1985) reported an experiment in a seminal paper where participantss were instructed to synchronize oscillatory movements of both index fingers with a metronome. Participants moved their fingers in either the same (in-phase) or in opposite directions (anti-phase) in reference to the body midline. With increasing movement frequency, the participants exhibited sudden, unintended changes in movement behaviour where switches from anti-phase to in-phase movement were observed. The authors modelled this behaviour as an instance of a self-organising system according to the theory of synergetics providing a link between the domains of movement organisation in neurobiological systems and physical dynamical systems.

In order to sufficiently discuss the implications of this finding, certain key concepts from synergetics will be briefly introduced in the following section. For an in-depth mathematical treatment of the topic compare Haken (1983) and for a more phenomenological introduction from a behavioral point of view compare Kelso (1995).

Synergetics and Physical Dynamical Systems

The theory of Synergetics deals with complex physical systems and its main goal lies in providing an explanation of how these systems achieve ordered behaviour without the necessity of an external, executive agent. Investigating the behaviour of lasers, Hermann Haken (1927-), a German physicist, was able to derive a set of lawful relationships which provided core concepts for the synergetics framework. Haken suggested that a laser constitutes a complex system which consists of countless interacting subcomponents, the laser atoms. During the activation of a laser an external energy source feeds energy into the system and releases energy through light into the environment. Thus, the laser system constitutes an open, non-equilibrium system which exchanges matter and energy with the environment. The energy fed into the system is stored within the atoms and lifts electrons to higher energetic level. The electrons are able to spontaneously jump from the higher to the initial energetic level thereby emitting light through photon emission. This emitted light can be absorbed by other atoms shifting their electrons to a higher energetic level where the same process of spontaneous emission can reappear. Further, when an electron which already resides in a higher energetic state is hit by a photon a so-called induced emission occurs where the electrons emit a photon with the same phase as the hitting photon had. Through this process of spontaneous emission, induced emission and absorption, the atoms are able to interact with each other. Initially the atoms emit light waves of all wavelengths resulting in microscopic chaos. When the energy pump reaches a certain excitation threshold, the uncoordinated behaviour of the atoms emitting light of all wavelengths experiences a dramatic change. Through their joint interaction the atoms start emitting light with a common wavelength yielding the actual laser light and the system settles into an ordered state. The external energy supplied to the system is completely random and contains no information whatsoever about the desired coherent state. Hence, the system is able to settle into a macroscopic ordered state without the necessity of an external agent deliberately forcing the atoms into a specific behaviour (Haken, 1983). Only through the interaction between the subcomponents a stable behavioural pattern emerges. This process is called self-organization and forms a key concept of the synergetic framework.

The theoretical concept that describes the orderly behaviour of the system is called an order parameter or an attractor. This attractor resembles a collective variable of the system describing the structure and dynamic behaviour of the system as a whole. Attractors usually need fewer arguments to describe their structure in comparison to the number of parameters needed to describe the behaviour of all subcomponents involved, yielding a compression of information. Further, the number of exhibited attractors in these systems are far less compared to the potential arrangements of these system based on its subcomponents yielding a compression of system degrees of freedom.

The subcomponents of a system and attractor states are connected by a tight interrelationship. Attractors are formed through the interactions of the subcomponents but at the same time, the order parameter supports the process of self-organization forcing the subcomponents into a collective pattern leading to a circular causality called the slaving principle (Haken and Wunderlin, 1991; Kelso, 1995). System parameters with shorter time scales, the subcomponents, are governed by parameters with longer time scales, the order parameters.

Related to the concept of attractors is the notion of control parameters. A control parameter describes a variable, which leads the system through transitions between different attractor states. The control parameter is unspecific in regards to the resulting order parameter and does not contain any prescription of the emergent pattern. In the laser example, the level of energy provided by the external source served as the control parameter, pumping random energy into the system and leading the system through different states.

The switching behaviour of the system is governed by several time scales inherent to the system and their respective relationships to each other. These times scales include the relaxation time τ_{rel}, the observation time τ_{obs}, the equilibrium time τ_{equ}, and the time scale of control parameter change τ_p. The relaxation time τ_{rel} is the time the system needs to reach one of its attractors from a nearby point. The observation time τ_{obs} describes the time period over which statistical averages of system variables are calculated and is primarily set by the experimenter. The time scale of control parameter change τ_p describes how long the system stays at a certain value of the control parameter. Finally, the time needed for the system to reach its stationary probability distribution from an initial distribution is called the equilibrium time τ_{equ} (Schöner, Haken, and Kelso, 1986; Schöner and Kelso, 1988a). The states of self-organizing systems can be differentiated into two main regimes: (1.) the system resides in the pre- or post-transition area, (2.) the system resides in the transition area (Schöner et al., 1986). During the first regime the following relationship holds true:

$$\tau_{rel} \ll \tau_p \ll \tau_{equ} \qquad (2.1)$$

In the case of a bimodal attractor layout (such as the finger-waggling experiment of Kelso, 1984) the probability distribution of the attractors usually has a higher peak at one of the attractors. Hence, because of the smaller τ_{rel} compared to the τ_p the system is only observed under the initial attractor and the much higher τ_{equ} makes transition to other attractors less likely. This relationship changes during the transition period under the second regime. Whereas τ_{rel} increases to the values of τ_p, τ_{equ} decreases towards τ_p during the transition time and the time scales collapse onto each other. The increase in τ_{rel} leads to increasing fluctuations of the attractor and the system undergoes a so-called critical instability (Kelso, Scholz, and Schöner, 1986; Schöner et al., 1986).

Using the laser example introduced earlier during the transition period after an additional energy burst fed into the system it would disrupt the laser light perhaps causing a flickering of the light for a longer time compared to the stable region were the same burst would be dampened out much faster. The increase of fluctuations is termed *critical fluctuations* and the increase of the relaxation time is called *critical slowing down* (Haken, 1983, p. 110; Haken, Kelso, and Bunz, 1985; Scholz, Kelso, and Schöner, 1987). Because the equilibrium time is decreased, the system is able to visit other attractor states more easily and transitions between attractor states is possible. Further manipulation of the control parameter re-establishes the initial time scale relationships, stabilizing the new attractor. These different time scale relationships and their accompanying features are inherent to physical complex systems (Haken, 1983).

Critical instabilities represent a key concept which will be highlighted in the following sections as the main entry point into unravelling the dynamics of the system. Hence, from a synergetics viewpoint when the system goes through phases of instabilities most information about its underlying dynamics can be obtained in contrast to other motor control theories like the information processing framework under which differences between stable states of the system are preferably investigated (Kelso, 1995; Kelso and Schöner, 1988).

Depending on the type of the phase transition that occurs, the system can also exhibit a so-called *hysteresis* effect (Haken, 1983, p.182). When the system is prepared in one state and the control parameter value is altered (e.g. increased) at a certain threshold, the system switches into a new state. Starting from this state and decreasing the control parameter value back to the initial level, the system stays longer in the second state than before and changes to the first state at a lower value of the control parameter. Hence, the system exhibits a dependence on the direction of control parameter change and switching from one state to another at different control parameter values.

In summary, synergetics provides a framework, which describes and formalizes how complex, open systems which are not in equilibrium with their environment are able to exhibit ordered system states through self-organization. The framework entails a set of theoretical concepts, which provide an analytical apparatus making predictions and experimental testing possible. Accordingly an experimenter can investigate whether a behavioural change is governed by the laws of self-organization or whether maybe some other dynamic underlies the observed behaviour.

Synergetics and coordination in dynamical neurobiological systems

In this section the general principles of synergetics will be related to the domain of motor control. The authors in the finger flexion-extension experiment (Haken et al., 1985) defined human behaviour as the result of a complex, open system and accordingly applied the theoretical apparatus of synergetics. By modelling the movement of the fingers using a model with two non-linear, coupled oscillators the authors were able to explain the movement outcome from a synergetics point of view.

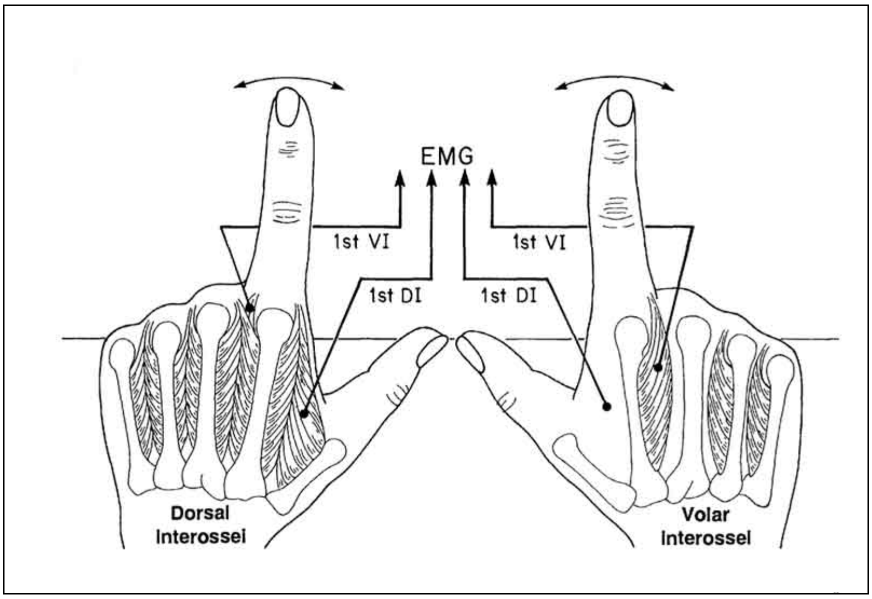

Figure 2-2: Anti-phase and in-phase finger movement. Adapted from Kelso and Schöner (1988, p.32)

Seeking to describe the movement of the fingers by a global parameter, Haken et al. (1985) operationalized the discrete relative phase of the fingers as the dependent variable. When the fingers moved in the same direction in relation to the body midline the movements were defined as an in-phase movement whereas when the fingers moved in opposite directions the movement was defined as anti-phase (see Figure 2-2).

When the participants began with an anti-phase motion, at an individual critical threshold reordering of the finger coordination occurred with increasing movement frequency and a transition to an in-phase motion could be observed. However, when the participants started with an in-phase movement pattern, no transitions in the opposite direction occurred. For the latter condition, this finding held for both directions of frequency change from low to high as well as from high to low (Haken et al., 1985). The combination of anti-phase, frequency increase, pattern switching and subsequent persistence in the in-phase pattern was interpreted by the authors as an occurrence of hysteresis.

Based on the peculiar behaviour of the relative phase dependent variable, Haken, Kelso, and Bunz (1985) interpreted this measurement as a direct representation of the attractor dynamics governing this specific movement model. Accordingly, the movement frequency served as a control parameter. Through this approach, the authors were able to directly identify properties of synergetics in the domain of human motor behaviour.

The mathematical model based on two oscillators which captured the dynamics of the behaviour is now known as the HKB-model (Haken et al., 1985). The behaviour was modelled on two different levels of observation: in abstract order parameter space based on the relative phase (Φ) and in movement space of the fingers based on the displacement of the finger tips. Both models lead to the same results showing how different levels of observations can be used in order to identify the dynamics of the system. The order parameter approach lead to equation (2.2).

$$\begin{aligned} \dot{\phi} &= -\frac{dV}{d\phi} \\ V(\phi) &= -a\cos\phi - b\cos 2\phi \end{aligned} \qquad (2.2)$$

V is the so called potential function and a and b are model constants (compare Haken et al., 1985). In a subsequent investigation the model was extended by including a stochastic noise term (compare equation (1.3), Schöner et al., 1986).

$$\dot{\phi} = -\frac{dV}{d\phi} + \sqrt{Q}\xi_t \qquad (2.3)$$

ξ is a Gaussian white noise process and Q>0 is the noise strength (compare Schöner et al., 1986).

Using this extended model the predicted time scale behaviour of the system could be assessed. Using a torque pulse which was applied to the right index finger during bimanual movements Scholz, Kelso, and Schöner (1987) were able to directly estimate τ_{rel} (see also Scholz and Kelso, 1989). The results confirmed the validity of the model and lead to further support of the synergetics modelling approach (Schöner et al., 1986).

The model was further extended included a measure of asymmetry between the two oscillators (Fuchs and Jirsa, 2000) in order to include further experimental findings and extend the generality of the model to account for different sized effectors.

$$\dot{\phi} = -(1-2\sigma)a\sin\phi - 2b\cos 2\phi + \sqrt{Q}\xi_t \qquad (2.4)$$

σ is a symmetry parameter (compare Fuchs and Jirsa, 2000).

The modelling approach made it possible to describe the movement as a trajectory in an abstract landscape. The shape of the landscape consisting of valleys and mountain ridges represented the properties of the underlying attractors. This phenomenological modelling enabled researchers to express movement behaviour in terms of the synergetic concepts in problems where rigorous mathematical treatment was not possible and a more phenomenological approach was necessary (compare Thelen, 1995).

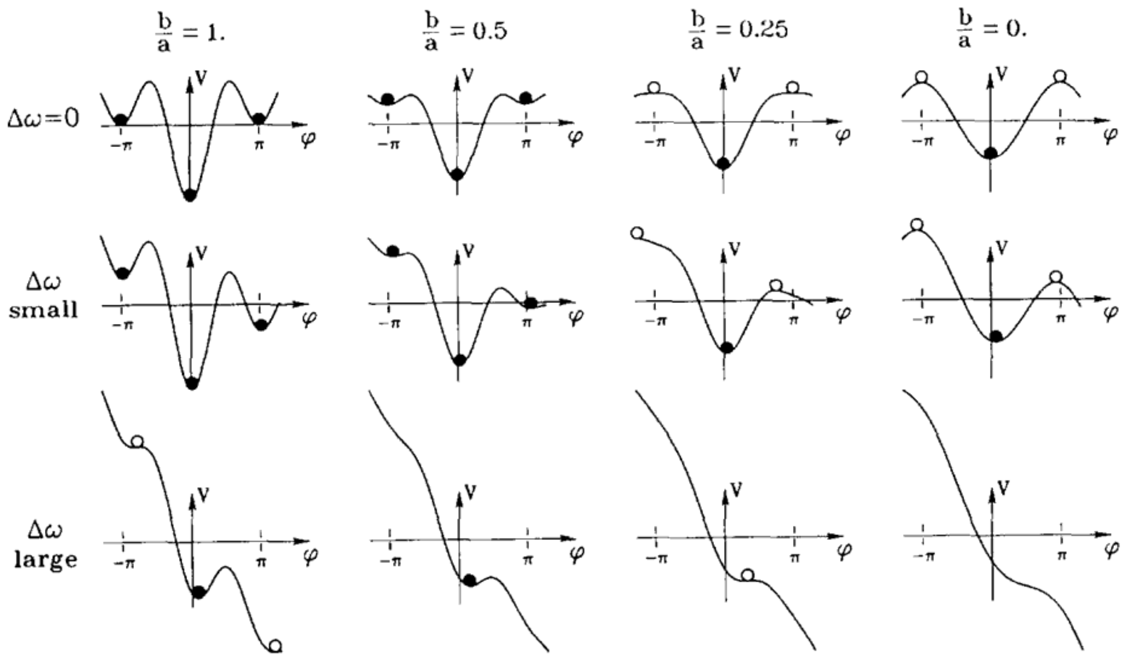

Figure 2-3: HKB-model as a function of the ratio b/a for different values of Δω. Adapted from Kelso (1994, p. 396)

In Figure 2-3 the landscape is shown for model 2.4 for different values of the asymmetry parameter. In the top row the switch from a bimodal attractor layout at the left hand side for low movement frequency to a uni-modal layout is shown. There are three different stable regions, thereby the two outer ones represent the same anti-phase movement pattern at relative phase values of π and $-\pi$. The in-phase movement is shown at the centre with a relative phase of zero. As movement frequency increases the outer stable regions become unstable until at the far right they completely disappear.

In the middle row a small asymmetry between the two oscillators is introduced. This asymmetry leads to a symmetry break yielding the preference of the right anti-phase pattern over the left pattern where one oscillator is leading the other. The minima are slightly shifted off from the pi and –pi positions. With increasing movement frequency the same effect as before is visible where the anti-phase patterns lose their stability properties and only the in-phase pattern remains stable. In the bottom row a strong asymmetry between the oscillators is present which leads to a destabilization of the anti-phase patterns which are only transiently stable. At the highest movement frequency the asymmetry leads to the vanishing of all stable states and only areas of slight transient stability are left. Due to these somewhat more stable regions a phenomenon comes into effect which is called intermittency, whereby the system resides longer in those regions where previously a stable attractor was present. However, the overall behaviour is marked by constant phase wandering (Kelso, 1994).

In conclusion, viewing movements of neurobiological systems modelled as complex, open, dynamical systems, provides an opportunity for analysis from a synergetics point of view. This approach has proved to be successful in several different instances (see following Section), leading to a direct connection between complex systems theory and neurobiological behaviour. The experimental approach used during the finger flexion-extension task where a potential control parameter was driven through a pre-specified parameter range has become a gold standard in studies of coordination under the dynamical systems perspective. Since the systems properties can be most easily identified during periods of instability, this approach provided a simple mechanism to trigger these instabilities and investigate changes in global behaviour of the system under scrutiny (Beek, Peper, and Stegeman, 1995; Kelso and Schöner, 1988). In the following section, the synergetics or dynamical systems approach to human movement will be validated against Bernstein's perspective on movement science in order to justify the viability of this particular framework.

Key principles of Dynamical Systems Theory and Bernstein's Insights

Bernstein's definition of movement coordination was principally concerned with the redundant degrees of freedom present in the movement system. From a dynamical systems theoretical approach these multiple degrees of freedom are welcomed in stark comparison to classical cybernetics control theories. As became clear from the discussion of attractors, the actual number of system states and the related degrees of freedom of a self-organized system at the global level are far less than those present at the component level resulting in the inherent information compression of the system (Kay, 1988). The interaction of the different degrees of freedom actually may provide the very basis for their own governance by harnessing inherent processes of self-organization. From a control perspective the process of self-organization reduces the complexity of the system and only a limited number of parameters are needed to control system behaviour. The remaining variables do not need explicit regulation since their behaviours are governed by the attractor properties, bound together through interaction and the resulting self-organization via the slaving principle. Accordingly the conversion of the system into a controllable unit is simplified and the regulating degrees of freedom are compressed to only a few important degrees (Kelso and Schöner, 1988, p.31).

Regarding the non-equivocality principle introduced by Bernstein, recent investigations of brain dynamics from a synergetics approach suggest that similar processes which govern behavioural dynamics are also present at the level of brain functioning connecting these two domains of neurobiology (Carson and Kelso, 2004; Fuchs, Jirsa, and Kelso, 2000; Kelso, 1998; Kelso et al., 1998; Lindenberg, Ziemann, Hajak, Cohen, and Faith Berman, 2002). Such research could potentially solve the problem of functional non-equivocality through a coherent mechanism working at several levels. As suggested earlier, explicit control and knowledge of specific contextual information is not needed by the controller. Many aspects of the actual movement generation and execution can be devoted to the substructures and to their interactions with each other, which in turn are governed by self-organization.

Bernstein's emphasis on morphological structures also fits well with the notion of attractors. Attractors do not represent static entities in time but are in constant flux under the influence of control parameters and their underlying generating structures. Accordingly, changes in one site of the structure can lead to changes in the interaction patterns of elements of the attractor and yet do not necessarily imply changes in global behaviour. Through this mechanism it is possible to ensure that a particular task goal is met while at the same time providing necessary adaptability, thereby yielding an elegant solution to the juxtaposition of adaptation and stability. Again, self-organization and the slaving principle serve as the integrative forces generating the morphological structures and establishing synergies. Saltzman and Kelso (1987) showed how under the dynamical systems framework these synergies can be assembled in a task-dependent manner thereby incorporating Bernstein's notion of task-dependent integration.

Finally, the notion of topological structures can also be well captured by the dynamical systems theoretical approach. As shown in the case of the finger flexion-extension task the very topological arrangement of the movements of the fingers which was represented by the relative phase resembled the collective variable that governed behaviour. Thereby the actual parameterization of the movement changed, e.g. the amplitude decreased with increasing movement frequency (Haken et al., 1985), but nevertheless the global appearance of the movement stayed constant. As will be shown in the next section this movement variable is found in many contexts in various effector systems, further strengthening its characterisation as a topological structure.

To summarise thus far, the synergetics or dynamical systems theoretical approach to human movement provides a potentially informative theoretical framework well suited to answering problems in movement coordination and control with the potential to integrate some of the key issues of movement coordination. Hence, pursuing further research using the dynamical systems theoretical framework as a worthwhile enterprise which provides the necessary rationale for using this specific framework as the theoretical underpinning for the present work. An overview of empirical studies relating dynamical system theory to human movement will be provided in the next section. This overview is by no means exhaustive and focuses mainly on work which will be related to the development of the research questions underpinning the line of work presented in this programme (see Kelso, 1995 for a broader overview).

Perception and Coordination

Through inclusion of ideas from ecological psychology into an overarching theoretical approach with dynamical systems theory further modelling of perceptual mechanisms became possible providing a direct link between perception and coordination. A seminal study investigating coordination between persons was undertaken by Schmidt, Carello and Turvey

(1990). They were able to demonstrate that the same nonlinear dynamics governing coordination within a single participant also applied to coordination between people. In the experiment two participants were seated opposite to each other and were instructed to swing one of their lower legs whilst watching the legs of the other person. Movement frequency was the postulated control parameter. When participants started with an alternating anti-phase pattern and the movement frequency was increased a switch to the symmetric pattern, the in-phase pattern occurred. Measuring the standard deviation of the relative phase between the legs the authors found an increasing instability of the movement as well as hysteresis. These results lead the authors to conclude that the switch between the two patterns resembled a phase transition (Schmidt et al., 1990, p.245).

Another study investigating perception-action coupling was conducted by Sternad (1998). The author used a ball juggling task and showed that through a direct linkage between action and perception in terms of a nonlinear dynamical system, regulation of the movement could be explained. Participants were instructed to bounce a ball with a racquet whilst keeping the ball's amplitude constant. The system was modelled using a differential equation approach. The model showed that the perceptual information interacted directly with the dynamics of the coordination task. The participants were able to discover the stability properties of the task and exploit these in order to ensure task achievement. Using different bouncing heights, Sternad (1998) was able to demonstrate the generality of the underlying system which was held invariant over different conditions exhibiting *"motor equivalence"* (Sternad, 1998, p.324).

In a follow-up study to the ball juggling task experimental results indicated a differential effect connected to performance level where skilled performers were better in exploiting the stability regions compared to novices. When decoupling the haptic information from the movement by using a lever to perform the bounce the performer fell into more unstable regions of the system indicating that haptic information is necessary to uncover the stability properties of the task. The same change was not observed when participants were deprived of visual information (Sternad, Duarte, Katsumata, and Schaal, 2000).

Further support for increased stability based on perceptual information was found in a study investigating the influence of visual information in a circle-drawing task. However, whereas increasing temporal movement stability was found when participants were offered a congruent visual stimulus the spatial performance was unaltered (Byblow, Chua, Young, and

Summers, 1999). The participants were asked to perform a circle-drawing task where movement directions of both hands were altered similar to the anti-phase and in-phase movements in the HKB-task. Results further indicated an *”anisotropic”* coupling between the hands where the non-dominant hand was stronger coupled to the dominant as in the opposite direction (Byblow et al., 1999, p.284).

Byblow, Carson and Goodman (1994) used a wrist pronation and supination task to investigate the influence of the timing of information on movement coordination. They used the term *“anchoring points”* in order to capture the phenomenon that the provision of *“essential information”* is confined to critical phases (p.6). The movement was executed bimanually with both hands. In the self-pace trials increased movement stability was observed when the additional information was provided during certain movement phases, supporting the notion of anchoring points. Subsequently, participants were instructed to either synchronize supination or pronation with a metronome tone. When synchronizing the pronation movement lower levels of movement variability were found compared to supination synchronization. The authors interpreted these results as indicative of different neuromuscular constraints on movement stability where different muscles show differential stability properties. Further, using a scaling approach, participants demonstrated highest stability during in-phase pronation movements and exhibited switching behaviour from anti-phase to in-phase movements. However, investigating stability prior to the transitions the authors were not able to identify critical fluctuations. The authors provided two possible explanations for the lack of critical fluctuations based on the peculiarities of the task. First, the participants were not only instructed to synchronize the movement with the metronome but with specific phases of the movement thereby imposing additional task constraints possibly altering the stability properties of the task. Second, in special cases, a variation of the time scale relations introduced earlier (compare equation 2.1) may be present. Assuming the time scale of control parameter change t_p is much higher than τ_{rel} and τ_{equ} leads to the following relation:

$$t_{rel} \ll t_{equ} \ll t_p \quad (2.5)$$

In this case the switching behaviour does not exhibit critical fluctuations because the equilibration time of the system is small compared to the t_p and therefore the system can settle into the new attractor without the loss of stability of the preceding state (Byblow et al., 1994, p.25). However, no investigations into parameter estimation of the time scales was conducted in this study and no further indication why the proposed time scales relationship should be present was provided.

A study investigating the influence of haptic information used a finger flexion-extension task. Kelso, Fink, DeLaplain and Carson (2001) found a differential effect of perceptual information on movement stability. Participants were instructed to either synchronize peak flexion or peak extension with a metronome tone. Haptic information was provided through padded stoppers which constrained the movement range of the fingers. When the haptic information was provided synchronous with the auditory tone the movement exhibited higher stability compared to when haptic information was syncopated with the auditory tone with increasing movement frequency indicating that critical phases for information provision exist.

The findings from the different studies presented so far highlight the importance of perceptual phenomena in shaping actual movement behaviour and how information from the environment can be utilized in order to control movements and alter stability properties. In this way information acts in the same domain where the attractors reside. Thus, the dynamics of the system can be captured by a single unified description. Through this theoretical description, information can be used by the system to guide behaviour by constraining system degrees of freedom. However, this relationship is by no means simple since for example as has been shown in the study made by Byblow et al.(1999).

A study conducted by Mechsner, Kerzel, Knoblich and Prinz (2001) showed that in some tasks the perceptual effects can provide the main source of pattern stability. Participants were instructed to rotate two vertical handles either in-phase or anti-phase. The handles were attached under a table and participants could only view the movement through two rotating pointers which were attached to the top ends of the handles above the table. When the pointers rotated synchronous with the handle movement the typical switch from anti-phase to in-phase movements with increasing movement frequency could be observed. However, when the pointers were primed to rotate in an anti-cyclical manner to the actual handle movement, no transitions could be observed when participants performed actual anti-phase movements with an apparent in-phase movement of the pointers. In contrast, during in-phase movement of the handles resulting in anti-phase movements of the pointers phase transitions to in-phase of pointers were observed. The authors interpreted the result as indicative of movement stability being less dependent on processes in the motor system and neuro-anatomical constraints but more on perceptual phenomena for this task (Mechsner et al., 2001, p.72). In response to this claim Carson and Kelso (2004) noted that it seems very unlikely that a singular domain should be the sole determinant of coordination and that it is rather the integration of perceptual, cognitive, and physiological phenomena which governs coordination. Hence, in the following section the influence of neuro-anatomical constraints on movement coordination from a dynamical systems perspective will be investigated.

Neuro-anatomical constraints

Beside the line of research investigating perceptual influence several studies have investigated the influence of neuro-anatomical constraints on movement behaviour from a dynamical systems perspective. In a variation of the wrist pronation-supination movement models, Carson (1995) investigated phase-transitions behaviour in self-paced trials and scaled frequency trials. Participants were instructed to perform supination-pronation movements using fixed manipulanda, resulting in isometric force production task (Carson, 1995). Participants had to synchronize the movement with a metronome either during the pronation or supination phase of the movement. In anti-phase mode the relative phase showed brief departures from the prescribed pattern with increasing movement frequency however no complete phase-transitions were observed. The relative phase showed higher stability during the in-phase movements corroborating the results from preceding experiments (see previous sections). Regarding the differences in torque between anti-phase and in-phase movement the former showed lower levels and higher variability in magnitude and frequency. For the in-phase condition, differential effects were observed between movements where either the supination or the pronation was synchronized with the metronome supporting the notion of anchoring points during movement execution (Carson, 1995).

Another variation of the wrist movement model investigated the influence of the position of the pivoting point in freely moving manipulanda using wrist supination-pronation movements (Carson, Riek, Smethurst, Pàrraga, and Byblow, 2000). Through variation of the pivoting point which affected the arm muscle geometry in the participants the authors introduced different task constraints between the conditions. In a first experiment, participants were instructed to either synchronize the maximal extension of the movement or the maximal flexion with a metronome. The results indicated a differential effect on movement stability which was contributed to the influence of the musculo-skeletal arrangement (Carson and Riek, 1998). Investigating the influence of wrist rotation on the stability in uni-manual flexion-extension movement of the right index finger Carson and Riek (1998) found further support for the influence of neuro-muscular geometry on pattern stability.

The application of the principles derived from the HKB-Model has not been confined only to the study of similar effector systems. There have also been various studies with different effector combinations used.

For example, Kelso, Buchanan and Wallace (1991a) investigated the coordination of synchronous movements in the elbow and wrist using the scaling paradigm. Participants were instructed to either coordinate elbow flexion-extension movements with wrist flexion-extension movement or elbow extension-flexion movements with wrist flexion-extension movements. Additionally the movement was to be performed either with the hand supinated or pronated. Results indicated a differential effect of the hand position on movement stability. When the hand was supinated with increasing movement frequency a switch from wrist-flexion/elbow-extension to wrist-flexion/elbow-flexion occurred. Whereas when the wrist was pronated the exact opposite behaviour was observed. Investigations into the movement path of the wrist exhibited that regardless of the underlying movement pattern with increasing movement frequency the wrist path changed from a more linear to a curvilinear pattern. The authors interpreted their findings also from a neuromuscular point of view where the different wrist positions lead to different signalling patterns (Kelso et al., 1991a).

In a similar realm Serrien and Swinnen (1997) investigated rhythmical coordination between the arms. The results showed that phase locking between the limbs was higher when homologous limbs were used compared to non-homologous limb combinations. Using a 2:1 frequency locking, higher variability was apparent during homologous limb motion compared to homo-lateral and cross-lateral motions. The authors interpreted these findings based on the different eigenfrequencies of the limbs which made deviations from a 1:1 phase relation easier. This indicated a stronger phase locking between homologous limbs (Serrien and Swinnen, 1997, p.1501), again highlighting neuro-anatomical constraints on movement coordination although this has yet to be confirmed.

Behavioural information and intrinsic dynamics

So far, the studies reviewed in this chapter have not been as concerned with the fact that human movement is influenced by the intentions of the actor. Schöner and Kelso (1988b) provided an operationalization which integrated intentions into the dynamical systems framework through a formal model. Intentions were conceptualized as *"behavioral information"* (p.506) describing in the broadest sense information which is meaningful and specific to the task. Behavioral information thereby includes information present in the environment, as introduced earlier, or memorized information acquired through learning. The information acts at the level of order parameters and can change or perturb the attractor layout. Intentional information under this view is conceptualized as an *"intended behavioral pattern"* (p.507) perturbing the attractor layout towards the desired pattern. Order parameter dynamics in the absence of behavioral information are captured by *"intrinsic dynamics"* (p.506). Intrinsic dynamics and behavioral information can therefore stand in either competitive or cooperative relations with each other. The authors provided support for their formalisation through a study where intentional switching between in-phase and anti-phase movements in a finger flexion-extension task was investigated. The results showed shorter times when switching from anti-phase to in-phase in contrast to the opposite direction. When participants were instructed to intentionally resist the phase transition from anti-phase to in-phase with increasing movement frequencies, the authors observed decrements in movement variability. The behavioral information was used to stabilize the intrinsic unstable movement pattern. These findings could be replicated using a wrist supination-pronation task (Carson, Byblow, Abernethy, and Summers, 1996) and elbow-elbow and elbow-knee flexion-extension task (Serrien and Swinnen, 1999).

The notion of intrinsic dynamics provided the necessary prerequisites for including learning processes into the dynamical systems theoretical framework. In order to experimentally investigate intrinsic dynamics a new experimental methodology was introduced termed 'scanning procedure' (Zanone and Kelso, 1992). Using a finger flexion-extension task Zanone and Kelso (1992) investigated learning of a 90° offset pattern between both hands. During the scanning procedure participants had to perform movements covering all phase relationships between 0° and 360° of the fingers. Plotting movement stability against the phase yielded a stability landscape. This landscape provided a summary of the stability properties of the intrinsic dynamics of each individual performer (Zanone and Kelso, 1992). The scanning procedure was conducted before, during and after the learning phase in order to provide information of how the stability landscape is affected by learning the new task. The 'to-be-learned' 90° offset pattern was trained for five consecutive days. Results showed a change in the layout of the stability landscape. Yet, the changes showed inter-individually different paths indicating a dependency between the initial stability landscape and the individual learning process.

When a region of high stability was present near to the 'to-be learned' pattern, during the training period the stable region shifted towards the desired region and subsequently stabilized the new movement pattern. However, when the regions of stable movement were further away from the desired pattern an existing region was deleted and a new stable region was established at the desired location. The authors termed the former process as a cooperative strategy whereas the latter was termed a competitive strategy (Zanone and Kelso, 1992).

In order to probe the concept of competitive and coordinative strategies Zanone and Kelso (1997) conducted a follow-up study. Using the same task participants underwent the scanning procedure and consecutively based on the individual stability properties were instructed to learn individually different patterns. The results corroborated the notion of competitive and cooperative strategies. In addition, the authors were able to show transfer of learning to a new movement pattern. Together with the desired pattern a mirror pattern offsetted by 180° was stabilized as well. The authors identified this as a spontaneous transfer of learning (Zanone and Kelso, 1997, p.1474). Seeking to generalize the transfer findings Kelso and Zanone (2002) investigated a flexion-extension task with the elbow and the knee. The results indicated that stable phase relations learned in one effector system which were initially unstable in the other effector increased their stability after training, supporting the notion of transfer of learning.

Extending upon these findings, Kostrubiec and Zanone (2002) investigated the connection between the movement variability and movement outcome based on memory mechanisms. The task consisted of a wrist pronation-supination movement using a joystick (Kostrubiec and Zanone, 2002). The authors hypothesized the presence of a metric on the stability landscape based on the phase distance between movement patterns in phase angles. The distance between an existing and a desired patterns was related to the two learning regimes where competitive regimes were expected with high distances and the cooperative regime with low distance. Using the probing procedure, distances between movement patterns for the participants were established. The authors assumed that for the cooperative regime the movement could be based on existing more similar memory structures which should affect the stability and accuracy of the pattern as opposed to the competitive regime where new structures have to be established (Kostrubiec and Zanone, 2002).

The interaction of the patterns with memory structures was analyzed through measurement of the persistence of the movement patterns without support of an external stimulus. A synchronized light stimulus was provided at the beginning of the trials which was withdrawn during the trials and the participants had to perform the newly trained patterns from memory. For the competitive regime the stability and accuracy of the patterns were lower compared to the cooperative learning condition and the movement deteriorated soon after withdrawal of the light stimulus supporting the expectations (Kostrubiec and Zanone, 2002).

Kostrubiec, Tallet and Zanone (2006) performed another study which investigated the persistence of a newly learned movement pattern. The same movement model was used and participants had to acquire movement patterns under either the cooperative or the competitive regime. The authors expected performance in a retention test to show differentiated responses for the two regimes. The authors hypothesized that under the cooperative regime where only a shifting of existing stability regions occurs the change would be transient as opposed to the competitive regime where a new region has to be developed yielding a more permanent change in memory structures. The results showed higher movement stability for the competitive pattern compared to the cooperative patterns during a retention test after three weeks supporting the model. Further, the cooperative regime the authors postulated the possibility that this strategy formed the necessary prerequisite for fast changes based on contextual changes which are not covered by learning but immediate adaptations to task requirements (Kostrubiec et al., 2006).

However, regarding the two regimes some contradictory findings have also been observed. In a study using pronation-supination movements of both wrists (Smethurst and Carson, 2001), participants trained 90° out-of-phase movements and no destabilization of the 180° pattern could be observed questioning the competitive regime. The authors argued that the competitive regime might be related to the very structure of the probing task. Participants had to voluntarily destabilize the momentarily executed pattern in order to achieve the different phase relationships during the scanning task. Therefore, the competitive regime might be a result of the procedure (Smethurst and Carson, 2001). Further experimentation is needed to investigate to what extent intrinsic dynamics and learning are linked to each other and whether a task-dependence exists.

Investigating the stochastic HKB-Model Post, Peper, Daffersthofer and Beek (2000b) raised the issue to what extent intrinsic and intentional dynamics could be regarded as separated from each other. Investigating in-phase and anti-phase movements in the elbow the authors estimated the different parameter of the model using a mechanical perturbation. Only participants who were able to produce both movement patterns without phase transitions over the complete frequency range were included in the study. Surprisingly, when estimating the parameters the authors found higher attractor stability for the highest frequency for the anti-phase pattern, but only when using group data, whereas the individual data showed high variations. The authors attributed this deviation from the model to the intentions of the participants which can apparently lead to strong changes in the attractor layout (Post et al., 2000b).

Putting aside the methodological difficulties in regards to segregation of intrinsic dynamics and behavioural information experimentally, the concepts discussed above highlight the individual character of movement coordination. Behavioural information as intentionality raises the issue of how to measure intentions experimentally, which at present is only possible based on specific assumptions made by the experimenters. Under this view coordination solutions to specific tasks will always be influenced by the individual histories of the performers represented by their intrinsic dynamics. It could be postulated that in a task where more degrees of freedom in movement choice are present, such as multi-articular actions, different task solutions are more likely to emerge.

Multi-articular actions

So far this review has focussed on either uni-manual or bi-manual movement models. The analysis of movement from a dynamical systems theoretical perspective has not been confined to these models but has been extended into the domain of multi-articular actions. These actions have been investigated to a much lesser extent and only incomplete support for all principles associated with bimanual movement has been found as noted below.

A multi-articular action in the present work is defined by a movement which involves more than two joints at the same time. This is based on the observation that for these models the segment movement cannot be captured by the traditional relative phase measure. In the following section several studies will be presented highlighting some of the results and issues observed using these movement models.

Buchanan, Kelso and de Guzman (1997) further investigated the elbow-wrist movement model used by Kelso et al. (1991a). Participants were instructed to perform curvilinear motions with the hand at constant movement speed. The motion was to be matched with a reference path provided online on a computer screen in front of the participants. Six different reference curves with varying curvatures were used which served as the potential control parameters. Path length was held constant between curvature conditions. Based on the ranges of motion of the wrist and shoulder, different movement patterns with varying curvatures were observed. Relative phase measures between the wrist and elbow indicated critical fluctuations in the vicinity of the transition. The results lead the authors to conclude that: (i) the pattern was based on self-organization processes; (ii) that the activation and respective suppression of involved joint degrees of freedom served to stabilize or destabilize the system; and (iii), that the curvature served as a control parameter (Buchanan, Kelso, and deGuzman, 1997; Fink, Kelso, Jirsa, and de Guzman, 2000). Subsequently, the authors were able to model the movement based on a nonlinear coupled oscillator model (DeGuzman, Kelso, and Buchanan, 1997).

Kelso and Jeka (1992) investigated movement coordination using a flexion-extension task but this time in concordance with parallel motions in the knee and elbow joints. Participants were seated in a chair with arms and legs were attached to levers permitting only flexion and extension movements in the arms and the legs. The dependent variable was the relative phase between the different limb pairs. The authors grouped the movement patterns according to the common movement direction as either D-mode were limbs were moving in opposite directions, and S-mode were the limbs were moving in the same directions. Phase transitions with increasing movement frequency were mainly identified from D-mode to the S-mode, with the S-mode showing higher stability. The transitions were always accompanied by increasing movement variability indicating loss of stability as the triggering mechanisms for phase transitions which was initiated mainly by the arm movements (Kelso and Jeka, 1992). At the highest frequency, the relative phase showed a phase wandering where no stable coordination pattern between the limbs could be established although the authors were able to show that the time spent in the vicinity of pre-existing stable movement patterns was longer, exemplifying an intermittency effect. These results were corroborated in a follow up study which showed that the muscle activation pattern influenced the transitions, with the majority of transitions following a non-homologous to homologous muscle activation pattern route (Jeka, Kelso, and Kiemel, 1993). Phase transitions were accompanied by increased movement variability. However, after the transition variability was maintained at a high level and did not relax back to the initial levels.

A somewhat different task from the preceding examples was investigated by Limerick, Shemmell, Barry, Carson, & Abernethy (2001). The authors used a cyclical lifting task where participants were instructed to lift a weight of 1kg onto different heights between 10 and 50 cm with the height changing systematically in both directions. The task can be considered different from the preceding task inasmuch as the task is rhythmical but does not follow a strict sinusoidal rule unlike most of the tasks introduced earlier (i.e., a concatenation of several interlinked movements). Based on the kinematics of the lower limbs the authors identified two different movement patterns: a squat pattern and stoop pattern. The two patterns are different in terms of the ranges of motion of the ankle, knee and joint angles as can be seen in Figure 2-4.

When the lifting height was varied 9 out of 11 participants exhibited switching behaviour between the two patterns. In general, the main route taken was switching from the squat pattern to the scoop with increasing height and in the opposite direction with decreasing height. Inter-individual differences were apparent with some participants exhibiting abrupt changes between the patterns whereas others presented a longer transition period using intermediate movement patterns.

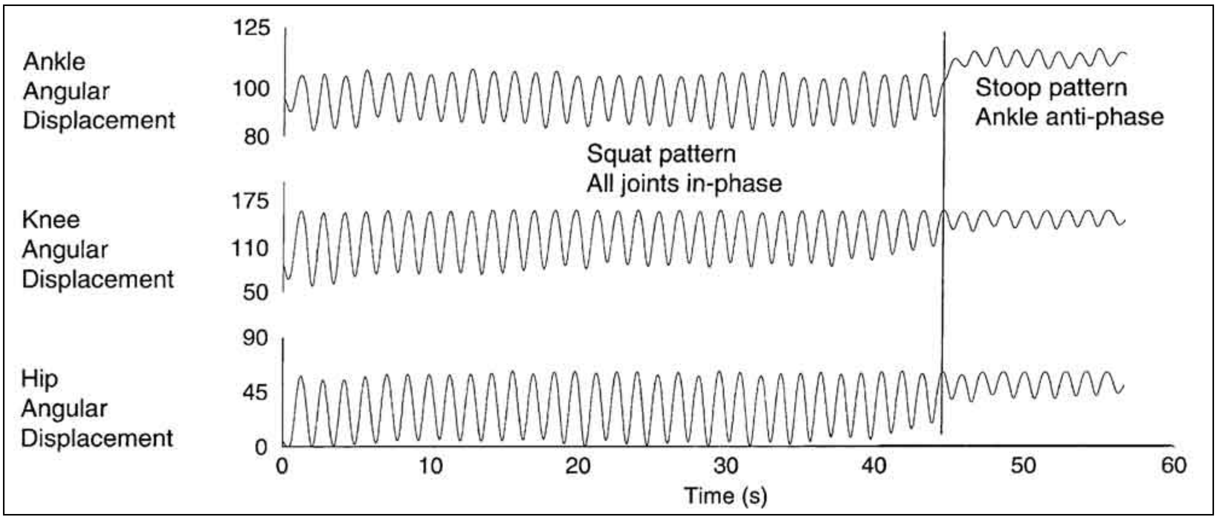

Figure 2-4: Ankle, knee, and hip kinematics during a complete trial of cyclic lifting and lowering. Adapted from Limerick et al. (2001, p.55)

The individual scoop and squat patterns showed differences between the participants where individual different ranges of motion in the knee could observed. The occurrence of the transitions exhibited a dependency with the direction of the height change where the switch from the squat to the stoop pattern occurred at a later height with increasing height compared to the condition where the height was decreased. The authors interpreted this finding as a hysteresis effect (Limerick et al., 2001, p.559).

Li, Levin, Cordero and Swinnen (2005) investigated coordination within- and between-arms using a rhythmical flexion-extension movement paradigm. Participants were instructed to perform several different movement patterns including anti-phase and in-phase movements between and within arms resulting in eight different movement patterns. All movements were performed at a frequency of 1.33Hz. Results showed higher movement stability when the elbow and wrist were used in the same direction compared to opposite directions and higher stability when movements between limbs were prepared in in-phase compared to anti-phase corroborating the findings in the four-limb task (Jeka et al., 1993). Movement variability between joints was lower in the elbows compared to the wrist. When participants performed anti-phase movements with the wrist, movement variability was lower when elbows were also prepared in an anti-phase manner compared to in-phase which indicated an interaction effect between the joints (Li et al., 2005). Overall the wrist played a higher role on movement variability than the elbow. The authors interpreted the results as indicative of a hierarchical organisation of the limbs with higher contributions of between limbs effects over intra-limbs effects and distal over proximal in intra-limb effects.

In an effort to provide a classification scheme which incorporates multi-articular as well as unimanual movement Newell, Liu, & Kress (2001) developed a hierarchical three-tier model of movement organization using dynamical systems perspective. The highest level describes macro phenomena representing the spatial-temporal outcome of the behaviour. The middle level describes mainly the dynamics of the segment kinematics whereas the lowest level describes behaviour of the underlying subsystems. The different levels are coupled with each other and usually the time scales of the levels get shorter from the higher towards the lower level (Newell et al., 2001, p.62). Using this classification scheme, most of the studies presented so far can be categorized by movement models where the middle and the top level are the same. The task outcome is equivalent to the actual movement pattern or rather the task outcome already prescribes to some extent the underlying movement pattern (Hong and Newell, 2006). This distinction is potentially of great importance, since based on Bernstein's

(1967) definition coordination is mainly challenged by the redundant degrees of freedom. When the two levels are equal the redundancy at least at the joint level is already somewhat reduced rendering this movement type as a special case. In this regard, the decoupling of the two levels potentially introduces another level of complexity where a specific task outcome can be achieved using various different redundant movements at the second level.

Conceptually, the term redundancy commonly refers to the fact that the same functionality can be provided by various structures of the same type which does not capture the actual circumstances in neurobiological systems. Usually, in neurobiological systems same functionality can only be achieved by structurally different components. For example a person can pick up a cup with either hand. Although both hands are similar they are not structurally equal. As has been noted by Edelman (1987) this strategy provides a robust mechanism against system failure and is common to biological systems. He termed this strategy "degeneracy" in order to separate it from redundancy. Degeneracy is defined as:

> *"[…] degeneracy is reflected in the capacity of structurally different components to yield similar outputs or results* (Edelman and Tononi, 2000, p.86)*"*

Degeneracy could be identified in various domains including the immune system (Edelman and Gally, 2001), embryogenesis (Edelman, 1988), neuronal organization in the central nervous system (Edelman, 1987; Sporns, Tononi, and Edelman, 2002; Tononi, Sporns, and Edelman, 1999) and motor control (Edelman, 1987; Sporns and Edelman, 1993) supporting its generality in neurobiological systems.

Directly investigating degenerate processes Chen, Liu, Mayer-Kress and Newell (2005) studied skill acquisition in a pedalo-locomotion task. Four participants trained 50 trials a day for 7 days. The authors operationalized the movement time and the smoothness of the movement as performance variables. When correlating the performance variables with a measure of the differences between successive movement trials the authors were not able to identify a significant correlation. The findings were interpreted as apparent degeneracy in the movement system where similar performance output can be achieved by varying movements (Chen, Liu, Mayer-Kress, and Newell, 2005). This finding could be further corroborated in a learning study using a ski-simulator task (Hong and Newell, 2006) highlighting that, when the possibility for further movement adaptations is present, the neurobiological system is able to take advantage of additional degrees of freedom.

In summary, studies that have interpreted multi-articular actions from a dynamical systems perspective show that coordination changes do not follow such a straight forward trend like in the uni-manual and bimanual cases but rather complex interaction effects between the different segments dynamics can be expected. Therefore, the simple bimodal attractor landscape described in the studies presented earlier may be merely a result of the specific task chosen and potentially is not present in multi-articular actions. Since in this movement the possibility for much more individually shaped behaviour is present it therefore seems likely that performers are able to take advantage of this inherent degeneracy and present much richer adaptation strategies between and within individuals. However, at present only limited knowledge and data is available.

Discrete movements

The research discussed thus far can all be categorized as employing rhythmical movements which represent the main movement model investigated from a dynamical system perspective. In contrast discrete movement types have not received attention to the same extent (Beek et al., 1995; Schöner, 2002; Summers, 1998). This is a surprising observation since Schöner (1990) provided a theoretical treatment of coordination of discrete movements under the dynamical systems framework although this has not been seriously investigated. In the following the model will be introduced shortly and some issues will be highlighted before some studies will be presented.

Regarding the theoretical modelling of discrete movements Schöner (1990) postulated that discrete movements represent a limit case of cyclical movements, a view which has been recently renewed (Jirsa and Kelso, 2005). Based on this notion he constructed a model involving two postural states, one initial posture and one final posture, which are represented by point attractors. Through intention (behavioral information) a limit cycle attractor can be generated within the system connecting the initial state and the end state with each other. Destabilizing the initial attractor leads the system to follow the limit cycle attractor and after half a period the final attractor is stabilized, onto which the system relaxes yielding the desired discrete movement. Intentions therefore form a crucial part of the model (Schöner, 1990, p.259). Coordination in this model deals with the timing of different components. Using this notion Schöner hypothesized that sequential and synchronous timing of the joints might constitute the discrete analogy to anti-phase and in-phase rhythmical movements.

However, analysis of discrete movement faces several characteristic issues. For example in order to measure time scale behaviour of movement which is necessary to estimate order parameter properties some strong differences between discrete and rhythmical movements need to be present. In the rhythmical case the movement stability can easily be measured because the movement time is usually longer than the typical relaxation time τ_{rel}. However, because of the nature of discrete tasks after a perturbation the system can only relax back to the unperturbed state when the relaxation time scale is sufficiently short compared to the execution time t_{exec} of a single trial. Hence, in order to estimate τ_{rel} in the same manner as in the rhythmical case the following relationship must therefore hold true ($t_{perturb}$:= time instant of perturbation).

$$\tau_{rel} < t_{exec} - t_{perturb} \quad (2.6)$$

In most common cases (e.g., throwing) discrete movements will already be finished before returning back to the initial state. Hence, *"pattern fluctuations cannot be used to measure stability"* (Schöner, 1990, p.264) as in the case for continuous rhythmical movement. In order to assess movement stability nevertheless Schöner (1990) recommended investigating inter-trial variability as a substitute measure.

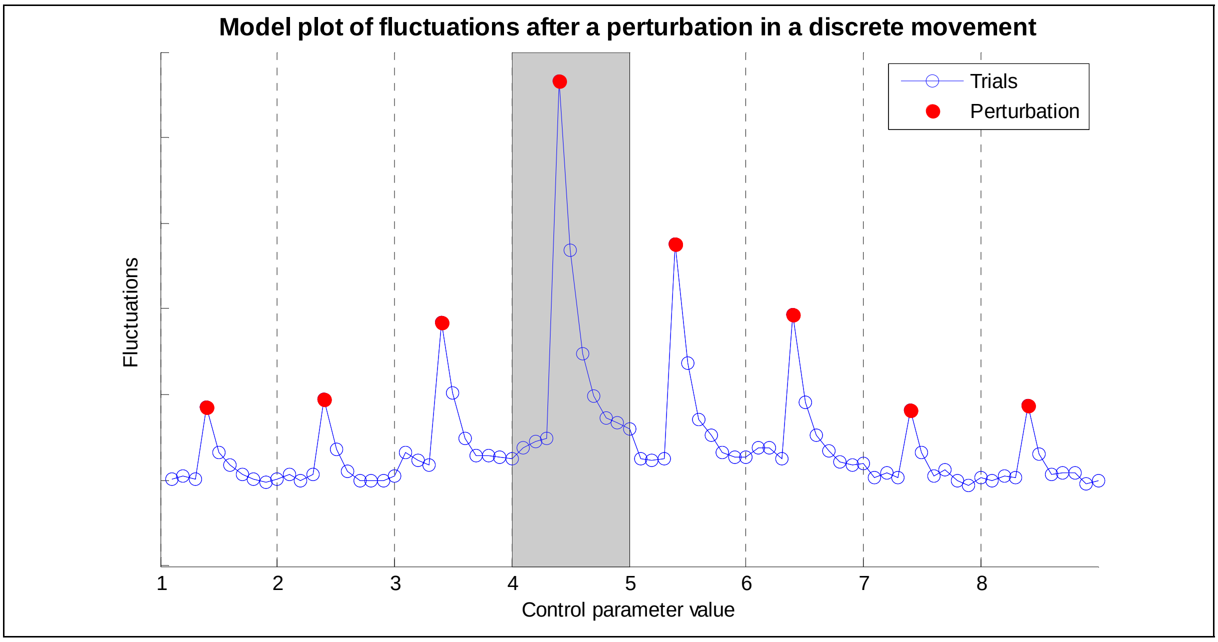

Figure 2-5: Model plot of fluctuations after a perturbation in a discrete movement.

Figure 2-5 represents a hypothetical model plot of the fluctuations according to this proposition. After each perturbation several trials are needed in order to relax back to the initial level of fluctuations. Thereby, the control parameter is held constant for several trials. Whereas at the beginning in the pre-transition area only a small number of trials is needed. When reaching the transition area (grey shaded area) the level of fluctuations increases and accordingly τ_{rel} increases translating into increased number of trials needed to relax back to the pre-perturbed base-line. Subsequently when the system exists in the transition area, τ_{rel} becomes smaller again and accordingly the fluctuations and the needed number of trials return to the initial level. However, the development of Schöner’s proposition has not been experimentally investigated yet.

Conceptually discrete movements form another challenge to the dynamical systems theoretical perspective, describing phase transitions between attractors as a trajectory between different loci in the system state space. For a rhythmical movement switching from one attractor to another cannot be achieved between consecutive trials since this would imply a discontinuous change in the attractor function leading to infinite acceleration in attractor space which is not possible for a biological dynamical system (Newell et al., 2001). However, in a discrete movement switching between attractors in consecutive trials is theoretically plausible because for a discrete movement after termination of the movement the system has to go back to its initial state in order to perform the subsequent trial. During this period, behavioural information gained from the just finished movement can be used to adapt the intrinsic dynamics. In turn, this potentially leaves the initial conditions in regards to the body posture unaltered but subsequently leads to a different end posture yielding a different movement pattern (compare Liu, Mayer-Kress, and Newell, 1999; Scholz and McMillian, 1995 for examples; Scholz, Millford, and McMillan, 1995).

Regarding common experimental procedures, information about the system’s state is always lost between subsequent trials since analytically trials are usually recorded from the beginning to the end where recording stops. For the recording of the subsequent trial the system needs to be set back to the initial state thereby going through a relative void where the mentioned additional influence may affect the subsequent behaviour unnoticed by the experimenter.

Nevertheless, dynamical systems theory has been applied to discrete movement models. Using a table-tennis movement model Sorensen, Ingvaldsen and Whiting (2001) tested some of the proposition made by Schöner (1990). The authors assumed that the spatial position of the ball served as a potential control parameter and the distance of the racket from the edge of the table resembled a kinematic collective variable as well as the type of stroke (forehand or backhand). The ball was delivered by a projection machine to positions between the right and left end of the table. Two different condition were applied: (1). The location of ball delivery was scaled from left to right and right to left, and (2.) random locations of ball delivery. The participants were instructed to return the ball to a fixed position for all trials. The starting distance from the table and the starting posture was standardized. The results indicated a switching behaviour from the backhand to the forehand pattern depending on the ball delivery. Further, the switching point was different in two directions in condition one indicating a hysteresis effect. Based on the different transition points the authors defined a *"hysteresis area"* (Sorensen et al., 2001, p.31). The switching in stroke behaviour was also present in the results for the racket-table distance which showed either sudden increases or decreases. However, one participant did not exhibit these sudden changes and used the same distance for both stroking patterns. Comparing the movement variability during the stable extreme positions with the movement variability in the hysteresis area results showed higher variability for the forehand stroke but not for the backhand stroke. During the random condition the same outcome was obtained when compared to condition one over both directions (Sorensen et al., 2001). The authors concluded that the results provide evidence that the approach derived by Schöner (1990) is capable of accommodating for the movement model used. However, they pointed out that the issue of instabilities is not sufficiently addressed because no critical slowing down based on perturbation could be investigated.

Button, Bennett and Davids (1998) conducted a study investigating differences in discrete and continuous movements in a reaching task. Participants were instructed to perform grasps between two dowels set at a specific distance. In the rhythmical condition the movement had to be synchronized to a metronome whereas in the discrete condition the movement was to be accomplished within a specific movement time which was matched to the movement times from the continuous condition. During a scanning procedure participants were instructed to adjust their final hand closure at different marked points along the distance between the two dowels. The point of final closure was systematically increased. Pre- and post-tests were conducted without any spatial instructions where participants self-selected the point of final closure. The results showed significant differences between the discrete and the rhythmical conditions. When comparing the self-selected with the most stable scanning condition the differences were higher for discrete compared to rhythmical movement. The scanning procedure during the discrete condition predicted in 4 out of 6 participants different preferred distances compared to the self-selected condition. An effect that was not observed during the rhythmical condition. The authors concluded that the organization of discrete and rhythmical movements appears fundamentally different (Button et al., 1998).

A second study from the same authors (Button, Bennett, and Davids, 2001) investigated the differences between discrete and rhythmical movement using the same task when no spatial constraint were imposed on the final hand closure but the movement time was changed in a scaling fashion allowing the movement to adapt spontaneously. No phase transitions between different patterns were found as well as no differences between the two conditions. The authors interpreted the result as supportive of Schöner's (1990) model in contrast to the preceding study. However, both studies assumed the time of relative final hand closure as a potential order parameter. At present it is not known whether this assumption is valid and accordingly whether the findings really relate to the used concepts.

Another study investigating a reaching and grasping task was conducted by Kelso, Buchanan and Murata (1994). The task included a bar which was prepared at specific angles with the horizontal line on a vertical clock face. Participants were instructed to rotate the bar back to the vertical twelve o'clock position. Based on the observations during the experiment the authors defined two different movements strategies: a forward projection with pronation of the wrist and a forward projection with supination of the wrist (Kelso et al., 1994, p.71). Based on the results the authors were able to identify two critical regions where the coordination was bistable showing the choice for one strategy depended on the preceding angle of preparation. The result was interpreted as a hysteresis effect supporting the findings made by Sorensen et al. (2001) in the table tennis task.

Lames (1992) investigated switching behaviour in golf swings due to changes in target distance in one participant. The author operationalized the relative timing of upswing and downswing as the coordination variables. Distances were changed between 10m and 100m in increments of 10 in either increasing or decreasing direction. The authors classified the movement patterns using a cluster analysis. The results indicated three different patterns which could be identified: a chip, a pitch and a full-swing. When starting from 100m at 90m distance the pattern switch from full-swing to pitch and remained in this pattern until 20m, with one erroneous full swing attempt at 65m. At 20m distance the participant changed to a chip strategy. However, when starting from 10m the switches occurred at 30m and at 70m indicative of a hysteresis effect (Lames, 1992).

Some investigations into discrete movements have been conducted using throwing tasks. Southard (1998) investigated changes in throwing patterns of the arm due to enforced changes in segment mass of the upper arm and changes in throwing velocity. Segment mass was altered by attaching additional mass to either the upper or lower arm, or the hand by using a heavier ball. The author modelled the throwing movement as an open kinetic-link in the throwing limb where positive segment lag of distal over proximal segments leads to a whipping like movement which is regarded as an optimal technique. Segment lag was defined as the difference of relative time to peak velocity of the according segments. Southard postulated lag as a potential order parameter and the throwing velocity and segment mass as potential control parameters. Using the model participants were rated on a four level scale according to exhibited segment lags between trunk, upper arm, lower arm, and hand. The author observed a better performance of weaker throwers either with increasing throwing velocity or addition of mass to proximal segments. Conversely, the added mass deteriorated performance for better throwers (Southard, 1998). Regarding the justification of segment lag the author failed to provide strong support for this assumption. Some changes between segments lag were accompanied by fluctuations in lag measure but not all of them. No investigations into time scale behaviour were performed and hysteresis was not shown since only scaling in one direction was performed.

In a follow-up study with children, Southard (2002) investigated in more detail how changes in throwing velocity alter movement patterning. Participants were grouped into four different skill levels and their individual maximum throwing velocities (v_{max}) were determined. Participants performed throws between 10% and 100% of v_{max} in increments of 10%. Increasing the throwing velocity lead only for the two weaker groups to changes in coordination. The author observed lower variability for better skilled throwers compared to weaker throwers and changes in lag sequencing was accompanied by higher variability in some cases. Again, the author failed to provide comprehensive evidence supporting for the assumption of segment lag as an order parameter.

Another study investigating a throwing movement from a dynamical systems perspective was conducted by Liu and Burton (1999). They investigated the influence of shooting distance on movement patterns of 20 novice throwers in basketball. The authors propose the distance as a control parameter without providing sufficient evidence for this claim other than anecdotal proof. The authors varied the distance between 1.5m and 12m in steps of 1.5m in a randomized fashion. Each participant performed 20 shots from each distance. Additionally the authors included a condition where the participants pretended only to shoot from each of the according throwing distances. The analysis was based on two unsynchronized VHS-Video cameras from both sides. Remarking that at the time of experimentation no analysis methods existed which could identify differences in shooting form for the basketball shots (Liu and Burton, 1999, p.833) the authors assessed the shooting patterns using a nominal scale rating foot placement, trunk rotation, hand shooting height and jumping height. For example, release of the ball above head height scored a 3 whereas releasing from below chin scored a 0. No explicit kinematic data was collected. The authors concluded that they were able to identify phase transitions between different movement patterns which were accompanied in some cases by increasing fluctuations although no description of the actual measurement of fluctuations was provided. The transitions occurred at different distances in the two conditions. During actual shooting the transition distance occurred at a lower distance compared to the simulated shooting condition. Although showing some interesting results the study suffers from some severe short-comings. The authors were not able to provide any evidence that their measurement method was able to pick up any meaningful differences in shooting patterning. Accordingly, it was not clear whether the so-called transitions between different movement patterns described actual transition behaviour or whether they were the result of adaptation of a single movement pattern. The investigation into the stability or in dynamical system terminology of critical fluctuations was not sufficiently explained. Based on their randomized distance approach, the authors were not able to show any hysteresis. Regarding the participants used in the study, the authors noted that pattern stability was likely to be influenced by playing standards (Liu and Burton, 1999, p.833). However, the movement patterns showed *"remarkable stability in all body components across distance and conditions"* (Liu and Burton, 1999, p.838) which contradicted the assumption and possibly pointed towards an insufficient analysis methodology. In conclusion, although the result appeared interesting the authors failed to provide sufficient justification for their results.

In summary, in regards to discrete movement models the support of the dynamical systems tenets is by no means as broad as it is in the case of cyclical bimanual movements. This his been pointed out by several authors (Button et al., 1998; Summers, 1998) and accordingly *"studies of phase transitions in the context of discrete movements such as* *reaching and grasping have been few and far between"* (Wimmers, Savelsbergh, Beek, and Hopkins, 1998, p.245). The studies discussed provide only weak support for the tenets of dynamical systems theory for discrete movements whereas hysteresis effect has often been established, proof for the remaining phase-transition criteria has not been typically presented. The difficulty with discrete movement models is further exacerbated due to the insufficient methodological treatment of discrete movement in regards to pattern stability and the subsequent investigation into time scale behaviour (Schöner, 2002). At present no clear analysis method recommendations exist. In regards to the methodological approach in studies with discrete movements the range of proposed order parameter varies vastly in stark contrast to the rhythmical domain. Whereas in the latter case mainly variants of the initial in-phase-anti-phase model were used, for discrete movements concepts like segment lag, time-of-closure, or throwing posture compete as potential order parameters. Accordingly, in some cases it seemes unclear as to what the actual rational for the proposed order parameter were.

However, connecting these presented discrete movement models with the hierarchical scheme introduced earlier, most of the studies also exhibited a separation of the second and third level where segment kinematics were not prescribed by task requirements. Hence, potentially indicating high complexity in order parameter behaviour when degeneracy constraints are relaxed.

Limitations of the dynamical systems theoretical framework of movement coordination

The dynamical systems theoretical framework of movement coordination has not been unchallenged. As DST marks a serious departure from pre-existing theories (i.e. information processing), criticisms concerning a number of issues have recently surfaced in the literature. In the following discussion, the criticised issues will be divided into internal and structural themes. Internal issues do not challenge the fundamental assumptions of the framework as a whole whereas the structural criticisms address fundamental assumptions of the framework and therefore lead to stronger implications regarding the validity of the framework.

Internal issues

Regarding internal criticisms, some debate over the HKB-Model has accumulated since its introduction. For example, Peper and Beek (1998) investigated extension-flexion movements of the wrist using the scaling methodology in which participants were instructed to keep the movement amplitude constant whilst the movement frequency was increased. Under this task constraint no phase transitions could be observed which lead the authors to postulate that the coupling term of the HKB-Model may be wrong and proposed a new model formulation (Peper and Beek, 1998). It remains unclear though to what extent the instructions actually influenced the dynamics of the system. Potentially the results were a consequence of the specific task raising the issue of the interactions between intentions and intrinsic dynamics which are not very well understood at present (Post et al., 2000b).

Further, criticism regarding the HKB-model was formulated by Kao, Ringenbach and Martin (2003). Investigating the transition behaviour from walking to running on a treadmill, the results showed no critical fluctuations preceding the transition from walking to running. The authors operationalized the relative phase between knee and ankle joint angle kinematics and between knee and hip joint angle kinematics as the dependent measures and estimated the variability of these parameters through standard deviations. When participants switched from walking to running no increase in the variability was observed, which lead the authors to conclude that the HKB model does not apply to lower limb kinematics in gait. As discussed earlier critical fluctuations are not always present in all cases of phase transitions, limiting the impact of this criticism. However in this particular study no justification was given as to why the chosen parameters should actually represent the order parameter dynamics in the first place. Walking represents a full body movement and obviously involves more components than only the knees, hip, and the ankle. Accordingly, the implications derived seem rather arbitrary.

Structural issues

Referring now to structural criticisms, a common issue raised in connection to the dynamical systems framework addresses the type of movement models studied (Walter, 1998). As became clear from the preceding overview, the overwhelming majority of the movement models used can be subsumed under the umbrella of cyclical movements using few biomechanical degrees of freedom. For these movements although being perceived as archetypes of human coordination (Turvey, 1990) the *"specific relevance of these models to most purposeful movements […] remains unclear"* (Walter, 1998, p.327). Support for this view recently gained momentum specifically regarding the lack of functional movements studied (Obhi, 2004, compare Figure). Accordingly, Walter (1998) concluded that *"the importance of nonlinear phase transitions in most purposeful skills has yet to be determined"* (p.327). This is a particularly serious concern for every theoretical framework since the application of concepts should be possible in the domain of everyday tasks as well laboratory simulations (Cordo and Gurfinkel, 2004).

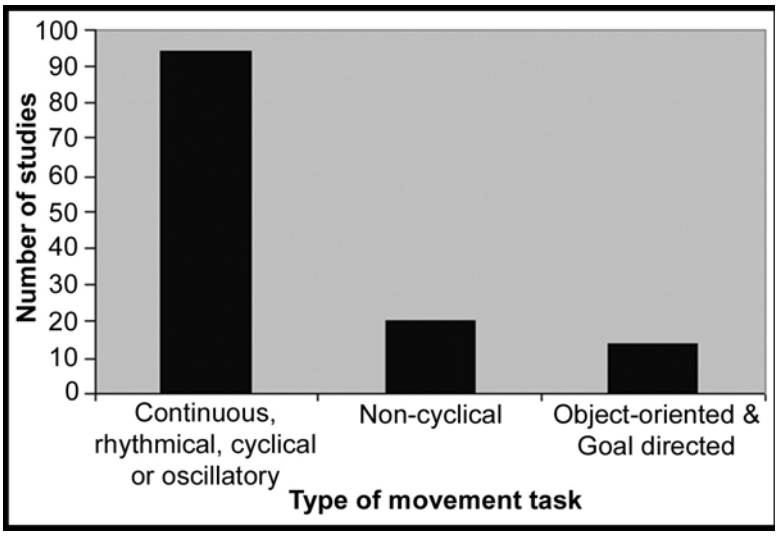

Figure 2-6: Types of movement tasks used in bimanual coordination studies. Adapted from Obhi (2004, p. 113)

Locating functional movement models or rather object/goal-oriented movements (Obhi, 2004) within the hierarchical structure introduced earlier (Newell et al., 2001), functional movements can be regarded as movements where the levels of the spatial-temporal outcome and the movement dynamics are separated from each other. In most studies discussed previously these two levels are identical. Hence, past research provides little information of how the coupling between these two levels is achieved. Accordingly, deeper insights into this coupling from a dynamical systems perspective remain elusive.

Regarding the external validity of movements with limited biomechanical degrees of freedom another problem arises. Using a low dimensional task the possible movement solutions are limited already a-priori which potentially introduces a bias in the way movement behaviour adapts (Fink et al., 2000). Hence, the mere set-up of a specific task, the behavioural information inherent to the task, already biases the possible movement outcomes leading potentially to false conclusion when generalized to other contexts (Heise and Cornwell, 1997; Hong and Newell, 2006; Sames, 2000). Accordingly, when a task provides several degrees of freedom and degeneracy is available to the system it seems reasonable to assume that the movement system is able to make use of these additional degrees of freedom yielding more complex behavioural outcome compared to a simple bimodal state as has been showed in the pedalo locomotor task (Chen et al., 2005).

From a conceptual standpoint this seems also problematic since a basic assumption of dynamical systems theory states that findings from low-dimensional movements do not necessarily transfer across to higher-dimensional movements (Swinnen and Carson, 2002). Hence, by limiting the chosen models to a specific subset the dynamical systems framework is able to incorporate only movements which are close to the utilized movements in terms of the degrees of freedom but is by its own virtue potentially not able to generalize to higher order movements. Further, applying Bernstein's definition of coordination, stressing the notion of redundant degrees of freedom, in some of the tasks reviewed earlier, the redundancy at the component level appears very limited and therefore it remains unknown to what extent these findings hold up in general. Yet, the necessity to conduct research using more than bistable, two-component movements has been acknowledged within the dynamical systems literature quite early on (Kelso and Schöner, 1988).

Regarding the apparent dichotomy between discrete and cyclical movements the confinement not only to low-dimensional tasks but to cyclical tasks seems especially problematic since recent investigation into the relation between discrete and rhythmical movements found some compelling evidence for fundamental differences between these movement classes (Obhi, 2004).

Schaal, Sternad, Osu and Kawato (2004) investigated wrist flexion and extension movements in participants whilst recording synchronously brain activation through functional Magnetic Resonance Imaging (fMRI). Results indicated that brain activation patterns differed significantly between rhythmical and cyclical movement even when executed in the same joint. Similarly, in a study investigating kinematic differences between rhythmical and discrete movement execution in a bimanual task (Wei, Wertman, and Sternad, 2003) significant differences were found. Participants performed a flexion-extension movement with the dominant arm and were instructed to add either a discrete movement or rhythmical movement in the non-dominant arm according to an imperative signal. Results indicated that movement initiation deviated significantly between the two conditions. In the discrete condition participant initiated the movement during all instances of the cycle of the dominant arm. In the rhythmical condition movement initiation was mainly distributed around the turning points of the rhythmical movement. The authors concluded that different movement preparations between the two movement types were necessary pointing towards significant differences between discrete and rhythmical movement execution (Wei et al., 2003). Similar, in the investigation of grasping Button et al. (1998) performed a comparison between rhythmical and discrete movement execution. The results indicated differences of the preferred grasping patterns between the two conditions which lead the authors to conclude that the two movements were *"fundamentally different"* (p.818).

Another structural criticism to the dynamical systems framework can be addressed to one of its fundamental conceptions. Whereas in the domain of physical systems like the laser example mentioned earlier a rigorous mathematical treatment of the interactions of the subsystem components is possible providing a cause-effect relationship between the processes on the microscopic level and directly connecting with the resulting behaviour at the macroscopic level. This approach is not readily available in the domain of biological movements because of the sheer complexity inherent to neurobiological systems (Hossner, 2000). The escape route proposed to this problem lies in using a phenomenological approach to the systems which applies to all of the studies mentioned so far (Beek et al., 1995; Haken and Wunderlin, 1991). In using this approach the question of why the movement behaves in a specific way cannot be answered and sometimes only a mere description of the movement can be derived missing the linking between the macroscopic and microscopic levels of observation with each other (Hossner, 2000; Lames, 1992; Sporns and Edelman, 1993).

This line of criticism can be further pursued in regards to the borders and boundaries[1] (Hossner, 2000) of the system. Crucial for the application of dynamical systems theory to the study of neurobiological coordination is the identification of the sufficient and necessary components of the system in order to capture the behaviour at a chosen level of observation. The definition of the level of observations and the included components seems often to be justified only because of ease of analysis. Herein lies the problem that postulated system as such could be something of an ontological fiction rendering the derived insights potentially less than useful (Hossner, 2000). For example, the study of Kao et al. (2003) investigating the transitions from walking to running presented earlier.

In order to overcome this problem some propositions regarding meaningful levels of observation and division of components were provided by Schöner (1995). Divisions of system borders have to be chosen in order to minimize the interactions between different components. If the different components are highly interactive with each other the behaviour cannot be investigated separated from each other leading to unreasonable results. The

[1] Translated from german: „Ränder und Grenzen“ (Hossner, 2000)

components still have to be related to the particular task at hand and therefore are always task specific. However, this justification has not been used in any of the studies presented.

In summary, several issues surrounding the dynamical systems framework can be identified which pose different levels of threat to the framework as a whole which need to be addressed by further research.

Conclusion – Part One

In this chapter, the dynamical system approach to movement coordination has been introduced. Based on a definition of coordination developed by Bernstein (1967) entailing several conceptual issues, it has been shown that the dynamical systems theoretical framework has the potential to address the basic definition and the accompanying issues.

The synergetics framework provides the theoretical basis for the process of self-organization in complex non-equilibrium systems. Key concepts from synergetics are attractors, control parameters and the notion of time scales entailing critical fluctuations, critical slowing down and hysteresis. The synergetics framework provided the necessary experimental apparatus which makes predictions and therefore scientific investigations of motor control under this framework possible and feasible. A subsequent brief overview of the existing literature concerning the dynamical systems framework showed that the framework has been successfully applied to various problems in movement coordination. Thereby, integrating several facets of human motor control including perceptual, intentional, and developmental phenomena. Thus, providing a coherent view on neurobiological motor control.

The key notion in many of these studies was the importance of stability as a mean to investigate the properties of the specific movement behaviour. Loss of stability and subsequent changes in global systems behaviour served as the focal point in these investigations and provided the main entry point into investigations under this framework.

However, the different findings even for apparent highly similar tasks highlighted that subtle changes in task specific requirements can lead to dramatic changes in behavioural outcomes (e.g. changing the pivoting point in the pronation-supination task or providing additional perceptual information) affecting the possibility to generalize beyond specific tasks. Incorporating intrinsic dynamics made investigations into motor learning possible which have highlighted the individual characteristics of movement coordination which are influenced by past and present behaviour of the performer.

Regarding recent criticism of the dynamical systems framework, the main issues could be appointed to the confinement to a specific kind of movement models. This confinement entailed several further issues which have been highlighted in the previous section. Hence, in order to address some of the issues with regards to the dynamical system paradigms experimentation using different movement models seems necessary. Three issues appear especially significant:

1. The dichotomy of discrete and rhythmical movements, where discrete movement pose several conceptual as well as methodological challenges.

2. Movement models using low numbers of biomechanical degrees of freedom vs. movements involving high numbers of biomechanical degrees of freedom.

3. Goal-directed degenerate movements vs. movement determined movement models.

In the following section the necessary prerequisites for addressing these issues will be developed resulting in the proposition of a potential movement model.

Prerequisites for a different movement model

As has been recently highlighted the domain of sport provides valuable sources for movement models which deviate from the movements traditionally used in studies of motor control (Davids, Button, Araújo, Renshaw, and Hristovski, 2006). In this regards a ballistic throwing movement could sever as a candidate. A strong argument in favour of this model is based on the fact that several authors have already investigated ballistic throwing movements from a dynamical systems theoretical perspective (e.g. Liu and Burton, 1999; Southard, 1998, 2002). Therefore, some guidance of how to proceed with the application of dynamical systems theory is present. However, as has been highlighted in this chapter, these studies suffered from some serious shortcomings but nevertheless it seems feasible to expand upon their approaches.

Relating ballistic throwing movements to the issues identified earlier the movement appears to provide a suitable candidate movement model. Ballistic throwing movements are discrete and usually incorporate movements of the whole body involving many biomechanical degrees of freedom (Hore, Watts, and Tweed, 1994). Further, defining an explicit target to be thrown at changes the task into throwing for precision and detaches somewhat the level of the task-goal from the level of coordination introducing the possibility of degenerate movement behaviour. As has been shown the throwing velocity and the throwing distance respectively may serve as potential control parameters triggering changes in throwing movement patterning. Facilitation of switching behaviour could be achieved by limiting task instruction in regards to the actual movement execution which limits the amount of behavioural information constraining possible movement adaptations.

In order to provide a connection between a new movement model and the existing body of literature introduced earlier it seems advantageous to choose a throwing movement where some properties in movement execution are present which can be related to already investigated movement models (such as the curvature of the wrist trajectory in multi-joint unimanual movements, see Buchanan et al., 1997). In the following chapter, a potential movement model, the Basketball Hook Shot, will be introduced.

Part two - Literature of basketball hook shot

As was discussed in the previous section, throwing movements may represent an excellent movement model with which to relate to the key principles of dynamical systems theory. In fact, Liu and Burton (1999) presented some interesting indications for changes in movement patterning in a basketball shooting task. As will be shown in this chapter, changes in kinematic variables have been found in numerous studies investigating basketball shots under varying distance requirements. The subtle adaptations that have appeared make it difficult to attribute changes in movement patterning as phase transitions between attractors. Further, because of the widespread familiarity of basketball set shots (or free throws) it might be likely that many people already possess specific behavioural information about the task which potentially hinders self-organized adaptations strategies (compare Post et al., 2000b). A classical basketball throw may not prove to be a suitable candidate movement model and there is a need to seek a less common shooting movement. A candidate movement model may be found in the basketball hook shot.

Defining the Hook Shot

According to Martin (1992) the hook shot itself can be distinguished into two basic techniques: the traditional hook or sky hook and the jump hook. Both techniques use a one-handed throw but exhibit some distinct differences. During the sky hook the shoulders are almost in line with the throwing direction. The throwing arm is on the opposite side to the basket. Therefore in a game situation the body provides cover from an opponent. The wrist of the throwing arm describes a wide arc and the elbow is extended during most of the movement. The jump off takes places from the leg opposite to the throwing arm and the ball should be released at the peak of the jump. During the jump hook the upper body is almost square to the throwing direction and both feet are used for jumping. The throwing technique is much more similar to the set shot technique though lacking the guidance of the ball by the non-throwing hand. The elbow is flexed at the beginning of the movement and stays flexed until the last phase of the throw (Martin, 1992). In game situations variations of these general movements can be observed and individual variations are expected to be high since individual modifications to general motion patterns are common (Satern and Keller-McNulty, 1992). The hook shot per se describes a broad range of movements and therefore even for players familiar with the hook shot sufficient room for adaptations due to contextual changes can be assumed supporting the hook shot as a candidate movement model. In this regards a basketball hook shot does not completely prescribe the throwing movement but some degenerate degrees of freedom are always present which can be potentially exploited by the performer.

As the hook shot is a ballistic throwing movement it falls into the class of discrete multi-articular actions. The ball release is performed whilst the thrower is airborne which means that small adaptations in movement patterning need to be accommodated by global reorganization because of inertial affordances (Hang, Cheung, and Roberts, 2001). As the hook shot is a unique and complex movement it can be assumed that people not familiar with basketball will have very limited knowledge of the movement and accordingly should exhibit relatively unconstrained behaviour depending on the specific task instructions. Potentially, this feature can be further investigated by juxtaposition of novice and skilled performers and potential differences in adaptation strategies.

Based on the movement of the throwing arm, which follows a curvilinear path, the movement pattern resembles some of characteristics of the movement used in studies using a curvilinear movement in one arm presented earlier (Buchanan et al., 1997; DeGuzman et al., 1997; Kelso et al., 1991a). Movement patterning from the hook shot can therefore be related to the results of existing investigations potentially providing some common ground between the basketball hook shot and more traditional movement models.

To date, no scientific studies investigating the hook shot have been published. However, in order to provide some frame of measurement the literature dealing with basketball set shots and jump shots will be investigated based on the assumption that some features found in these actions should apply to some extent to the hook shot.

Research on basketball throwing actions

Several basketball studies described in this section have used a motion capturing approach based on the 2D kinematics of the thrower. At present, it is not known to what extent these measurements are valid therefore some uncertainty regarding the validity of the results may exist (Debicki, Gribble, Watts, and Hore, 2004; Gard, Knowx, and Childress, 1996). The type of motion capturing will be stated for each investigation (2D vs. 3D).

Hudson (1982) investigated differences in free throw shots between participants of different skill levels using 2D motion capture. The author found significant differences in relative release height between the different groups with the better throwers using higher ball release heights. The experts revealed an increased shoulder angle between the trunk and the upper arm compared to the intermediate and the novice groups and successful shots were released higher than unsuccessful shots (by 4 cm). No differences between groups for release angle and release speed could be identified but the data showed considerable intra-group variability (Hudson, 1985 2D). Another basketball study investigated the continuous segment kinematics during the throwing movement (Hayes, 1987, 2D). It was shown that the sequencing of the maximum segment velocity started at the lower limbs and proceeded along the shoulder, upper arm, lower arm, and the hand to the ball . The movement was analysed from the instance of the crouch prior to throwing until ball release. However a small sample of only nine shots (all successful) were analyzed (Hayes, 1987).

In a 2D kinematic analysis of the jump shot of female basketball players, Elliot and White (1989) found greater ranges of motions for the throwing shoulder and wrist angle in 3 point shots compared to free throws. The results may have been influenced by the task instruction to use the same take-off technique during the two shots (Elliot and White, 1989, p.7) which highlights the influence of restrictive behavioural information that potentially limits movement adaptations in throwing tasks. Using 2D kinematic analysis, Elliot (1992) compared jump shots from male and female basketball players shooting from 4.25m (free throw line), 5.25m and 6.25 (3 point distance). A significant difference in the velocity of the throwing shoulder for the females between the closest and the further distances could be found. The shoulder angle was also the only angle parameter which was significantly different between genders. The authors observed that the male shooters tended to release the ball closer to the peak height of the wrist compared to the female players who released the ball during the ascent of the ball. The authors attributed this fact to the weaker strength of the female players who were able to transfer momentum from the vertical and horizontal velocity of the body to the rising ball (Elliot, 1992, p.116).

This finding was supported in a study using 3D motion capturing and comparing basketball jump shots from three different distance ranges (<3.66m, 3.66m-5.49m, >5.59m) where it was shown that the release height decreased with increasing distance (Miller and Bartlett, 1993). The authors observed an increase in the throwing elbow angular velocity with increasing shooting distance which was achieved despite decreased elbow joint range of motion. The wrist showed the opposite trend. The authors suggested that the influence of the elbow joint in force production increased with higher distances (Miller and Bartlett, 1993, p.289). In a study with three participants shooting at different distances (Miller and Bartlett,

1991) observed the same trend in results using 3D motion capturing. When re-evaluating the pooled data the authors suggested that the data analysis used may have been misleading and proposed an approach based on regression analysis instead of ANOVA since shots within a certain distance factor came actually from different distances (Miller, 1996).

A follow-up study (3D) investigated the influence of distance on shooting kinematics in relation to playing positions (i.e., guards, forwards, and centers). The results corroborated the findings from the preceding study (Miller and Bartlett, 1996). The authors found a slight trend for guards and forwards to use the jump differently from centers. Where the former smaller players used the jump mainly for increasing the release height the latter taller players used the jumping velocity in order to accelerate the ball at higher distances.

Differences between the 2D kinematics of players of varying playing position have also been identified by Walters, Hudson and Bird (1990). Investigating four participants shooting from 4.3m, 5.2m, and 6.1m at a angle of 45° to the basket board, significant differences were found for release speed which increased with increasing distance for all participants. The authors concluded that long distance shooters adapted their release speed in a more systematic fashion than the middle distance shooter.

Satern, Messier and McNulty (1989) investigated the influence of varying basket height (3m and 2.4) and ball size (normal and intermediate) in 13-year-old adolescents. Significant differences were found only for ball release angle and the release angle of the shoulder in relation to height. The authors concluded that the movement patterns were possibly already too established as the different conditions did not elicit adaptations in the movement. The authors remarked that because of data pooling the individual differences could have been masked by the analysis (Satern et al., 1989, p.133).

Rojas, Cperot, Oña and Guiterrez (2000) investigated the influence of a defending player on shooting kinematics of the jump shot using 3D motion capturing. Participants were instructed to perform a jump shot at the corner of the free throw line after receiving a pass from another player. A defender ran up towards them at random times and tried to interfere with the shot. The set-up was arranged in order to simulate an actual game situation. Results indicated a faster release at increased height during the presence of an opponent. Participants used a more upright position especially with higher shoulder angles. The authors concluded that despite small differences between the conditions the coordination demands might be altered between the two conditions (Rojas et al., 2000, p.1659).

Investigating the variability of discrete variables at ball release in the free throw, Miller (2000) found greater coefficients of variation in release angle and release height for successful shots compared to non-successful shots. The non-successful shots exhibited greater absolute variability for linear velocities of segment endpoints. All shots showed increasing variability with increasing shooting distance. In a follow-up investigation, inaccurate shots were again not characterized by higher variability compared to accurate shots (Miller, 2002). Changes in release parameter variability followed no obvious trend pointing towards individual strategies for increasing shooting distances. Regarding the segment variability, decreasing values from lower to upper extremities were found with the lowest variability in the wrist. Miller (2002) concluded from his analysis that it was not possible for the participants to perform the same movement pattern twice.

Except for Hayes (1987) all studies presented so far used only discrete data points during key events in order to assess the kinematics of the basketball shot which provides very limited information about the actual process of coordination during the throw. In general, approaches focussing on continuous kinematics are sparse (Satern and Keller-McNulty, 1992). A recent exception is a study conducted by Button, MacLeod, Sanders and Coleman (2003) who investigated movement variability during the free throw adapting a time-continuous approach. Kinematic data of the throwing arm was captured in 2D with six female participants of varying performance abilities. Performance outcome was rated using a four point scale (Landin, Herbert, and Fairweather, 1993) and all throws irrespective of success were included in the subsequent analysis. Joint angle kinematics showed a tendency for decreasing variability with increasing abilities. Inter-trial variability at ball release was only decreased for the best throwers and variability at the wrist was generally lower compared to the elbow. Movement variability plots showed increasing variability from start to mid-point of the movement followed by decreasing variability scores towards ball release in all participants. Investigations into the sequencing of joints based on a cross-correlation technique indicated a proximal-to-distal sequence for the two participants with the highest ability apparent. With regards to the literature, the authors highlighted that at present mainly investigations of discrete key events with grouped data were executed and that more investigations using an individualized approach were needed.

Satern and Keller-McNulty (1992) conducted a study investigating the free throw in 20 participants (10 male, 10 female) using time-continuous measurements of four successful throws per participant (2D). Based on time-angle curves and angle-angle plots the authors were able to identify different inter-individual styles in free throw execution. The results showed interdependence between elbow and knee where flexion and extension occured simultaneously in both joints (Satern and Keller-McNulty, 1992, p.22). The authors investigated the possibility of analysing the data with time-normalized angle plots but discarded this type of analysis based on differences in the length of the time curves which lead to skewing of the data plots thereby introducing spurious differences. Their reference points where offset of motion for the start of the trial to 0.1s past ball release as the endpoint of trial. The curves showed differences in the individual preparatory motions possibly caused by the observed differences in trial lengths. However, no quantitative analysis of observed differences was provided. The authors emphasized that information obtained from discrete key-events did not provide information about the temporal relations between limb segments which is needed if coordination should be assessed (Satern and Keller-McNulty, 1992).

Conclusion: Part Two

In the preceding section, research regarding basketball shooting was reviewed since no literature concerning the hook shot could be located. The findings from these studies supported the initial notion that shooting distance might serve as an influential parameter acting upon movement coordination. A robust finding was that increases in ball velocity and hand movement speed were associated with alterations in joint angle kinematics. This information potentially provides a link between the basketball shot and studies investigating throwing for movement speed (Southard, 1998, 2002) and uni-manual rhythmical movements (Buchanan et al., 1997; DeGuzman et al., 1997; Kelso, Buchanan, and Wallace, 1991b). Hence, it can be postulated that throwing distance acts as a candidate control parameter which can be used in a scaling type experiment. Also, since a curvilinear pattern of the throwing hand is explicitly used during movement execution of the hook shot one can assume a connection between the unimanual studies discussed earlier. However, the literature presented showed that alterations in movement kinematics were highly influenced by individual prerequisites like experience and anatomical characteristics (for example body height and strength). This fact stresses the importance of individualized analysis approaches which also ties in with the theoretical implications derived earlier in regards to intrinsic dynamics.

No previous research has studied changes in global movement patterning from a dynamical systems theoretical point of view. Arguably the restrictive regulations for performing a basketball set-shot narrowly constrain the phase space, thereby hampering the occurrence of phase transition. Hence, the basketball set-shot might not be a suitable movement model for the observation under the current purpose. The potential for the basketball hook shot in this regard has received much less attention.

Regarding the level of information concerning basketball set-shots it has to be stressed that the data base generally derived from applied studies seems quite weak. As has been pointed out most studies used a 2D motion capturing approach often paired without the use of markers which makes correct estimation of joint positions and subsequent calculations of correct joint angles difficult at best (Bartlett, Bussey, and Flyger, 2006). Further, as can be seen in Table 2-1 the actual number of throws investigated in the presented studies were very limited and can be only explained by past difficulties in data collection and data processing. Accordingly, usage of such a limited number of throws per participant strongly constrain the amount of information available about intra-individual adaptations.

Table 2-1: Summary table of reported studies indicating type of motion capturing (2D/3D), number of participants (N), number of throws (No. Throws), and whether only successful shots were investigated.

Authors	2D/3D	N	No. throws	only successful
Hudson (1982)	2D	18	54	no
Hudson (1985)	2D	22	66	yes
Hayes (1987)	2D	NA	9	yes
Elliot and White (1989)	2D	10	20	yes
Elliot (1992)	2D	24	72	yes
Miller and Bartlett (1991)	3D	3	6	yes
Miller and Bartlett (1993)	3D	NA	15	yes
Miller (1996)	3D	15	15	yes
Walters, Hudson and Bird (1990)	2D	4	12	yes
Satern, Messier and McNulty (1989)	2D	13	104	yes
Rojas, Ceperot, Ona and Guiterrez (2000)	3D	10	80	yes
Miller (2000)	NA	NA	NA	no
Miller (2002)	3D	12	360	no
Button, MacLeod, Sanders and Coleman (2003)	2D	6	180	no
Satern and Keller-McNulty (1992)	2D	20	80	yes
Total		157	1073	
Liu and Burton (1999) (ordinal)	2D	10	1600	no

An apparent departure was the study made by Liu and Burton (1999) where a significantly higher number of trials was recorded from each participant. Yet, the data were analyzed only on an ordinal scale (see Paragraph on discrete movements in Chapter 2) which again limits the amount of information available.

Another point of criticism concerns the heavy emphasis placed upon successful shots. An implicit assumption taken with this line of investigation is that shots were taken from the exact same spot in order to be comparable to each other. This seems especially unlikely for jump shots and to some extent also for the free throw. For example, assuming a successful shot made by a performer from 4m distance, the exact same shot from 4.1m will quite probably lead to an unsuccessful shot without any observable change in the recorded kinematics. Yet, in making the shot successful the kinematics have to be adapted to the altered task constraints. Hence, the exact location of ball and performer in 3D space in relation to the basket has to be taken into account in order to make the comparison between successful and non-successful shots meaningful. Thus, focussing solely on successful shots seems not necessary.

Finally, since the basketball shot derives directly from an applied setting it seems somewhat surprising that only a single study investigated how the presence of an opponent affected throwing behaviour. From a practical point of view, information about change in throwing kinematics due to distance alterations are only of theoretical interest unless it is known whether the similar procedures are in place when performers face an opponent.

3 Chapter Three: Analysing the basketball hook shot

Introduction

As discussed in the previous chapter, the basketball hook shot represents a promising movement model for the application of dynamical systems theory to the study of coordination of discrete, multi-articular actions in degenerate neurobiological systems. However, a first necessary step for this programme of work was to consider to what extent adaptations in the hook shot due to changes in task constraints could be expected. Hence, the first study investigated adaptation of coordination in the basketball hook shot due to changes in two interacting constraints required to be satisfied in the context of basketball: (i) changes in throwing distances; and (ii), the presence of a defender. Based on the conjecture that increasing throwing distance leads to increasing throwing speeds (Dupuy, Mottet, and Ripoll, 2000) the throwing distance was identified as a potentially influential parameter. A key question was whether changes due to alterations in throwing distance remain the same independent of the presence of a defender. The presence of a defender can impose spatial and visual constraints on the thrower, limiting movement space and sight of the intended target (i.e., the hoop), hence it seems plausible that the presence of the defender might affect movement patterning. However, concrete predictions other than those observed by Rojas et al. (2000) like increased shoulder angle and decreased movement time when throwing against a defender. could not be inferred from the literature. Conceptually, the manipulation of constraints can be viewed from a dynamical systems perspective as the emergence and decay of constraints as formulated by Guerin and Kunkle (2004). The importance of constraints in shaping behaviour varies in time depending on the current control parameter value. Hence, whereas one constraint might be highly influential in certain regions of phase space, its influence can potentially decay as a different constraint gains importance and starts to emerge over time

As was pointed out earlier, it seemed advantageous to investigate potential commonalities between the basketball hook shot and previous movement models used. Accordingly a two-fold strategy was used. First, in line with the work of Southard (1998, 2002) which highlighted the influence of throwing velocity on selected joint lag coordination the joint lag in the basketball hook shot was investigated. However, the task constraints of neither of Southard’s previous studies greatly emphasised throwing precision since participants were only instructed to aim at a mat which was placed five metres away. Further, no attempt was made to analyse lower body kinematics during performance and all measurements were pooled for group comparisons. Hence, it was not clear to what extent the same trends could be identified for the basketball hook shot. Second, during the execution of a hook shot the trajectory of the wrist describes an arc-like pattern very similar to experiments investigating uni-manual movement coordination (Buchanan et al., 1997; DeGuzman et al., 1997; Kelso et al., 1991a). Therefore, potentially similar coordination dynamics might be exhibited by the basketball hook shot. Accordingly, constrained by increasing throwing speed, the curvature of the wrist joint trajectory should increase and in turn the radii of the wrist trajectories should decrease. An interesting issue arises when interpreting the radii from a biomechanical viewpoint using the distinction between throwing for distance and throwing for precision. During the former, a curvilinear path would be expected as opposed to throwing for precision where a more rectilinear path appears desirable (compare Kreighbaum and Barthels, 1996). Hence, in both cases, as the distance increases, the radii should increase.

In regards to the different arm coordination patterns between the hook shot and the basketball set shot, detailed investigation of the arm movement is necessary, since in set shots the throwing elbow appears to play a bigger role in the movement with increasing distance (Miller and Bartlett, 1993). Furthermore, participants of different skill levels have been observed to exhibit different levels of movement variability in free-throwing (Button et al., 2003). In order to investigate whether a similar trend was present for the basketball hook shot, participants from a range of different skill levels were observed in the study. It seems likely that expert players should possess more detailed behavioural information regarding the concept of a hook shot (apart from the instructional constraints of this experiment) due to their prior experience (see also Kudo, Tsusui, Ishikura, Ito, and Yamamoto, 2000; McDonald, van Emmerik, and Newell, 1989). Since the DST framework highlights significant levels of inter-individual variation in movement patterning, a multiple single-participant design approach was used (Bates, 1996; Williams, Haywood, and VanSant, 1998; Zhan and Ottenbacher, 2001), with a concordant emphasis on intra-individual adaptations during analysis.

Method

Participants

Four participants (Age = 22.25±3yrs; Height = 1.88±0.14m) were involved in the study. Participant 1 was a professional basketball player, participants 2 and 3 (female) were intermediate players (regional club level) and participant 4 was a novice. Each participant signed a consent form approved by the University of Otago Ethics Committee before taking part in the study. All participants used their dominant right hand for throwing and had not experienced any injuries in the six months preceding the study.

Procedures

Participants were instructed to score baskets (without using the backboard) with a hook shot technique. The movement started with the participants' back facing towards the basket and they performed one ball bounce before shooting. This pre-shot routine was intended to resemble the task constraints of a typical game situation. A mobile basket fixed at a conventional height of 3.05m with a Plexiglas backboard and a standard sized basketball (Size 7, FIBA approved) was used for all shooting trials. Replicating the scaling procedure used by Southard (2002), throwing distance to the basket was varied from 2m to 9m in increments of 1m after each trial block comprising eight shots. In the 'no-defender condition' the participant performed shots unopposed. During the 'defender-condition' a skilled basketball defender was positioned at 3m distance from the shooting location. He was instructed to run towards the throwers after they performed the bounce, and to stop 1 m in front of the shooter before jumping vertically with arms reaching directly upwards. Before data recording, participants performed a self-selected warm-up for 15 minutes. Next they performed 10 shots each from 2m, 5m, and 7m to familiarize themselves with the procedure. During data recording for all shots either with or without defender from 2m to 9m was performed sequentially. In between trials, 30s recovery time was provided to prevent fatigue effects. The order of defender and no-defender conditions was randomized.

Data Analysis

Joint centres of participants were identified using passive reflective markers to enable recording of joint trajectory data with a 12-digital-camera system (Motion Analysis Corp., USA) set at a sampling frequency of 100Hz. Participants were prepared with reflective markers (5mm diameter) at the left (l) and right (r) acromion, C7, sternum, lateral epicondyles humerus (l/r), mid wrist (r/l), spina illica anterior superior (r/l), spina illica posterior superior (r/l), sacrum, lateral and medial epicondyles, femoris (r/l), lateral and medial malleolus (r/l), heel and toe marker (r/l) in order to identify anatomical landmarks. In addition one marker each was placed on the tibia (r/l), on the lateral part of the femur (r/l), the humerus (r/l) and on the distal, dorsal part of the forearm.

The position of the hip joint centre was estimated using the procedure of Bell, Pedersen and Brand (1990), and position of the shoulders by using the procedure by Rab, Petuskey and Bagley (2002). After visual inspection of the frequency spectra, raw displacement data were filtered using a second order Butterworth filter set at a cut-off frequency of 10Hz From the marker trajectories, a 12-segment body model was established. Joint angles were calculated using the Euler convention but only angles in the primary joint plane of motion were used for further analysis. Shoulder joint kinematics were estimated through the included angle between the upper arm and the trunk. Movement time commenced from the instance of maximum crouch and finished at the instance of maximum wrist height (i.e., assumed to represent ball release). In order to obtain angle-angle plots, trials were time normalized to 50 data points. All velocity measurements were based on the filtered data, not on the time normalized data.

Discrete variables, including angles of the right and left elbow, shoulder, hip, knee, and ankle joint at ball release were chosen for analysis. In order to obtain an estimate of throwing velocity, maximum linear wrist velocity was determined. Segment lag was estimated using the instance of maximum linear velocity with the determined trials. Naming convention following Southard (2002, 2006) was always based on the distal segment (Wrist lag: right wrist lag – right elbow lag). Shoulder lag was calculated as right shoulder lag – left hip lag, to investigate the sequencing between upper and lower body along the kinematic chain. Movement coordination was qualitatively examined using angle-angle plots of the right shoulder joint and the right elbow joint, the left shoulder joint and the left elbow joint, and the left knee joint and the left hip joint with time normalized plots (Button et al., 2003).

Following the methods used by Buchanan et al. (1997) the radius of the wrist trajectory was estimated by minimizing the sum:

$$\sigma^2 = \frac{1}{N}\sum_{k=1}^{N}\left(R_0 - \left[\left(x_k - a\right)^2 + \left(y_k - b\right)^2 + \left(z_k - c\right)^2\right]^{1/2}\right)^2 \quad (3.1)$$

Over the parameters (R_0, a, b, c) where R_0 was the desired radius and a, b, c estimated the mid-point in space of the virtual circle, x_k, y_k, z_k where the actual position of the wrist at time frame k, and N was the number of total time frames. The sum was minimized using the lsqnonlin function in Matlab 7.1.

Following the suggestions of Reboussin and Morgan (1996) for statistical analysis of multiple single-participant designs the responses of the discrete angle kinematics at ball release were analyzed using a mixed-effects model (compare Boyle and Willms, 2001; Laird and Ware, 1982; Pinheiro and Bates, 2000; Sullivan, Dukes, and Losina, 1999; Verbeke and Molenberghs, 2000 for an overview). Through this approach, changes in individual joint angle kinematics could be separated into population effects which were shared across participants represented by a fixed-effects structure and inter-individual differences which were represented by a random effects structure. After visual inspection and preliminary separate model fits for each participant, a linear regression model using a linear and a quadratic distance trend was deemed sufficient to represent the changes in kinematics due to changing throwing distance. In order to represent the influence of the defender an additional factor with 2 levels was included representing the two conditions. Accordingly, together the quantitative linear and quadratic regression components and the qualitative direction component represented the fixed-effects structure of the model. As discussed earlier, the basketball literature suggested some common trends across angles across participants rendering this assumption feasible.

Regarding potential individual differences in movement adaptation strategies, participants were regarded as random samples from a wider population introducing a random component into the model. Accordingly inter-individual differences were modelled as random effects which were included into the model yielding the mixed-model approach. For the random effect, a two-level nesting was chosen. The first level represented a random effect structure with an individual intercept and linear slope for the throwing distance for each participant. This way different intercept terms representing different mean joint angles and a different slope representing inter-individual differences in adaptation strategies due to the varying throwing distance could be estimated. Further, in order to represent interaction effects between defender condition and distance, a nested random effect was included. The effect was nested within participants based on the assumption that interactions between the defender condition and distance would show inter-individual differences. Since different skill levels were used, the impact of the defender were assumed to vary between participants. Following this rational the following full model could be formulated:

$$y_{ijkl} = \beta_0 + \beta_1 d_{ijkl} + \beta_2 d_{ijkl}^2 + \beta_3{}_j + b_{0i} + b_{1i} d + b_{1j,i} + \varepsilon_{ijkl} \quad (3.2)$$
$$i = 1,...,8,\ j = 1,2, k = 2,...,9, l = 1,...,10$$

With β representing fixed effects and b and ε representing random effects with: β_0 = general intercept, β_1= linear coefficient, β_2 = quadratic coefficient, β_{3j} = condition coefficient, b_{0i} = participant intercept, b_{1i} = participant linear coefficient, $b_{1j,i}$ = distance by condition interaction, and ε = residual variance. The random effects were assumed to be independently within- and between- participants and normally distributed with a mean equalling 0 and diagonal covariance matrix.

$$b_{0i} \sim \mathrm{N}\left(0, \sigma_s^2\right), b_{1i} \sim \mathrm{N}\left(0, \sigma_{sl}^2\right), b_{1j,i} \sim \mathrm{N}\left(0, \sigma_{cd}^2\right)$$

Since several measures were observed from the same individual it seemed likely that the measurements were strongly correlated between successive trials within participants. Further, based on preceding investigations of movement variability (compare Button et al., 2003) the typical linear model assumption of independent identical normally distributed residuals seemed unlikely a-priori. Accordingly, an extended linear mixed-effects model was used to accommodate the correlation and potential heteroscedasticity structure of the data. In order to represent the correlation within- participants, a first-order autoregressive correlation term was included. Heteroscedasticity was modelled through different variance terms for each participant strata. Therefore, the covariance matrix for the residuals consisted of a blocked diagonal matrix again assuming independence between participants.

$$\varepsilon_{iijk} \sim \mathrm{N}\left(0, \sigma^2 \Delta\right)$$

Where Δ was a blocked diagonal matrix. Based on the algorithm used for this procedure, in order to obtain unique estimates for the variance strata, one variance stratum was constrained to equal 1 and the remaining strata were estimated as ratios of the first stratum (see Pinheiro and Bates (2000) p. 209 for details).

As a first approach the full model was fitted to the data and if possible simplification of the nested random effects structure was investigated based on assessment of confidence intervals for the random effects. Only those random effects were maintained where the confidence intervals were well bounded away from zero indicating significance. Reduced models were always compared with the more complex model using likelihood ratio tests. The reduced model was accepted when no significant differences between the models were indicated (Pinheiro and Bates, 2000; Sithole and Jones, 2002; Verbeke and Molenberghs, 2000). When the estimation algorithm for the full model failed to converge, indicating a misspecification of the model, the next simpler marginal model was used and the simplification procedure was applied to this reduced model. The final model fit was investigated based on the distribution of standardized residuals and the congruence of the fitted and actual collected data The fixed-effects coefficient was tested using a Wald-statistic which provided approximate F-tests, a common approach of testing fixed-effects in mixed-models (Boyle and Willms, 2001; Brown and Prescott, 1999; Greenland, 2000; Pinheiro and Bates, 2000; Verbeke and Molenberghs, 2000). All statistical analysis where performed using the R software (R Development Core Team, 2006) and the nlme package (Pinheiro, Bates, DebRoy, and Sarkar, 2006) for mixed-effects modelling. All remaining calculations were performed using Matlab 7.1 (see Appendix B). Test results were deemed significant if $p < 0.05$ and highly significant if $p < 0.01$.

Performance scores were measures using a four-point scale, where a direct hit scored 1, an indirect hit using the back board scored 2, a miss with either rim or board scored 3, and an air ball scored 4.

Results

This section is divided in several subsections. First, the results from the mixed-modelling statistics for the joint angles at ball release, the radius of wrist trajectory, wrist displacement velocity and movement time will be reported. Subsequently, the results from the performance measure, temporal joint lag, and joint lag variation will be described. Finally, a description of angle-angle plot of the movement is provided.

Mixed-modelling of ball release data

F-Tests for joint angles

Table 3-1 shows the results of the population F-Tests for the fixed-effects for each body angle at maximum wrist height obtained from the mixed-model analysis. For the right elbow a significant quadratic effect of distance could be identified. The model estimated a coefficient for β_2 with 0.1, which indicated a significant trend of increasing elbow joint extension with increasing throwing distance.

Table 3-1: Results of significance test for fixed-effects for distance, squared distance and direction. See equation 3.2 for details. * = significant, ** = highly significant

Angle	Distance	Distance^2	Direction
right elbow	0.04	4.30*	9.23
right shoulder	1.89	0.60	1.88
left elbow	3.26	0.00	1.12
left shoulder	0.13	0.51	3.60
right hip	11.14**	11.55**	0.77
right knee	37.00**	8.66**	0.10
right ankle	3.98	0.32	0.47
left hip	38.04**	1.16	0.04
left knee	0.15	1.82	2.15
left ankle	1.57	0.85	0.08

For the right hip joint angle, significant effects for the linear and quadratic term could be identified with $\beta_1 = 0.44$ and $\beta_2 = -0.16$, resulting in greater values with increasing distance (i.e., greater hip flexion). In contrasts, for the right knee joint the estimated coefficient ($\beta_1 = -0.54$, $\beta_2 = 0.25$) resulted in greater extension angles with increasing throwing distance. Similar, the left hip joint angle demonstrated a significant positive linear trend only ($\beta_1 = 0.38$) which indicated that the participants used greater extension angles with increasing shooting distance. All remaining angles failed to show significant main effects for the population. In summary, the mixed-effect procedure identified common trends for the right elbow, the right and left hip and the right knee.

Standard deviation of intercept, slope, and slope^2

Table 3-2 : Estimated standard deviations for model parameter. Participant intercept = σ_s, participant by distance = σ_{sl}, condition by distance within participants = σ_{cd}, residual = σ.

Angle	participant intercept	participant by distance	condition by distance within participant	Residual
right elbow	5.73	0.86	0.42	2.27
right shoulder	26.88	1.73	0.53	3.02
left elbow	29.75	3.45	0.77	10.97
left shoulder	26.99	3.81	0.59	8.60
right hip	20.61	0.73	0.35	3.62
right knee	21.70	NA	0.86	4.48
right ankle	6.22	0.49	0.43	1.82
left hip	7.50	0.14	0.18	1.86
left knee	6.21	0.41	0.27	1.26
left ankle	16.49	0.82	0.36	1.16

Table 3-2 shows the estimated standard deviations of the random effects for the intercept and the slope for participants, the condition by distance interaction which was nested within participants, and the remaining residuals obtained from the mixed-model analysis. For all model fits, the confidence intervals for the intercept and the distance coefficient were bounded well away from zero. All model fits were compared to models without random effects indicating that the random effects models significantly improved the model fit using likelihood ratio tests and information criterion values (Akaike Information criterion (AIC) and Bayesian Information Criterion (BIC), see Pinhéiro and Bates (2000), page 10 for details). For the right knee the model fit indicated a very small value for right knee close to the parameter boundary of zero. Hence, the effect was neglected and likelihood-ratio comparison showed no significant differences which indicated that the simpler model fitted the model equally well.

With regards to standard deviation comparisons, only the participant intercepts and the residuals could be compared directly because they share common units. The former reflected the mean angles across trials used by each participant, whereas the latter indicated the deviations from the model which were also calculated in angles units. Comparison of the participant intercepts and the residual errors showed that in all cases the inter-individual difference was greater compared to the residual variance. In particular, the right shoulder, left arm complex and right hip and right knee showed extremely high inter-individual variances (population standard deviations of > 26°) which suggested that the four participants showed considerable variation in body postures at ball release. Relatively low inter-individual variations was found in the left hip and knee, the right ankle and the right elbow, however (population standard deviation of < 10°). Investigation of the residuals exhibited similar levels between the different angles except for the right elbow and the left shoulder which showed that the highest errors were almost two-times greater in magnitude compared to the next smaller value.

Except for the right hip and knee variation in slopes was greater between participants compared to the variation within participants between conditions. The standard deviations for the left elbow and the left shoulder showed the highest scores (> 3) indicating the adaptation strategies between participants showed high inter-individual variation. In contrast, for the left leg, especially hip and knee joints, the variations were only minimal (< 0.5) signalling a common trend between participants. The right knee showed the highest inter-individual variation between conditions which was partly due to the missing estimate for the between-participant slope since some of the variations was contained within the between-condition variation. Again, the left leg showed the lowest values with greater variation between condition for the upper segments.

Individual model coefficients

Using the mixed-modelling approach the best linear unbiased predictors (BLUP) of the individual random coefficients can be obtained which described the intra-individual progression. These were used in order to investigate the intra-individual variation for those angle kinematics which showed no significant fixed-effects for linear and quadratic distance. Through this approach, the inter-individual differences could be investigated in more detail and an assessment was possible whether the non-significant main effects were partly a result of contrary strategies used by participant or genuinely small effects.

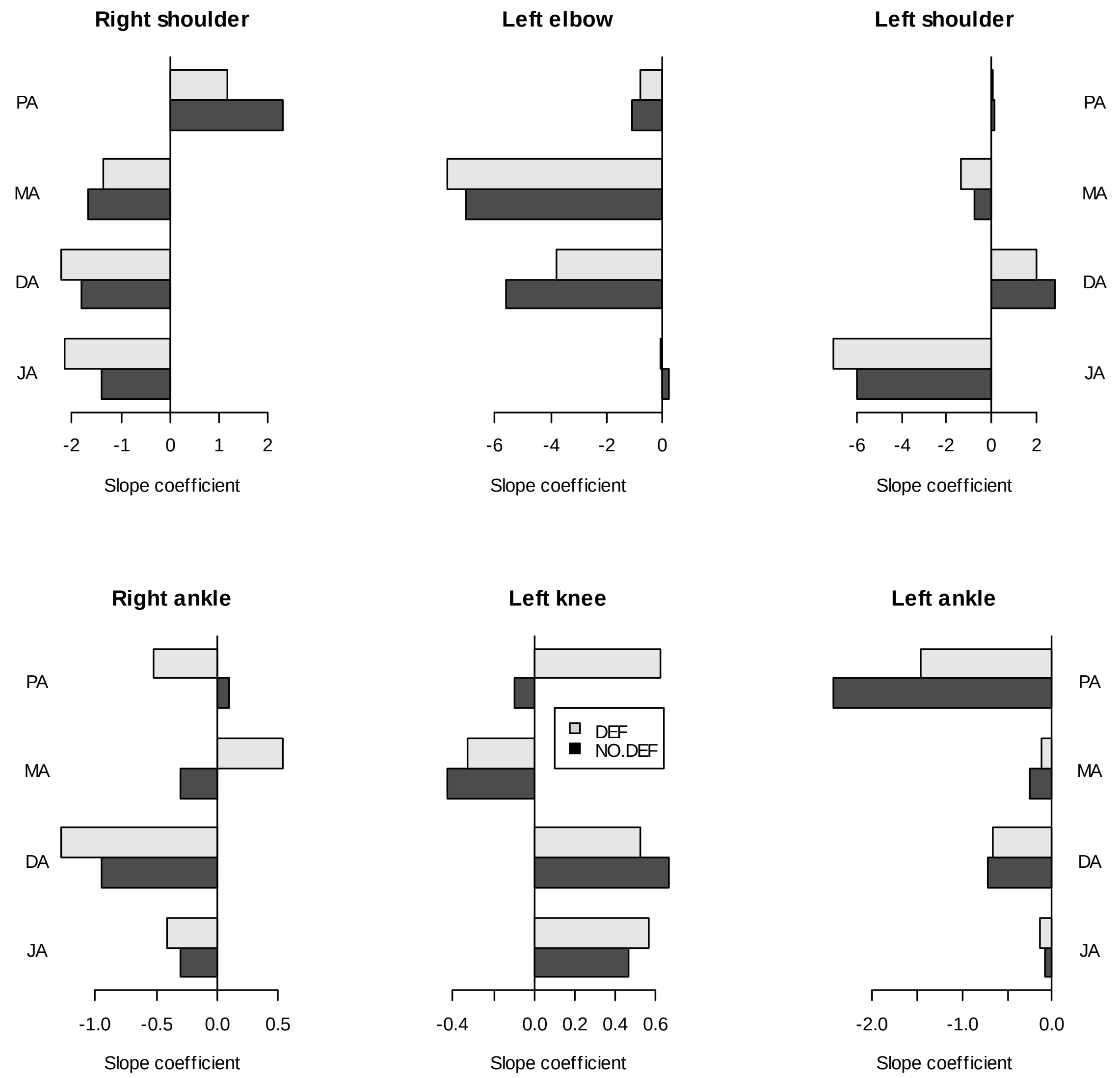

Figure 3-1: Best linear unbiased estimates of individual random coefficients for each participant for the right shoulder, left elbow, left shoulder, right ankle, left knee, left ankle.

A striking feature of the individual plots in Figure 3-1 was the range of different adaptations across angles and within angles. For the right shoulder participant PA showed the exact opposite trend compared to the remaining participants who appeared to use very similar strategies. In contrast, for the left elbow, participants MA and DA both showed decreasing angles with distance whereas JA and PA showed only minor changes with distance. For the left shoulder all four participant show different adaptations from each other. Whereas PA held the shoulder angle more or less constant, DA increased the angle with distance where MA decreased it slightly. This mixed approach contrasted with the pattern of JA who exhibited much smaller shoulder angles with increasing distance. For the right ankle, participants PA and MA showed opposite signs between conditions but were mirror-inverted between participants. The left knee showed in general relatively small adaptations with distance, as indicated by the small magnitudes of slope coefficients, but nevertheless showed variations between participants in the direction and for PA also between conditions. Similarly, changes in the left ankle were relatively small except in participant PA, who showed coefficient correlations which were twice as high in magnitude compared to the remaining participants.

Variation in estimated inter- participant residual variances

Table 3-3 : Estimated heteroscedasticity parameters for each participant compared to the residual variance of participant JA and the Ratio between the maximum and the minimum estimate.

	JA	DA	MA	PA	Ratio
right elbow	1.00	1.24	1.55	1.47	1.55
right shoulder	1.00	1.09	0.99	1.18	1.18
left elbow	1.00	0.98	1.19	0.71	1.67
left shoulder	1.00	1.14	1.02	0.59	1.92
right hip	1.00	1.13	1.59	0.87	1.83
right knee	1.00	1.12	1.45	1.32	1.45
right ankle	1.00	1.25	2.34	1.44	2.34
left hip	1.00	1.02	1.26	1.24	1.26
left knee	1.00	1.65	1.56	1.49	1.65
left ankle	1.00	1.03	1.29	1.92	1.92

Table 3-3 shows the estimated variance components for each participant for each angle representing the heteroscedasticity between participants. For all model fits, the necessity of the heteroscedasticity models was based on visual inspection of the model residuals and likelihood ratio test between the same model with and without the heteroscedasticity component which resulted in all cases in significant improvements of model fits indicated by significant ratio tests. The ratio of the maximum to the minimum estimated variance showed a similar spread across the angles. However, for the right ankle the highest variance was more than twice as high as the lowest variance value. In Table 3-4 the rankings of the variance components are indicated. With regards to the variability of the lower body segments, participant JA showed the smallest variation across participants as well as in the elbow. For the remaining participant the variations were not as clear.

Table 3-4 : Ranking of heteroscedasticity parameter for each participant. 4 = smallest variation, 1 = highest variation.

	JA	DA	MA	PA
right elbow	4.00	3.00	1.00	2.00
right shoulder	3.00	2.00	4.00	1.00
left elbow	2.00	3.00	1.00	4.00
left shoulder	3.00	1.00	2.00	4.00
right hip	3.00	2.00	1.00	4.00
right knee	4.00	3.00	1.00	2.00
right ankle	4.00	3.00	1.00	2.00
left hip	4.00	3.00	1.00	2.00
left knee	4.00	1.00	2.00	3.00
left ankle	4.00	3.00	2.00	1.00

Analysis of wrist displacement velocity and trajectory radius

Results for wrist displacement velocity indicated a significant population effect for the linear distance ($F_{lin}(1,501) = 889.80$, $p < 0.01$, $\beta_1 = 0.41$), which suggested that the velocity followed a positive trend with increasing distance. The model fit indicated that no individual slope was necessary. Standard deviations (between- and within- participants) showed greater variation between participants compared to the residuals ($\sigma_s = 0.06$, $\sigma = 0.29$) and all participants exhibited the same increasing trend with distance.

The mixed-modelling for the wrist trajectory showed significant main effects for the linear and the quadratic trends ($F_{lin}(1,501) = 33.84$, $p < 0.01$; $F_{quad}(1,501) = 13.4$, $p < 0.01$) with coefficients, $\beta_1 = 0.06$ and $\beta_2 = -0.002$ which resulted in an increase of the radius with distance (compare Figure 3-2). Interestingly for the participant JA in the defender condition, the curvature data showed a pattern where the observed values at shorter throwing distances were smaller compared to the fitted and the opposite pattern for the greater distances. This finding indicated that a non-linear model following a sigmoidal curve would provide a better fit for the data for this participant. Standard deviations and variations between coefficients between participants and within participants showed similar values (SD $\sigma_s = 0.06$, $\sigma = 0.05$).

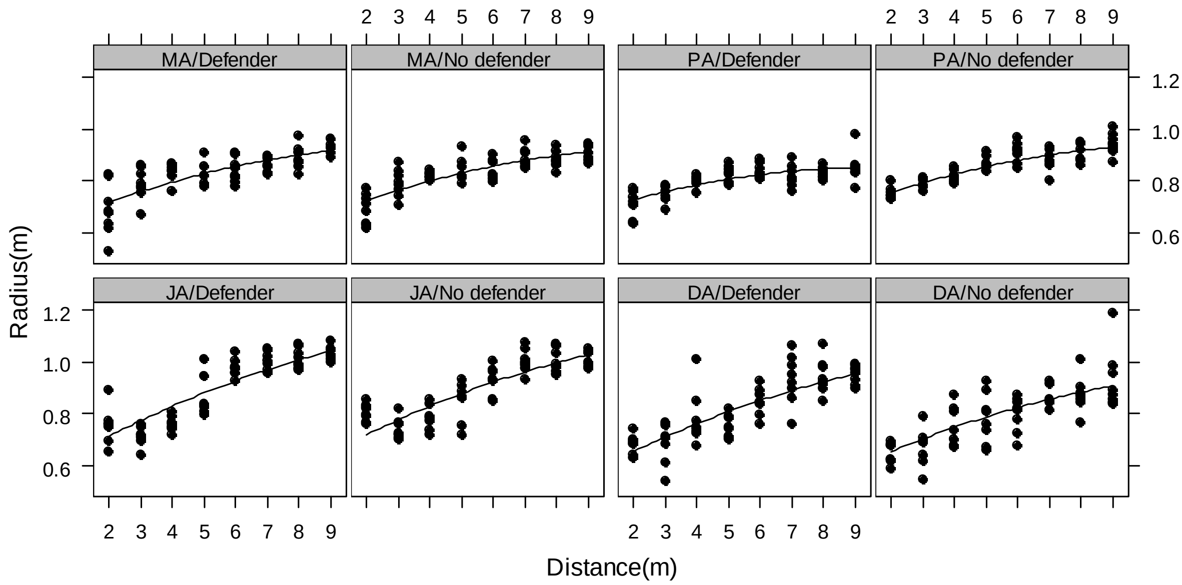

Figure 3-2: Estimates of wrist trajectory radii for each participants for each condition with superimposed model fit.

Movement time

Mixed-effects analysis of the movement time indicated no significant effects or interactions for distance and condition. Between- participants differences in mean movement time showed a standard deviation of σ_s = 2ms and total mean movement time was at 30ms (±4 SD).

Performance scores

In Figure 3-3 the performance scores for the four participants are shown.

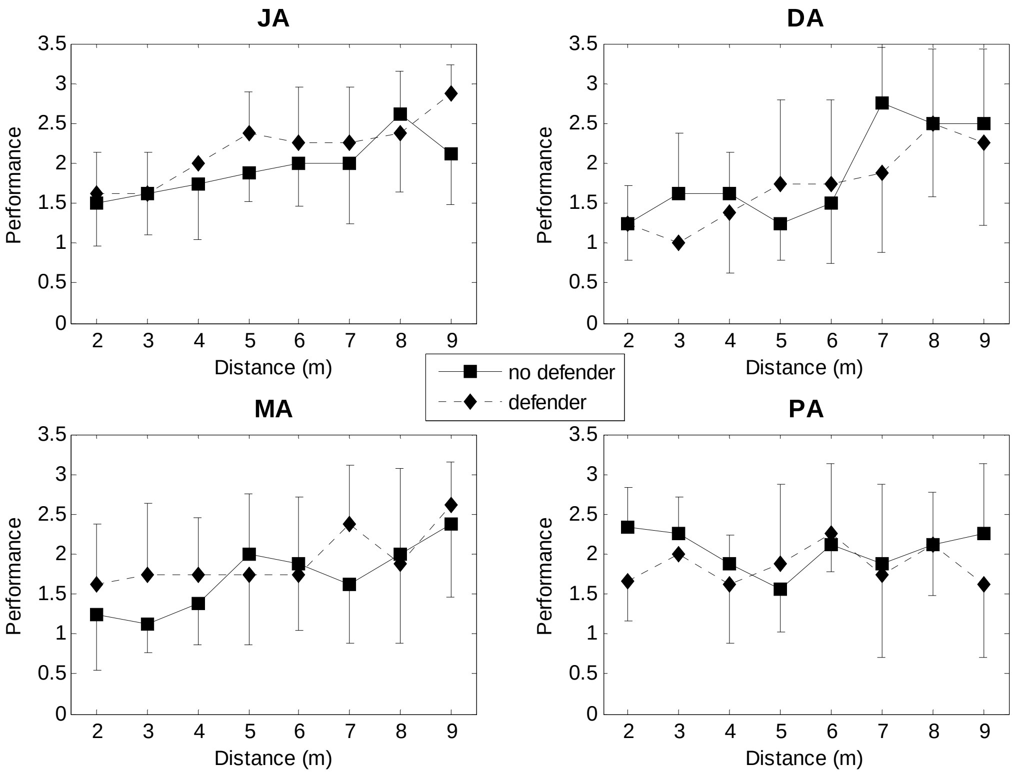

Figure 3-3: Individual mean performance scores for each throwing distance for each condition with standard deviations.

In general, the expected trend was found for decreasing performance with increasing distance. Friedman Rank-Sum tests indicated a marginally significant effect for distance when averaged over participant and distances and blocking for condition $\chi^2_7 = 13.41$, $p < 0.07$. Further, the distance effect was significant when averaging over conditions and blocking for participants $\chi^2_7 = 16.15$, $p < 0.03$. The random participant comparisons showed only a marginally significant effect when averaging over conditions and blocking for distance $\chi^2_3 = 6.65$, $p < 0.09$. No significant effects for condition were observed.

Temporal joint lag

Residual plots of the mixed-modelling for the lag data indicated some serious deviation from normality. Therefore, a factorial generalized least square model was used instead where the distance was treated as a qualitative factor like in a traditional ANOVA framework as opposed to a continuous covariate. In order to accommodate for the high serial correlation and heteroscedasticity of the data, the covariance matrix was chosen such that a lag-1 autocorrelation structure and separate variance estimates for each participant, similar to the mixed-effects model introduced earlier (for details see Pinheiro and Bates, 2000), were estimated. Accordingly only population effects are presented in this analysis.

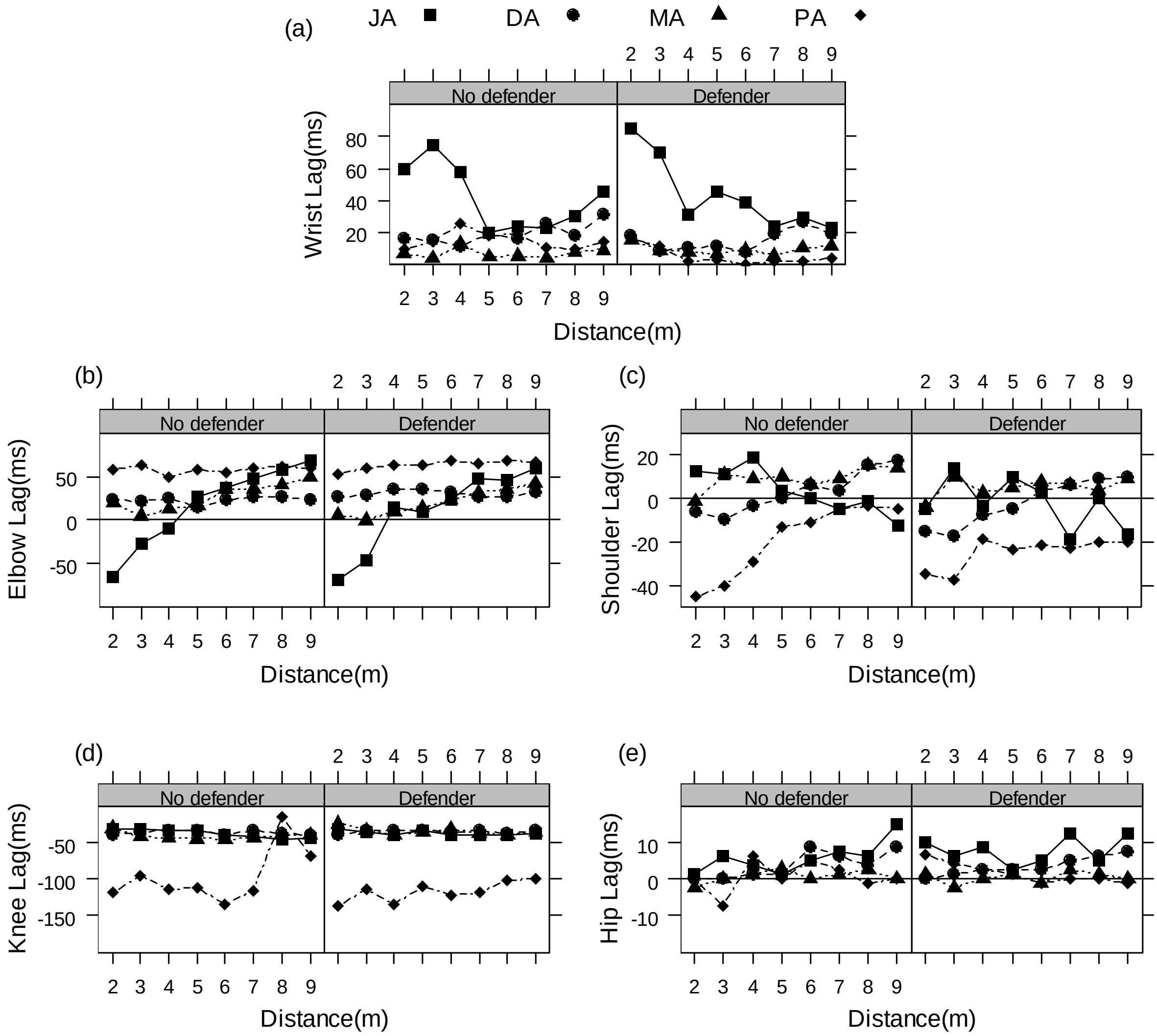

Figure 3-4: Individual mean joint lags at each throwing distance for each condition for (a) wrist lag, (b) elbow lag, (d) shoulder lag, (d) knee lag, (e) hip lag. (■) JA, (●) DA, (▲) MA, (♦) PA

In Figure 3-4 the mean wrist lag for the four participants can be observed. Whereas participants DA, MA and PA exhibited similar trends with minor changes over distance and between conditions, participant JA demonstrated a greater lag for smaller distances. The analysis demonstrated a significant main effect for condition $F(1,505)=9.54$, $p < 0.01$ and a distance by condition interaction $F(7,505) = 2.29$, $p < 0.05$. All four participants exhibited positive wrist lag values indicating that the maximum velocity of the elbow occurred before the instance of maximum velocity of the wrist, supporting the kinetic chain principle (Kreighbaum and Barthels, 1996). The mean elbow lag in Figure 3-4 showed similar trends for all participants except for participant JA. For the smaller distances, participant JA exhibited a negative lag which switched to positive values at 4m distance. Hence, for the smaller distance participant JA did not depend on a summation of the segment velocities in order to satisfy the distance constraint. No significant effects of elbow lag were observed. Mean shoulder lag values were differentially distributed for the four participants. Participant PA showed a negative shoulder lag for all distances, whereas participant DA started with a negative lag and increased the positive lag values for greater distances. Participant MA exhibited positive lag values for almost all trials, whereas participant JA started with positive values which decreased to negative values during the no-defender condition, showing a similar trend during the 'defender-condition' ($F(1,495)=12.68$, $p < 0.07$, and condition $F(1,495)=2.75$). For hip lag, a significant effect for distance $F(1,495)=9.61$, $p < 0.01$, was reported. Post-hoc analysis indicated a significant difference between 9m and 2m distance with an estimated difference of 0.65 indicating that the lag became more positive with increasing distance. Values for all participants were mainly positive. Knee lag showed a different trend compared to the other plots where the instant of maximum velocity for the ankle always occurred after the maximum knee angle velocity for all four participants. No significant effects were recorded.

Joint lag variation

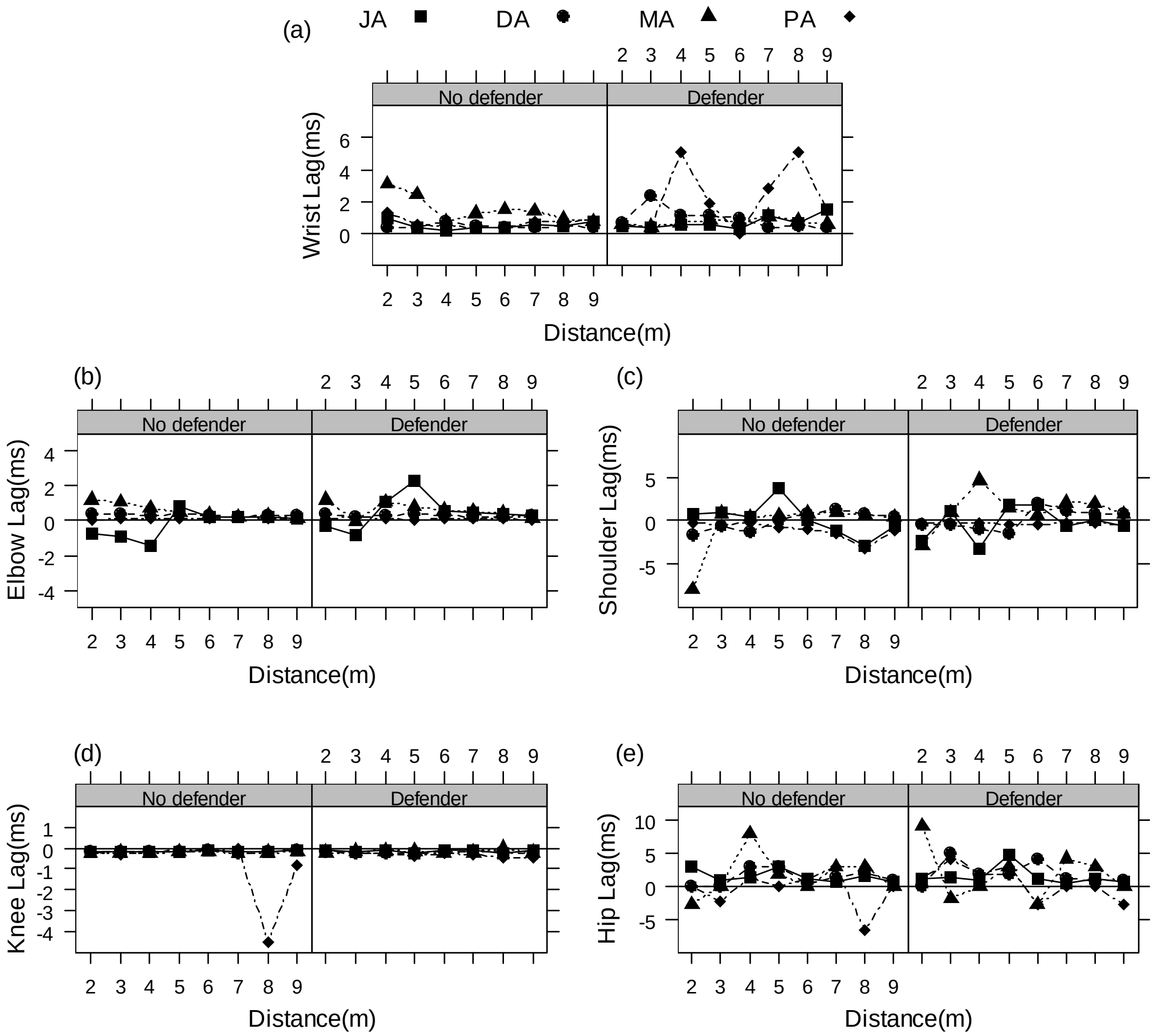

Figure 3-5: Joint lag coefficient of variation for each participant for each throwing distance for both condition. (a) wrist lag, (b) elbow lag, (c) shoulder lag, (d) knee lag, (e) hip lag. (■) JA, (●) DA, (▲) MA, (♦) PA

Figure 3-5 shows the coefficient of variation (CV) for different joint lags for each participant. Absolute values were overall very low. Especially Wrist, Elbow, and Knee CV indicated very high stability of lag sequencing in these segments. For Knee CV there was an apparent outlier for 8m during the 'no-defender' condition caused by two trials where participant PA did not perform a jump, turning only on the left foot whilst shooting. Highest variability can be observed in the Hip CV and Shoulder CV mainly from participants PA and MA indicating some instability in lag coordination between the upper and lower body segments and between the arm and the trunk. No differences between the conditions were apparent from the plots and for the remaining joints no clear differences between participants were noted.

Angle-angle plots

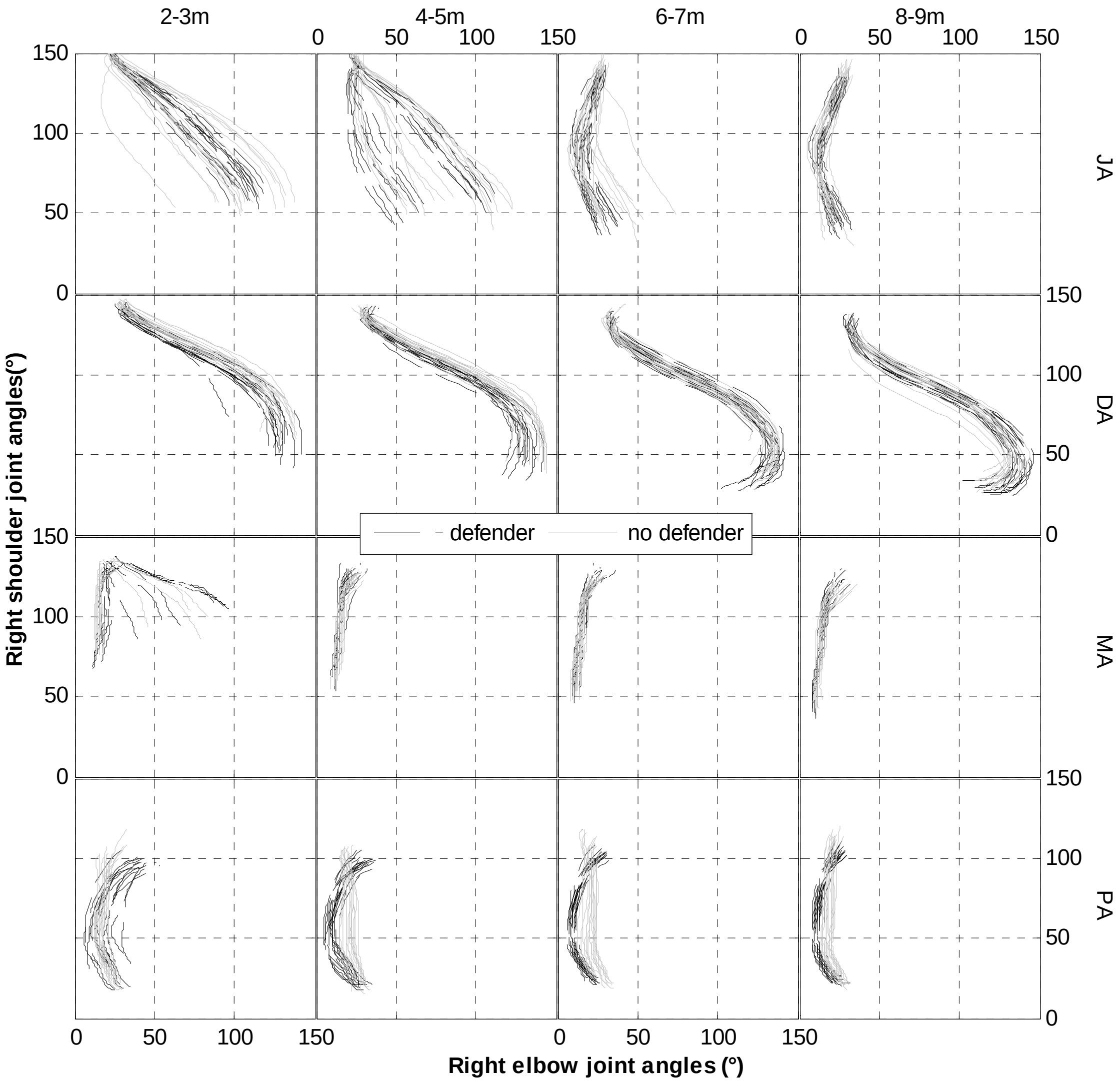

Figure 3-6 : Angle-angle plot of right shoulder and right elbow joint kinematics for each participant (horizontal) grouped for 2-3m, 4-5m, 6-7m, and 8-9m (vertical).

Figure 3-6 shows the angle-angle plots of the right shoulder and the right elbow for the participants where each row represents a single participant. There were clear qualitative differences in elbow and shoulder joint coordination between participants. For participant JA two movement patterns based on the range of motion of the shoulder could be identified. One pattern was prominent at smaller distance values (less than 6m), whilst the other was used at greater distances. At smaller distances the plots showed a parallel extension of the elbow and elevation of the shoulder, as indicated by the near diagonal direction of the plots. For the greater distances, the elbow remained almost completely extended over the whole movement duration and only a slight flexion at the end of the movement was apparent. Hence, wrist acceleration was mainly achieved by elevation of the shoulder, whereas for smaller distances, the elbow had a much greater influence. The variability of the plots was greater at smaller distances, especially at the beginning of the movements. However, at the end of the movement, the different plots converged into a similar region.

Participant DA showed some changes over distance in the angle-angle plots. At smaller distances, the movement was initiated with an elevation in the right shoulder joint and a flexed elbow joint followed by a simultaneous extension of shoulder and elbow joints. For larger distances, the elbow was slightly more flexed at the beginning and was extended during the first part of the movement. Subsequently the same parallel movement in the elbow and shoulder joint as for the smaller distances was adopted. The initial flexion angle of the elbow was very similar to the angle used by Participant 1 for smaller distances. Both participants JA and DA exhibited similar ranges of movement in the shoulder joint. However, whereas participant JA changed to another pattern with increasing distance, participant DA appeared to adapt an existing pattern, indicating that the coordination pattern for the throwing arm in participant DA was not affected by the presence of a defender.

Participant MA showed high variability for the two smallest distances at which some patterns were used in both conditions and which deviated quite strongly from the remaining trials. The distinction between the trials was mainly due to different ranges of motion in the elbow joint, which started from a more flexed position (joint angles $< 50°$). For the remaining trials, range of motion in the elbow was very limited, and the wrist acceleration seemed to be solely a result of movement in the shoulder with no differences between the two conditions. With increasing distance, the starting value for the shoulder angle decreased, indicating a lower upper arm position at the beginning of the movement. The pattern appeared to be more similar to the trials by participant JA for the greater distances compared to participant DA.

Participant PA exhibited differences between the conditions which were most pronounced in the final elbow angle. In the baseline condition the elbow flexed more compared to the defender condition. This difference decreased with increasing distance. This participant showed the smallest shoulder angles at the beginning and the end of the movement compared to other participants. For the largest distances the pattern was somewhat similar to the pattern exhibited by participant JA.

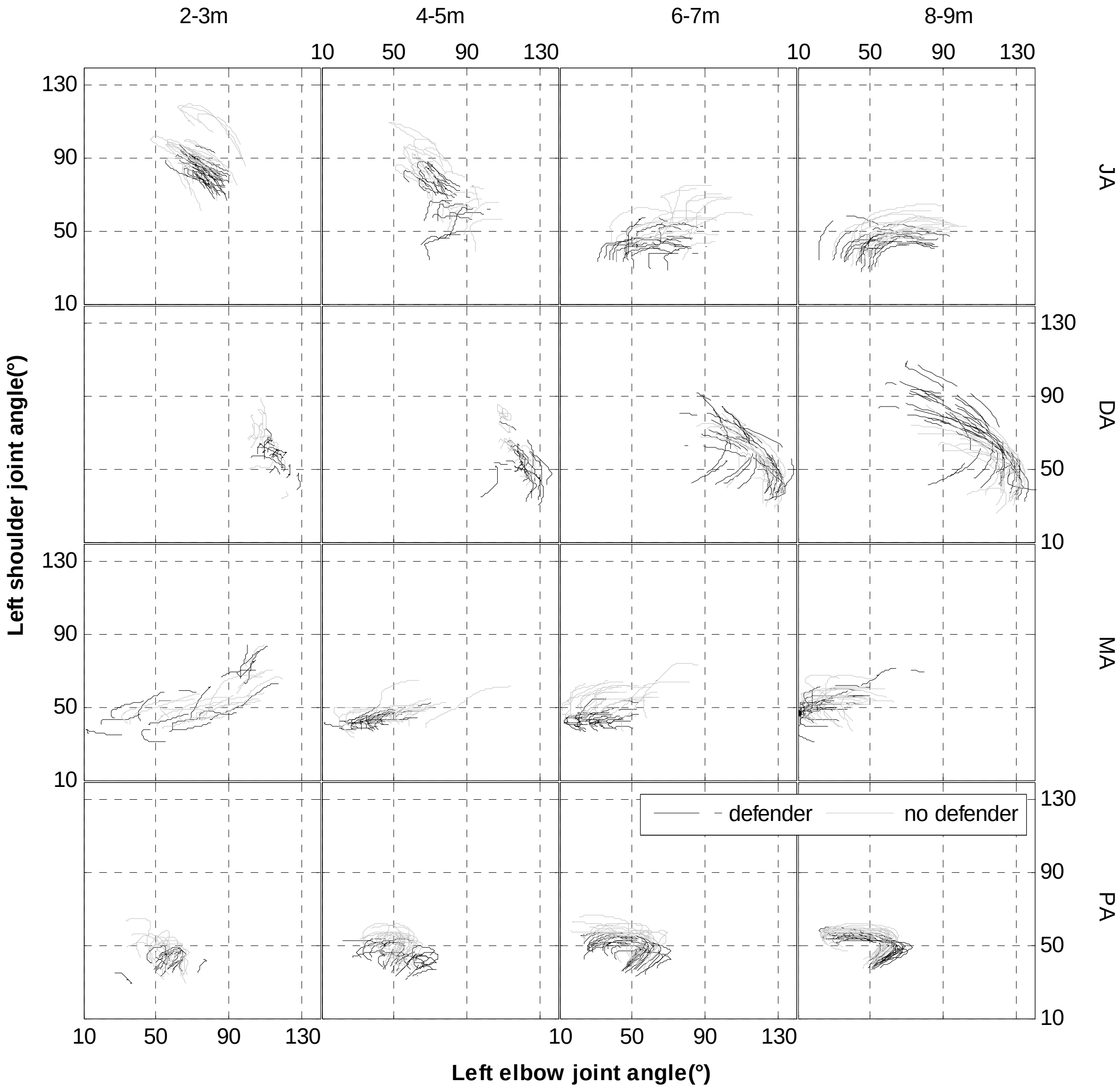

Figure 3-7: Angle-angle plot of left shoulder and left elbow joint kinematics for each participant (horizontal) grouped for 2-3m, 4-5m, 6-7m, and 8-9m (vertical).

In Figure 3-7 the same plot for the left shoulder and left elbow can be viewed. Comparing across participants the four different plots suggested that there were considerably greater differences in the coordination of the non-throwing arm between the participants compared to the throwing arm. participant JA showed the same distinction in two qualitatively different patterns, with the main differences stemming from the position of the shoulder. During the trials from the smaller distances the shoulder showed higher angles at the beginning of the movement and stayed at elevated angles compared to the shots from greater distance. Between conditions some differences were apparent at distance 6-7m. Regarding the apparent variability of the pattern, there appeared to be a trend for more similar patterns with greater distances. Regarding the range of motion of the elbow during the smaller distances the elbow showed somewhat smaller ranges as compared to the coordination pattern at greater distance indicative of activation of movement degrees of freedom with increasing distances. For participant DA the alteration of the movement patterns across distance showed some distinct peculiarities. For distances between 2m and 5m the movements of the left arm complex were quite constrained and only minimal ranges of motion were visible with slightly greater magnitudes at 4-5m during the defender condition. However, from 6m onwards the range increased dramatically with some differences between conditions becoming even more pronounced during the highest throwing distance together with an increase of movement range of motion. The elbow joint at the beginning of the movement (bottom right) showed high angle values indicative of high flexion followed by a joint extension during movement execution. However, the differences between the conditions seemed to stem mainly from the position of the shoulder which was smaller during the defender position suggesting a lower raised arm. Again, a completely different pattern could be observed in participant MA. The participant mainly varied the flexion angle of the elbow only and held the shoulder relatively constant during all throws. During the initial distances the pattern showed high fluctuations and seemed to settle into a more consistent pattern only for the greater distances with some separation between conditions during distance 6m-7m. Participant PA also showed trends for greater stability with increasing distance and qualitatively the pattern was again different from the patterns of the remaining participants. The shoulder exhibited only minor ranges of motion and the movement mainly stemmed from motion in the elbow joint.

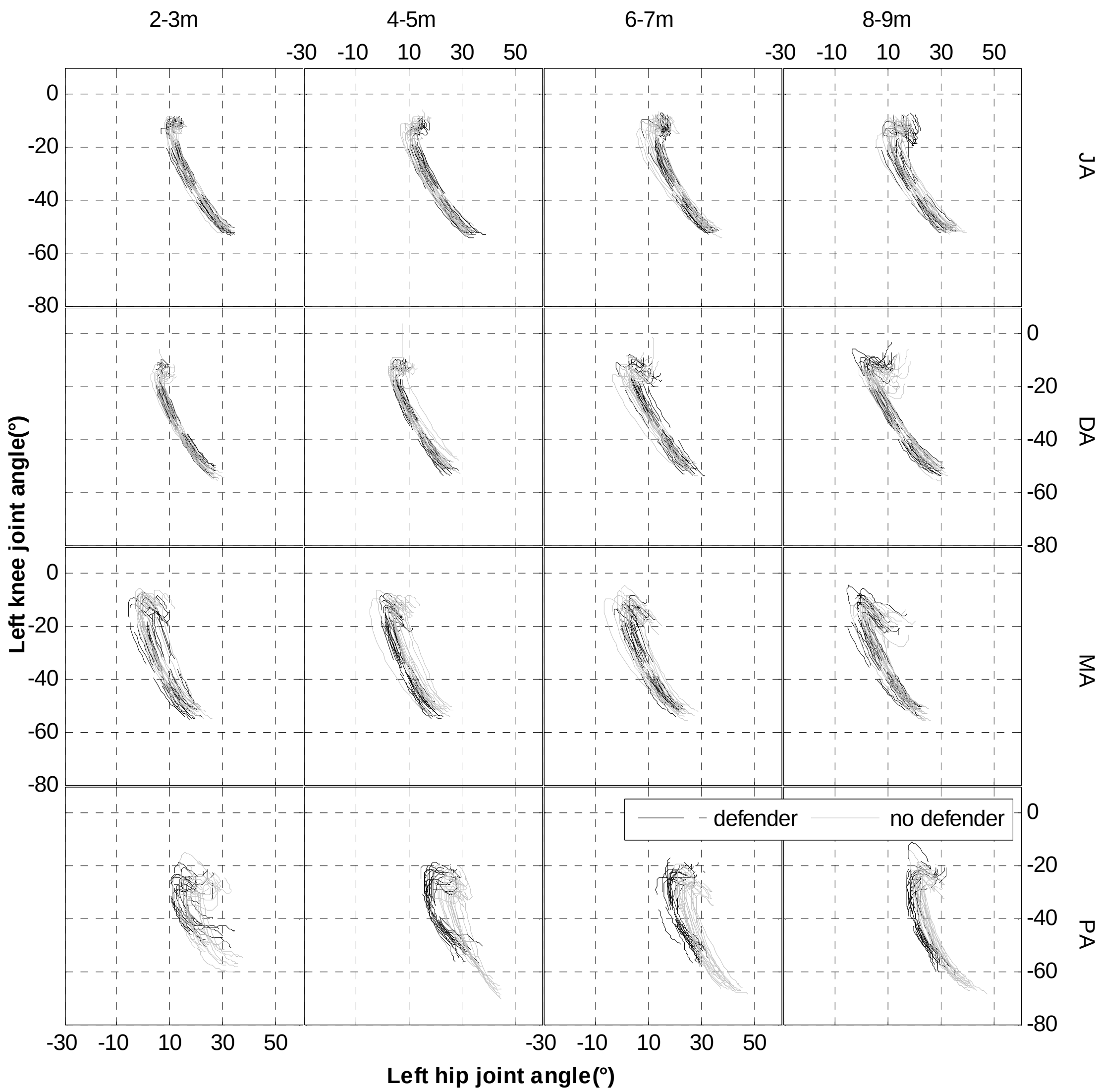

Figure 3-8: Angle-angle plot of left hip and left knee joint kinematics for each participant (horizontal) grouped for 2-3m, 4-5m, 6-7m, and 8-9m (vertical).

In Figure 3-8 the angle-angle plots for the left hip and the left knee joint are shown. The most obvious aspect of the plot was the similarity across participants and distances. Only participant PA seemed to show a somewhat different pattern but only for the lowest distances. This participant was also the only one showing some differences between conditions. For the remaining participants the range of motion in both hip and knee seemed quite similar and stable across distances, especially for the smaller and intermediate distances.

Discussion

In regards to the expectations formulated earlier, the results showed that the conjecture of greater throwing speeds, estimated by the resultant velocity of the wrist, with increasing throwing distance was correct. The results indicated a strong linear trend for increasing velocity with increasing distance in all participants. Investigation of joint lag revealed that the lag showed only marginal changes with increasing distance and only the hip showed a significant improvement with distance. However, the lag values were in general mostly positive suggesting that joint lag was inherently better in this movement compared to the standard throwing pattern investigated by Southard (2002). This was further supported by the joint lag variability which was also much more consistent compared to the study by Southard (2002). Particularly, the CV values for wrist lag for all participants were low.

One explanation for the joint lag differences reported in this study and in Southard (2002) could be the differences in task constraints between the hook shot and the overarm throw. Being an airborne movement, the hook shot could be viewed as inherently unstable compared to a standard throwing movement where a support base is present. Therefore, the margin of error for this unstable movement was arguably smaller and accordingly movement variability had to be tailored to this restriction. In support of this idea, it is notable that Van Emmerik and van Wegen (2000) reported in a standing task that postural sway amplitudes changed depending on the body position. When individuals leaned forward, shifting their centre of mass closer to the boundary of the support area, the postural sway decreased in comparison to upright standing. The authors interpreted this finding as an indication that participants were able to detect the stability boundaries of the task and adapted their body sway according to this constraint (van Emmerik and van Wegen, 2000). A similar phenomenon was reported earlier in a ball-juggling task (Sternad, 1998)

The hip and shoulder lags showed the highest variations, indicating some variability in the coupling between the upper and lower body segments. Participant PA was the only individual who showed a constant negative lag for the shoulder for all conditions and also the highest variability in the angle-angle plots for the left leg as well as opposite trends for the right ankle and the left knee between conditions at ball release. This finding was harmonious with other research showing effects of skill level on coupling differences between upper and lower body degrees of freedom with a multi-articular action (Vereijken, Emmerik, Bongaardt, Beek, and Newell, 1997; Vereijken, van Emmerik, Whiting, and Newell, 1992). In summary, the trend observed by Southard (1998; , 2002) in the overarm throwing movement was not present in the basketball hook shot for this population.

The results also provided no support for the hypothesis that the radius of the throwing hand trajectory increased with distance and therefore changed from a curvilinear to a more rectilinear pattern. Instead, in the hook shot movement the opposite trend was present. Hence, the results stood also in opposition to the traditional biomechanical accounts of ‘push-like’ and ‘throw-like’ movements (Kreighbaum and Barthels, 1996). In the present study, all participants tended to use a throw-like movement during the smaller distances and a more push-like movement when throwing from further away. Similarly, whereas Keighbaum and Barthels postulated that during the push-like segmental rotations are performed synchronously in order to generate the rectilinear path, the presented results did not support this hypothesis. For example, participant DA exhibited clear synchronous movements in shoulder and elbow joints over all the distances despite altering of the radii. When combining the radius data with the angle-angle plots, the results did not generally reveal different movement patterns with different radii as were visible in the uni-manual shoulder-elbow-wrist flexion-extension movement (Buchanan et al., 1997). However, for participant JA the radii showed some indication for bimodal behaviour in both angle-angle plots of the upper limbs and the radius data where freezing movement degrees of freedom in the elbow was accompanied with changes in the radii.

Regarding the presence of emerging and decaying constraints only participant PA showed different movement patterns for the right elbow and left hip joint between the two conditions which diminished at further throwing distances (see Figures 3-8). These findings might be interpreted according to the skill level of that participant. It is possible that the presence of a defender provided an unfamiliar context imposing a behavioural constraint. For a relative novice, the influence of the defender may decrease with increasing distance, showing how the two constraints interacted with each other. For the smaller distances, the defender acted as the primary constraint, which subsequently decayed as increasing throwing distance emerged as the main constraint. For the remaining participants, all of whom had prior experience of competitive performance in basketball, the defender constraint was less influential. In this study, it was assumed that all participants used the same movement pattern as they would in a competitive performance environment. Therein lay a possible explanation for the lack of strong kinematic differences between conditions, due to the peculiarities of the hook shot where the actual throwing movement takes place on the opposite side of the shooter’s body away from the defender. The shooter’s body provides cover from direct interference of the opponent to the shooting arm and therefore it can be expected that differences in shooting kinematics with and without a defender should be somewhat smaller than for a standard basketball set-shot. A set-shot often occurs with a defender immediately in front of the shooter. This notion was supported by previous data showing a lack of a more upright position of the shooter during the presence of a defender compared to a standard jump shot (see Rojas et al., 2000). However, movement pattern differences based on skill level have to be interpreted cautiously because of the single participant design. In summary, the expected interaction between the task constraints of shooting distance and the presence of a defender was not shown for experienced basketball players who used similar movement patterns for defender and no-defender conditions.

Regarding the result of the discrete and continuous kinematic variables both the mixed-modelling approach and the angle-angle plots suggested strong similarities between participants in the lower body segment kinematics. Especially the hip segments which exhibited highly significant effects for both sides (see Figure 3-8). Similarly the variations in strategies used during ball release showed only minor variations and little inter- participant variability for the lower limbs. With regards to skill related variability, the measurements of the lower body supported the hypothesis that the most skilled performer showed the lowest levels of movement pattern variability. In contrast, measurements for the upper body showed high variations between participants and high intra-individual variations in the case of the left elbow as well. The investigation of the individual adaptation strategies in the discrete measurements further emphasized the different strategies used by the participants. Herein, the results of the present study for the hook shot vary strongly from results obtained from a basketball free throw where decreasing variability in linear speeds were found from lower to upper body segments (Miller, 2002).

The unique action of the hook shot might also be responsible for the decreasing influence of the elbow joint with increasing distance, putatively different from a standard basketball jump shot (Miller and Bartlett, 1993). In the present case, except for participant DA, all other participants used an extended elbow movement pattern and accordingly the acceleration of the wrist was mainly provided by shoulder movements. Hence, some precautions have to be executed when transferring results obtained from a standard basketball shot to a basketball hook shot.

Regarding variations observed in the angle-angle plots, the difference between the four participants highlighted the importance of intra-individual analysis methods and process-orientated analysis measurements, where this effect could have been masked when relying on discrete measurements only (Schöllhorn, Nigg, Stefanshyn, and Liu, 2002). Due to the different experience and skill levels of the participants, differences in movement pattern adaptations were expected. Yet the range of different solutions to the given motor problem was striking, illustrating the role of degeneracy in neurobiological systems and consequent effects on the indeterminacy of goal-directed movement patterns (see Edelman & Gally, 2001; Chow et al., in press; Davids et al., 2006; Hong & Newell, 2005; Liu, Mayer-Kress & Newell, 2006).

The distinct coordination patterns adopted between participants illustrated how the same functionality, although with varying success, could be achieved by different arrangements of neuro-mechanical structures (Edelman and Gally, 2001). The hook shot was performed either with synchronous flexions of the elbow or by movement of only the shoulder which in turn could be combined with different movements in the non-throwing arm. In case of the skilled participant, two completely different patterns were present clearly indicating degenerate functioning. Such distinct changes in movement patterning were not apparent for participant DA at least for the throwing arm, but did surface in the non-throwing arm. Furthermore this characteristic could be also observed in participants MA and PA. It is possible that these participants tried to maintain constant movement patterning in the throwing arm and used the non-throwing arm as a sort of damping mechanism in order to accommodate for perturbations like increasing throwing distance. By investigating only the throwing arm, one could mistakenly conclude that the movement stayed relatively constant over distance and conditions. In contrast, a different conclusion could be made based on the coordination of the non-throwing arm as well. This observation ties in with Bernstein's (1967) notion of morphological structures where perturbations to the movement can lead to alterations far from the actual source, in this case stemming from the increasing force requirements in the throwing arm.

Focussing on the behaviour of the throwing arm for participants DA, MA, and PA, the changes in movement patterning seemed to be gradually scaled as opposed to the sudden, qualitative reorganization of participant JA. From a dynamical systems theoretical viewpoint, this kind of behaviour was not suggestive of transitions between distinct attractors. Instead the movement adaptation can be interpreted as a change of an existing attractor layout in order to accommodate the necessary changes in constraints. These data are consistent with findings reported by Kostrubiec and Zanone (2002) who showed transient changes in attractors in a learning study using a wrist supination-pronation task. In their work, an existing attractor was transiently shifted towards a ‘to-be-learned’ pattern in order to accommodate environmental constraints. However, without investigating time scale behaviour in the present study, this interpretation of movement patterning as adapting an existing attractor layout remains speculative (see Liu, Mayer-Kress & Newell, 2006).

Conclusion

In conclusion, participants adapted their movement strategies to the emerging distance constraints, and only for the novice did the secondary constraint of the defender impact on movement patterning. Based on the individual routes of change taken by each participant, the task constraints seemed to interact with their intrinsic dynamics (individual abilities). And the behavioural information intrinsic to the task was differentially used. Whereas participants DA, MA, and PA sought to stabilize a specific pattern to achieve the task outcome, participant JA was able to switch between completely different patterns. Based on these findings and those of Southard (2002), throwing distance was postulated as an important control parameter for the organisation of discrete over arm throwing actions such as the hook shot.

The presented study demonstrated the value of the basketball hook shot as a potential movement model to investigate the application of dynamical systems theory to the study of coordination in a degenerate, discrete multi-articular action. All four participants showed adaptations in movement kinematics due to the alterations of throwing distance. Participant JA showed some peculiarities in the movement kinematics in the upper body segments which were potentially indicative of order parameter behaviour. For the remaining participants, main differences between conditions could be observed in the non-throwing arm. In general, the findings confirmed the necessity for intra-individual analyses of coordination data and a greater future focus on process-orientated approaches. The relatively minor differences between conditions indicated that the secondary constraint of the defender could be dropped from further investigations.

Regarding potential investigations of time scales in the basketball hook shot the movement time observed indicated that it would not be possible to investigate the relaxation of the movement after a perturbation within a single trial since the observed movement times would not provide participants with enough time to alter movement execution. Hence, time scale behaviour can only be investigated using the between-trials approach proposed by Schöner (1990).

4 Chapter Four: Analyzing discrete multi-articular actions

The preceding chapter showed that the basketball hook shot resembles a potential movement model that is well suited to the investigation of a degenerate, discrete multi-articular action from a dynamical systems theoretical perspective. However, the analysis methods used in Chapter 3 did not allow to determine a candidate order parameter for the basketball hook shot. Hence, alternative analytical tools which take the coordination of the whole body into account are needed to enable the analysis of phase transitions in discrete, multi-articular actions. In this chapter several available candidate tools will be assessed. In order to enable systematic comparison the required properties for a suitable method will be derived first.

Prerequisites for a measurement tool

Typically in studies of movement coordination from a dynamical systems theoretical perspective order parameter behaviour has been established using measurements of the movement kinematics. In studies of bimanual coordination, for example, the derived kinematics are usually transformed into phase angles and the relative phase is used to describe the coordination of the involved segments (e.g. Carson et al., 2000). The underlying assumption in this approach is that the derived measurements are closely related to the order parameter dynamics of the system. Based on these measurements, differences between movement patterns (or the respective order parameters) are inferred. Accordingly, the first prerequisite for an analysis tool is the ability to distinguish between movement patterns on a global scale allowing the categorisation of separate movement patterns into distinct groups.

The distinction between movement patterns in cyclical movement models has been mainly derived from changes in the temporal arrangement of the moving segments and/or changes in range of motions (Buchanan et al., 1997; Haken et al., 1985). Hence, a tool suitable for discrete, multi-articular actions should be able to pick up variations in movement patterning along these lines incorporating information from all involved moving segments. However, the mere derivation of distinct changes between different movement patterns does not suffice by itself to establish phase transitions behaviour. Based on derivations presented earlier in regards to attractor time scale behaviour, transitions should be accompanied by several characteristic events. Therefore, it follows that an analysis tool should also provide information about the time scales of the movement. Hence, the following hallmark features of phase transitions should be identifiable: (i) critical fluctuations, (ii) critical slowing down, and (iii) hysteresis. Further, with regards to the discrete nature of the proposed movement model it seems necessary that no assumption about the periodicity of input signals should be made.

Existing analysis methods

Relative phase

The most widely applied measurement tool in studies from a dynamical systems perspective is discrete relative phase (DRP). DRP describes the phasing of two oscillators in relation to each other (Hamill, Haddad, and McDermott, 2000) by measuring the succession of three time points: two subsequent instances of time of peak of a reference signal (t_1, T) and the time of peak of the second signal (t_2) in between the two events.

$$\Phi = \frac{t_1 - t_2}{T} \qquad (4.1)$$

Hence, DRP does not provide any information about the amplitude of the signal and its use is confined to periodic movement models. Therefore DRP cannot account for discrete movement models which makes it unsuitable for the proposed movement model.

An extension of discrete relative phase is the continuous relative phase (CRP), which measures the continuous deviation in phase space between two segments.

$$CRP(t) = \Phi_1(t) - \Phi_2(t) \qquad (4.2)$$

The phase angle is calculated from:

$$\Theta = \arctan\left(\frac{\omega}{\varphi}\right) \qquad (4.3)$$

The CRP is also confined to use with sinusoidal signals. As Peters, Haddad, Heiderscheid, van Emmerik and Hammill (2003) showed using simulated non-sinusoidal signals, the results can be highly misleading and do not represent the actual coordination pattern inferred.

Both DRP and CRP measures also suffer from the limitation that only two segments and their relative motion can be investigated at the same time which makes their application to multi-articular movements in general questionable (Corder, Levin, Li, and Swinnen, 2005). On this basis the relative phase measurements do not qualify for application to the proposed movement model.

Principal Component Analysis

Recently, principal component analysis (PCA) has been proposed as a measurement tool suitable for investigating movements with multiple biomechanical degrees of freedom. Analytically, the extraction of principal components is based on the estimation of the eigenvalues of the sample correlation matrix between the different input dimensions. A set of principal axes can be obtained which represent orthogonal components of the variation in the data and which are ordered according to the magnitude of the according variation (Stuart, 1982). This procedure yields a compressed representation of the input space where redundancies can be filtered out. The correlation is based on the linear model assumption and accordingly PCA extracts only the linear dependencies between input signals.

Post, Daffertshofer and Beek (2000a) investigated cascade ball juggling during self-paced and fast-paced trials using a PCA approach. Based on their modelling approach of the three balls' flight paths four dimensions were deemed sufficient to model the behaviour of the system. The subsequent application of PCA analysis to the ball kinematics corroborated this a-priori modelling. Comparing fast and self-paced juggling, a switch from four to two main components from the former to the latter condition indicated how PCA analysis was able to extract important information about movement organization regarding dimensionality. The authors stressed the importance of studying time series and the spatiotemporal variability which assists in identification of the most significant events during movement execution without biasing measurement a-priori in contrast to traditional discrete measurements (Post et al., 2000a).

PCA was also applied in the study of Chen, Liu, Mayer-Kress and Newell (2005) introduced earlier. The pedalo-cycling movement was recorded using 3D displacement data of joints of the whole body resulting in a 45-dimensional input space. Three to six components extracted by PCA were sufficient for describing 95% of the variance in the data. The first component accounted for more than half of the variance and its influence increased over the training period. The loading of the components varied between participants.

Corder, Levin, Li and Swinnen (2005) investigated the application of PCA to rhythmical parallel flexion-extension movements of elbows and wrists. The authors calculated the relative phase between the different segments and processed the resulting data with PCA. The identified movement patterning based on PCA matched the a-priori known differences in coordination patterning. e.g. when all four segments were used in an in-phase manner a single principle component was sufficient in order to capture data dynamics. This finding lead the authors to conclude that the PCA approach provides valid results. Investigating the limitation of PCA the authors noted that for actions where movements other than strict in-phase-anti phase patterns are prescribed, the resulting principal components structure will be more complex and accordingly more difficult to analyse. Further, when the input signals do not approximate sinusoidal signals the principal components will contain some additional noise components which will complicate the analysis (Corder et al., 2005).

Therefore, it comes as no surprise that the application of PCA has been mostly confined to rhythmical movement models. Even in a publication serving as a tutorial for the application of PCA (Daffertshofer, Lamoth, Meijer, and Beek, 2004) sinusoidal signals are used to demonstrate the feasibility in a simulation study and an investigation into walking on a treadmill. One exception was a study conducted by Hodges, Hays, Horn and Williams (2005) who investigated skill acquisition of a soccer chipping task. Using lower limb kinematics as input variables the results indicated no changes in the number of extracted dimensions from the PCA. These preliminary findings do not lend strong support to the suitability of PCA with discrete multi-articular actions.

Moreover, since non-linear system behaviour on a global and local scale forms the building blocks of the dynamical system theoretical perspective, it seems highly questionable whether PCA represents a suitable measurement tool for analysing movement. Attempting to address this limitation, Balasubramaniam and Turvey (2004) investigated coordination in hula hooping using a non-linear variant of traditional PCA. Instead of the correlation matrix, the authors used the mutual information between input signals to uncover redundancies in input space (Steuer, Kurths, Daub, Weise, and Selbig, 2002). Movements represented by 3D kinematics of the lower limbs joint positions served as input signals. By using the mutual information the authors hoped to protect against non-linearities and non-stationarities occurring in the input signals (Balasubramaniam and Turvey, 2004, p.180). However, estimation of the mutual information itself is not easily accomplished (Steuer et al., 2002) and Balasubramanaiam and Turvey (2004) provided no guidelines about how parameters were fitted to the model. Further, it can be argued that the chosen task resembled a highly constrained rhythmical task where high correlation between the different segments can be expected and it seems unlikely that a ballistic throwing movement would exhibit similar underlying relationships between movement components.

In regards to the criteria formulated earlier, PCA per-se does not identify attractors but serves primarily as a compression device. Simply recognising that two movements can be represented by a number of dimensions does not provide information about whether they are the same or whether there are fundamentally different. In order to identify commonalities or differences between movement, the projected signals in the compressed space still have to be investigated. Hence, with PCA the problem of identifying different movement patterns is only delayed, not solved, although admittedly, a compressed representation of differences between movements might make this problem somewhat easier.

In conclusion, the application of PCA aims at identifying the number of degrees of freedom in a given dataset (Chen et al., 2005) which does not necessarily provide information about phase transitions between different coordination patterns. Without the information about the attractor dynamics time scale behaviour cannot be investigated. PCA in itself does not satisfy the necessary criteria derived earlier.

Self-organizing maps

Acknowledgement of the non-linear relationship between input variables in motor control research has lead to investigations using unsupervised artificial neural network modelling. Due to the inherent properties of neural networks this class of analysis method can accommodate for non-linearity in input data and may be suitable for studies in motor control (Perl, 2004; Schöllhorn, 2004). Several authors have used varying approaches involving the application of self-organizing maps (SOMs). Similar to PCA, application of SOMs results in a compressed representation of an input space in which relationships between input dimensions are preserved (Kohonen, 1990).

Barton (1999) applied a SOM to classify different walking patterns using a two-stage approach. During the first stage, a 2D-SOM (15x10 nodes) was trained with the joint angle kinematics of the pelvis, hip, knee, and ankle yielding a compressed representation of the movement. Subsequently, a second smaller SOM (5x3) was trained with the representation from the first SOM in order to obtain a low dimensional identification of different walking patterns. The time-series nature of the data was preserved by presenting each time-slice at time t together with the slices at t+1 and t+2. Applying the approach to gait data from a clinical population the results showed that patients with similar conditions were mapped onto similar regions in the second SOM which was regarded in support for the analysis approach.

A recent application of this method by Barton, Lees, Lisboa and Attfield (2006) to the study of gait patterns used only one SOM (15x10). Using data from the Derby gait and movement laboratory database 3D displacement, moment, and power measures were obtained. Although the data stemmed from different domains the authors argued against normalizing input angles using z-scores (mean of zero and variance equal 1) based on the fact that offset information between angles would be lost. Further, for different participants different ranges can be observed which would be cancelled out by formulation of the z-scores (Barton et al., 2006). Therefore, a simple range normalization was applied to each input signal. To accommodate for the time-series property of the signals, the authors formed an augmented input vector which contained the current time frame plus input vectors which followed 5% and 10% after the current frame. Based on this approach the authors were able to qualitatively identify differences between normal and pathological gait patterns.

Bauer and Schöllhorn (1997) used SOM to investigate different movement patterns in a discus throw. Fifty three throws from two discus throwers were collected over a period of one year. Using 3D motion capture, joint angle displacement and velocity curves were obtained and time-normalized to 51 points. These data served as the training set for a SOM (11x11). The authors determined the necessary number of nodes based on a criterion which measured the neighbouring preservation between input and output space. Accordingly, trials which are close to each other in input space should be grouped closer together in output space. By recording the activation of the nodes based on the actual times series an activation sequence of map nodes was obtained. The input space data was normalized using z-scores which provided better results according to the authors compared to no normalization and pre-processing using PCA. Based on this representation differences between trials were established by imposing a metric on the 2D topology of the node grid. Differences were calculated using the Euclidean distances between active nodes yielding a distance matrix for all trials. This distance matrix was subsequently entered into a clustering analysis which determined groupings in the trial difference structure. The results indicated a learning effect for one of the participants and that trials within sessions were more similar than trials between sessions.

Another application to gait by one of the authors using the same approach demonstrated a better identification rate of the SOM using time-continuous measurements compared to traditional discrete data analysis (Schmidt, Schöllhorn, and Bauer, 1997; Schöllhorn, Stefanyshyn, Nigg, and Liu, 1999).

Analytically, self-organizing maps are based on a so-called winner-take-it-all algorithm (Kohonen, 2001). Following an iterative training procedure at each step the current input vector is compared with the current weights of the nodes and the node which is closest based on a specified metric is the winning node. Subsequently, the weights of the winning node and nodes in its immediate proximity are adjusted closer to the current input vector until convergence of the map is reached. Since the output space usually is of much lower dimension compared to the input space this procedure results in a compression of the data. Based on the properties of the SOMs the topology of the input space together with non-linear relationships between the different input spaces is preserved (Kohonen, 1990; Kohonen, 2001).

Although the SOM technique seems promising some significant problems accompany this approach. The validity and representativeness of the results obtained from SOM modelling obviously depends on the properties of the input space. For example, in a simulation study comparing SOM, PCA, and several other measures it could be shown that especially with high-dimensional data, the results from SOM can be misleading (Bezdek and Pal, 1995). More importantly the results obtained from the SOM procedure are highly dependent on the chosen architecture of the map. Whereas Bauer and Schöllhorn (1997) investigated different map dimensions holding the number of nodes constant, the other studies discussed failed to do so. Accordingly, it is difficult to interpret whether the results were unrepresentative of the data and just a result of the specific architecture chosen.

Further, the SOM by itself does not accommodate for time-series structure of the data. Only in the recent application by Barton et al.(2006) a potential solution has been provided (i.e., the embedding of the input vectors was based on a dynamical embedding procedure). Unfortunately, it still seems likely that this embedding structure is highly dependent on the chosen task and its proper estimation is far from being a trivial task by itself (compare Kay, 1988). Hence, two architectural problems regarding the embedding of the input space and the embedding of the output have to be solved before further application of SOM appears feasible.

Finally, SOMs by themselves are not the solution to the problem of grouping movement patterns but merely serve a similar purpose as PCA does. Whereas most studies analyse the maps qualitatively, the study by Bauer and Schöllhorn (1997) used a cluster analysis in order to group objects. However in using cluster analysis the authors must have assumed an Euclidean metric in node space. This assumption is questionable since the actual node space only identifies which nodes represent neighbouring objects, not necessarily how similar there weights are. Since the grid space can be intricately folded the assumption of an Euclidean metric can be highly misleading which unfortunately has not been investigated in the literature.

In conclusion, SOMs provide some promising features, potentially supporting their application as a valuable analysis tool for human movement studies in the future. However at present several methodological questions require further investigation before SOMs can be seen as a feasible analysis tool. Since, these problems were beyond the scope of the current programme of work, the feasibility of SOMs was no longer pursued.

Root mean square approaches

One of the more traditional approaches comparing the analysis of movement patterns based on time continuous data is the root-mean-squared-error (RMSE) criterion (Magill, 1989). In its simplest formulation the deviations between two curves (e.g. a trial pathway and a criterion pathway) at successive time points of a trial pathway are calculated, squared, summed, and the square root is taken from the resulting deviation score. Basically, the procedure calculates the Euclidean distance between two vectors in $\mathbb{R}^n$ where n refers to the number of time points of the two curves.

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(x_{trial,i} - x_{criterion,i}\right)} \qquad (4.4)$$

A condition inherent to this approach comprises that both curves must have the same number of time points otherwise a comparison is not possible.

Sidaway, Heise and Zohdi (1995) developed an extension of this approach to estimate the variability in coordination between two joint angles which can be obtained from angle-

angle plots. The procedure was called Normalized-Root-Mean-Square (NoRMS) method and measures the deviation of a group of trials from a mean trial. The desired angle kinematics of two angles are time normalized in order to obtain the same number of time slices for each trial. The underlying assumption therefore is that movements are scaled in a similar fashion and the relative placement of key events does not change between trials. Based on the time-normalized representation of the group of trials, a mean trial is calculated and subsequently the deviation from the mean trial for each trial using the RMSE for each angle is calculated (similar to the standard deviation in univariate statistics). Two variation scores per trial are obtained which are again squared, summed and the square root yields a single score which describes the deviations of the current trial from the mean trial. The resulting score is scaled according to the number of data frames and the excursion of the mean curves.

$$R_k = \sqrt{((Angle_1 - MeanAngle_1)^2 + (Angle_2 - MeanAngle_2)^2)}$$

$$RMS_i = \sqrt{\frac{\sum_{k=1}^{n}(R_k)^2}{n}} \tag{4.5}$$

$$NoRMS = \frac{\left(\sqrt{\sum_{i=1}^{J} RMS_i}\right)}{J * L} * 100$$

Sidaway et al. (1995) (1995) applied the method to data from a rhythmical ski simulator task. The results indicated that skilled performers showed higher consistency in movement execution compared to novice performers in the knee-knee and hip-knee angle-angle plots. The procedure was identified by Mullineaux, Barlett and Bennett (2001) as suitable to identify consistency in non-linear movement patterns.

Recently Hodges, Hays, Horn and Williams (2005) applied the procedure to skill acquisition data from a novice player in a soccer in-step movement. Using a 3D motion capturing system, a model representation of the movement was obtained which provided the desired joint angle kinematics. The results showed decreasing NoRMS scores throughout the learning period indicating less variability in movement execution in the lower limb segments (Hodges et al., 2005).

A procedure similar to NoRMS was used in the study made by Chen, Liu, Mayer-Kress(2005) described earlier. A Cauchy criterion which measures the differences between movements pattern performed on consecutive trials was used. The criterion was based on the differences between the spatial joint displacement in 3D space using a time-normalized representation of the movement. The differences were squared, summed over all variables, the square root was taken and divided by the number of trials – 1 and number of input spaces.

$$C_k = \frac{1}{45*(n-1)} \sum_{j=1}^{n} \left(\sum_{i=1}^{45} (x_{i,j,k+1} - x_{i,j,k})^2 \right)^{0.5} \quad (4.6)$$

Hence, when movements in subsequent trials was very similar a small C_k was obtained. Participants movements in the pedalo-locomotor task were recorded by a motion capture system in 3D and a whole body model was obtained. Results indicated a decrease of the Cauchy scores during the learning period (Chen et al., 2005).

In summary, the three approaches presented all apply the RMSE to estimate deviations between executed trials. The Cauchy criterion estimates the differences between two trials, whereas the NoRMS procedure estimates the variability of several trials together. The basic procedure therefore holds very few assumptions regarding the distributions of the raw data and only penalize higher deviations greater in magnitude than smaller deviations by squaring the deviations which seems to be an intuitively valid assumption. By using a whole body representation in the Cauchy-score differences in movement coordination in all segments can be assessed at the same time. Since no weighting of the different deviations is introduced, neither in time nor between different segments, equal importance is assigned to all segments and to all time instances. Hence, regarding the scalar nature of the dissimilarity scores obtained in all three procedures information is lost about the occurrence of deviations.

Important for all procedures is the assumption that time normalizing trials does not influence the variability of the signal and accordingly biases the deviation scores (Cordero, Koopman, and van der Helm, 2006; Page and Epifanio, 2007; Satern and Keller-McNulty, 1992). A potential confounding factor might be the introduction of the range normalization used in the NoRMS procedure. When the scores are range normalized the underlying assumptions is that small deviations in one angle with only small range of motions are as important as high deviations in another angle possessing a high range of motion. This line of reasoning seems counterintuitive since one can argue that for the CNS, limiting the range of motion in one angle represents a control problem by itself. Similar, like for a moving segment a joint angle cannot be held constant without determined control. Hence, range normalization of this angle masks this information and potentially biasing the results (Schöner and Scholz, under review).

A problem in particular with the NoRMS procedure is related to the calculation of the mean trial which implicitly assumes a normal distribution of the angle data which has to be checked on a task specific basis. Since the mean is quite sensitive to outliers, such trials will increase the deviation score disproportionately and potentially yield incorrect conclusions. Similarly, if the kinematics exhibit clustering behaviour where the investigated group of trials contain sub groupings, the level of variability within each group may be very small but because of the formulation of a mean trial, the dissimilarity score could be potentially inflated.

In conclusion, the RMSE procedures provides an intuitive approach in order to estimate the differences between different trials. However, the score itself only provides information about deviations in kinematics between trials, and not an absolute indication of movement patterning. Hence, regarding the formulated prerequisites the RMSE procedure alone does not prove sufficient for the present programme of work.

Cluster analysis

Cluster analysis represents a heuristic tool of analysis which aims at uncovering grouping structure in populations of different objects. Usual in application of cluster analysis the experimenters are faced with large amounts of data which need to be organized according to the underlying structure in the data in order to be more easily understood. Application of cluster analysis is common in various fields of research including biology (Handl, Knowles, and Kell, 2005) medicine (Blashfield, 1980; Everitt, Landau, and Leese, 2001), economics (Ketchen and Shook, 1996; Punj and Stewart, 1983).

In regards to studies in motor control, several applications of cluster analysis have been undertaken. Howard and Wilson (1983) used a cluster analysis to describe movement patterning in the backstroke swim start in ten participants. Using 2D motion capture, the authors calculated joint angles based on a 14 segment body model. Digitizing started from movement initiation and ended at entry of the head into the water. Using each 14 dimensional posture representation as an input vector, the movement postures or modal action patterns (MAP) were grouped according to their similarity in a hierarchical clustering algorithm. Based on the groupings of the data the authors identified twenty-one MAPs which were required in order to distinguish between different starting techniques. Interestingly, when one specific participant was discarded from the analysis only six distinct patterns remained (Wilson and Howard, 1983).

Other applications of cluster analysis to golf movement patterning were performed by Lames (1992) and more recently by Ball and Best (2007). The latter authors highlighted the usefulness of cluster analysis "*especially for identification of different styles, or movement strategies*" (p.3). Ball and Best's (2007) study investigated weight transference during the golf swing of 62 participants during ten simulated golf drives. Based on the centre of pressure path way during several key events of the movement, the authors were able to distinguish between different movement strategies. A two-stage cluster analysis was used where during the first stage a hierarchical cluster analysis was used. Subsequently all likely solutions were fed into a non-hierarchical cluster analysis and the different solutions were assessed using several validation measures indicating a best fit solution. The authors stressed the importance of validating the cluster analysis results using several measures.

One of the most consistent advocates in regards to the application of cluster analysis for motor control research has been the movement scientist Wolfgang Schöllhorn (1993, 2003, 2004). Schöllhorn has used several different approaches for the analysis of time-continuous representations of movements based on kinematics and kinetics eventually assessed through a cluster analysis. For example, using 3D motion capture, Schöllhorn (1993) investigated discus throws in one participant using eight trials in total. Estimating a Hanavan body model, kinematic and kinetic data of the joint angles was derived. PCA was applied to the time curves of the data from each trial and a factor loading matrix for each trial was obtained. These loading matrices were compared to each other and the derived dissimilarity scores were fed into a cluster analysis algorithm. The results showed a division of the eight trials into two groups (Gp 1 = 6 trials, Gp 2 = 2 trials). However, these different movement patterns were not apparently related to effectiveness as no association with performance could be identified within this small sample.

Jaitner, Mendoza and Schöllhorn (2001) investigated the run-up phase in long jumping using a cluster analysis. The authors obtained joint angle displacement and velocity data using 2D motion capture of 57 trials across 17 participants. The joint curves were time-normalized and range normalized. The pair wise differences between all trials were calculated and arranged in a distance matrix which was subsequently analyzed using a cluster analysis.

Based on the obtained clustering the authors were able to determine differences in the execution of the steps prior to the take-off. Further, strong indication for individual different movement patterns was exhibited. However, in both Jaitner et al. (2001) and Schöllhorn's (1993) studies no validation of the cluster analysis was performed.

Another prominent area where several applications of cluster analysis have been undertaken concerns the study of gait in cerebral palsy patients. O'Byrne, Jenkinson and O'Brien (1998) investigated gait pattern in 146 patients with cerebral palsy using a cluster analysis approach. Sagittal plane kinematics consisting of range of movement and maximum flexion and extension of hip, knee, and ankle were used as input vectors for the cluster analysis using a hierarchical k-means clustering algorithm. The resulting grouping was indicative of different walking styles and was used to establish a reliable identification scheme for clinicians. A similar approach was used by Kienast, Bachmann, Steinwender, Zwick and Saraph (1999). Based on 3D motion capturing and successive calculation of angles of the lower limbs a k-means clustering was performed. The cluster analysis was able to distinguish between normal and pathologic gait patterns. Furthermore, the cluster containing the pathological gait patterns exhibited a subdivision into different expressions of typical gait pathologies (Kienast et al., 1999).

A significant investigation into the use of cluster analysis for gait pathologies was performed by Toro, Nester and Farren (2007). The authors criticized preceding investigations that have not validated the cluster analysis noting that it remained unclear how in many studies the optimum number of patterns was assessed (Toro et al., 2007). The authors proposed a hierarchical clustering algorithm where a-priori numbering of clusters was not determined, rather the cluster solution and optimal number was post-priori assessed. The investigation was based on the kinematics of the lower limbs using a 3D motion capturing system with 67 subjects. The subject pool contained eleven children with no gait abnormalities, the other subjects had some form of gait pathology. Movement cycles were normalized to 100% of gait cycle and a mean curve from each subject, based on 20 trials was determined. Initial contact, maximum stance extension and maximum swing flexion from the hip and similar measurements from the knee and the ankle were chosen as input variables to the cluster analysis. The authors postulated three criteria in order to determine the optimality of the cluster solution: (1) The gait patterns of the non-pathological children should be grouped together into one single cluster separate from the other gait patterns; (2) Standard deviations between data cases within a cluster should exhibit stable values over a range of different cluster solutions; (3) A post clustering visual inspection of the normalized angle plots should exhibit distinctive differences between the clusters for at least one joint (Toro et al., 2007, p.4).

Based on the three criteria and using a furthest neighbourhood algorithm the authors identified a 14-cluster solution which best represented the data. One cluster consisted only of a single trial which exhibited high variability and was discarded from the analysis. The gait patterns of the normal subjects were all grouped into a single cluster. Subsequently, detailed investigation of the angle curves made significant differences between the clusters apparent.

In summary, cluster analysis appears to be promising methodological approach that can distinguish between globally similar and different movement patterns. The combination of RMSE approach and cluster analysis used in the investigations of Schöllhorn and co-workers seems well placed to address the first prerequisite of the desired analysis method. Using a time-continuous approach makes it is possible to assess timing between different segments together with range of motion information. However, as has been highlighted, the issue with the application of cluster analysis is related to the assessment of the validity of the obtained solution and how to identify a valid clustering scheme.

Further, in regard to the second prerequisite identified earlier, cluster analysis might prove especially useful since the results can be directly used to identify hysteresis effects (see Lames, 1992). However, in its present form the cluster analysis technique has not yet been used to identify other hallmark dynamical systems features such as critical fluctuations or critical slowing down.

Conclusion

In this chapter several analytical methods have been investigated which could be used to identify phase transition behaviour in a discrete, multi-articular action. At present there is no universally agreed upon analytical tool available which could be directly applied to studying this type of movement model. Based on the identified prerequisites for a potential tool, different methods from the extant literature were assessed and cluster analysis was identified as showing the highest proximity to the desired properties. However, the application of cluster analysis still presents unresolved issues which, unfortunately, have yet to be addressed sufficiently in the literature. An interesting feature of this approach is that through cluster analysis, the grouping of different movement patterns can be derived in a systematic manner. Typically, in investigations from a dynamical systems theoretical perspective, movement patterning and related order parameters have been derived either through a-priori knowledge obtained from previous investigations or from formal mathematical modelling. Potentially, the systematic approach underlying cluster analysis enables access to movements which have not been investigated before by movement scientists. Hence, it seems viable to investigate further the potential of cluster analysis in studies of motor control, especially in regards to application to discrete multi-articular actions like the basketball hook shot.

5 Chapter Five: Analyzing movement through a novel cluster analysis approach

Based on the assessment of the different analysis methods in the preceding chapter, cluster analysis was identified as a potential analysis tool for this research programme. In this chapter, a brief overview of the cluster analysis methodology is provided. Subsequently the feasibility of cluster analysis is assessed through several empirical, validation studies.

Cluster analysis basics

The basic aim of cluster analysis as a research method is to find groupings or clusters of objects belonging together within a greater population which is usually investigated by multivariate measurement techniques. Application of cluster analysis typically involves three successive steps (Handl et al., 2005): 1) Pre-processing; 2) Cluster analysis, and; 3) Cluster validation. In this introduction, each of the three steps is discussed in detail.

Pre-processing

During pre-processing, the input variables are chosen which serve as the determinants from which differences between objects can be assessed. The input variables have to be chosen by the experimenter based on application of a-priori empirical information or by theoretical rationale in the absence of data. For example, when investigating gait patterns one would usually include those variables which have been identified in the literature to be influential in regulating gait. Usually the input variables span a high multi-dimensional space which prevents the use of other statistical methods.

When the dimensionality of the input space has been determined, the measurement scales of the input variables are investigated. An important decision concerns whether all input variables stem from the same domain or whether they exhibit different units and scales (e.g. ordinal, nominal and interval) as in other statistical methods. This process entails the issue of data normalization. Typical normalization schemes involve either the formation of z-scores or simple range normalization. When a mixture of scales differing in quality are present, other schemes might be needed (Everitt et al., 2001). However, when the input variables all stem from the same domain and share a common meaning, then normalization is not necessary but potentially yields misleading results (Kaufmann and Rousseeuw, 1990; Schaffer and Green, 1996). Hence, pre-processing procedures need to be tailored to a specific data set. For example, again referring to gait analysis when using angle and displacement data a different scheme is necessary compared to only angle or angle and nominal data reflecting characteristics of different patient cohorts.

The following stage of pre-processing involves the definition of a dissimilarity score which represents the relation of the different objects to each other. The score should exhibit high values when objects are dissimilar from each other and accordingly low values when the objects are more alike. When interval scaled variables are used (e.g. joint angles) a common choice for a dissimilarity score is the Canonical or Euclidean distance between two input vectors which is basically the RMSE score mentioned in the previous chapter. The dissimilarities between all input objects are plotted and the results are arranged in a distance matrix **D**. Rows and columns of this matrix represent the different inputs so that, for example, the difference $d_{6,10}$ between the sixth and the tenth object can be found at the entry of the sixth row and the tenth column (compare). The matrix is symmetric and has zero entries on the main diagonal.

$$\mathbf{D} = \begin{matrix} 0 & d_{12} & \cdots & d_{1n} \\ d_{21} & 0 & & \vdots \\ \vdots & & \ddots & d_{(n-1)n} \\ d_{n1} & \cdots & d_{n(n-1)} & 0 \end{matrix}$$

Cluster analysis

In the next step, a clustering algorithm is used which performs the actual cluster analysis. Two main schemes can be distinguished: hierarchical and non-hierarchical clustering. The main differences between these two methods are that, in the former, no knowledge of the number of clusters is present, whereas during non-hierarchical clustering, the number of clusters formed is decided by the experimenter a-priori. Since for the present research programme the number of clusters is not known, following the arguments by Toro et al. (2007) further discussion will focus on hierarchical clustering and on agglomerative methods.

Agglomerative hierarchical clustering partitions the data into clusters in a succession of steps. During the first step, the number of clusters equals the number of input objects. The algorithm searches for the two objects with the smallest dissimilarity based on the dissimilarity matrix and merges these objects into a single object. Depending on the choice of the clustering algorithm, the dissimilarities between the newly formed cluster and the remaining objects is calculated and the same step is repeated until all objects belong to a single cluster. The results of the clustering algorithm are typically presented in a so-called dendrogram which illustrates the successive merging steps and indicates at what dissimilarity score the merger was achieved through the relative height of branches. For example, Figure 5-1 shows a cluster analysis that was performed on data of gross domestic product (GDP) and percentage of working population from different countries (Eurostat, 1994). The dendrogram indicated the presence of two clusters with the left cluster containing 8 countries and the right one containing 4 countries. The height of the branches indicated that the countries in the left cluster were all very similar to each other and showed high dissimilarity to the countries in the other cluster which was represented by the high connection point between the two clusters.

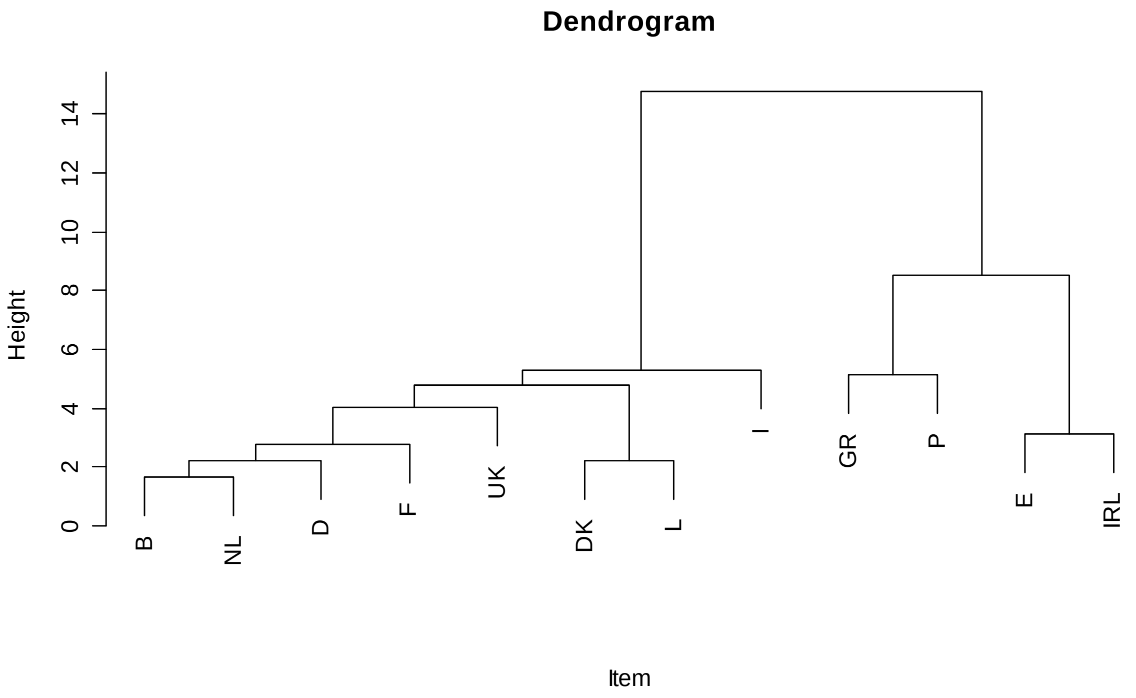

Figure 5-1: Dendrogram obtained by cluster analysis on GDP and percentage of working population of 12 different countries (see text for details).

Several different clustering methods are available and there are no clear-cut criteria about which algorithm is superior (Blashfield and Aldenderfer, 1978). However, the choice of clustering algorithm will impact upon the resulting clustering scheme, hence care should be taken during its choice. The algorithms which have received the most investigation in the literature are the single-linkage, complete-linkage, group-average, centroid linkage, median linkage and the Ward method. Coincidentally, these were the types of algorithms used in the studies of human movement presented earlier. In Table 5-1 the different algorithms are shown together along with some of their properties (Everitt et al., 2001; Kuiper and Fisher, 1975).

Table 5-1: Properties of different cluster algorithms according to Everitt et al. (2001, p.62)

Method	Distance between clusters defined as	Remarks
Single linkage	Minimum distance between pair of objects, one in one cluster, one in the other	Tends to produce unbalanced and straggly clusters (‘chaining’), especially in large data sets. Does not take account of cluster structure.
Complete linkage	Maximum distance between pair of objects, one in one cluster, one in the other	Tends to find compact clusters with equal diameters (maximum distance between objects). Does not take account of cluster structure.
(Group) Average linkage	Average distance between pair of objects, one in one cluster, one in the other	Tends to joint clusters with small variances. Intermediate between single and complete linkage. Takes account of cluster structure. Relatively robust.
Centroid linkage	Squared euclidean distance between mean vectors (centroids)	Assumes points can be represented in Euclidean space. The more numerous of two groups clustered dominates the merged cluster. Subject to reversals.
Median linkage	Squared Euclidean distance between weighted centroids	Assumes points can be represented in Euclidean space for geometrical interpretation. New group intermediate in position between merged groups, subject to reversals.
Ward’s method	Increase in sum of squares within clusters, after fusion, summed over all variables	Assumes points can be represented in Euclidean space for geometrical interpretation. Tends to find same size, spherical clusters; sensitive to outliers.

The group average algorithm tends to be quite robust against outliers and is not strongly affected by unequal group sizes. Based on its mathematical properties, Kaufman and Rousseeuw (1990) recommend the group average algorithm as a good choice in many situations (see also Punj and Stewart, 1983).

The main issue with hierarchical cluster algorithms is that the result is potentially only representative of a sub-optimal solution. Due to the nature of the stepping procedure, if a mistake in the algorithm occurs during one of the earlier steps, there will be an impact on all of the following steps. Since it is difficult to identify such mistakes once the analysis is completed, the results of a cluster analysis should not be accepted as correct at the termination of this stage but still need to be validated (Ball and Best, 2007; Blashfield, 1980; Everitt et al., 2001; Halkidi, Batistakis, and Vazirgiannis, 2002a).

Cluster validation

Validation of the results is an important part of cluster analysis and therefore it is surprising that this step has been omitted in most of the studies presented earlier. According to Handle, Knowles and Kell (2005), validation techniques can be classified as either external or internal measures. External measures are possible if a ‘gold-standard’ for a given set of data is available and the obtained cluster analysis results can be compared to this standard which provides a direct assessment of cluster analysis performance. Internal measures work on the information inherent to the given dataset and aim at assessing the quality of the clustering without pre-existing data. Several different internal measures have been developed without a universally agreed-upon procedure. Thus, it is recommended to use several different measures to accommodate for internal biases of the different methods in order to obtain valid results (Ball and Best, 2007; Halkidi et al., 2002a; Halkidi, Batistakis, and Vazirgiannis, 2002b; Handl et al., 2005).

Regarding the internal measures, several different properties can be identified: (1) Compactness: assessment of cluster compactness or homogeneity; (2) Connectedness: assessment to what degree the clustering scheme represent local densities in the distribution of the data; (3) Separation: how well are the different clusters separated; (4) Combination: validation schemes which use properties 1 to 3; (5) Predictive power/stability: through resampling methods the stability of the clustering results is investigated; (6) Compliance between an obtained partitioning and distance information. Based on the distance matrix and the cluster analysis partition it can be assessed whether the obtained result conforms with the information in the distance matrix. For example, when a specific partition has been obtained and one cluster contains two objects which are according to the dissimilarity matrix highly different from each other the compliance measure would penalize this inconsistency.

Hence, to make an informed decision about the cluster analysis results, a combination of several validation procedures seems necessary. Following the validation procedures the final partition of the cluster analysis can be identified since one is usually not interested in the compete hierarchy but only a few partitions.

In conclusion, as has been pointed out, the cluster analysis per se does not represent a singular procedure but demands the execution of several informed decisions by the experimenter at various stages during the analysis. Nevertheless, cluster analysis apparently shows the necessary properties to make it a feasible analysis method to study discrete, multi-articular action. However, before proceeding, the approach has to be validated in regards to the remaining prerequisites identified in Chapter 4 related to the identification of phase transitions (i.e., critical fluctuations, hysteresis, and critical slowing down).

Cluster analysis and scaling experiments

Hallmark features associated with phase transitions such as critical fluctuations, hysteresis, and critical slowing down, need to be empirically testable using the proposed method. Hysteresis could be indicated by the cluster solution if changes between different clusters occurred at different values of a proposed control parameter depending on the direction of change (compare Lames, 1992). Critical fluctuations cannot be assessed directly, based on the clustering itself, but the dissimilarity score could be utilized as a surrogate measure. When critical fluctuations are present, mean dissimilarity scores for a given control parameter as represented in the distance matrix should exhibit a sharp rise, denoted as a 'knee' in the plot of the mean dissimilarity scores against the control parameter. Accordingly, if peak behaviour of mean scores occurs in the vicinity of switching areas, this occurrence may be interpreted as indicative of critical fluctuations. According to Schöner (1990), inter-trial variability can be used in order to assess the stability of the movement (Scholz and Schöner, 1999; Schöner, 2002) and subsequently to identify critical slowing down after a perturbation (Schöner, 1990). Dissimilarity scores between trials should decrease between subsequent trials after the application of a perturbation, similar to the Cauchy criterion applied by Chen, Liu, Kress & Newell (2005). Hence, during phases of instability the dissimilarity scores should take longer (i.e., more trials) to relax back to the unperturbed state compared to the number of trials needed in stable regions. The information can be directly obtained again from the dissimilarity matrix **D** since the first main diagonal of the **D** represent the differences between subsequent trials.

In the present form, the proposed cluster analysis approach is based on a single-participant design. According to the theoretical foundations of DST explained earlier, variability at several levels of observation is inherent to neurobiological systems and although archetypical responses, like for example phase transitions, are observed across participants, strong inter-individual differences usually are present (compare Thelen, 1995). For example, in the study by Kelso et al. (1992), using a multi-articular movement model, the authors observed different switching strategies between participants (see also Buchanan et al., 1997 for similar findings). Similar, in the study by Sorensen et al. (2001) the hysteresis areas were located at individually different positions. Hence, when using a multi-articular degenerate movement it seems likely that even greater inter-individual differences would be observed. This expectation is also supported by the findings from Chapter 3, where the four participants exhibited strong inter-individual differences during movement execution. Accordingly, it seems necessary to adopt an analysis approach, which is centred around a single-participant design. This has also been recognized in the literature (Button et al. 1998; Button et al. 2003; Button et al. 2006). Using such a "*coordination profiling*" approach (Button et al. 2006, p. 138) has the advantage that detailed analysis of individual responses is possible. This approach prevents masking effects of individual variability which can occur when adopting a group based analysis (Schöllhorn et al. 2002). Further, extending the individual analysis and using a multiple-baseline single participants design overcomes some of the inherent limitations of single-participants designs in terms of generalizing the findings (Bates, 1996; Reboussin and Morgan, 1996, Zhan and Ottenbacher, 2001).

In summary, cluster analysis potentially provides the necessary features to investigate all of the prerequisites of a dynamical systems theoretical analysis. At the same time it could relieve researchers from requiring extensive a-priori knowledge about order and control parameters allowing them to test the tenets of dynamical systems theory with a wide range of movement models based on a systematic approach. To probe the feasibility of the cluster analysis some sort of validation has to be performed. Hence, in the following sections a proposed cluster analysis method will be explained and subsequently a validation of the method shall be conducted.

Proposed cluster analysis method

The technical method is based on the assumption that kinematic similarity between different movement trials is related to the similarity of underlying order parameters. In the examples from the literature where a-priori knowledge of order parameters was available, the argument in favour of designating a specific variable as an order parameter was partly based on the kinematic properties of the task. For example, in the finger flexion-extension task, the relative phase was assumed as an order parameter based on the switching between 'in-phase' and 'anti-phase' behaviour which in turn is a result of the neuro-mechanical properties of the index finger segments (Assisi, Jirsa, and Kelso, 2005; Carson and Riek, 1998; Carson et al., 2000; Haken et al., 1985). Changes in movement patterning can also be indicated by activation and suppression of active biomechanical degrees of freedom as has been shown in a elbow-wrist flexion-extension task (Buchanan et al., 1997; DeGuzman et al., 1997), in a lifting task (Limerick et al., 2001), or discrete prehension (Button et al., 1998). Through analysis of the movement kinematics the relative timing between components, which are assumed to play an important role in discrete movement patterning, can be identified (Schöner, 1990). Hence the assumption appears reasonable although some reservations do exist on the extent of its validity (Saltzman and Kelso, 1987).

The mathematical basis for the proposed technical procedure is a generalization of the normalized root mean square (NoRMS) procedure (Sidaway et al., 1995) followed by a cluster analysis, based upon the approach developed by Schöllhorn and co-workers (see Chapter 4). All joint angles input curves are presented in time-normalized form, meaning that trials are trimmed according to specific events in the movement execution and interpolated in order to obtain plots of equal length.. As pointed out earlier, it can be argued that input data stemming from the same input domains do not necessarily demand normalization since they all share a common metric, and might also lead to false conclusions (Schaffer and Green, 1996). Therefore, the proposed procedure does not include amplitude normalization because only joint angles are involved which through anatomical constraint exhibit similar potential ranges of motion. Herein, the proposed method differs from the approach of Schöllhorn (1998) who used amplitude normalized input data.

Accordingly, the procedure can be explained as follows:

Let $\mathbf{T_1}$ and $\mathbf{T_2}$ be the matrices representing the angular data of two trials, where columns represent the M different input variables and rows represent N successive time points.

$$T_1 = \begin{bmatrix} a_{111} & a_{112} & \cdots & a_{11N} \\ a_{121} & \ddots & & \\ \vdots & & & \\ a_{1M1} & \cdots & & a_{1MN} \end{bmatrix}, T_2 = \begin{bmatrix} a_{211} & a_{212} & \cdots & a_{21N} \\ a_{221} & \ddots & & \\ \vdots & & & \\ a_{2M1} & \cdots & & a_{2MN} \end{bmatrix}$$

The dissimilarity between these two matrices can be obtained by subtracting the matrices from each other and calculating the Euclidean norm of the resulting difference matrix yielding a dissimilarity score (**D**).

$$D = \left\| T_1 - T_2 \right\|_2$$

When two trials are performed with exactly the same movement pattern, the score will be zero, and accordingly, the more the kinematics between two trials differ from each other, the higher the **D** value yielded. Calculating all possible permutations of trial pairings, the obtained **D** scores can be arranged in a distance matrix which can be subsequently submitted to a hierarchical cluster analysis following the approaches of Wilson and Howard (1983) and Schöllhorn (1995; , 1998). According to the the literature, the average distance method has desirable mathematical properties, is widely used and is robust against outliers and unequal cluster group sizes (Kaufmann and Rousseeuw, 1990; Kuiper and Fisher, 1975). Since it is possible that the experimenter a-priori does not know whether equal groups sizes will be obtained or that participants may show outlying behaviour between trials, it seems reasonable to make the average distance algorithm the method of choice for the proposed analysis approach.

In order to secure the results against the possible identification of false structures following the arguments presented earlier, a two-fold validation scheme is proposed.

First, a bootstrapping method developed by Shimodaira and co-workers (2002; , 2004; Suzuki and Shimodaira, 2004) can be used. This method assesses the stability of the clustering through multi-scale bootstrapping, testing the reliability of a particular cluster solution. During the multi-scale bootstrapping procedure, several bootstrap replicates are generated by sampling from the experimental data. Multi-scale bootstrapping refers to the fact that the sample sizes are varied. Through this approach, by recording the number of times a specific partitioning obtained from the "bootstrap replicates" matches the initial clustering, the stability of the specific cluster can be assessed. Subsequently each node in the cluster tree can be rated with p-values indicating the level of statistical probability of the specific node representing true clustering (Shimodaira, 2002, 2004). In regards to the bootstrapping procedure, an important question deals with the number of bootstrap replicates necessary to ensure convergence of the procedure. Following the propositions of Suzuki and Shimodaira (2006b), once the range of all p-values ± 2*standard errors falls between 0 and 1, the number of iterations can be deemed sufficient. All necessary procedures are available through the R software package (R Development Core Team, 2006) and the add-on packages pvclust (Suzuki and Shimodaira, 2006a) and scaleboot (Shimodaira, 2006). Second, the results can be checked using the Hubert-Γ value which estimates the compliance between the distance matrix and the clustering structure (Halkidi et al., 2002a). High Hubert-Γ scores indicate the existence of compact clusters and one usually inspects a plot of Hubert-Γ scores plotted against several partitions where the best solution is indicated by a significant knee of the graph (Halkidi et al., 2002b). Together, the two methods test different properties of the cluster solution and one can assume some robustness of this particular validation scheme.

Error influences

Because the calculated dissimilarity score forms the input for the clustering algorithm, an investigation into possible error sources is necessary. A simple model with only two linear curves will be used to highlight further issues which might occur during the analysis.

Let f_1 be the reference graph with f_1 := a*ti (i=1,..N) where a is a constant slope, N is the number of time frames and f_2 is the testing graph. Three different influences will be investigated: (I) Different intercepts, (II) different slopes, and (III) different offsets between the graphs.

(I) Different intercepts: Let f_2 := a*ti + b

$$D = \sqrt{\sum_{i=1}^{N} (at_i - at_i - b)^2} = \sqrt{N} b$$

(II) Different slopes: Let f2 := c*ti, with c:=a+b.

$$D = \sqrt{\sum_{i=1}^{N} (at_i - ct_i)^2} = b \sqrt{\sum_{i=1}^{N} t_i^2}$$

(III) Different offset: Let f2 := a(ti + b).

$$D = \sqrt{\sum_{i=1}^{N} (at_i - a(t_i + b))^2} = \sqrt{N} ab$$

In case (I), the error term consists of two parts. The first square root term affects all trials in the same way since all trials should have the same length after time normalization. Therefore, only the second part is of interest. From a movement coordination perspective the different intercepts represent differences in actual movement execution, from where it follows that the obtained score is actually intended. In case (II) two cases have to be distinguished. In the case of a true difference, the former argument applies. In the case of an erroneous difference when the true slopes are equal (e.g. the differences in the slope can be introduced either if one of the cutting points is not the same in the two trials or when the trial lengths differ), the dissimilarity is erroneous and gets multiplied by the squared time points. Similarly, in case (III) the difference can be introduced when inaccurate cutting points are being used. The error term gets inflated, not only by the offset error, but can also be multiplied by the slope and the square root of the number of points which will always be >1. Both cases (II) and (III) highlight the importance of using trials that cannot differ much in length before time normalization in order to obtain meaningful data. Further, trimming points must be used which can be reliably identified in all used trials.

Method Evaluation

In order to show that the procedure extracts meaningful data from the analysis of movement kinematics, studies will be used where some a-priori knowledge about possible movement patterning is present and hence the validity of the cluster solution can be externally assessed.

Three studies were chosen in order to fulfil two requirements. On the one hand it should be validated whether the proposed method was able to extract the same information when compared to traditional measures for a task where both methods could be applied. For this reason, a task from the rhythmical bimanual coordination domain was chosen which could be analyzed with the proposed method as well as a traditional method. In regards to the present programme of work, obviously the feasibility of the method with the proposed new movement model had to be investigated as a prerequisite for further investigations. Here, a relatively simple experiment was chosen were the cluster analysis method should show its potential in identifying clearly different discrete, multi-articular movement patterns. In a second step it was checked whether the sensitivity of the method was high enough in order to pick up alterations between similar movements, a property which would be desirable for further investigations.

Experiment 1

Methods

In the first experiment, a wrist supination-pronation task was investigated similar to the movement model used by Carson et al. (1996). A case study approach was used in which the participant was seated in front of two manipulanda and instructed to synchronize an anti-phase movement with a metronome. Movement frequency was scaled from 1 Hz to 2.5 Hz in steps of 0.25 Hz and each step lasted for 8 seconds. As is the convention in many studies of phase relations in cyclical movements, the participant was instructed that, if the movement patterning were to become unstable, the most comfortable pattern should be adopted. The recording frequency of accelerometers attached to the manipulanda was set at 500Hz and data from 12 trials in total were collected. Single movement trials were determined according to the occurrences of maximum pronation of the right hand and time normalized to 100 data points. Discrete relative phase (DRP) data were calculated according to the method of Kelso (1995) using the displacement data from the accelerometers. Displacement data were also used for the clustering procedure and dissimilarity scores were calculated according to the procedure explained earlier. For the bootstrapping procedure 10,000 iterations were performed and the standard errors of the p-values were investigated.

All statistical analysis were performed using the R software with the pvclust, scaleboot, and fpc packages for the cluster analysis and validation. All remaining calculations were performed using custom programs written in Matlab 7.1.

Results

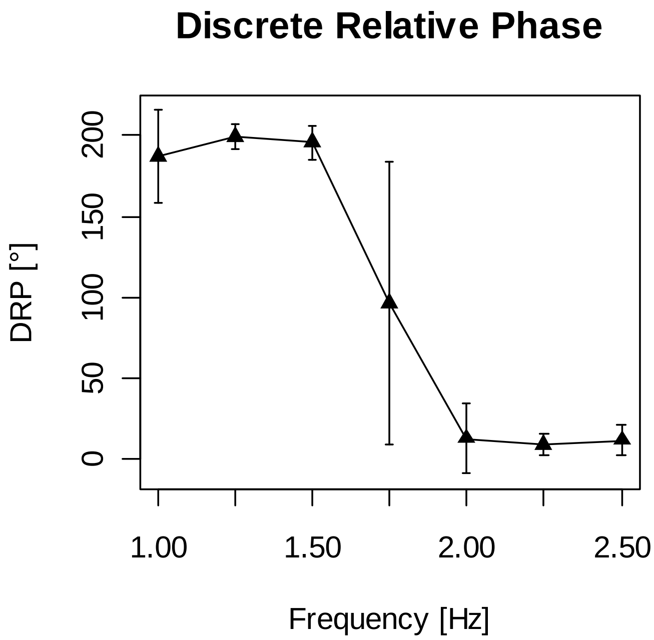

Figure 5-2: Mean discrete relative phase and standard deviations from one trial.

Figure 5-2 shows the mean DRP for each movement frequency bin from all trials. As expected from previous studies, the anti-phase pattern was stable for the lower movement frequencies and a shift to an in-phase pattern was apparent at a critical frequency of 1.75 Hz. The error bars indicated a high increase in the variability of the movement pattern at the critical frequency. Since the results for the individual scaling trials were all very similar, only a single representative scaling trial will be discussed and the results of DRP and the cluster analysis compared.

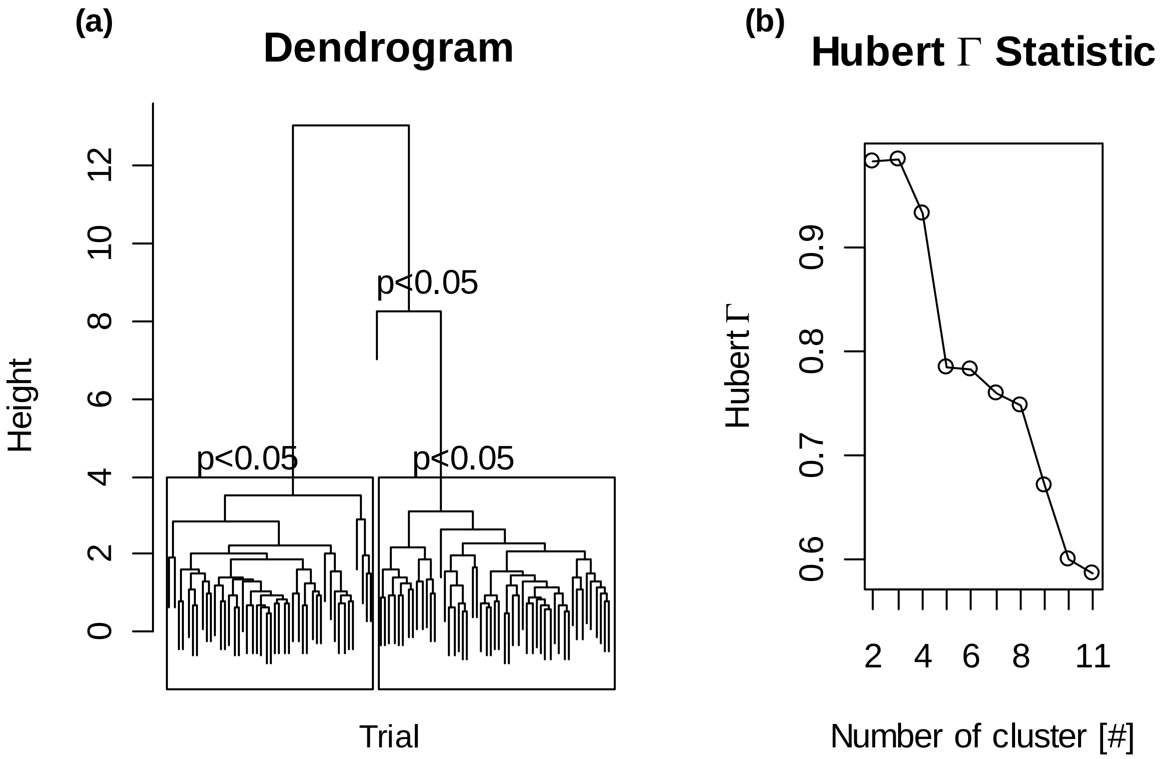

Figure 5-3: (a) Results of cluster analysis approach for bimanual movements. P-values of boostrap procedure are plotted next to the according clusters. (b) Results of Hubert-Γ scores against different number of clusters.

Figure 5-3.a shows the dendrogram of the cluster analysis clearly indicating a three-cluster solution. The p-values of the bootstrapping procedure supported this notion ($p<0.05$) providing evidence for a true clustering. Figure 5-3.b shows the Hubert-Γ statistic which also supported a three-cluster solution. The result represented a two-cluster solution (grey shading) with a third cluster consisting only of a single movement trial.

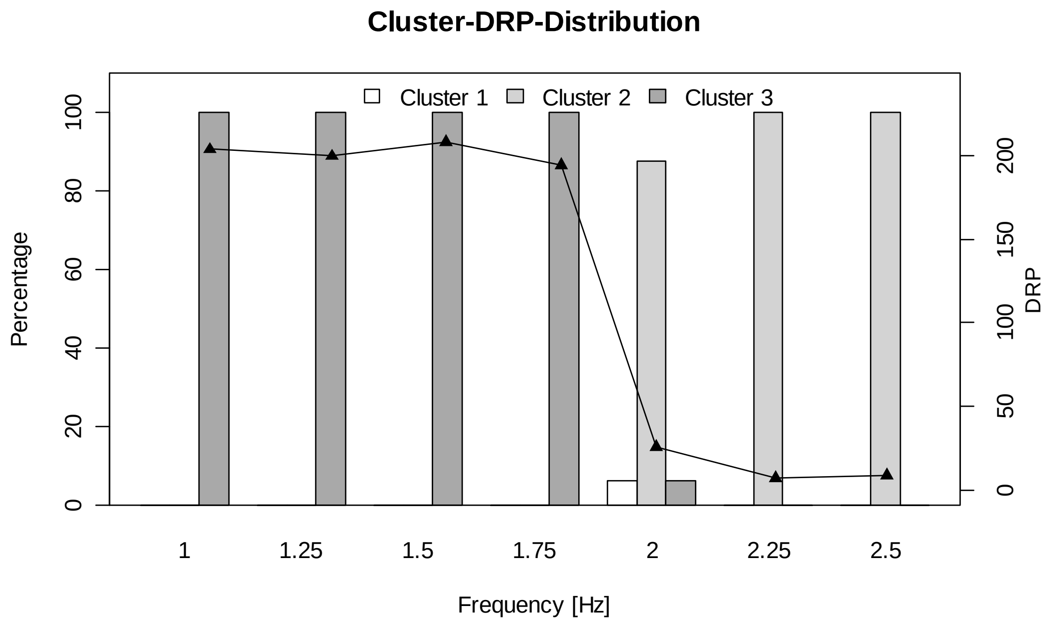

Figure 5-4: Percentage of identified clusters against movement frequency with results from mean discrete relative phase superimposed.

Figure 5-4 shows the cluster distribution as a function of movement frequency with the associated mean DRP superimposed. The plot provided clear evidence for a relation between the clustering and the movement frequency. For the lower frequencies, the participant used Cluster 3, which represented in the present case the anti-phase movement. At 2Hz, a switch from Cluster 3 to Cluster 2 took place. Further, a single occurrence of the Cluster 1 was present which represented the singular object visible in Figure 5-3.a. As can be seen from the DRP graph Cluster 2 represented the in-phase movement pattern.

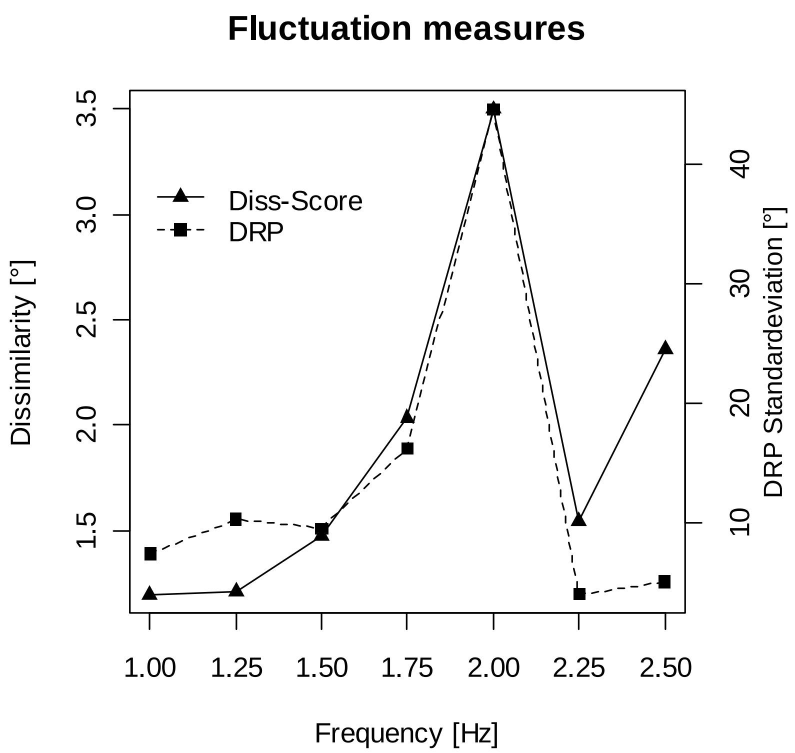

Figure 5-5: Plot of deviations scores obtained from the cluster analysis approach (left y-axis) plotted against the movement frequency and standard deviations obtained from discrete relative phase analysis (right y-axis).

In Figure 5-5, the fluctuations of the movement patterns are plotted by using: (a) the dissimilarity scores obtained from the clustering approach, and (b) the standard deviation of the DRP measures. The two measures mirrored each other quite closely with a sharp rise at 2 Hz. However, the dissimilarity scores showed an increase for the highest movement frequency which was not as strong in the DRP measure. This difference stemmed from the lack of sensitivity of the DRP measurement where only three points of the movement cycle were used to estimate the value, whereas for the dissimilarity score, information over the course of the whole trial was used. Analysing the kinematics of the trial showed that for the higher frequency even the in-phase pattern showed some variation in the range of motion of the wrist which was not identified by DRP.

In summary, the results of the clustering analysis closely resembled the results obtained from the discrete relative phase measure identifying the different collective states of the system (Haken, Kelso & Bunz, 1985), thereby providing the necessary information for subsequent analysis. In addition, the cluster analysis showed some enhanced sensitivity over the DRP technique which resulted from the analysis of continuous kinematics in contrast to DRP which estimated the movement patterning solely based on three time slices and discarded all information regarding movement amplitude.

Experiment 2

Methods

In order to assess the feasibility of cluster analysis as a method for differentiating between discrete movement patterns, a multi-articular throwing task was investigated. Four professional basketball players (age = 22 ± 4 yrs, height = 1.91 ± 0.8m) were instructed to try and score baskets using three different shooting techniques from appropriate distances: ‘free throws’ from 4.6m distance, ‘three point’ shots (6.5m), and ‘hook shots’ (4m). As experienced players, the participants were familiar with the required techniques and throwing distances. The protocol did not resemble the standard scaling methodology protocol, but was used to highlight the validity of the technical analysis method for clearly distinguishing between different established movement patterns.

Participants were prepared with passive reflective markers (5mm diameter) on the left (l) and right (r) acromion, C7, sternum, lateral epicondylus humerus (l/r), radial styloid (r/l) and ulnar (r/l), back of the right hand, spina illica anterior superior (r/l), spina illica posterior superior (r/l), sacrum, lateral and medial epicondyles femoris (r/l), lateral and medial malleolus (r/l), heel and toe marker (r/l) in order to identify anatomical landmarks. In addition one marker each was placed on the tibia (r/l), on the lateral part of the femur (r/l) and the humerus (r/l) and on the distal, dorsal part of the forearm. Sampling frequency was set at 100 Hz during motion capture with a three-dimensional motion capture system (Motion analysis corp.) using 12 digital cameras. A mobile basket fixed at a conventional height of 3.05 m with a Plexiglas backboard and a standard sized basketball (Size 7, FIBA approved) was used as the target for all shooting trials.

From the position of a marker, hip joint centres were estimated using the procedure by Bell, Pedersen and Brand (1990), and positions of the shoulder joints using the procedure by Rab, Petuskey and Bagley (2002). Subsequently a 13-segment rigid body model was established using Visual3D software (C-motion). Joint angles were calculated using the Euler convention but only angles in the primary joint plane of motion were used for further analysis. Shoulder joint kinematics of the right and left shoulder were estimated through the included angle between the upper arm and the trunk. The trials were trimmed from the instance of maximum hip flexion before throwing to the instance of maximum wrist height. All trials were time normalized to 50 data points. The resulting joint angle plots were then used with the proposed clustering method. The number of bootstrapping samples was chosen according to the standard errors of the p-values ranging between 10,000 and 20,000 iterations. As before, all statistical analyses were performed using the R software and further calculations were performed using custom programs written in Matlab 7.1.

Based on a-priori experiential knowledge assuming a three-cluster solution corresponding to the three shooting techniques, it was predicted that the free throws and the three point shots should be more similar compared to the cluster of patterns for the hook shots since these techniques appear more similar to each other.

Results

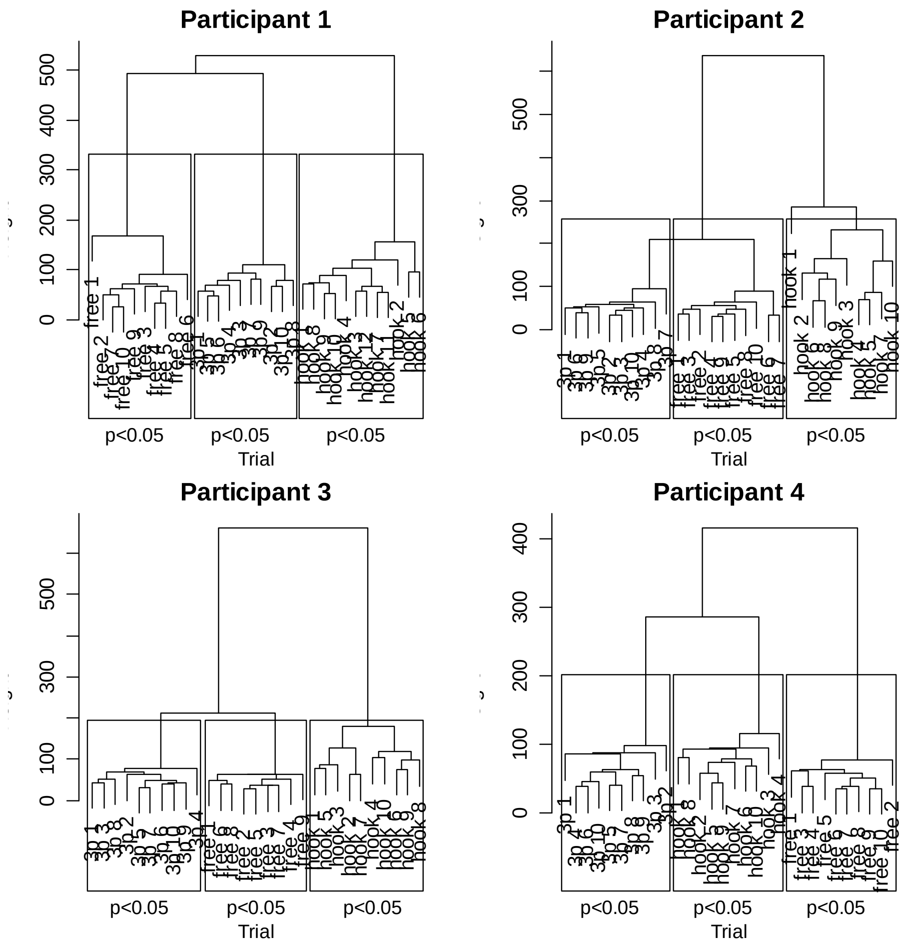

Figure 5-6: Individual dendrogram obtained from the results of the cluster analysis approach. P-values for each cluster are plotted underneath the according cluster.

Figure 5-6 shows the cluster solutions for the different participants with the three predicted main clusters for all four participants. The p-values obtained from the bootstrapping procedure supported the reliability of the three-cluster solution. The performance of participants one to three support the prediction of greater similarity between the free throw and the three-point shot, although some individual variability in the extent of this support was present in the data. For participant one, the free throws were well separated from the three-point shots compared to participants two and three where the merging between the clusters occurred at a much lower dissimilarity value. For participant four, the cluster analysis grouped the three-point shots and the hook shots together. Further qualitative inspection of the kinematics for participant four revealed a special technique for the hook shot, a so-called “jump-hook” which is much more similar to a jump shot (Martin, 1992), and explains the outcome of the cluster analysis. The variations in dissimilarity values when comparing the different techniques for the individual participants were supported by the Hubert-Γ values in Figure 5-7.

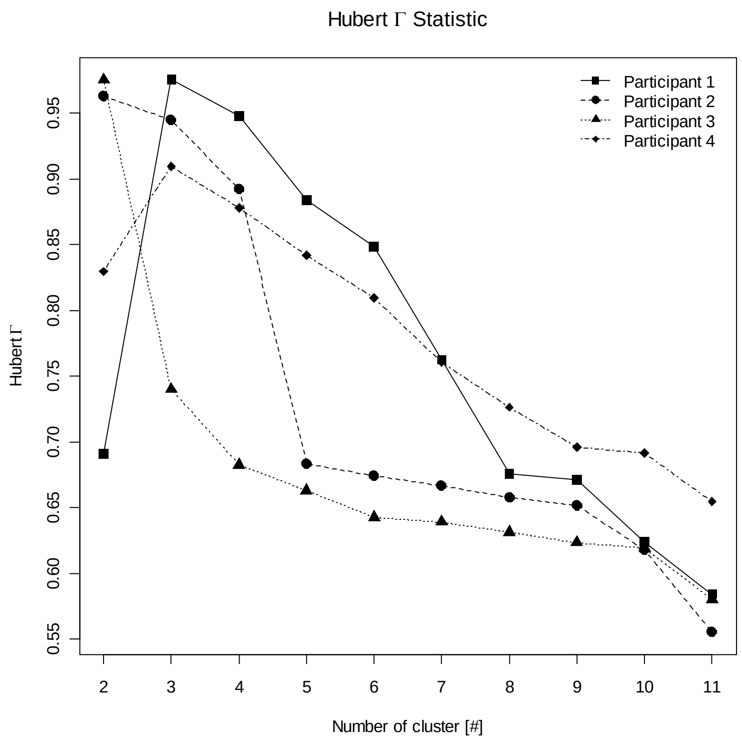

Figure 5-7: Plot of Hubert-Γ scores for each participant against number of clusters.

For participant one and participant two, the three-cluster solution showed the highest score whereas participants three and four demonstrated a peak at two clusters. However, in participant four’s case the decrease to the 3-cluster solution was relatively small indicating a possible differentiation using three clusters. The differences observed between the Hubert-Γ and bootstrapping procedure indicated that some interpretation in their use is needed.

In summary, the cluster analysis applied to three different shooting techniques performed by skilled performers lead to entirely expected results. The method was able to identify a-priori known differences between the different movement patterns supporting the application of the methodology for analysing performance of discrete multi-articular actions.

Furthermore, the technique was also able to identify some interesting individual differences in relation to the amount of dissimilarity between three basketball shooting techniques.

Experiment 3

Methods

The third validation study used a scaling methodology with a discrete multi-articular action. Two professional basketball players (age=20 and 21 yrs, height=1,93 and 2.00m) were instructed to score baskets using a hook shot technique from distances between 2m to 9m. Both participants typically played as forwards and were experienced at the hook shot technique. The changing distance imposed different strength and coordination requirements on participants and was assumed as a potential control parameter (Southard, 1998, 2002). The study was performed in a gymnasium with a ceiling height of only 4.5m. This physical environmental characteristic imposed a spatial constraint on the shooting technique because the ball trajectory arcs normally exhibited during basketball shots from further distances were not available to the performers. The experimental set-up was chosen after initial pilot work, the rationale was to facilitate a strong division between techniques used for close- and far-range shots. Therefore, at least a two-cluster solution was expected to result from this particular experimental manipulation. During shots from closer distances participants could perform their typical techniques since the ceiling did not limit selected throwing arcs, whereas for greater distances it was believed that the height constraint would lead to a forced adaptation in movement patterning, which would be identified by the cluster analysis.

Participants were prepared in the same way as in the preceding experiment and the same recording set-up was used. After a 15-minute warm-up period each participant performed eight trials from each distance starting at 2m and ending at 9m in increments of one metre. Afterwards the same procedure was applied in reverse starting from 9 metres. Data analysis was performed in the same way as in experiment 2.

Results

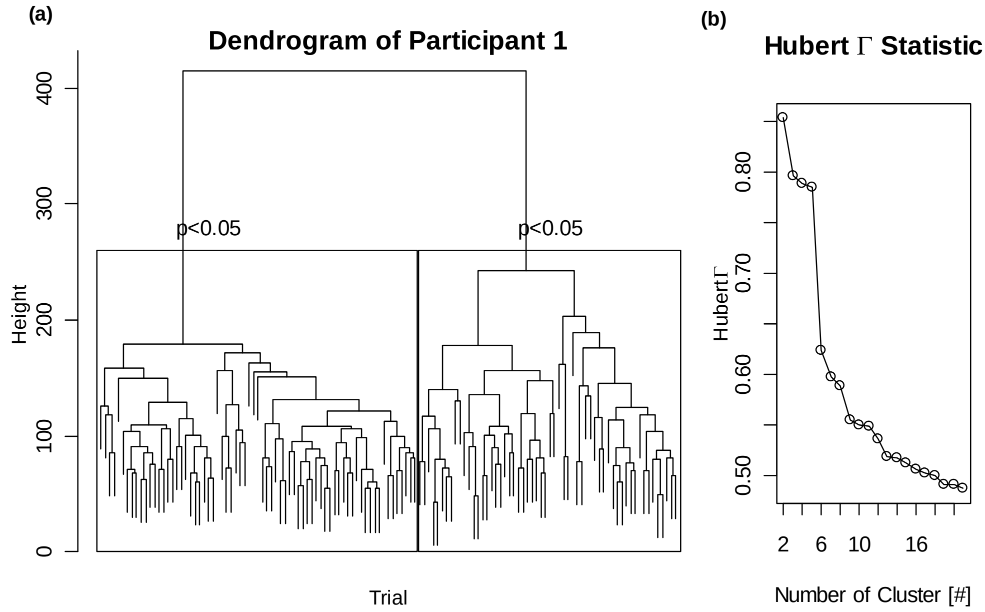

Figure 5-8: (a) Dendrogram of participant 1 based the results from the cluster analysis approach. P-values of bootstrap procedure are plotted above according clusters. (b) Plot of Hubert-Γ scores for participant 1 against number of clusters.

Figure 5-8.a shows the cluster solution obtained from the hook shots performed by participant one. The dendrogram presented a clear two-cluster solution with high dissimilarities between the two clusters indicated by the height of the tree branches. This visual impression was also supported by the bootstrap procedure where both p-values for the according cluster were < 0.05. The Hubert-Γ scores also supported the two-cluster solution (compare Figure 5-8.b) with a maximum for two clusters. The left cluster contained trials from greater distances and the right cluster captured trials from smaller distances, indicating usage of different movement patterns by participant one as distance changed. With increasing distance, movement patterns belonging to cluster 1 were observed until the 6m location, where a switch to cluster two took place and accordingly a transition to a different movement pattern (see Figure 5-9.a). This movement pattern was retained until the final distance for shooting. When starting to shoot from 9m, the participant used movement pattern two until the distance value reached 4m, and only switched to movement pattern one at 3 m. This observation is consistent with a hysteresis effect, with the movement patterning dependent on the direction of control parameter change, although this suggestion needs to be ratified by further research.

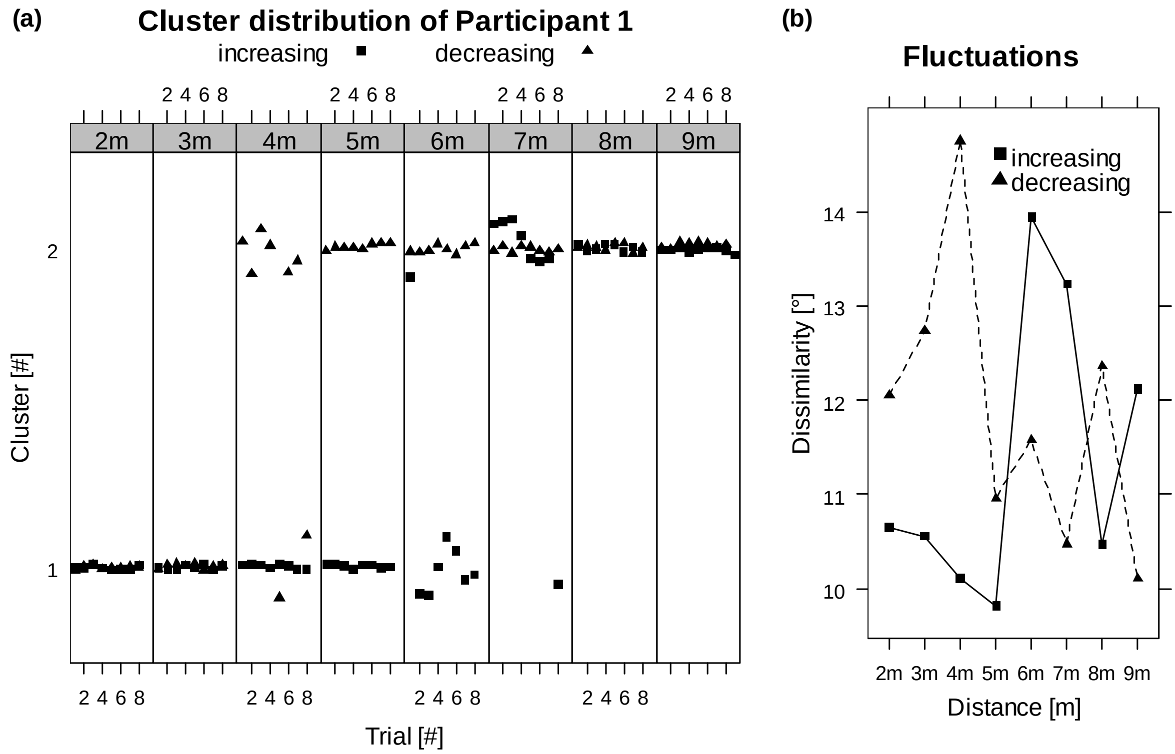

Figure 5-9: (a) Plot of obtained clusters for participants 1 against trials grouped by throwing distance for increasing throwing distance (■) and decreasing throwing distance (▲). (b) Plot of dissimilarity scores for participant 1 against throwing distance for increasing (■) and decreasing (▲) throwing distance.

Figure 5-9.b shows the mean dissimilarity scores at each distance for the two conditions. The scores during the increasing distance trials showed a sudden jump from 5m to 6m followed by high values at 7m distance. At 8m, the dissimilarities faded away and increased slightly afterwards at 9m. For the decreasing condition, a similar sudden jump was present at distance 5m to 4m, with a first sudden rise at 8m distance. Relating these findings to data in the movement patterns associated with distance, it was apparent that, in both cases, sudden jumps in movement pattern dissimilarity accompanied the transition from one cluster solution to another. In light of the propositions discussed earlier, this observation could be interpreted as the presence of critical fluctuations just before a phase transition.

In summary, for participant one the two expected movement patterns were identified. Further key indicators were observed providing good support for the occurrence for a phase transition but further investigations of time-scale behaviour are necessary in order to make conclusive statements.

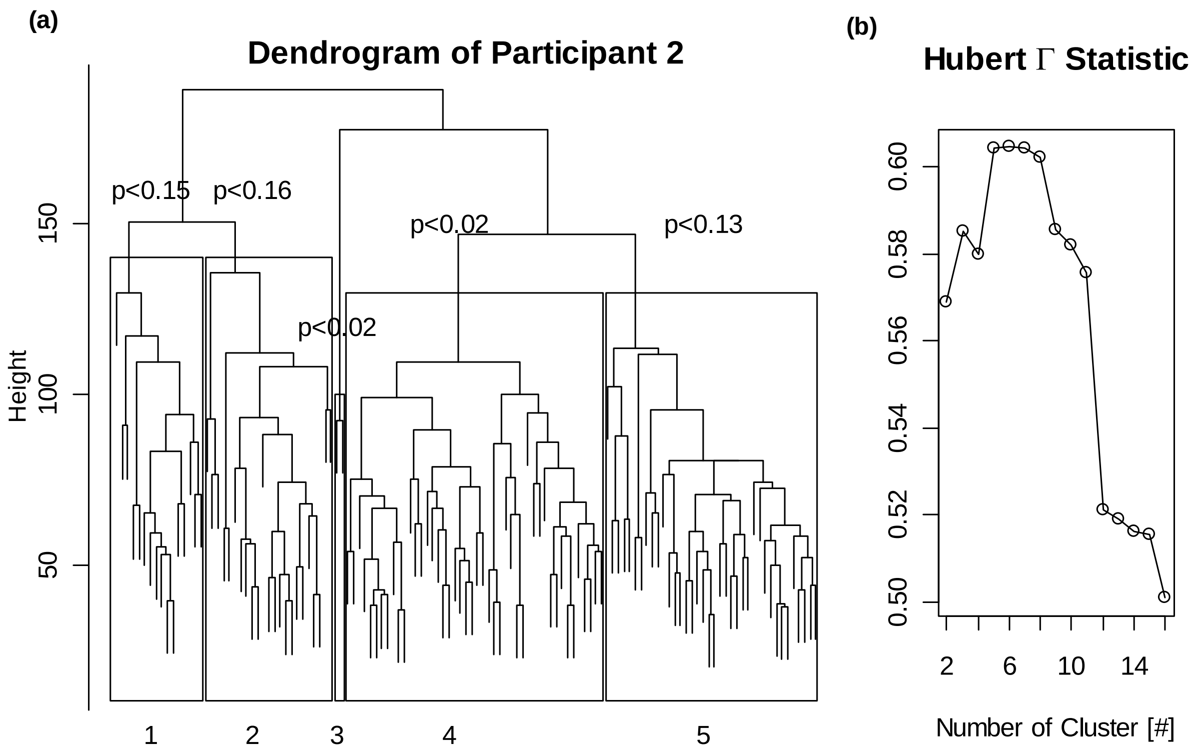

Figure 5-10: (a) Dendrogram of participant 2 based the results from the cluster analysis approach. P-values of bootstrap procedure are plotted above according clusters. (b) Plot of Hubert-Γ scores for participant 2 against number of clusters.

Figure 5-10.a shows the cluster solution for the hook shots performed by participant two. The dendrogram showed a distinction into two main clusters with both containing two further subclusters and one small cluster which contained only two trials. The Hubert-Γ scores indicated a preference for partitions of 5 to 8 clusters which was also supported by the bootstrapping procedure. Overall, the height of the dendrogram was lower compared to participant one. This finding indicated that in general the dissimilarity between the clusters was not too high, potentially indicating the presence of a scaling strategy where a single movement pattern is scaled according to distance affordances, in contrast to switching behaviour between globally different patterns. For ease of discussion the numbering scheme of the clustering can be seen by the number at the bottom of the rectangles (Figure 5-10.a). The lower p-values for clusters 1, 2, and 5 indicated that these partitions were not as stable as cluster 4 and that some trials might have changed clusters between bootstrapping replications.

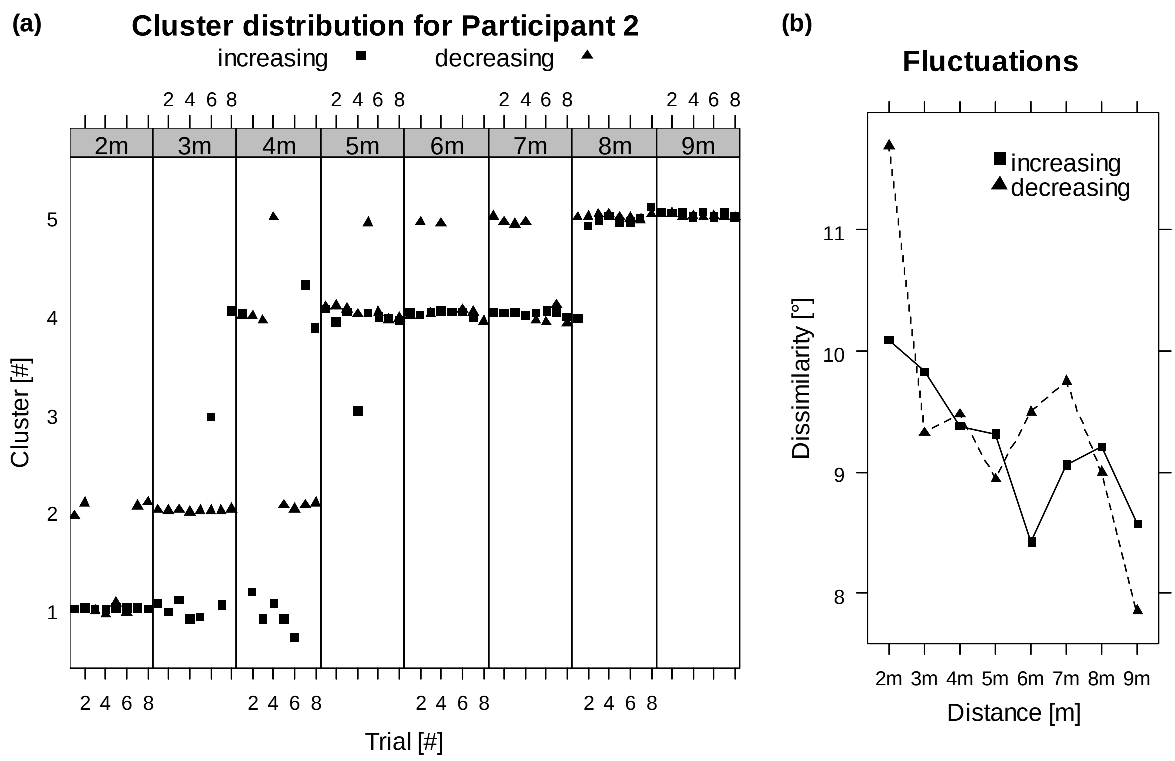

Figure 5-11: (a) Plot of obtained clusters for participants 2 against trials grouped by throwing distance for increasing throwing distance (■) and decreasing throwing distance (▲). (b) Plot of dissimilarity scores for participant 2 against throwing distance for increasing (■) and decreasing (▲) throwing distance.

Plotting the cluster solution against distance to targets in Figure 5-11.a made a differential effect for the two conditions apparent. During the increasing distance condition, participant two preferred three different patterns with cluster 1 for distances between 2m and 4m, cluster 4 for distances between 5m and 7m and cluster 6 for 8m and 9m accordingly. A different picture was apparent for the decreasing distance condition. Starting from 9m, pattern 5 was used until 7m where the participant switched to cluster 4 just like in the increasing condition. However, as cluster 4 was maintained until 5m some fluctuations towards cluster 5 were apparent. At 4m initially movements from cluster 4 were used, followed by one instance of cluster 5and subsequent use of movement patterns which belonged to cluster 2 which pre-dominated until 2m. At this location some alternating behaviour with cluster 1 was apparent.

In regards to the branching of the main clusters in the dendrogram, clusters 1 and 2 could be assigned to lower throwing distances whereas cluster 3 and 4 represented shots from higher distances. Comparing the transitions between the two main clusters between conditions, the clustering provided some indication for a hysteresis effect.. Whereas cluster 1 was mainly used during the increasing condition, cluster 2 was more prominent during the decreasing condition. Similar, the occurrences of cluster 5 during the decreasing condition for distances between 4m and 7m indicated some memory effect which potentially arose through the previous usage of cluster 5 in contrast to the increasing condition. Potentially, for this individual the intrinsic dynamics were influenced by the manipulation of the task constraints yielding the observed behaviour.

Regarding the mean dissimilarity score in Figure 5-11.b a decreasing trend with increasing distance was apparent. For the increasing condition from 2m to 5m, the fluctuations decreased with a minimum at 6m followed by increases for 7m and 8m, accompanying the switch from pattern 10 to pattern 6. For the decreasing condition the scores rose from a minimum at 9m to a peak value at 7m followed by a minimum at 5m and rising to their highest value at 2m. At 7m the switch from pattern 6 to pattern 10 took place.

In summary, the patterning for participant 2 was more varied than for participant 1 but also followed a distance-related trend. Some indication of a hysteresis effect but no critical fluctuations could be observed.

In conclusion, the results of the scaling experiment in a constrained physical environment justified the application of the cluster analysis. Particularly for participant one, the results showed strong indications of phase transitions where all predicted criteria were fulfilled. For participant two the results were not as clear cut, with the movement patterning showing a hysteresis effect only and smaller distinctive differences as distance varied. Possibly, the constrained environment influenced the movement patterning in a different way for this participant as compared to participant one. Both participants showed a trend for differential use of movement patterning as throwing distances changed, which was expected a-priori and which was identified by the cluster analysis to support its feasibility. However, the bootstrapping procedure and the Hubert-Γ values showed that, when interpreting results of a cluster analysis, a validation approach is necessary so that no naïve interpretation of the cluster analysis is made.

Conclusion

In this chapter a technical method for analysing joint kinematics data from discrete movements based on a cluster analysis was introduced. The method provided information about similarities in the kinematics between movement trials assuming only limited a-priori knowledge of their underlying structure. Based on the assumption that movement similarity resembles some information about the involved attractors, the method can be used in combination with a scaling procedure to investigate phase transitions in discrete movements. The postulation of potential collective system states can be made objectively and apparent arbitrary divisions between different movement patterns are avoided. Further, the analysis enables the investigator to identify different accompanying characteristics of phase transitions like hysteresis, critical fluctuations and directing subsequent research. Using data from three different studies, the method could be successfully applied exemplifying its relevance for studying movement coordination.

However, the method can only be used as a first approach investigating the underlying order parameters of the specific task at hand since no explanation about the actual construction of the order parameters is obtained from its implementation. Therefore, whilst the method would be enhanced by subsequent kinematic investigation, crucial information regarding the dynamic structure of different movement models can be gained. Especially regarding the results from experiments 2 and 3, the methods are suitable to investigate the proposed degenerate, discrete movement model. Further, based on the results in experiment 3 some further support was found for interpreting shooting distance as a candidate control parameter, highlighting the feasibility of using a basketball hook shot as an exemplar model for studying phase transition behaviour in discrete, multi-articular actions. Accordingly, in the following chapters, an investigation of the basketball hook shot from a dynamical systems theoretical perspective will be presented.

6 Chapter Six: Phase transitions in a discrete multi-articular action

Introduction

Summarising the progression of the research programme thus far, the findings from Chapter 3 supported the candidacy of the basketball hook shot as a suitable movement model, i.e., a discrete, multi-articular action with degenerate properties. In Chapters 4 and 5, the necessary analytical procedure was developed to enable systematic investigation of the hook shot. Both studies indicated that the throwing distance resembled an influential task constraint. Therefore, the following requirements set out within this research programme have been met: (i) identifying the basketball hook shot as a movement model, (ii) the use of a cluster analysis approach combined with a scaling experiment, and (iii) manipulating throwing distance as a candidate control parameter. Accordingly, the main aim of the present chapter was to ascertain whether phase transitions in movement patterning for the basketball hook shot would be triggered by changes in throwing distance.

With regards to the experimental procedure adopted thus far, several possibilities exist to improve the methodology. For example, the instance of maximum wrist height was used in Chapters 3 and 5 to determine the occurrence of ball release. However, the true point of ball release may show some variation during movement execution and may change systematically with throwing distance (Elliot, 1992; Miller and Bartlett, 1996). Hence, precise estimation of the actual instance of ball release could reduce the influence of noise on derived movement kinematics. For example, the kinematics of the throwing arm showed some peculiar differences between participants (see Chapter 3), and increasing the precision of movement kinematics regarding the arm could serve to further highlight differences in movement patterning.

In this chapter the term ‘scaling’ will be used in two different contexts. When referring to the experimental methodology scaling describes the continual manipulation of a candidate control parameter in either an increasing or decreasing direction. When used in the context of movement patterning, scaling describes the fact that a specific movement pattern is continuously adapted into a different form which emphasises the way that movement patterns are related to each other.

The results from Chapter 3 provided evidence for two distinct strategies used by the participants dependent on manipulations of throwing distance. Whereas participant JA used two different movement patterns, one at shorter distances and one at longer distances, the remaining participants seemed to adapt a single movement pattern throughout the experiment. For them, pattern alterations according to throwing distance were less distinct. Their scaling strategy involved keeping the movement kinematics of the supporting leg and the throwing arm relatively stable and varying mainly the kinematics of the non-throwing arm according to throwing distance. In contrast, participant JA held the lower body kinematics stable but exhibited peculiar changes in movement patterning in both arms. In regards to the skill level of the participants, JA was a professional basketball player whereas the other participants were either novices or intermediate players with prior experience at club level.. These results suggested that the differences in movement patterning were influenced by skill level. However, based on the single-participant design no strong conclusions could be made. Further, the identification of phase transitions was hampered as the systematic scaling of throwing distance in both directions was not employed and therefore hysteresis behaviour could not be investigated.

In Chapter 5, a similar movement adaptation scheme was identified for the two participants investigated. Results from the cluster analysis for participant one clearly indicated a division into two distinct movement patterns according to throwing distance. Measurement of pattern dissimilarity showed increased values within the switching regions for one participant, suggestive of critical fluctuations, and comparison of the transition points between the two movement clusters indicated hysteresis behaviour. Together, these results provided support for the occurrence of global reorganization of movement patterning due to alterations in throwing distance, indicative of phase-transition behaviour. In contrast, cluster analysis applied to the movement kinematics of participant two showed less peculiar differences between movement patterns according to throwing distance. This finding could be indicative of scaling behaviour as observed in the three less skilled participants in Chapter 3. Since no critical fluctuations were identified for this participant, further support for a scaling scheme rather than global reorganization was provided. Nevertheless, analysis of the transition points between movement clusters for participant two indicated hysteresis behaviour.

Both participants studied in Chapter 5 were professional basketball players which questioned the relationship between choice of throwing strategy and experience level, although no investigation of throwing performance was undertaken. Potentially, classification of participants' skill level, purely based on prior playing experience, was insufficient. However, as this study was conducted with the special constraint of a low building ceiling some caution must be exercised since this could have affected movement patterning. Therefore, to further investigate the connection between throwing strategy and skill level it was necessary to explore the movement behaviour of participants with a range of different skill levels. Unfortunately, because of the complexity arising from the analysis method it was not feasible to conduct an experiment with groups of sufficient sizes in order to make conclusive statements on skill group membership. In addition, due to local difficulties in accessing a large sample of professional basketball players, made it impossible to establish an expert group either. Therefore, maintaining a range of different skill levels was decided on, but to rate participants rather on actual performance during the experiment as reported in the study by Button et al. (2003, N=6) and accordingly discuss results based on this performance rating. This way, differences in adaptation strategies, despite similar levels of prior 'experience' as reported in Chapter 5, could be observed according to actual shooting performance.

Accordingly, the following predictions in regards to movement patterning were formulated. Based on the results from Chapter 3 where two different movement patterns were identified only for the skilled performer, for skilled participants, the movement patterning should follow a clear distinction into two different strategies which can be divided into movements more prevalent at smaller distances and movement patterns more prevalent at higher distances. The differences between the movement patterns should show changes in the kinematics of both upper body segments, paired with high stability for the kinematics of the supporting leg. Transitions between the movements should be accompanied by critical fluctuations, possibly occurring at different distances depending on the direction of distance change (indicating hysteresis behaviour). In contrast, according to the results from the three less experienced performers in Chapter 3, less skilled players should show a scaling approach where a single movement pattern is adapted across all distances and conditions. Movement kinematics of the support leg and the throwing arm should reveal small changes and higher deviations should be present in the kinematics of the non-throwing arm. Modifications to the movement pattern as identified by the cluster analysis approach should show no critical fluctuations however hysteresis behaviour should be present as in the case of participant 2 in study three of Chapter 5. Hence, the first strategy exhibited by more skilled participants can be attributed to a phase-transition following a bimodal attractor layout (Haken et al., 1985) whereas the strategy adapted by less skilled performers resembles a uni-modal attractor layout with transient modification of the attractor (Kostrubiec and Zanone, 2002).

As was argued during Chapter 2 providing a link between movement models used in previous studies from a dynamical systems perspective and the basketball hook shot would provide a better understanding of shared properties between discrete, multi-articular movements and more traditional bimanual movements. Accordingly, in Chapter 3 the curvature of the wrist trajectory was investigated and results were contrary to those inferred from the literature on rhythmical movement patterns (Buchanan et al., 1997; Kelso et al., 1991b), highlighting the need for further investigation. Based on these findings it was expected that the radius of the wrist trajectory would increase with throwing distance as a consequence of hand velocity increasing with throwing distance.

Further, in order to keep the analysis consistent with the biomechanics literature on basketball movements, it appeared advantageous to maintain analysis of discrete kinematics at the point of ball release as well as the mixed-effects modelling approach. In Chapter 3, the time of occurrence of ball release was actually estimated from the instance of maximum wrist height. As noted earlier, since this could have been a misleading measure, further investigation based on the actual instance of ball release seemed necessary. Results from Chapter 3 indicated also consistent patterning of the kinematics of the lower body across participants and distances with the lowest variability exhibited by the professional player. In contrast, the discrete kinematics of the upper body showed greater variations both across distances and participants. In detail, the results showed increasing extension angles in the right elbow, the right knee, and the left hip and greater flexion in the right hip with increasing throwing distance. The most peculiar result in Chapter 3 concerned the high inter-participant residuals in comparison to the intra-participant residuals which was much greater for all joint angles. Performance scores obtained in Chapter 3 indicated a decreasing trend with greater throwing distance. Based on the different experience levels of the participants it was expected that performance levels during the experiment should follow the prior experience levels. Together, these results served as the guiding hypotheses for the present experiment. However as suggested, some unexpected differences in movement kinematics might occur because of the altered task constraints in the present study (no defender).

With regards to the distinct properties of discrete movements (compared to rhythmical movements) another hypothesis can be investigated. As discussed earlier, behavioural information could be used by the performer in between trials to alter movement patterning in subsequent trials. For example, when receiving information about the outcome of the movement, an actor can use this information to alter execution in a subsequent trial (compare Liu et al., 1999 for an example). A simple postulation could be formulated indicating that low performance scores should be followed by high differences in the kinematics between subsequent trials. This approach seems intuitively reasonable since when an actor provides a poor performance (e.g. overshoots the target), he/she typically adjusts movement kinematics in order to perform more successfully on the subsequent trial, therefore exhibiting greater dissimilarities between these subsequent trials. When performance is good, it seems reasonable to expect that movement kinematics would be kept similar in order to replicate the trial outcome, resulting in low dissimilarities between subsequent trials. A limitation of this approach would be that potential effects of the candidate control parameter distance would not be taken into account. Analytically, the comparison of the similarity between subsequent trials can be easily obtained from the calculations necessary for the cluster analysis approach. Since, during the calculation of the distance matrix **D** the dissimilarities between all trials are calculated, differences between subsequent trials present only a subset.

Materials and Methods

Participants

Eight males (Age=27±5, Height=175cm±16, Weight=81kg±14) participated in the study. Participants JA, NI, and CA were semi-professional basketball players for the Otago-Nuggets (New Zealand national franchise) in the national league. Participants DU, KE, RY, and BR had at least played at club level whereas participant SH had no prior experiences in playing basketball. All experimental procedures were approved by the University of Otago Ethics committee. All participants used their dominant right hand for throwing and had not experienced any injuries in the six months preceding the study.

Apparatus

A mobile basket fixed at a conventional height of 3.05m with a Plexiglas backboard and a standard sized basketball (Size 7, FIBA approved) was used for all shooting trials. Sampling frequency was set at 100 Hz during three-dimensional motion capture (Motion analysis corp.) using 12 digital-cameras. A DV-camera was synchronized with the motion analysis system to enable visual determination of the time of ball release.

Participants were prepared with passive reflective markers (5mm diameter) at the left (l) and right (r) acromion, C7, sternum, lateral epicondyles humerus (l/r), radial styloid (r/l) and ulnar (r/l), back of the right hand, spina illica anterior superior (r/l), spina illica posterior superior (r/l), sacrum, lateral and medial epicondyles femoris (r/l), lateral and medial malleolus (r/l), heel and toe marker (r/l) in order to identify anatomical landmarks. In addition one marker each was placed on the tibia (r/l), on the lateral part of the femur (r/l) and the humerus (r/l) and on the distal, dorsal part of the forearm. In contrast, to the preceding chapters an extended marker set was used where information about the wrist flexion and rotation as well as shoulder movement flexion, abduction, and rotation could be obtained.

Procedure

Participants attempted to score baskets without the help of the backboard using a hook shot technique. The technique was verbally explained by an experimenter as a shot performed with the dominant right hand whilst being airborne. The participant was asked to place their body between the basket and the throwing arm as if to prevent a potential defender from interfering with the throw. The throwing arm should thereby resemble a curvilinear pattern. If the participants felt the need to adapt the movement to the specific distance in a certain way they were allowed to apply the necessary changes. Participants started the movement with their backs facing towards the basket and performed one ball bounce before shooting. This routine was intended to resemble a typical game situation.

The throwing distance to the basket was varied from 2m to 9m in increments of 1m after each trial block comprising ten shots and resulting in a total of 160 shots per participant. During the 'increasing condition' (INC) the distance was scaled progressively from 2m to 9m whereas during the 'decreasing condition' (DEC) distance was decreased from 9m to 2m resembling the typical scaling procedure used in previous studies (see Chapters 3 and 5, Kelso and Schöner, 1988; Schöner et al., 1986) where the throwing distance resembled a candidate control parameter. Before data recording, participants performed a self-selected warm-up regime for 15 minutes with instructions to perform a range of different shooting techniques. When signalling they were ready for testing, the participants were prepared with the markers and the particular throwing instructions were given after which they performed 10 shots each from 2m, 5m, and 7m to familiarize themselves with the procedure. All participants performed the same protocol starting with the INC condition followed by the DEC condition. In between shots, 30s recovery time was provided to help prevent any fatigue effects.

Performance score was judged for each trial and recorded by an experimenter on a seven-point scale (see Table 6-1).

Table 6-1. Basketball hook shot scoring system (adapted from Landin et al., 1993)

Score	Criteria
1	Airball; Ball misses completely by at least 2m
2	Airball less than 2m
3	Ball hits backboard first; no score
4	Ball hits backboard first; score
5	Ball hits outside of rim; score or no score
6	Ball hits inside or top of rim; score or no score
7	Ball passes cleanly through the basket without touching rim

Data processing

Coordinates of the reflective markers were reconstructed and three dimensional-coordinates were obtained using Evart 4.6 software (Motion analysis corporation). After visual inspection of frequency spectra of the displacement data, a 2nd order Butterworth filter set at a cutoff-frequency of 10Hz was applied in both time directions. From the position of markers, the hip joint centre was estimated using the procedure by Bell, Pedersen and Brand (1990), and position of the shoulder joint by using the procedure by Rab, Petuskey and Bagley (2002). Subsequently a 13-segment rigid body model was established using Visual3D software (C-motion). Joint angles were calculated using the Euler convention, but only angles in the primary joint plane of motion were used for further analysis, except for the right shoulder joint, assumed to be the main contributor to throwing performance, for which all three Euler angles were maintained. Shoulder joint kinematics of the left shoulder were estimated through the included angle between the upper arm and the trunk for ease of calculation. As in Chapter 3 and Buchanan et al. (1997), the radius of the wrist trajectory was estimated by minimizing the sum:

$$\sigma^2 = \frac{1}{N}\sum_{k=1}^{N}\left(R_0 - \left[\left(x_k - a\right)^2 + \left(y_k - b\right)^2 + \left(z_k - c\right)^2\right]^{1/2}\right)^2 \quad (6.1)$$

Over the parameters (R_0, a, b, c) where R_0 was the desired radius and a, b, c estimated the mid-point in space of the virtual circle, x_k, y_k, z_k where the actual position of the wrist at time frame k, and N was the number of total time frames. The sum was minimized using a nonlinear least-square algorithm (lsqnonlin, Matlab 7.1).

Data analysis

The data analysis followed a two-fold strategy. The mixed-effects modelling approach for the discrete ball release data was used, as in Chapter 3. This approach allowed population and individual differences of discrete kinematic measurements at ball release to be identified. The full mixed-effects model was:

$$y_{ijkl} = \beta_0 + \beta_1 d_{ijkl} + \beta_2 d_{ijkl}^2 + \beta_{3j} + b_{0i} + b_{1i} d + b_{1j,i} + \varepsilon_{ijkl} \quad (6.2)$$
$$i = 1,...,8,\ j = 1,2, k = 2,...,9, l = 1,...,10$$

With β representing fixed effects and b and ε representing random effects with: β_0 = general intercept, β_1= linear coefficient, β_2 = quadratic coefficient, β_{3j} = condition coefficient, b_{0i} = participant intercept, b_{1i} = participant linear coefficient, $b_{1j,i}$ = distance by condition interaction, and ε = residual variance. The random effects were again assumed to be independently within- and between-participants and normally distributed with a mean equal to zero and diagonal covariance matrix.

$$b_{0i} \sim \mathrm{N}\left(0, \sigma_s^2\right), b_{1i} \sim \mathrm{N}\left(0, \sigma_{sl}^2\right), b_{1j,i} \sim \mathrm{N}\left(0, \sigma_{cd}^2\right)$$

In this experiment no defender was present but two different conditions in regards to the direction of distance changes were present, the same fixed-effects and nested random-effects structures were utilized. Acknowledging that the occurrence of hysteresis can vary between participants, the nested random-effects structure seemed appropriate in order to represent inter-individual differences.

Subsequently, the continuous recording of each individual's joint angle kinematics was analysed using the cluster approach derived in Chapter 5. Movement trials were cut from the instance of minimum knee joint flexion before jump-off to the instance of ball release as determined from the DV-camera recording. The right wrist joint flexion angle, the right shoulder joint flexion, abduction, and rotation angles, the included angle of the left shoulder joint, right and left elbow joint flexion angles, right and left hip joint flexion, right and left knee joint flexion, and the left ankle flexion angle were used for analysis. Typical trial lengths were between 15 and 25 frames. Accordingly in order to avoid skewing the time-series, as described in Chapter 5, movement trials were normalized according to mean trial lengths which resulted in different lengths of normalized times series between participants. However, since data analysis followed a single-participant approach the different lengths did not affect further analysis. A switch between clusters was defined when three criteria were met: (1.) the majority (i.e., at least 60%) of trials from an initial cluster changed at a specific distance. (2.) the initial cluster had to provide the majority of trials in the preceding distance and (3.) the new cluster had to provide the majority of trials at the subsequent distance. This approach ensured that a switch between stable movement patterns occurred. Following the recommendations of Toro, Nester and Farren (2007), differences between clusters were subsequently investigated using angle-angle plots.

Skill levels of the participants were rated according to mean performance during the experiment. Differences of the kinematics between subsequent trials were extracted from the dissimilarity matrix **D** (see Chapter 5) from the entries of the first main diagonal and were normalized according to the individual length of time series. Performance and dissimilarity scores were analyzed using Friedman-Rank sum tests. The association between performance scores and changes of kinematics in subsequent trials were analyzed using Kruskal-Wallis rank-sum tests. In case of significant effects, post-hoc tests were performed using the procedures described in Siegel and Castellan (1988, see p. 180-181 and 213-214). All statistical analyses were performed using the R software (R Development Core Team, 2006). As described in Chapter 5 the pvclust (Suzuki and Shimodaira, 2006a), scaleboot (Shimodaira, 2006) and fpc (Henning, 2006) packages were used for the cluster validation procedures and the lme package for the mixed-model procedures (Pinheiro and Bates, 2000). Nonparametric post-hoc tests were performed using the pgirmess package (Giraudoux, 2006). All remaining calculations were performed using custom software written in MATLAB 7.1 (see appendix). Significance levels for all statistical analysis were set at $p < 0.05$ and deemed highly significant if $p < 0.01$.

Results

The results section is divided into sub-sections examining data from the performance scores, mixed-modelling of joint angle kinematics, wrist radius and wrist linear velocity, followed by the results from the cluster analysis and performance scores in relation to kinematics.

Performance scores

In Figure 6-1 the rating of participants according to their mean performance scores is shown. Two of the three expert players (NI and JA) were also the two best performers during the experiment whereas participant CA was the second least successful thrower. Surprisingly, participant SH, the novice performer with no prior experience in using the basketball hook shot or in playing basketball, achieved an intermediate performance in comparison to the remaining participants. The data indicated that the range of ability levels was spread more towards the intermediate-skilled side of the experience continuum with no participants scoring less than 3 out of 7 on average.

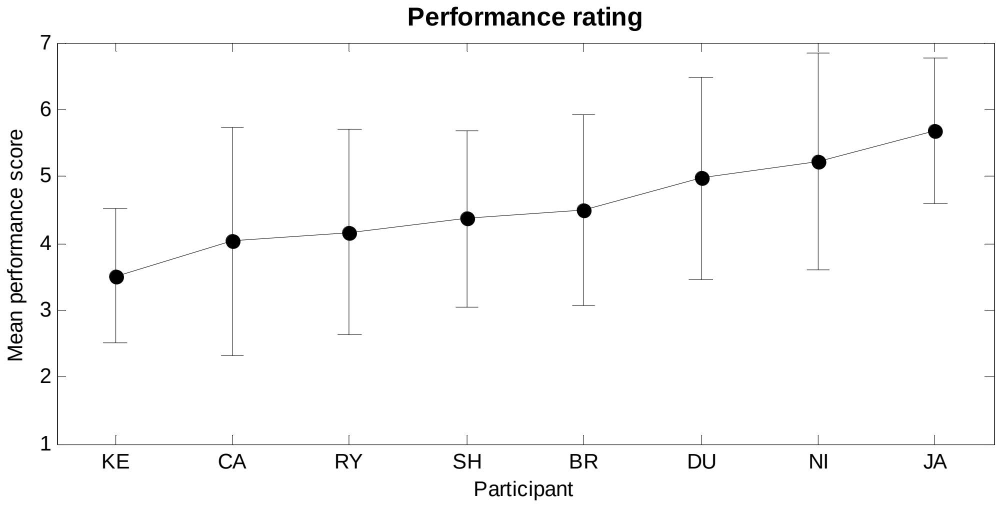

Figure 6-1: Mean performance and standard deviation for each participant.

In Figure 6-2 the individual performance scores across throwing distances and condition are shown.

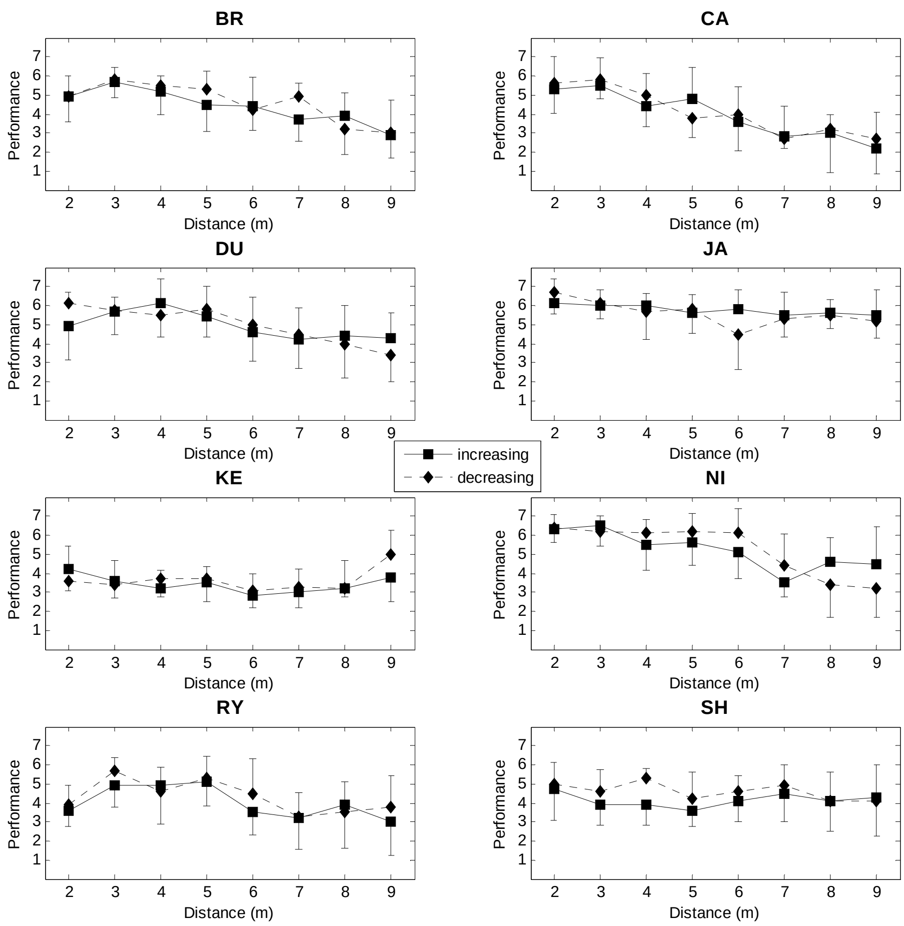

Figure 6-2: Mean performance scores and standard deviation for each participant at each throwing distance for increasing (■) and decreasing (♦) throwing distance.

Friedman Rank-Sum tests for throwing distance attained almost conventional levels of statistical significance, $\chi^2_7 = 13.3$, $p < 0.07$ when averaging over participants and blocking for condition. Further, the distance effect was significant when averaging over conditions and blocking for participants $\chi^2_7 = 31.15$, $p < 0.01$. Post-hoc analysis showed significant effects between distances 3-5m, 3-7m, 5-6m, and 5-8m, which all indicated deteriorating performance with increasing distance. Comparisons between participants showed a significant effect when averaging over conditions and blocking for distance $\chi^2_7 = 635.65$, $p < 0.01$. Post-hoc analysis indicated significant effects between CA-JA, CA-NI, JA-KE, JA-RY, KE-NI which supported the findings obtained from the mean performance scores (compare Figure 6-1). Condition effects were significant when blocking for participants $\chi^2_1 = 4.5$, $p < 0.05$ which indicated that the participants were better during DEC compared to INC.

Mixed-effects modelling

Application of the mixed-modelling to the right shoulder rotation angles showed serious deviations from normality for the residuals which could not be remedied applying different model-fits. Therefore, no mixed-effects analysis of the right shoulder joint rotation angles was undertaken.

Fixed-effects F-tests

Table 6-2: Wald-tests for fixed-effects structure for each joint angle. See equation 6.2 for details. * = significant, ** = highly significant

Angle	Distance	Distance^2	Direction
right elbow	0.44	0.37	1.55
right shoulder flexion	1.75	0.85	7.51*
right shoulder abduction	140.29**	0.18	6.49*
right wrist	12.83**	0	39.31**
left elbow	3.27	38.55**	23.5*
left shoulder	0.04	0.08	0.01
right hip	0.58	30.35**	6.95*
right knee	1.86	0.18	0.18
left hip	4.61*	17.97**	7.45*
left knee	0.06	0.83	5.2
left ankle	19.13**	23.89**	3.03

Table 6-2 shows the results of the tests on the fixed effects structures for the different joint angles at ball release which represented trends for the whole sample. For the right elbow, left shoulder, right knee, and the left knee joint, no significant effects neither for throwing distance nor for condition could be identified. For the right shoulder joint flexion angle, a significant direction effect was identified with $\beta_3 = -2.31$, indicating reduced flexion in the upper arm during the DEC trials. The right shoulder abduction angle showed significant effects for both linear distance and direction with $\beta_1 = 3.99$ and $\beta_3 = -3.28$, resulting in decreasing abduction angles with increasing distance and higher abduction angles in the DEC condition compared to INC. A similar trend was visible for the right wrist joint angle at ball release with $\beta_1 = 1.61$ and $\beta_3 = 6.64$, which indicated higher flexion angles with increasing distance and higher values during the DEC condition. In contrast, the left elbow showed a significant quadratic trend paired with significant differences between conditions. The according estimated coefficients were $\beta_2 = 0.39$ and $\beta_3 = -4.98$, indicative of a more flexed arm during the DEC condition and increasing values with distance.

The right hip also joint showed significant effects for the quadratic trend and between conditions with $\beta_2 = -0.14$ and $\beta_3 = 1.43$, suggesting increased extension angles with increasing shooting distance plus greater hip joint extension during the DEC condition. The left hip joint showed significant effects for all three population effects with coefficients of $\beta_1 = 1.05$, $\beta_2 = -0.07$, and $\beta_3 = -0.71$ which resulted in increasing joint extension angles with throwing distance and lower mean extension angles during the DEC condition. The left ankle joint showed a significant increase in plantar flexion with increasing distance (coefficients $\beta_1 = 0.75$ and $\beta_3 = -0.13$) and no differences between conditions. Together the results for the lower body indicated a more extended position at ball release with increasing distance. Similarly, the results for the right shoulder and right wrist indicated greater joint extension with increasing distance.

Standard deviation of random effects

In Table 6-3 the estimated standard deviations for the random effects parameter for the different angles are shown. For the left shoulder a different random effects structure was indicated by the data where both linear and quadratic effect were nested in condition within participants. This model formulation was needed because some participants showed considerable intra-individual differences between conditions resulting in inclusion of an additional variance term for the quadratic effect ($\sigma_{cdd} = 0.55$).

Table 6-3: Sample standard deviations of random effects for each joint angle. σ_s = sample standard deviation of participant-specific intercepts, σ_{sl} = sample standard deviation of participant-specific slopes, σ_{cd} = sample standard deviation of slopes between condition, σ = sample standard deviations of residuals

Angle	σ_s	σ_{sl}	σ_{cd}	σ
right elbow	13.15	2.01	0.64	17.53
right shoulder X	10.31	1.73	0.55	7.61
right shoulder Y	21.81	0.65	0.6	10.55
right wrist	15.31	1.1	0.79	9.77
left elbow	20.02	2.8	0.36	7.94
left shoulder	29.48	NA	4.97	8.59
right hip	17.47	0.74	0.32	2.73
right knee	39.61	1.11	0.54	5.25
left hip	5.4	0.31	0.09	2.24
left knee	5.31	0.42	0.21	3.22
left ankle	7.06	0.58	0.38	2.61

With the exception of the right elbow and the left knee, the between-participant residuals (σ_s) were all greater compared to the general residuals (σ) showing that the inter-individual variation of chosen mean angles was greater compared to the remaining intra-individual variation. The highest inter-individual variations in mean angles (σ_s) were exhibited in the left shoulder and the right knee (> 29°) compared to the lowest values shown by the left leg complex (< 7.1°). The right shoulder-arm complex exhibited a somewhat intermediate level of variation with the left shoulder-arm complex showing more variation. Similarly, the right leg complex showed elevated variation values. The left leg complex showed the lowest slope values ($\sigma_{sl} < 0.6$) and the highest values were exhibited by both elbows with the left elbow showing more inter-individual variation (> 2). The interaction effects between participants and distance were greatest for the right arm and again smallest for the left leg. This effect indicated that the participants varied their ball release postures between conditions mainly in the upper arm without changing the position of the left leg. The left shoulder showed the greatest variation in slopes between participants, which was in part a result of the model fit because no participant specific slope was fitted which inflated the estimate for the nested slope. Accordingly, the value could not be directly compared to the remaining models which contained participant-specific slopes. As explained earlier, the participants showed considerable variation between conditions which lead to the necessity of fitting these different models in the first place. In regards to the residuals, the same general trend as before was visible with the lowest values exhibited for the left and right leg and high variations for the right shoulder-arm complex, indicating high levels of intra-individual variation.

Individual model coefficients

Best linear unbiased predictors (BLUPs) were estimated in order to investigate the intra-individual variation for those angle kinematics, showing no significant main effects for linear and quadratic distance (compare Chapter 3 for details).

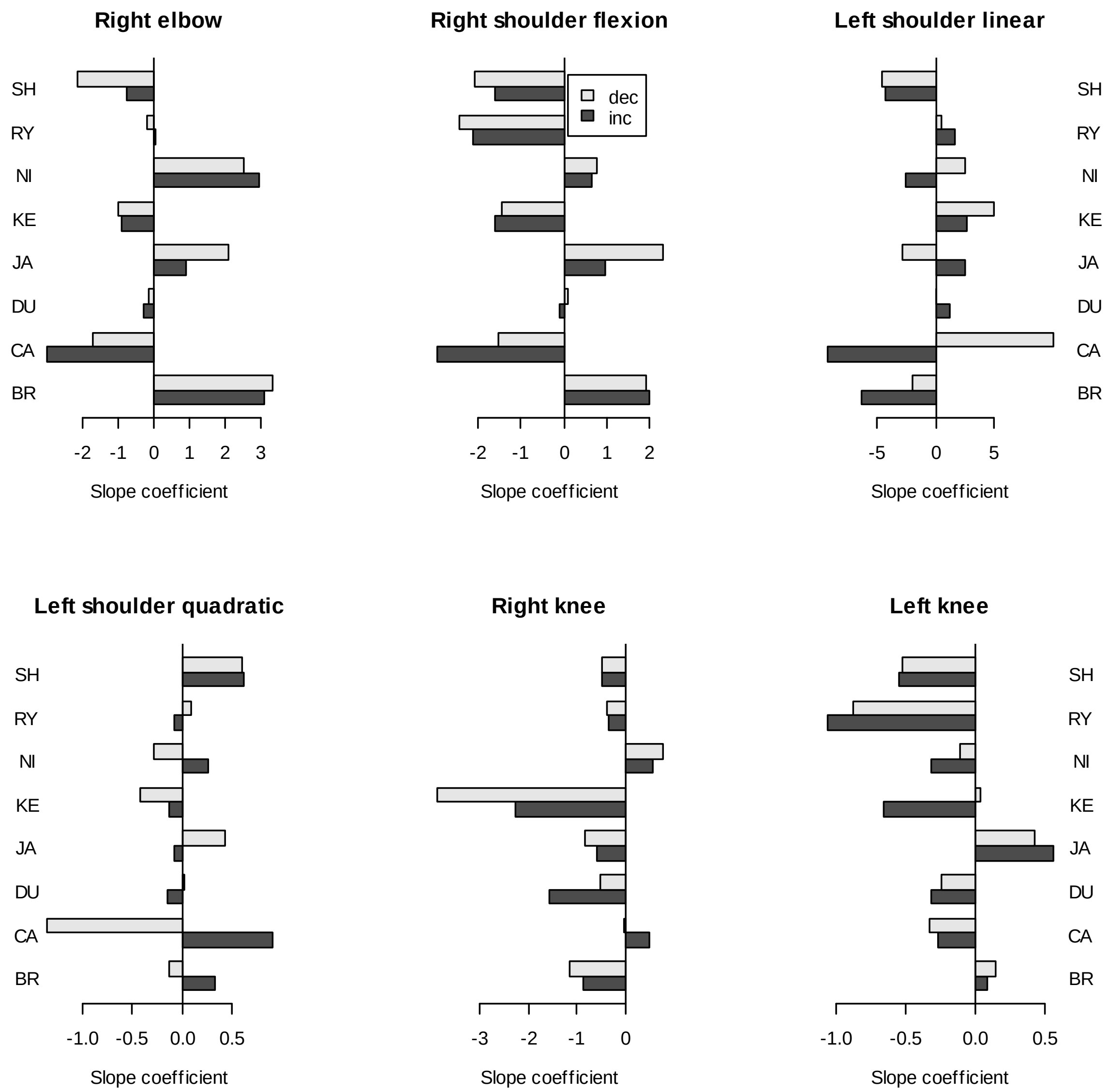

Figure 6-3: Best linear unbiased estimates of model coefficients for each participant for the right elbow joint, right shoulder joint flexion angle, left shoulder joint linear and quadratic coefficient, right knee joint, and the left knee joint.

Figure 6-3 shows the resulting coefficient for the distance coefficients based on the combined fixed-effects and BLUPs of the mixed-models. For both right elbow joint and the right shoulder joint flexion angles it was apparent that the adaptations to throwing distance lead to high variation in the inter-individual strategies. For the right elbow joint, three participants used greater flexion angles (CA, KE, SH), three used smaller flexion angles (BR, NI, JA) and two showed only minor changes with distance (DU, RY). Similar for the right shoulder joint flexion angle the relative split was 4:3:1. Potentially this high variety in participant-specific responses lead to the non-significant main effects. A somewhat different trend was observed for the left shoulder joint where four participants showed different trends between conditions for the linear trend and three of them also showed differences between conditions in the quadratic coefficient. Especially pronounced were the differences between conditions for participant CA. The linear trend of the left shoulder conditions were over 18 units apart from each other indicative of completely different strategies used. A similar effect was apparent for the quadratic coefficient. These opposite linear and quadratic trends lead to an effect where differences in angles at the lower distances were almost 30° apart from each other. With increasing throwing distance they converged into a similar region, clearly indicative of a hysteresis effect for this participant. For the right knee, the magnitude of the slope coefficients were relatively small indicating only small changes in the ball release posture of the right knee with increasing distance (except perhaps for participants KE and DU). Similarly for the left knee, the estimated slopes were all quite shallow and followed similar trends. Hence, for these variables there were potentially no true effects for distance.

Heteroscedasticity

In Table 6-4 the rankings of the heteroscedasticity and the ratio between the maximum and minimum variance are shown (compare Chapter 3 for details).

Table 6-4: Ranking of estimated heteroscedasticity values for each participants for each joint angle and ratio of highest residuals divided by smallest residuals for each joint.

Angle	BR	CA	DU	JA	KE	NI	RY	SH	Ratio
right elbow	1	3	8	4	7	2	5	6	3.7
right shoulder X	2	1	8	5	7	6	4	3	2.35
right shoulder Y	3	2	8	6	3	1	7	5	1.38
right wrist	4	1	8	2	7	6	3	5	1.56
left elbow	3	2	6	5	8	7	1	4	1.63
left shoulder	4	1	8	2	7	5	3	6	2.3
right hip	5	1	3	6	4	8	2	7	2
right knee	5	2	4	6	3	7	1	8	2.7
left hip	6	3	1	7	4	8	2	5	1.23
left knee	4	5	1	7	2	6	3	8	1.63
left ankle	7	3	1	5	2	8	4	6	2.25

The right elbow joint showed a high ratio value of 3.7 indicating that the difference in intra-individual variations between the most and least variable participant was almost fourfold. All remaining ratios were much lower ranging and fluctuating around a ratio value of 2.

With the exception of participant CA, who tended to show the lowest variance, and SH, who showed the highest variance across angles, there was no clear trend for participants to exhibit consistently low or high variances across all joint angles. The ranks within participants actually appeared randomly distributed with different trends between participants. For example, participant DU showed high variability in the upper body and low variability in the lower body. In contrast, participant BR showed higher variation in the lower body compared to the upper body. Kruskal-Wallis rank-sum test indicated a significant main effect for participants, however post-hoc tests indicated significant differences only between participants KE and NI and CA and RY. In conclusion, heteroscedasticity values showed no clear pattern in relation to skill level. Only differences between two participant pairings became significant which were, in the cases of KE and NI between the second best and the least successful performer, and in the cases of CA and RY between two less successful performers.

Wrist velocity and trajectory radius

The mixed-model for the wrist velocity showed no general trends across participants which indicated similar adaptation schemes for distance with only inter-individual differences concerning the magnitude. The population effects for linear and quadratic distance ($F_{1,1266}$ = 4203, $p < 0.01$, $F_{1,1266}$ = 8.266, $p < 0.01$) were significant with coefficients ($\beta_1 = 0.63$ and $\beta_2 = -0.01$) indicating an increase of the resulting wrist velocity with distance. The standard deviation of the participant intercepts and residuals were $\sigma_s = 0.9$ and $\sigma = 0.58$ indicating higher inter-individual variances between mean angles compared to intra-individual variation. Hence, the displacement velocity of the wrist of the throwing arm clearly increased with distance.

For the radius of the wrist trajectory, the mixed-model fit indicated homoscedasticity. Further, no effects between conditions were observed and again a likelihood ratio test indicated that the random effects structure for condition could be dropped. The fixed-effects showed significant F-values for the linear and quadratic terms ($F_{1,1266}$ = 3.93, $p< 0.05$, $F_{1,1266}$ = 6.62, $p< 0.05$) with a small negative linear coefficient ($\beta_1 = -0.01$) and a small positive quadratic coefficient ($\beta_2 = 0.001$) which resulted in a small increase of the trajectory radius with distance leading to a difference in the radius of only 9 cm. Standard deviations for the participant effects were higher compared to the residuals ($\sigma_s = 0.14$ and $\sigma = 0.09$). Regarding the differences in slopes between participants, a standard deviation of $\sigma_c = 0.9$ was estimated which resulted in high variations in the slopes between participants. As can be seen in Figure 6-4 the actual change in distance was negative for some participants (JA and NI) and only participant SH showed clear increases of the wrist radii with distance.

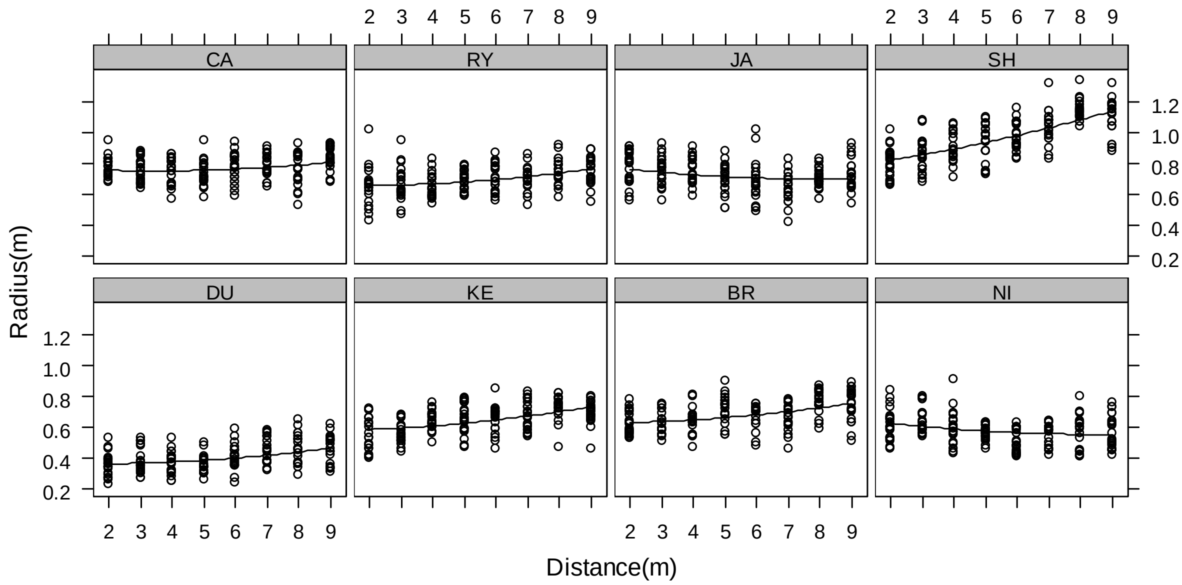

Figure 6-4: Estimates of wrist trajectory radii for each participant for each condition with superimposed model fit as estimated by the mixed-model.

Hence, overall the radii showed strong overlap across throwing distances indicating only minor alterations with distance.

Intra-individual time-continuous results

Cluster analysis

The number of clusters was determined according to the bootstrapping values and the results of the Hubert-Γ scores (see Chapter 5 for details). In Table 6-5 the results of the bootstrapping procedure together with the number of trials contained in each cluster for all participants are shown. All detailed results from the bootstrapping and the Hubert- Γ can be seen in Appendix C. Since p-values could be established only if the cluster nodes contained more than one item, clusters which consisted only of a single trial were marked NA. The range of determined clusters varied between six and three clusters.

Table 6-5: Results of multi-scale bootstrapping procedure (p-values) for each cluster for each participant and number (no.) of trials contained in each cluster.

Subject	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 6	
	p	no.	p	no.	p	no.	p	no.	p	no.	p	no.
BR	NA	1	94	48	92	4	96	23	67	5	79	78
CA	98	4	56	19	93	18	78	9	NA	1	82	109
DU	98	56	95	4	95	43	87	43	79	13		
JA	94	40	81	25	56	41	92	54				
KE	99	119	96	8	NA	1	90	13	96	7	NA	1
NI	98	12	98	66	94	5	100	76	NA	1		
RY	99	29	99	125	NA	1	NA	1	100	4		
SH	NA	1	93	131	100	28						

Cluster 5 of Participant CA exhibited a very small p-value. However, the next branch underneath that particular node contained only one main cluster and a singular object with a p-value of 99 for the former which indicated strong validity for this particular node (see Appendix C). However, because further separation was rejected by the Hubert-Γ scores this inferior solution was nevertheless chosen for consistency. A similar situation was present for cluster 5 for participant BR where the next branch underneath this node contained two main clusters with p-values of 93 and 97 indicating high stability of these clusters (see Appendix C). In contrast, for cluster 3 of Participant JA, p-values were small even several steps further down the dendrogram indicating that this particular cluster was not very stable. For participants CA, KE, RY, and SH 2/3 the total number of trials were contained each in one big cluster, whereas for the remaining participants the trials were spread more evenly over several clusters.

Individual cluster solutions

In order to facilitate comparisons with results from Chapter 3, angle-angle plots of right shoulder-right elbow, left shoulder- left elbow, and left hip – left knee will be presented.

Since this represented only a two-dimensional representation it should be noted that this representation does not always necessarily lead to clear separation between clusters since the actual clustering was determined using the full 12 dimensional input space. The individual results will be presented together, whereas discussion of the relation of skill level and adaptation scheme is provided in the subsequent general discussion. The sequence of the participants follows from lowest performance to highest performance according to Figure 6-1.

Participant KE

Regarding the clustering results for participant KE only one main cluster could be identified which contained 119 trials in total with three smaller clusters and two singular trials. Investigation of the angle-angle plot of the right elbow and the right shoulder abduction angles indicated relatively consistent behaviour across movement clusters (compare Figure 6-5.a). The plots followed a similar pattern with minimal movement in the elbow joint. All motion of the throwing arm was achieved through movement in the shoulder joint and with starting angles of -52°±9° STD and final abduction angles at ball release of -99°±11° STD. For the kinematics of the left arm some differences between cluster 5 and the remaining trials were visible (see Figure 6-5.b). In general, motion in the non-throwing arm was relatively constrained with maximum ranges of motion for the elbow of 21° and for the shoulder joint around 31°. Lower limb kinematics again showed very little variations across movement clusters, with the exception of two outliers.

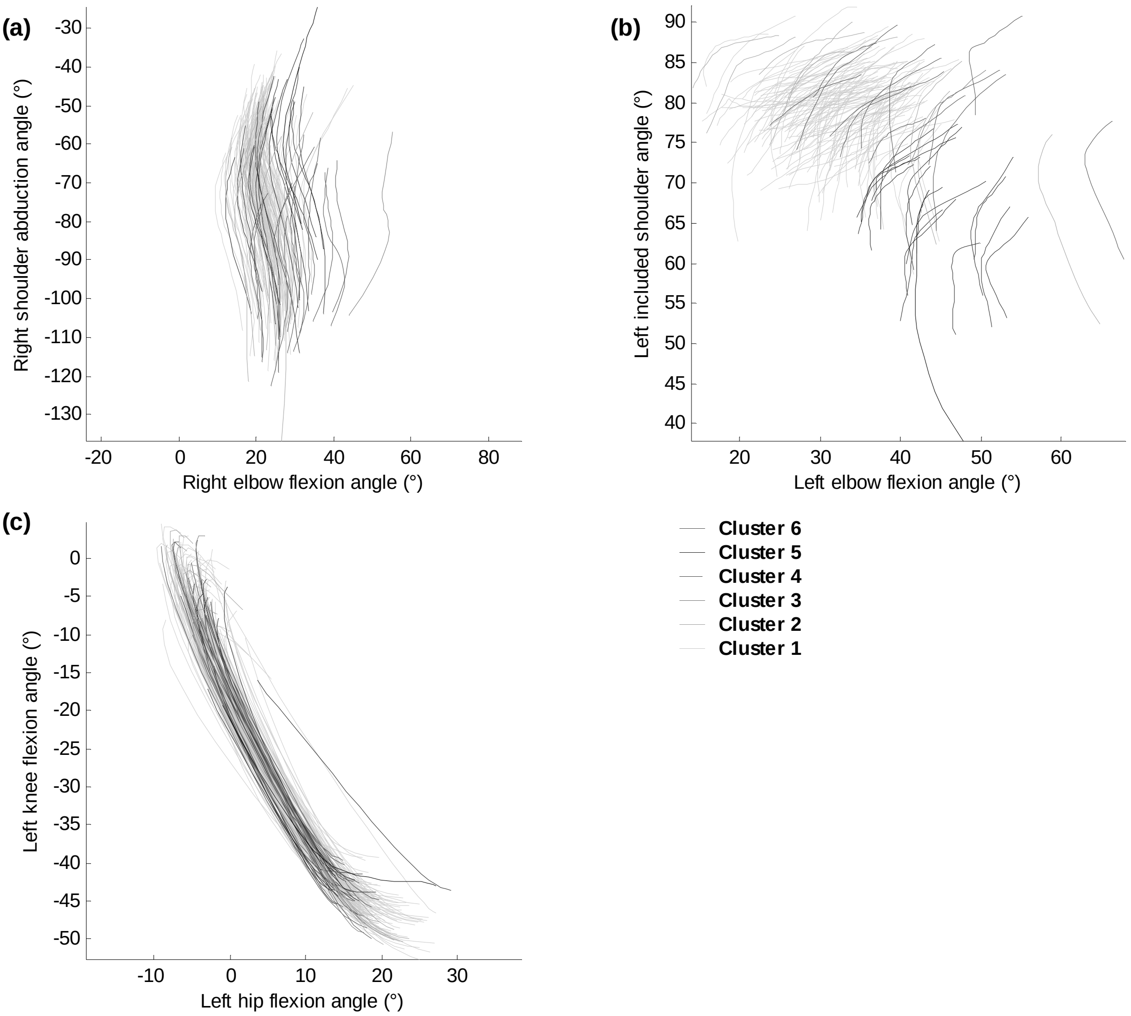

Figure 6-5: Angle-angle plots for all movement clusters of participant KE. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

Investigation of the movement cluster distribution gave clear indication of a distance related change in movement patterning. Clusters 4 and 5 were used during smaller throwing distances whereas cluster 6 was used for all intermediate and greater distances. Regarding switching behaviour, transitions between movement clusters could be identified from cluster 4 to cluster 1 at 4m (INC) and from cluster 1 to cluster 5 (DEC) at 3m. This observation indicated a hysteresis effect. Cluster 1 was maintained longer during the DEC condition compared to the INC and the final movement pattern was different from the initial movement pattern. Both instances of movement cluster transitions were accompanied by rises in mean dissimilarity scores (cluster 4 to cluster 1: 119°→141°, cluster 1 to cluster 5: 93°→148°) with a third peak at 7m distance.

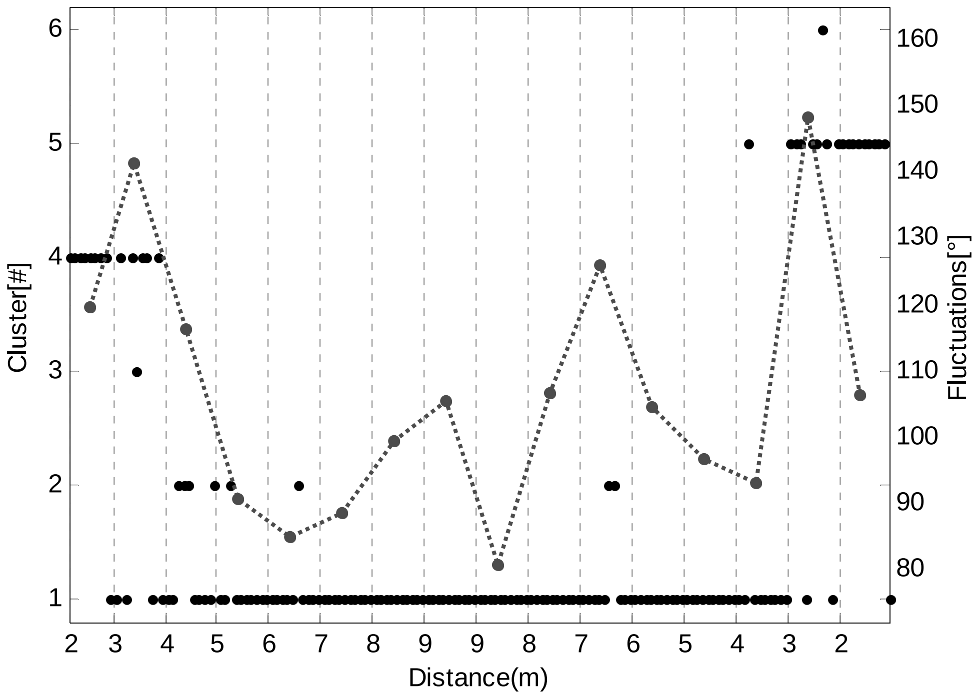

Figure 6-6: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant KE. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

Regarding the analysis of kinematics the adaptations of movement patterns expressed by participant KE clearly resembled a scaling scheme, where a single pattern was altered according to throwing distance. However, although no clear changes between movement clusters were identified in the angle-angle plots, in both cases movement cluster transitions were accompanied by increasing mean dissimilarity scores, indicating that loss of pattern stability was used in order to change movement patterning. This observation is usually a typical indicator for critical fluctuations suggestive of global movement reorganization.

Participant CA

For participant CA, six movement clusters in total were identified. The distribution of trials across clusters was highly skewed with cluster 6 containing 109 out of 159 trials. Further, cluster 2 showed a p-value of only 56 which indicated very small stability. Inspection of the movement kinematics showed quite distinct differences in the coordination of the right shoulder-arm complex as can be seen in Figure 6-7.a. Focussing on movement clusters 2, 3, and 6, two qualitatively different strategies could be identified between them. The difference stemmed from different ranges of motion in both the shoulder and the elbow joint of the right side. For the right elbow joint during movement cluster 6 only a small range of motion was present (20° - 40°), whereas during movement clusters 2 and 3 ranges of 40° - 100° were present. The starting angle for the shoulder abduction showed only small differences between the movement clusters. However, at ball release shoulder joint abduction angles were much lower for clusters 2 (-129°±8° STD,) which indicated greater joint abduction compared to the remaining trials (-98°±14° STD). A similar clear distinction between movement patterns was visible in the kinematics for the left shoulder-arm complex (compare Figure 6-7.b). Whereas the movement started with similar joint angle combinations (bottom/left), the plot greatly diverged at ball release. For cluster 6 the left shoulder joint showed little movement range, paired with greater range of motion in the elbow joint, moving from a more extended position (~60°) to a much more flexed position (~100°). Investigation of the variation within cluster 6 showed considerable differences in the magnitude of the left shoulder joint angle which ranged between 22° and 83°, without changing the overall appearance of the individual plots. Comparing the variability of cluster 6 between the throwing-arm and non-throwing arm, kinematic variations in the non-throwing seemed somewhat higher. During the remaining trials the movements in the elbow joint were much smaller and exhibited greater shoulder abduction angles at ball release (67° - 107°). Investigation of Figure 6-7.c indicated only small differences in the lower limb kinematics of the left leg with some variations between the movement clusters. The kinematics of movement cluster 6 showed greater ranges of motion in the left knee joint, with greater flexion at the beginning of the movement and similar extension angles at the end of the movement, although some trials from movement cluster 3 showed similar movement ranges.

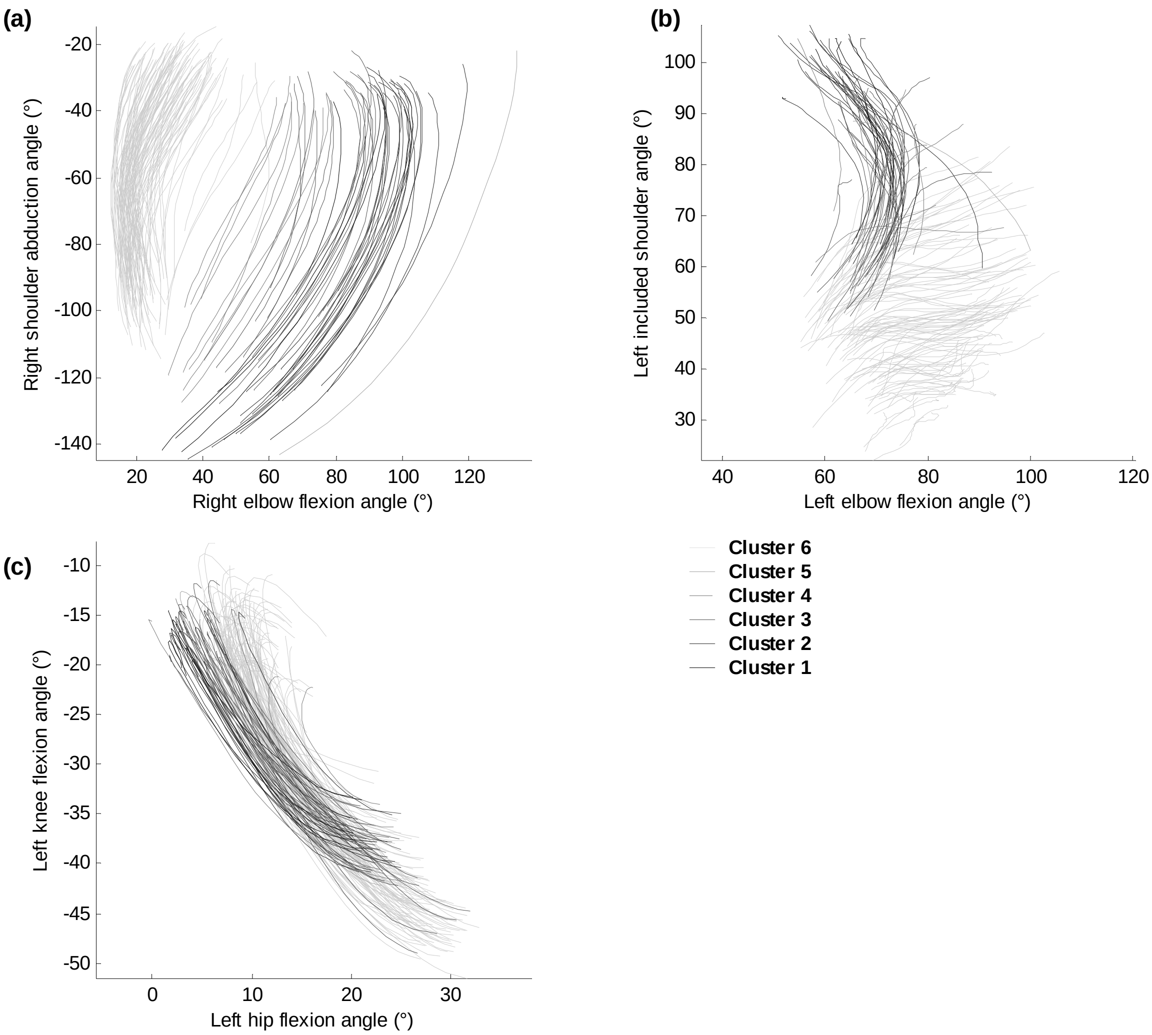

Figure 6-7: Angle-angle plots for all movement clusters of participant CA. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The distribution of clusters indicated that clusters 1 to 4 were used from 2m to 6m without exhibiting particularly high stability (see Figure 6-8). Potentially, a bias for movement cluster 2 for the lower distances and movement cluster 3 for the higher distances was present. At 7m, a switch to movement cluster 6 occurred which was maintained for all of the remaining trials except for a few trials during 5m (cluster 3) and 4m (clusters 5 and 2). The distribution of the dissimilarity scores showed increasing values just prior to settling on cluster 6 (242°→293°), and subsequently lower values. A second peak was visible at 4m (205°→363°) where for some trials cluster 2 was used, which is indicative of switching behaviour between highly different movement patterns in subsequent trials. Participant CA finished the experiment with a different movement compared to the movement at the beginning which indicated hysteresis behaviour.

In conclusion, together the results of the cluster analysis and the inspection of the movement kinematics provided strong support for a bimodal adaptation scheme according to changes in throwing distance. Participant CA showed clear changes in both upper body kinematics paired with relatively high stability of the kinematics of the supporting leg. Mean dissimilarity scores showed a clear rise during the transition period and movement patterning indicated hysteresis behaviour. Further, regarding the higher variability of the non-throwing arm, once participant CA switched into movement cluster 6, it was possible the participant adopted the unimodal scheme. Since the throwing distance includes all distances between 2m and 9m, he tried to hold the kinematics of the throwing arm relatively constant at the expense of varying the kinematics of the non-throwing arm.

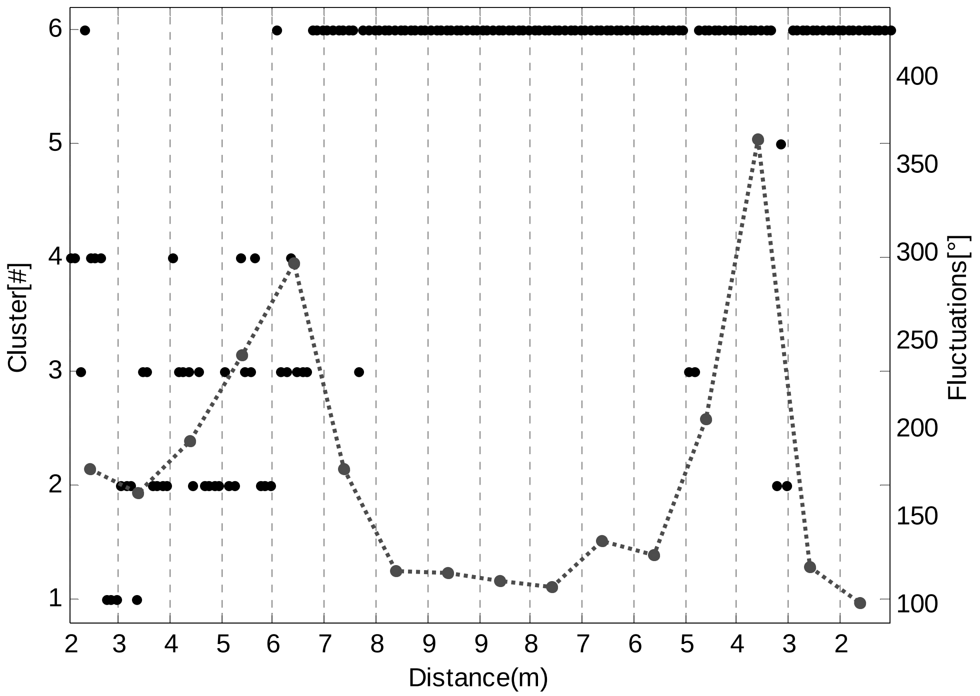

Figure 6-8: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant CA. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

Participant RY

For Participant RY, the cluster analysis identified mainly a single movement pattern which was maintained over all distances with some minor groupings of trials belonging to cluster 1 and some isolated trials from clusters 3 to 5. Angle-angle plots of the throwing arm (compare Figure 6-9.a) indicated that participant RY used a movement pattern with very limited movement in the elbow joint, and accordingly, ball acceleration was mainly achieved through motions in the shoulder joint. Mean ranges of motion for the elbow joint were 7°±7°

STD compared to 53°±9° STD for the shoulder. Four clear outliers were present which were contained in movement cluster 5. Although cluster 1 and cluster 2, based on the kinematics of the throwing arm, showed considerable overlap, inspection of the kinematics of the non-throwing arm showed clearly visible differences (compare Figure 6-9.b). The differences stemmed mainly from the movement in the left elbow joint with mean angles of around 33°±6° STD for cluster 1 and 70°±3° STD for movement cluster 2. Qualitatively, the two movement pattern exhibited great similarity. The plots showed a small range of overlap between the two movement clusters but were in general quite well separated from each other. In contrast, the plots of the lower leg kinematics (see Figure 6-9.c) showed considerable overlap between the different clusters with some higher variation in cluster 2 compared to cluster 1. But all plots followed a very similar pattern with a near -45° alignment.

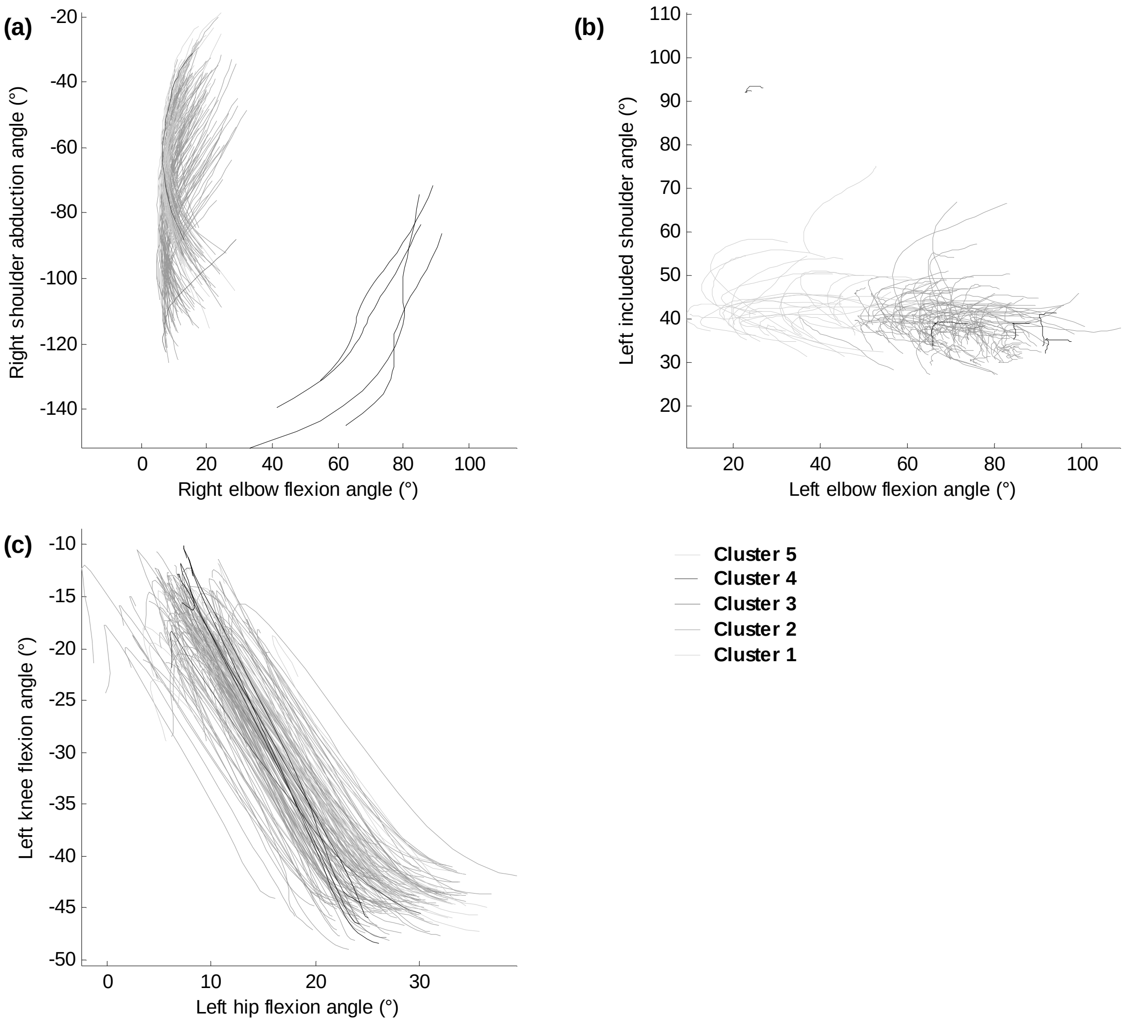

Figure 6-9: Angle-angle plots for all movement clusters of participant RY. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The distribution of the movement clusters indicated some relation to throwing distance, where movement cluster 1 was used mainly during greater distance, although cluster 1 was present throughout all distances. Accordingly hysteresis could not be identified for participant RY. Fluctuations scores showed an increasing trend during the increasing condition with a peak plateau in the vicinity of the main distribution of cluster 1 trials. During the decreasing condition strong increasing values were visible from 4m downwards where mean dissimilarity scores jumped from 122° to 168° from 4m to 3m and from 168° to 185° degrees from 3m to 2m.

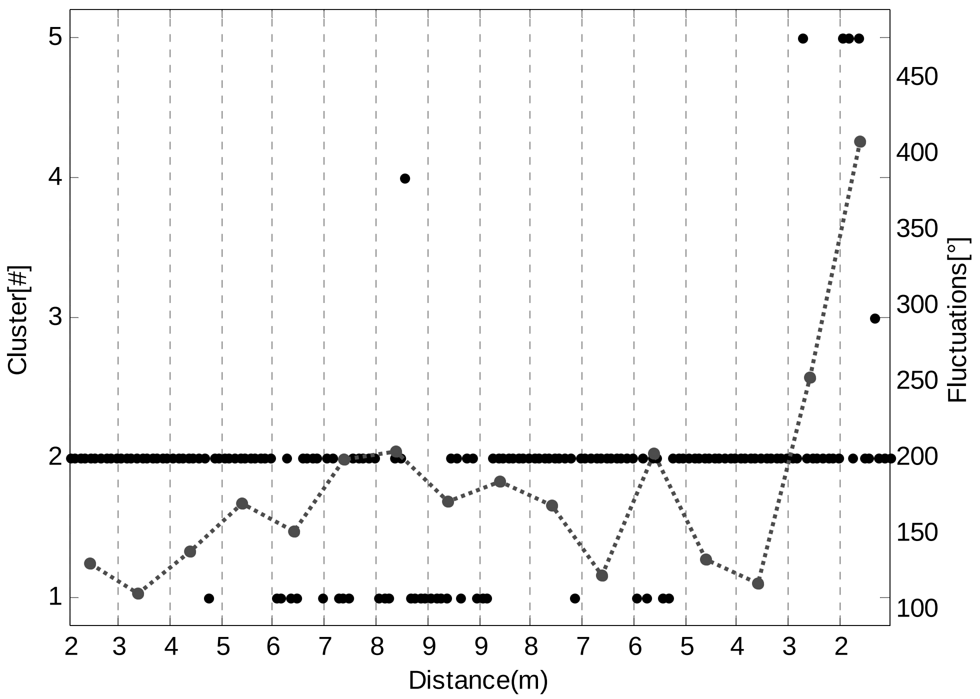

Figure 6-10: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant RY. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In summary, for participant RY a single movement pattern was used throughout the experiment which was scaled according to the throwing distance. At greater throwing distance a second pattern was used which showed some peculiar differences in the non-throwing arm but was never stabilized for a longer period of time. Absence of critical fluctuations gave further support for a scaling regime.

Participant SH

Cluster analysis indicated a three-cluster solution for participant SH, the smallest number of clusters observed in all participants in the present study. Since cluster 1 contained only a single trial only a two-cluster solution was obtained. The majority of trials were contained in cluster 2 (131 trials) whereas cluster 3 contained only 28 trials. Investigation of the angle-angle plots for the right elbow joint and the right shoulder joint abduction angles indicated some strong differences between the two movement clusters (see Figure 6-11.a). For movement cluster 2 the right elbow was almost completely extended during the whole movement and maximum ranges of motion were small for both movement clusters (cluster 2: 16°, cluster 3: 18°), but showed peculiar differences in mean angles (cluster 2: 23°±2°, cluster 3: 51°±3°). During movement cluster 2, at the beginning of the movement shoulder joint abduction angles were between -55° and -12°, whereas for movement cluster 3 starting angles were between -110° and -67°. In contrast, shoulder angles at ball release showed similar values across movement clusters (~-110°). For movement cluster 3 the plots indicated, to some extent, a sequential strategy where the movement started with flexion of the elbow joint followed by abduction of the shoulder, as indicated by the rectangular shape of the plots. Kinematics in the left arm showed high variations across trials with no clear separation between the two clusters (see Figure 6-11.b). The appearance of the plots were distinctively different between the two movement clusters. Kinematics of the left leg exhibited high stability across all trials, showing considerable overlap between trials.

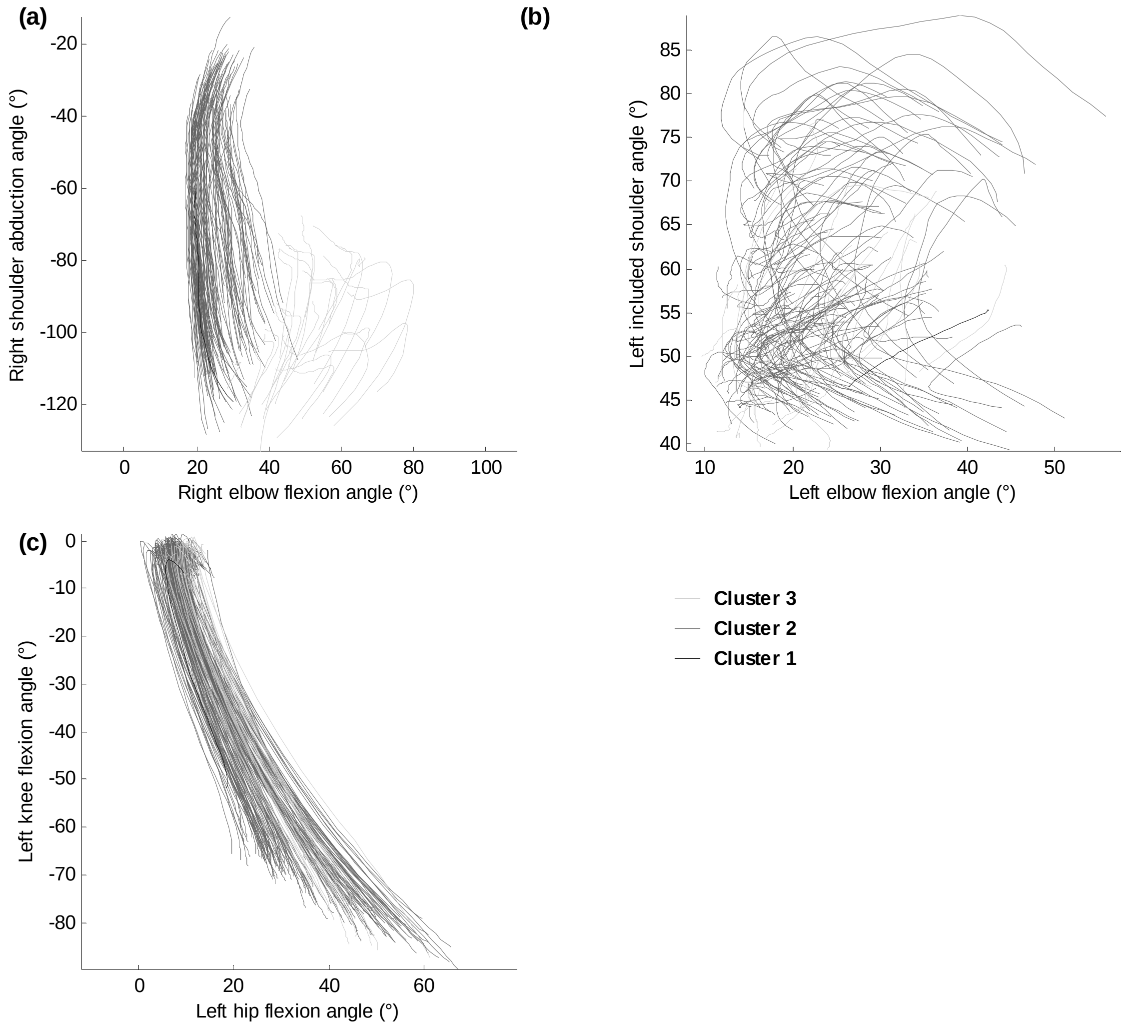

Figure 6-11: Angle-angle plots for all movement clusters of participant SH. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

Cluster distribution showed that movement cluster 2 was used from the beginning of the experiment until 4m distance during the DEC condition where a transition to movement cluster 3 occurred. Hence, these data clearly indicated a hysteresis effect (see Figure 6-12). The fluctuations showed some minor variations in the usage of cluster 1 only. During the switch between the clusters, a peak was visible where dissimilarity scores jumped from 132° to 188° and high values were maintained for the remaining distances.

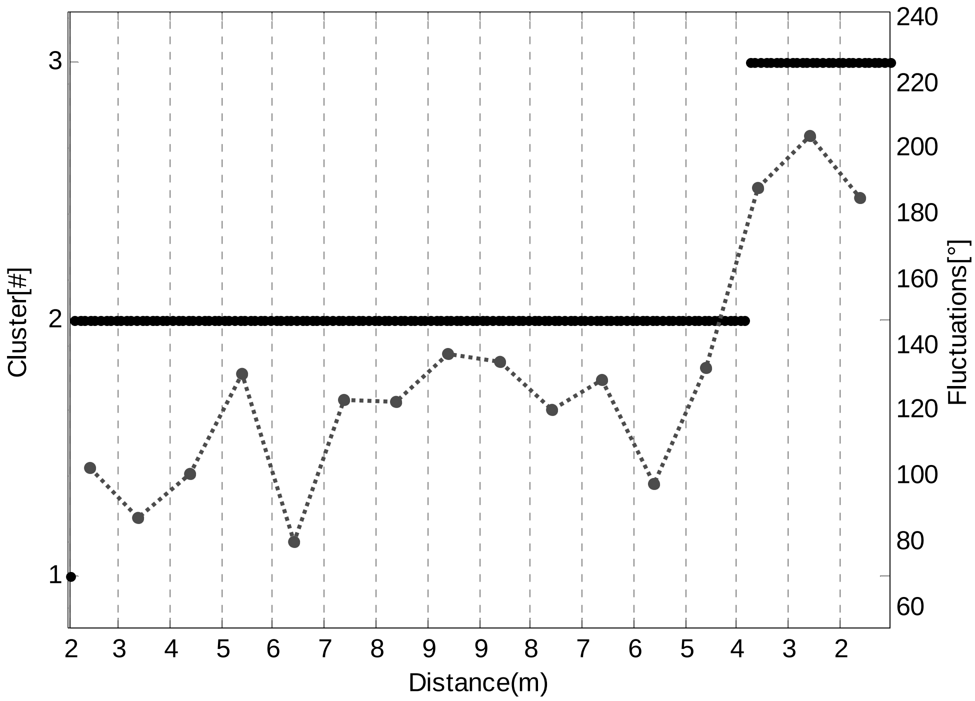

Figure 6-12: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant SH. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In conclusion, for participant SH, movement patterning resembled a bimodal attractor layout. One movement pattern was used throughout most of the throwing distances until loss of stability, indicated by critical fluctuations, leading to a transition to a new movement pattern, also indicating a hysteresis effect.

Participant BR

For participant BR six clusters were identified with a relatively even spread of trials across the clusters. The angle-angle plot of the right shoulder abduction and right elbow flexion showed considerable overlap between the different movement clusters (see Figure 6-13.a). In all trials the elbow started from a flexed position (> 90 °) and was extended during the throwing movement accompanied by a parallel abduction of the shoulder. In contrast, the joint angle relationship was similar at the start of the movement between the movement clusters (denoted by overlapping trials, top/right of graph). There seemed to be some differences in the ball release position between the clusters with movement cluster 6 showing increased abduction of the shoulder. Differences were more pronounced in the angle-angle plots of the left shoulder complex (see Figure 6-13.b). The distribution of movement clusters 6, and movement clusters 2 and 4 were quite distinct. Similarly to the right shoulder-arm complex, the differences were pronounced at the end of the movement and stemmed mainly from the elbow joint angles (bottom of graph, cluster 2: 84°±10° STD, cluster 4: 102°±9° STD, cluster 6: 64°±6° STD). Whereas during the trials of movement cluster 6 the elbow joint performed a pure extension movement, during movement clusters 2 and 4 the elbow joint first flexed and then extended during the end of the movement. The left leg kinematics exhibited much lower variations over distances and between movement clusters, a very similar trajectory across trials, indicating a stable coordination pattern for the left leg (compare Figure 6-13.c). Potentially, trials from movement cluster 4 (-10°±3°) exhibited marginally higher flexion angles in the knee and the hip compared to cluster 6 (-14°±3°).

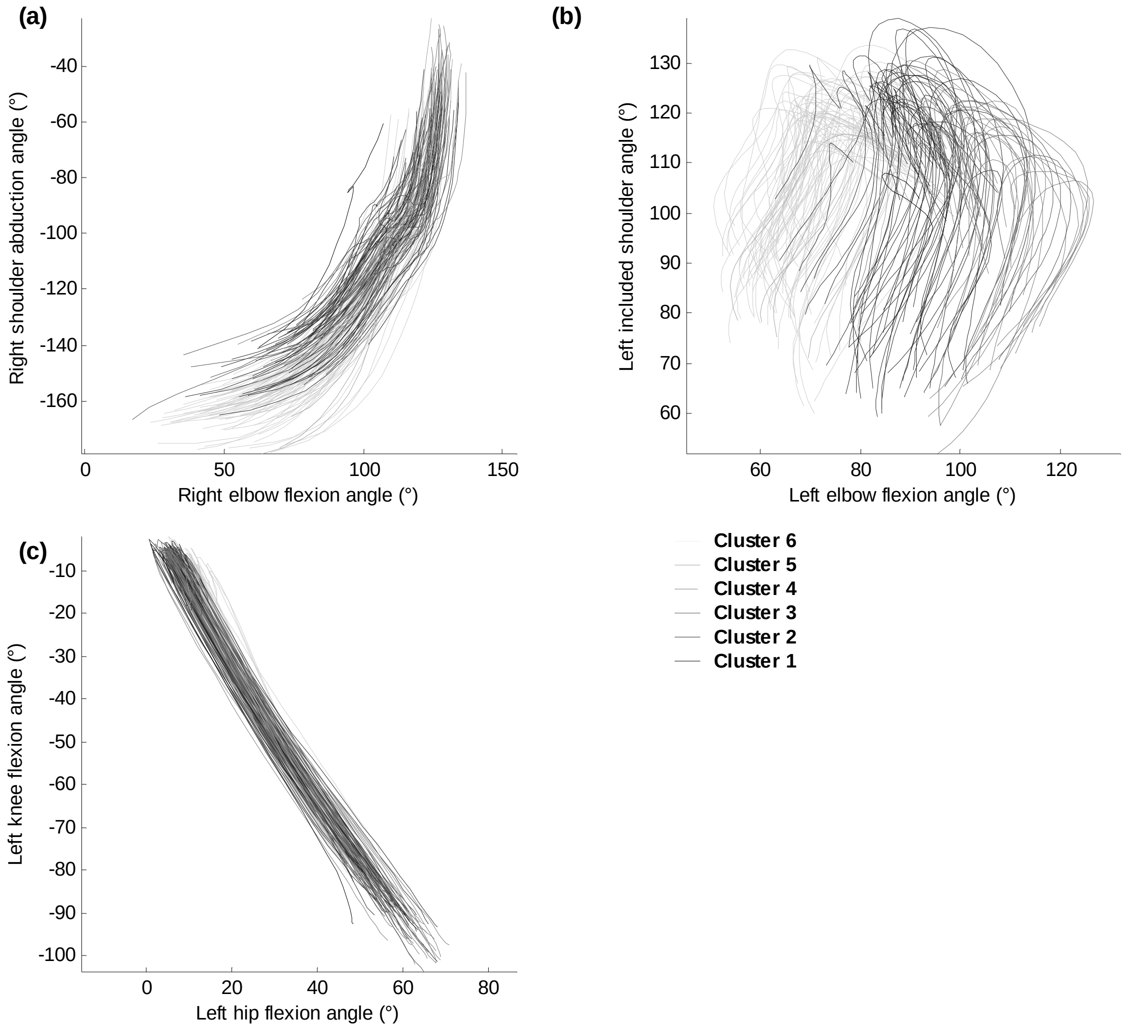

Figure 6-13: Angle-angle plots for all movement clusters of participant BR. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

Investigation of the cluster distribution over distance in Figure 6-14.b showed that cluster 6 was initially the primary movement cluster chosen during throwing distances between 2m and 7m (INC). At 7m distance the movement pattern changed and a transition to movement cluster 2 occurred which was used until 9m. Subsequently, movement cluster 4 was used until 8m where some fluctuations between the movement clusters 4, 3, and 2 were apparent. From 7m onwards cluster 2 was again the prominent cluster and lost stability at 5m, and accordingly at 4m a switch to movement cluster 6 occurred. This movement pattern was maintained until the end of the experiment. Hence, the clustering showed a clear relation to throwing distance. Movement cluster 6 was the prominent movement pattern for the smaller throwing distances, whereas clusters 2 and 4 were used for the intermediate and greater distances accordingly.

Connecting the cluster distribution and the angle-angle plot, the progression of clusters 6→2→4→2→6 appeared to be mainly a result of adaptations in the kinematics of the left arm, with relatively high stability in the kinematics of the left leg and the right throwing arm. Therefore, participant BR belonged clearly in the unimodal adaptation category, with high consistency in the kinematics of the throwing arm and the supporting leg and high variations in the kinematics of the non-throwing arm. Regarding the mean dissimilarity scores in Figure 6-14, increasing values occurred just prior to switching of 2→4 (124°→173°), 4→2 (174°→186°), 2→6 (157°→186°), but no increase during switch 6→2, was observed. However, in general the levels of fluctuation seemed to increase during the experiment and accordingly the increases for the latter two transitions were only of smaller magnitude. With regards to switching distances, participant BR showed hysteresis behaviour where movement clusters were maintained for longer distance periods during the DEC condition compared to the INC condition supporting the hypothesis. In conclusion, for participant BR clear support for a scaling regime according to throwing distance was obtained.

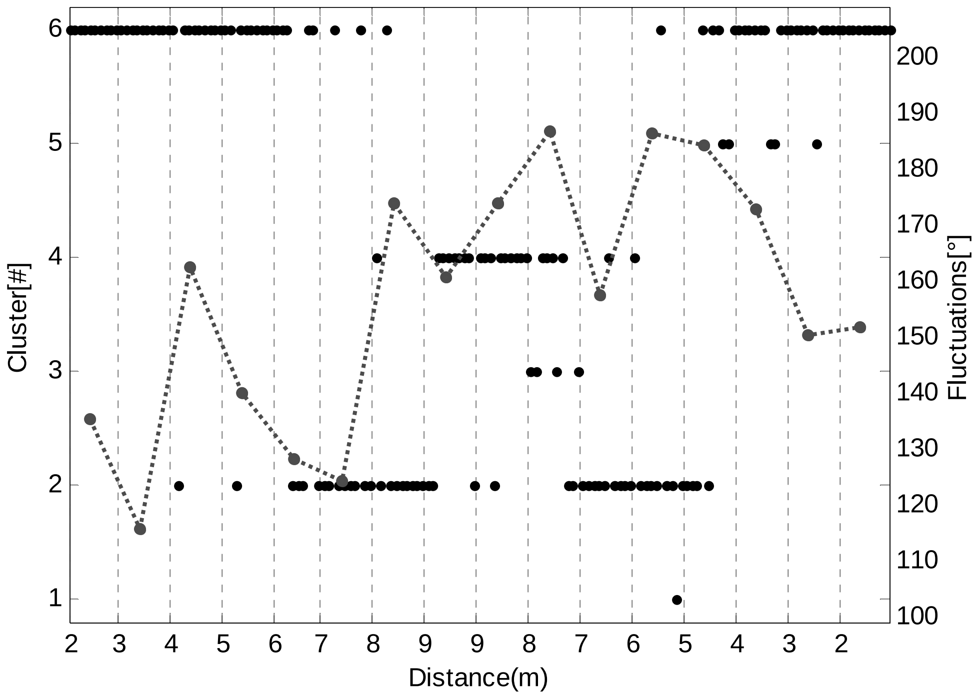

Figure 6-14: Distribution of movement clusters(●) against trials grouped by distance in ordering of actual occurrence for participant BR. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

Participant DU

Participant DU exhibited a 5-cluster solution with a relatively equal spread of trials across the clusters. Only clusters 5 and 2 were somewhat smaller with only 13 and 4 trials accordingly, whereas the remaining cluster contained between 43 and 56 trials. Inspection of the angle-angle plot of the throwing arm showed small ranges of motion (< 10°) in the right elbow joint for most of the trials (see Figure 6-15.a). Although higher ranges were present from some of the trials of movement clusters 4 and 5, comparison of the abduction angles of the shoulder joint indicated that the motion ranges varied between the movement clusters (e.g. clusters 1: 24°±6°, cluster 5: 31°±6°). However, no qualitative differences between the movement clusters could be identified as differences mainly followed a linear trend. From the plots for the left shoulder-arm complex, no clear separation between the clusters could be observed either (see Figure 6-15.b). The plots showed only small ranges of motion for the elbow joint and almost no motion in the left shoulder which was held constant around an angle of 48°±1° for all trials. Compared to the coordination patterns of the right arm, the left arm showed somewhat less structure and was marked by somewhat more aberrant behaviour. Angle-angle plots of the left leg indicated high stability and strong repetition of the same movement pattern across trials (see Figure 6-15.c).

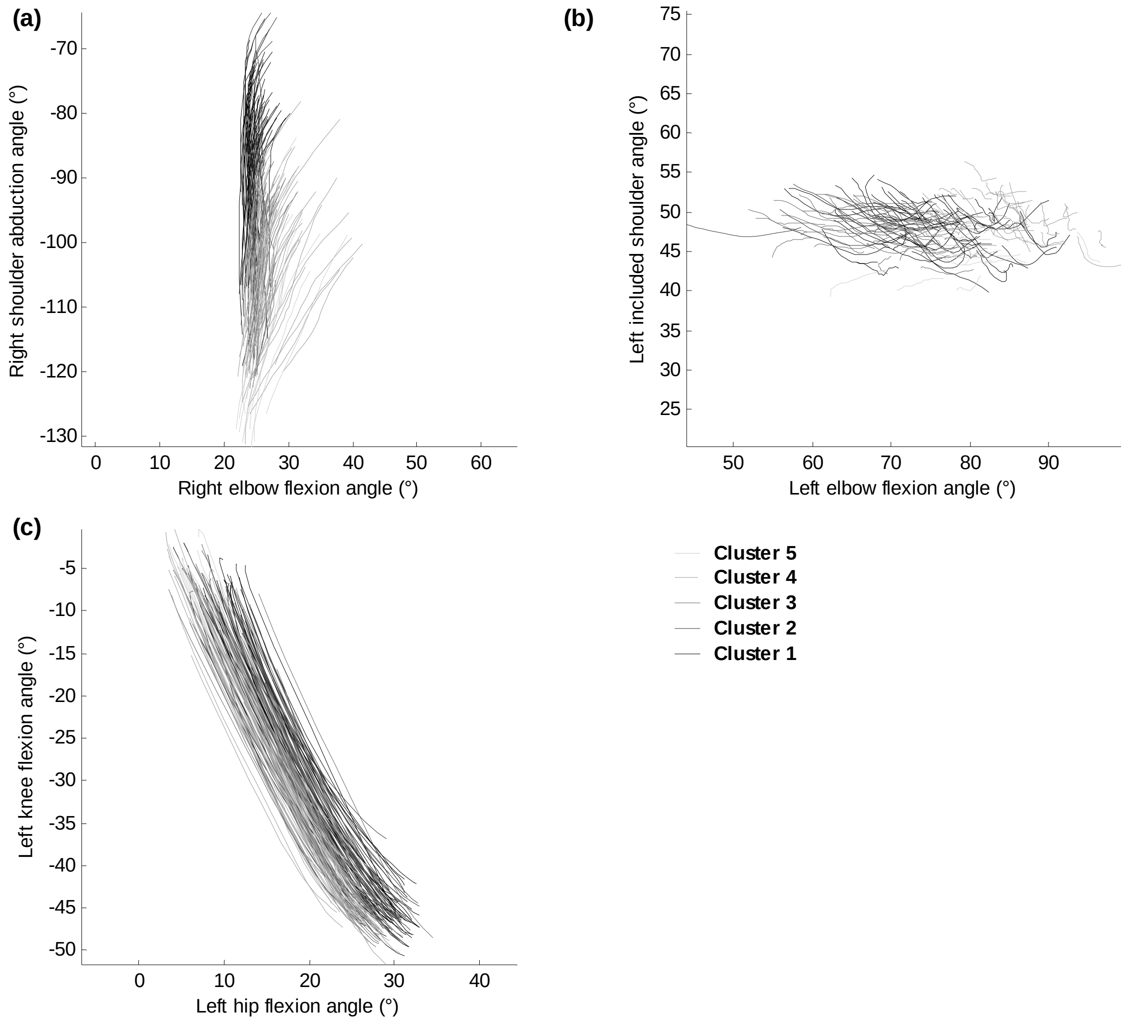

Figure 6-15: Angle-angle plots for all movement clusters of participant DU. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The distribution of the cluster in Figure 6-16 showed a distance-related progression of the movement clusters starting with movement cluster 5 for the lowest differences during the INC condition. Subsequently, there was a switch to movement cluster 3 at 3m distance and a switch to movement cluster 1 at 7m, distance which was maintained until 6m where a switch to cluster 4 occurred. The cluster distribution exhibited high stability indicated by low fluctuations between different movement clusters. Overall, Figure 6-16 gave clear indication for a hysteresis effect since during the experiment no cluster was accessed twice (5→3→1→4). Regarding the progression of the dissimilarity scores, the plot showed relatively small variations across throwing distances and conditions since the maximum differences between the smallest and the greatest value was only 33% (compare Figure 6-16). A small rise at, 7m distance occurred (62°→86°) which also marked the transition between two clusters with subsequent decreasing values. The switch between movement cluster 1 and 4 showed only a minor increase in the dissimilarity scores and the scores showed another smaller jump up from 5m to 4m (63°→84°) and staying at a somewhat elevated level similar to the values at this distances during the INC condition. Therefore, it could not be conclusively stated that the switch from movement cluster 1 to 4 was accompanied by increased fluctuations.

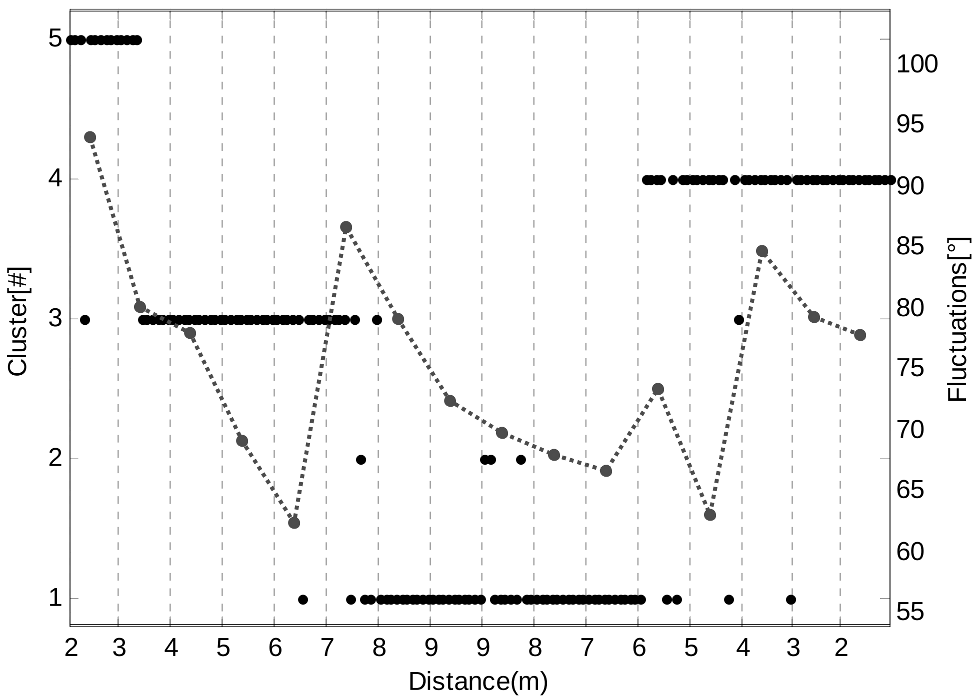

Figure 6-16: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant DU. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In conclusion, for participant DU a scaling scheme could be identified which resulted from the adaptation of single unimodal movement pattern. However, as the hysteresis effects indicated there were some differences in the detailed kinematics between the movement patterns used at the beginning of the experiment and those at the end of the experiment. Potentially, the attractor layout was changed during the course of the experiment similar to a learning effect.

Participant NI

Participant NI showed two main clusters (2 and 4), two smaller clusters (1 and 3), and a singular trial. The angle-angle plot of the right shoulder joint abduction angle and the right elbow joint angle showed a relatively consistent behaviour across movement clusters, where the elbow and shoulder were extended synchronously resulting in a near 45° plot (see Figure 6-17.a). Although the different plots showed considerable overlap there seemed to be a trend for movement clusters 1 and 2 to exhibit somewhat smaller shoulder joint abduction angles (-85°±7° compared to -74°±7°). Similar for movement cluster 4 the shoulder angles at ball release were also somewhat greater (-113°±11°) compared to the remaining angles (-139°±8°). For the left arm complex the different clusters showed strong overlap between each other with some outlying behaviour during movement cluster 2 (see Figure 6-17.b). The pattern started with similar joint angle combinations across clusters and varied more so towards the end of the movement. Variation in the left arm seemed to be higher compared to the throwing arm. Coordination patterns of the left leg were marked by stability small differences across trials (see Figure 6-17.c).

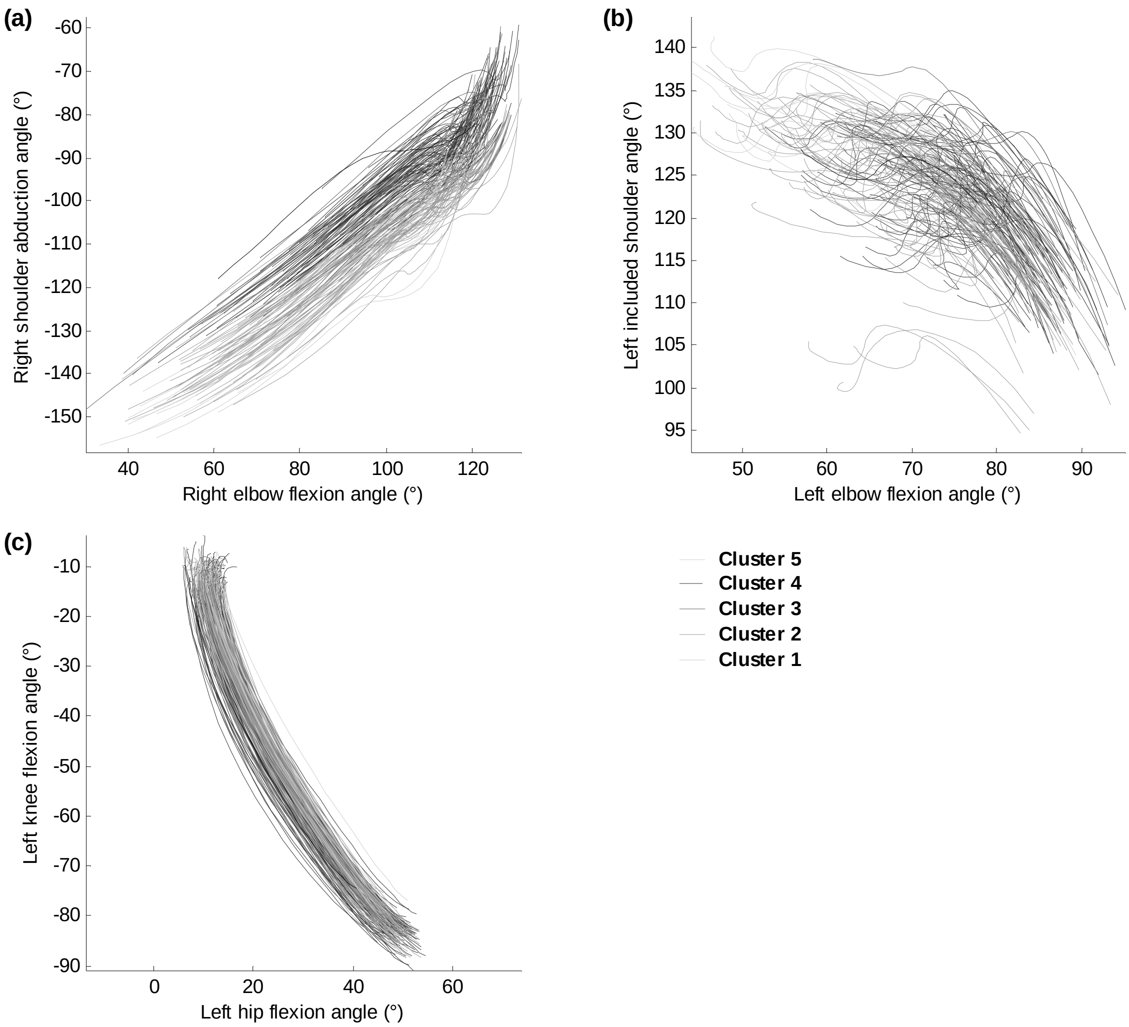

Figure 6-17: Angle-angle plots for all movement clusters of participant NI. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The distribution of the cluster indicated a relation of movement patterning and throwing distance, as apparent in Figure 6-18. Participant CA started with movement cluster 1 which was used until 4m where a transition to movement cluster 2 occurred. This movement pattern was maintained until 6m distance followed by a switch to movement cluster 4. This movement pattern was used until 5m distance during the DEC condition, followed by switch to movement cluster 2 which was not stabilized until 4m. At 2m some reoccurrences of cluster 4 could be observed. Hysteresis effects were therefore present between clusters 1 and 2 and between cluster 2 and cluster 4, where the preceding cluster was always maintained for longer. Fluctuation scores showed a somewhat unstable pattern with constant changes in levels. Starting with high levels (121°) at 2m distance, the fluctuations showed a small decrease which accompanied the switch from movement cluster 1 to movement cluster 2 (82°→102°). Rising scores were again visible around the distances where the switch from cluster 2 to cluster 4 occurred (112°→146°), showing a plateau of greater values at 9m and 8m distance during the decreasing condition. Another peak was present during the switching between movement clusters 4 and 2 (104°→129°) with a final peak at the 2m throwing distance (132°), where some of the trials from movement cluster 4 mixed with movement cluster 2. Whether critical fluctuations were present could not be conclusively determined.

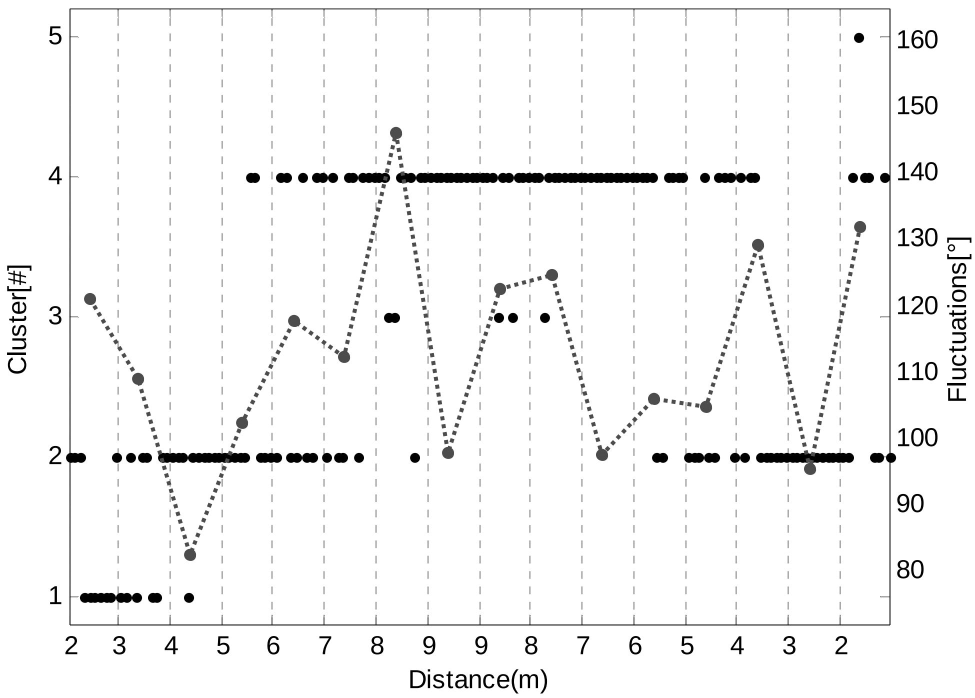

Figure 6-18: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant NI. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

The movement patterns used by participant NI followed an 'up-scaling' and 'down-scaling' strategy without strong qualitative differences between patterns from small and greater distances. The scaling strategy affected the patterning as the occurrences of the transitions between the different movement clusters seemed to be delayed through hysteresis effects. Hence, participant NI can be classified according to the scaling scheme exhibiting no critical fluctuations but providing some evidence of hysteresis behaviour.

Participant JA

The cluster analysis identified four movement clusters for participant JA with clusters sizes varying between 25 and 54 trials. The coordination pattern of the right elbow joint flexion and shoulder joint abduction in Figure 6-19.a showed a highly stable coordination pattern with synchronous extension of the elbow joint and abduction of the shoulder joint. Across trials the arm position at ball release converged into a similar region and the main differences between the movement clusters appeared to stem from the starting joint angles. Whereas movement clusters 1, 2, and 3 showed relatively high overlap between each other (shoulder: -72°±11° STD, elbow: 104°±4° STD), cluster 4 seemed to be somewhat distinct although only by a very small margin (shoulder: -52°±8° STD, elbow: 113°±4° STD). In contrast, the coordination of the left upper limb complex showed some stronger differences between the different movement clusters. Cluster 4 showed only very limited movement in the elbow joint (range of motion: 9°±5°), which was mostly held constant around 96°±1° STD. In contrast, clusters 1 and 2 showed much higher ranges of motion (22°±11°) but were individually paired with different shoulder joint angles. During movement cluster 3 shoulder motion was only relatively constricted (15°±4°), movement cluster 2 showed somewhat greater motion 20°±6°, making the two movements quite distinct from each other. During cluster 1 an intermediate strategy seemed to have been used by the participant with intermediate ranges of motion in both shoulder and elbow joints. Hence, movement cluster 3 showed clear differences compared to the remaining movement clusters whereas cluster 1, 2, and 4 were somewhat similar and were differently scaled versions of the same movement pattern. Lower leg kinematics indicated no differences between the trials and showed high consistency across trials. Comparing the variation between left and right arm the angle-angle plot of the left arm seemed to present more variability across trials.

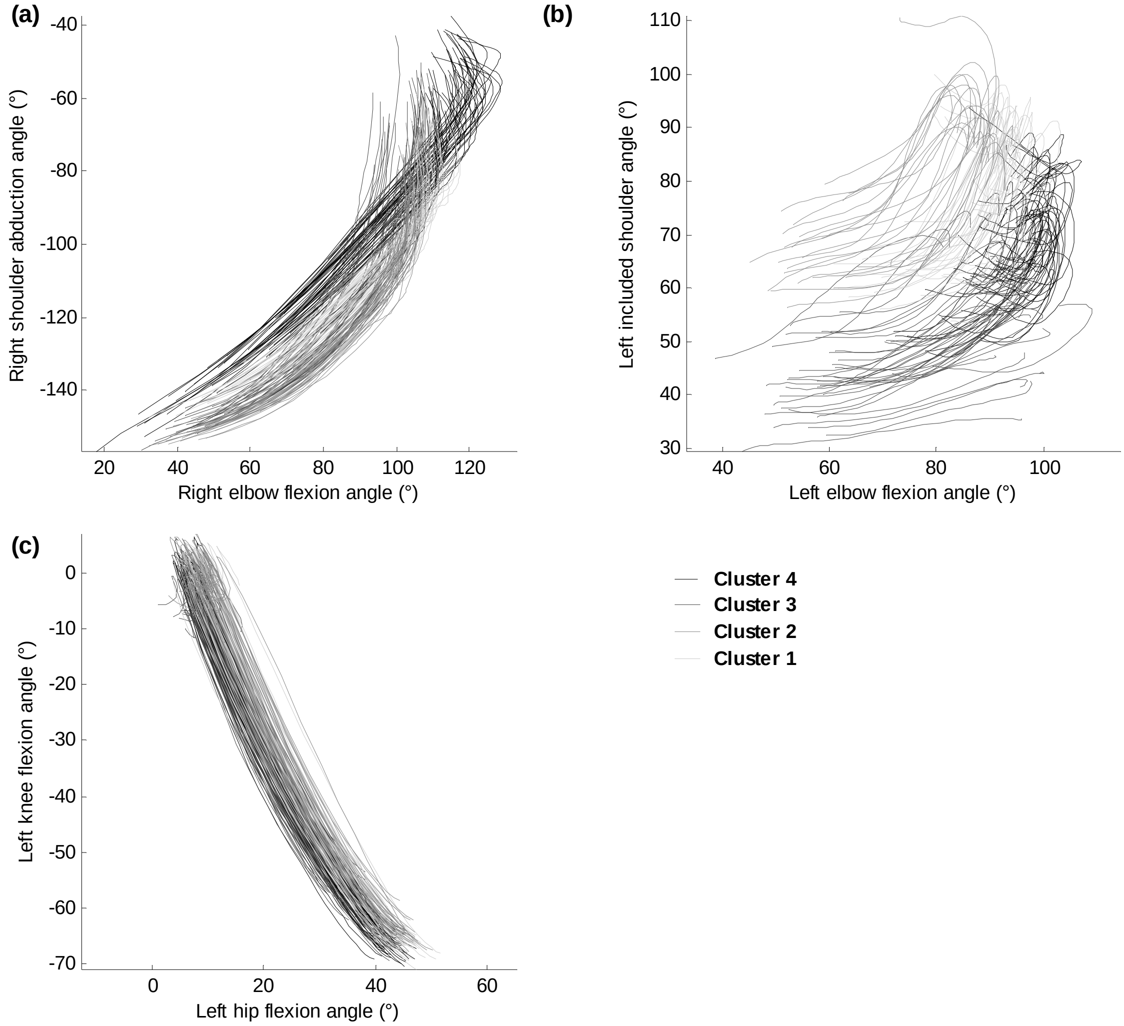

Figure 6-19: Angle-angle plots for all movement clusters of participant JA. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

As can be seen in Figure 6-20 the progression of the movement cluster followed roughly 3 → 4 → 1 → 2. Regarding switching behaviour, participant JA showed a transition from movement cluster 3 to movement cluster 4 at 7m distance. However, at 6m distance movement cluster 7 was transiently used without being stabilized. Subsequently movement cluster 4 was used until the 7m throwing distance, where a switch to cluster 1 occurred which was stabilized and maintained until 4m, where the final switch to movement cluster 2 was performed. Progression of the movement clusters clearly indicated hysteresis effects. Regarding the transition between movement clusters 3 and 4 as pointed out earlier, the movement kinematics of the non-throwing arm exhibited quite distinct patterns. Accordingly the following transitions followed a scaling procedure, where subsequently between cluster 4, 1, and 3, the ranges of motion were increased.

Dissimilarity scores showed a small peak only for the transition between movement clusters 3 and 4 (130°→161°) and followed a decreasing trend for the remaining trials. Transitions 4→1 and 1→2 were not marked by increased fluctuations.

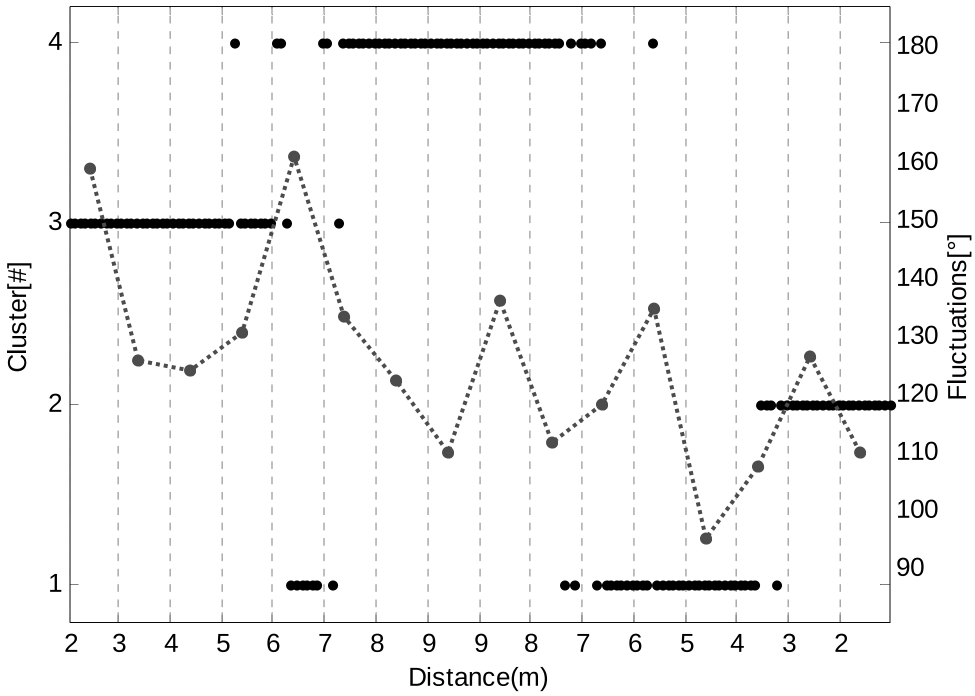

Figure 6-20: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant JA. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In summary, for participant JA the kinematics followed a scaling scheme in which a unimodal pattern was adapted across distances and conditions. However, as for several other participants, the movement patterns at the beginning and the end of the experiment showed some distinct differences.

Changes in kinematics due to performance scores

In Figure 6-21 the performance scores were plotted against the summed differences in joint kinematics between successive trials.

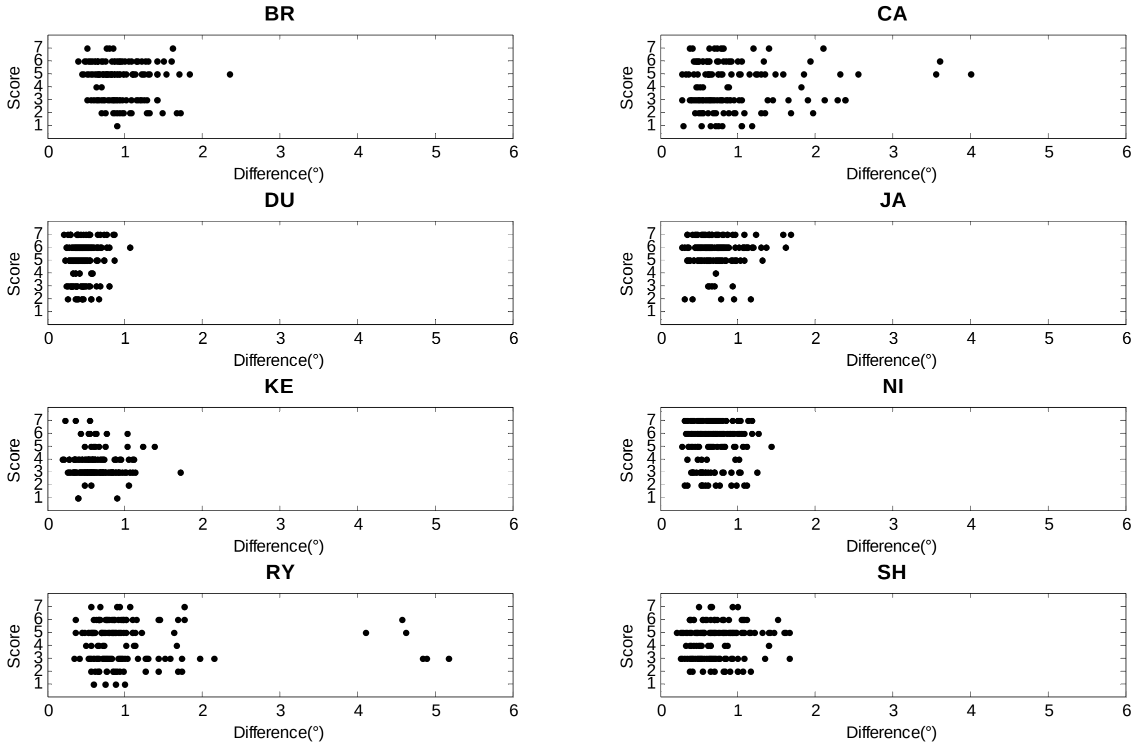

Figure 6-21: Individual plots of the performance scores against the kinematic dissimilarities between subsequent trials for each participant.

For all eight participants, the differences showed considerable overlap between different performance scores which indicated no simple relationship between the performance score obtained in one trial and the similarity in kinematics with the subsequent trial. Accordingly, individual Kruskal-Wallis Rank-sum test expressed no significant effects for performance on kinematic differences. Participants showed very similar ranges, except for RY, who exhibited several exceptional high deviations between subsequent trials, and to a lesser extent participant CA.

Discussion

The present experiment investigated the effects of altering the throwing distance in a basketball hook shot movement through a scaling procedure. The results presented evidence for common trends across participants as well as inter-individual variations in adaptation strategies. The results indicated partial support for the hypotheses, but also some specific differences from the expectations.

It was hypothesized that the wrist velocity would increase with increasing throwing distance. The results obtained in this study clearly supported this hypothesis with a highly significant effect for the distance coefficient. In contrast, an increasing radius of the wrist trajectory with increasing distance was expected but was not supported by the data. Although significant effects for linear distance and squared distance were obtained, they resulted in only very small increases of the radius. As visible in Figure 6-4, different adaptations to the throwing distance were exhibited by the individuals and included both increasing as well as decreasing radii. Only one participant gave clear indications for increasing radii with increasing throwing distance. It has been suggested that a change of the radius trajectory could be linked to changes between throwing for precision and throwing for distance (Kreighbaum and Barthels, 1996). A similar trend, although in a different setting, has been observed in studies of uni-manual coordination (Buchanan et al., 1997). Hence, the present data did not provide strong support for this hypothesis and, in general, the adaptation of trajectory radii of the wrist seemed to be influenced more by individual intrinsic dynamics rather than by distance affordances alone. Similarly, no clear relation between skill level and change in radii could be established either.

Performance was expected to show a general trend for decreasing scores with increasing throwing distance and to exhibit differential effects between skill levels. The former hypothesis was supported by the current findings, whereas for the latter, no conclusive evidence could be obtained. Participants JA and NI demonstrated the highest performance scores and belonged to the most experienced group. In contrast, participant CA showed the second lowest performance despite being a semi-professional basketball player. Similarly, participant SH who was a complete novice to basketball showed intermediate performance better than participants CA, KE, and RY, with the latter two belonging to the intermediate experience group. Accordingly, post-hoc analysis of performance scores between participant indicated significant differences between participants JA and NI and the three least successful performers.

The results from the mixed-effects modelling provided some support for the hypothesis that the main sources of variations were located in the upper body kinematics whereas lower body kinematics were kept stable. Nevertheless, the present study showed some deviations from the results obtained in Chapter 3. For example, no significant effects for the right elbow were found and the plot of individual coefficients showed high inter-individual differences (compare Figure 6.3). Also, the left elbow joint showed a strong significant quadratic effect of distance which was not found in Chapter 3. In both studies significant main effects for the right hip joint angles were found, yet the estimated coefficients were different between the two studies with greater hip flexion in Chapter 3 compared to the present chapter. For the left hip joint angle, both chapters noted significantly higher extension angles with increasing distance. These differences could be potentially explained based on the notion that the hook shot movement *per se* did not prescribe the movement of the right leg. Accordingly, actors could choose to use either a one-legged or a two-legged jump-off similar to the distinction between a classic sky hook hot and a jump hook shot (see Chapter 2). Therefore, in the former case higher flexion angles with distance could have been used. Investigation of the standard deviations indicated that inter-individual variances were greater compared to the intra-individual variances in the joint angles from Chapter 3. In both studies variances of the left leg complex showed the lowest deviations with much higher variations in the right leg, left arm and the right shoulder joint. Which supports the explanation regarding the differences of the kinematics of the right leg. The results in the present study indicated a strong increase in wrist flexion angles which was not investigated in Chapter 3. Regarding the inter-individual differences in adaptation represented by the slopes in Chapter 3, the left shoulder joint and the left elbow joint showed greater deviations across participants. This result could be confirmed for the left elbow joint in the present study. Investigation of the individual coefficient for the non-significant joint angles provided further support of high inter-individual variations and in some cases intra-individual variations between conditions. Both of these findings support the results from Chapter 3. The kinematics of the left shoulder joint showed great differences with some participants applying only minor adjustments over distances and others showing strong adaptations. Regarding heteroscedasticity, the present study showed that intra-individual variance was not a simple function of skill level across participants and that the variance could be differentially distributed across limbs (see also Chapter 3 and Button et al., 2003). In conclusion, the results from the ball release data confirmed high variations for the upper body segments between participants across distance, and low variation for the left leg-segments.

Interpreting the trends observed for the kinematics of the supporting leg and the upper body, the behavioural information inherent to this task may have acted in such way that the movement of the left leg was determined to a large extent through the task constraints, yielding common effects across participants. In contrast, movement in the upper body segments were possibly less determined by the behavioural information but more influenced by the intrinsic dynamics of the performer and shaped by musculo-skeletal constraints (Carson and Riek, 1998). From this view, intrinsic dynamics and behavioural information would interact within a single performer and coordination dynamics would show a much higher inter-personal variation when behavioural information of the task was relaxed.

The main aim of the current experiment was to identify different adaptation strategies according to throwing distance and investigate whether these strategies were linked to performance levels. Of the eight participants only two, participants CA and SH, showed a clear distinction into two different movement patterns across throwing distances. Investigation of angle-angle plots gave clear indication for qualitatively different movement patterns based on the kinematics in both arms. For the remaining participants (BR, DU, JA, KE, NI, and RY) the adaptation strategies identified resembled more of a scaling approach, where a single movement pattern was varied over distance. For these participants, movement patterning for the support leg and the throwing arm showed high stability across distances and conditions and variations between distances were visible in the kinematics of the non-throwing arm. Therefore, the results obtained in this study supported the results obtained in Chapter 3 and 5.

It was also hypothesized that the two-pattern strategy transitions between movement clusters would be marked by increasing mean dissimilarity scores exhibiting critical fluctuations as well as hysteresis effects. For both participants, the findings supported this hypothesis, providing good evidence for transitional behaviour between different attractors similar to observations from studies of bimanual coordination (Kelso et al., 1986). Therefore, the results for these particular participants supported the notion of a bi-stable attractor layout. For the single pattern strategy, based on the results obtained in Chapter 3 and 5, a hysteresis effect but no critical fluctuations were expected, which was confirmed in the present study as well. Accordingly, a shallow, unimodal attractor layout seemed to be present for these participants.

Regarding the postulated connection of higher skill level with a bimodal attractor layout, the present results were not supportive since both participants showed somewhat intermediate performance. Similarly, for the unimodal strategy, participants covered the whole range of performance levels from the best to the least successful. In this regards the results of the present study resembles to some extent those reported by Sorensen et al. (2001), Limerick et al. (2001), and Buchanan et al. (1997) where different strategies between participants could be identified. Limerick et al. (2001) proposed that potentially "*anthropometric variability*" (p.560) might have contributed to the observed differences in their study. In the present case though, a purely anthropometric explanation seems somewhat implausible since participants SH and CA showed great differences in anthropometric measures ($Height_{SH}$ = 168, $Weight_{SH}$ = 63, $Height_{CA}$ = 188, $Weight_{CA}$ = 90) despite using the same strategy. Sorensen et al. (2001) did not provide any explanation for the observed differences in pattern strategy between the participants. In the study conducted by Buchanan et al. (1997), which investigated uni-manual movements, different strategies between participants could be identified but no explanation was presented by the authors who stated that "*many reasons may exist*" (p.271) including "*physiological aspects, skill level, athletic ability, experience in specific prior task*" (p.271). Similarly, in the study presented earlier by Post et al. (2000b) only participants who were able to perform anti-phase and in-phase movements over all frequency ranges without exhibiting phase-transitions were included in the experimentation. Unfortunately, the authors did not give any indications in what regards these participants may have differed from "typical" participants exhibiting phase transitions. Accordingly, in the present programme of work the actual reasons for adopting a specific pattern strategy could not be inferred. Potentially, some interactions between neuro-muscular constraints and the task may have contributed to the inter-individual differences and further investigation seems necessary.

Comparing across participants for each strategy group, there were inter-individual differences in actual movement patterning between the participants. For the unimodal sub-group, in regards to coordination of the throwing arm, two main patterns were visible. For participants BR, JA, and NI, action of the throwing arm was marked by a synchronous extension of the elbow and abduction of the shoulder joint with similar ranges of motion (elbow: 150°-50°, shoulder: -40- -150°). However, movements of the non-throwing arm showed considerable differences between the participants and none of the patterns were similar between participants. Participants JA and BR showed relatively ordered changes in the kinematics of the non-throwing arm with changes over throwing distance, with relatively clear separation between movement clusters. Conversely, participant NI showed great overlap across movement clusters. Participants DU, RY, and KE showed a completely different movement pattern in the throwing arm with small movements in the elbow joint and a large range of motion in the shoulder joint. Similar to the other three participants, participant RY showed clear differences in the non-throwing arm. The differences between the two movement patterns could again be linked to the differences between a jump-hook and a sky-hook shot (see Chapter 2). There were also subtle inter-individual differences between patterns at the beginning and the end of the experiment. Whereas participants BR, NI, and RY used the same movement clusters at the beginning and the end of the experiment, participants JA, DU, and KE finished with different movement clusters compared to the start. Although the movement coordination seemed to be constantly scaled, similar to the proposition made by Kostrubiec et al.(2006), for some participants the attractor layout showed some persistent changes resembling a learning effect (compare Zanone and Kelso, 1992; compare Zanone and Kelso, 1997).

For the bimodal sub-group, the adaptations between participants also showed some strong differences. Although both participants switched between movement patterns involving either more active elbow or shoulder motion, the direction of change was different. Participant CA switched from a movement pattern with synchronous movement in the shoulder and the elbow joint of the throwing arm to a movement mainly using movement in the shoulder. In contrast, participant SH started with the latter pattern and switched to the former. Whilst the movement patterns using only the shoulder were very similar between participants, the 'elbow-movement patterns' were quite distinct. For participant CA, the motion was more similar to the patterns observed in the unimodal group with a great range of motion in both shoulder and elbow joints. In contrast, participant SH used a sequential pattern with much smaller ranges of motion in both joint. Comparison of the movement pattern in the non-throwing arm indicated further differences between the participants, where CA showed relatively ordered behaviour across movement clusters, and SH showed great variation and more aberrant movements.

Together, the results obtained across attractor groups and participants provide support for the concept of degeneracy in multi-articular movements (Hong and Newell, 2006). It appears that when several movement patterns are available, performers are able to individually exploit redundant degrees of freedom leading to richer movement dynamics. Potentially, for these tasks, intrinsic dynamics play a much higher role in movement organization than in the case of relatively constrained movements, usually observed in studies using uni- or bimanual movements. Although the results gave indication for relatively simple attractor layouts (unimodal and bimodal), the range of movements which were encompassed within these attractors deviated strongly from the attractors found in traditional movement models. Seemingly, the mere fact that movement patterns were quite distinct from each other does not necessarily indicate presence of different attractors, but potentially the route taken between these movement patterns provides the necessary information about the attractor layouts (Haken and Wunderlin, 1991). Revisiting the study by Limerick et al. (2001) on weightlifting, two different movement patterns were revealed but individually different transformation strategies existed between these two patterns. Whereas some participants exhibited abrupt changes between the two movement patterns, others showed transitions more like a continuous change between the two patterns (Limerick et al., (2001). Taken together, these findings could imply that similar movements are represented by different numbers of attractors for different actors. This is a major issue for future research on degenerate, dynamical movement systems.

In this chapter, the coordination patterns observed in the non-throwing arm appeared to be of equal importance as the movement of the actual throwing arm. Potentially, the movements of the non-throwing arm were used in order to stabilize the kinematics of the throwing arm similar to a dampening mechanism. Through this mechanism perturbations could be redistributed across movement components in order to ensure task-achievement (Saltzman and Kelso, 1987) and would underpin the notion of morphological structures (Bernstein, 1967). In this case, recruitment of degrees of freedom could have been used in order to stabilize attractors similar to the findings introduced earlier (Buchanan et al., 1997; Fink et al., 2000).

As mentioned in the introduction of this chapter, it seemed likely that there would be an interaction between the performance outcome and the distance affordance which would influence differences between successive movement trials. Analysis of the relation between performance outcome and adaptations in movement kinematics did not provide evidence for a simple mapping between these two domains since no consistent effects could be found. Potentially, this effect can be embedded into the framework of emerging and decaying constraints where the emerging distance constraints overrides behavioural information obtained from previous performance outcome (Guerin and Kunkle, 2004). Although this interpretation remains speculative because it was not specifically tested in the present experimental set-up, it remains an important issue for future research.

Another point of interest in the present study was related to postulated differences between rhythmical and discrete movements derived earlier in chapter 2. Investigation of the movement clusters distribution gave clear indication for switching behaviour between distinct movement clusters in subsequent trials which is not possible for continuous movement. This important finding marks a distinct difference between these two movement models in the case of the basketball hook shot as representative for the class of discrete, degenerate multi-articular movements.

Conclusion

The results of the present study provided further support that the basketball hook shot resembles a useful movement model to investigate the application of dynamical systems theory to the study of coordination in discrete, multi-articular actions. Using a scaling methodology ubiquitous to investigations from a dynamical systems perspective, the results provided evidence for phase transition behaviour in two participants. In both cases the participants switched between two qualitatively different movement patterns which were identified and validated by the cluster analysis approach. For the remaining participants no such clear transitions were found and movement pattern adaptation appeared to follow a continual scaling with the highest differentiations between the smallest and the greatest distances. In order to provide further evidence for phase-transitions further investigations into time-scale behaviour especially in regards to critical slowing down appears necessary.

The results also provided evidence for distinct differences between traditional movement models utilized in studies from a dynamical systems perspective and the movement model in the current chapter exemplifying a discrete multi-articular action. In this chapter, great variations in selected movement patterns between participants became apparent, which highlighted the degenerate features of the chosen movement model. Further, based on observed switching between highly dissimilar movement patterns in subsequent trials, distinct differences with rhythmical movement models, where such behaviour is not possible, were highlighted in this chapter.

7 Chapter Seven: Investigation of critical slowing down in a discrete multi-articular action

Introduction

In Chapter 6, a scaling experiment using the basketball hook shot was conducted. Following the studies from Chapter 3 and Chapter 5, throwing distance was systematically manipulated and movement kinematics were recorded. Application of the cluster analysis approach (see Chapter 5) provided evidence for two different movement coordination strategies used by the participants. Participants used either a single type of movement pattern and adapted this pattern in a scaling fashion to the throwing distance or they used two qualitatively different movement patterns. Based on further investigation of hysteresis and critical fluctuations, the two strategies were linked to the presence of attractors and accordingly represented either a bimodal or a unimodal attractor layout. For the bimodal layout, the two movement patterns could be clearly distinguished according to the movements of the upper body. For the unimodal strategy, the kinematics of the throwing arm showed high stability alongside greater variability in the non-throwing arm. In both strategies, the movements of the supporting leg varied little across throwing distances, conditions, and between participants. The literature review in Chapter 2 highlighted the importance of analysing behaviour over different time-scales in order to determine whether behavioural changes followed phase transitions. Given that for the bimodal movement strategy hysteresis and critical fluctuations were identified, it is necessary to investigate critical slowing down using a perturbation experiment to enhance understanding of the different attractor layouts.

Typically perturbation experiments investigate either the effects in body segments other than the perturbed segment or the response in different phases during the movement due to the perturbation. Accordingly, when a perturbation applied to one segment results in behavioural changes in another segment, one can conclude that the segments are coupled to each other during action. Similarly, if a perturbation applied during a specific phase of the movement leads to changes in subsequent movement phases, the coordination of these different phases are said to be dependent on each other (see Haggard, 1994). For example, Button et al. (2000) investigated coordination in a ball catching task. A perturbation was applied to the wrist of the catching-hand of the participants using a hysteresis brake which was attached through a cord with a sweatband worn by them. The brake applied a resistive force to the arm during the transport phase prior to the catch. For some participants changes in hand aperture due to the perturbation were found, which indicated coupling between the transport and grasp phases. Similar results were obtained by Haggard and Wing (1991) for a prehension task. The perturbation was again applied during the arm transport phase. However, from a dynamical systems perspective, perturbation experiments typically are not concerned with the type of immediate coordination responses due to an applied perturbation but rather with the time the movement systems needs to relax back to the state prior to the perturbation. Through this approach, the stability of an attractor which underlies the movement can be tested (see Chapter 2). According to this view, for a bimodal attractor layout the time scales for relaxation (τ_{rel}), control parameter change (τ_p), and the equilibrium time scale (τ_{equ}) should exhibit two different relationships depending on the value of the control parameter (Schöner et al., 1986). During the pre- and post-transition areas the relationship $\tau_{rel} \ll \tau_p \ll \tau_{equ}$ should hold, whereas within transition regions the time scales should collapse onto each other and follow $\tau_{rel} \sim \tau_p \sim \tau_{equ}$ (see Schöner et al., 1986 and Chapter 2). Accordingly, τ_{rel} should exhibit greater values within transition regions compared to the pre- and post-transition regions (compare also Figure 2-5). This effect is called critical slowing down (Haken, 1983; Scholz et al., 1987; Schöner et al., 1986).

A classic study of critical slowing down in the context of movement coordination was conducted by Scholz and Kelso (1989; compare also Scholz et al., 1987) who investigated rhythmical extension-flexion movements of both index fingers. Participants performed either in-phase or anti-phase movements synchronized to a metronome. Prior to the experiment individual critical frequencies which lead to transitions from anti-phase to in-phase movements for the participants were determined. Accordingly, participants started with individually specified movement frequencies which were increased every 10s by 0.2Hz. A torque, triggered by the occurrence of peak velocity during finger flexion, was applied to the right index finger approximately 3s into each frequency plateau. This way the authors ensured sufficient time for transient influence due to changes in movement frequency to become negligible. At each frequency plateau, one perturbation was applied and participants were instructed not to anticipate the occurrence of the perturbation. Critical slowing down was defined as the time after perturbation until two successive stable phase trials were visible by the authors. Results indicated no changes in critical slowing down during the in-phase pattern. However, during the anti-phase movements τ_{rel} increased with increasing movement frequency. Further, the perturbations lead to increasing numbers of phase transitions from anti-phase to in-phase movements, the closer the movement frequency values came to the predetermined critical movement frequency. Further increases beyond the critical frequency indicated decreasing τ_{rel} which were similar to those obtained during in-phase movements only. Hence, the experiment clearly corroborated the hypothesized critical slowing down (Scholz and Kelso, 1989; Scholz et al., 1987). Post et al (2000b) applied a similar perturbation methodology using an elbow flexion-extension movement. Investigation of τ_{rel} showed no differences between anti-phase and in-phase patterns and indicated a general trend for increasing values with increasing movement frequency. However, as pointed out in Chapter 2, participants for this study were chosen based on the prerequisite that they were able to perform the anti-phase pattern at all movement frequencies without phase transitions to in-phase patterns. Both these studies utilized rhythmical movement models and no experiments investigating discrete movements with a combined scaling and perturbation approach have been reported in the literature. Therefore, it remains unclear to what extend these findings can be generalized to discrete, multi-articular actions.

In summary, in order to investigate attractor stability and accordingly infer time-scale behaviour, application of a mechanical perturbation to a moving segment has been traditionally used in the dynamical systems literature. For this reason, it was decided to utilise a similar procedure to the throwing movement in the basketball hook shot to investigate effects on critical slowing down. For the bimodal throwing scheme identified in the basketball hook shot, one might expect the occurrence of critical slowing down as movement patterning undergoes a phase transition. In contrast, for the unimodal patterning which never enters a critical region either no changes of the decay parameter or following the results from Post et al (2000b) a linear decreasing trend should be present. With regards to the actual pattern of decay for each control parameter plateau, according to the literature, the fluctuations after a mechanical perturbation should follow an exponential decay pattern (Post et al., 2000b; Schöner et al., 1986) as was indicated by the modal plot in Chapter 2. In Chapter 3 typical movement times for the basketball hook shot were shown to be around 30ms, making it unlikely that relaxation behaviour could be observed within a single trial. Hence, the surrogate measure proposed by Schöner (1990), based on differences in movement execution between subsequent trials, needs to be used with the basketball hook shot.

To investigate relaxation behaviour for both strategies (uni- vs bimodal) it was necessary to investigate performance of participants from a range of different skill levels since in Chapter 6 it did not become clear what the actual source for the two different strategies was. Following the arguments provided in Chapter 6, further investigation of discrete kinematics at ball release could uncover deviations in movement patterning across the three different studies. Additionally, since in Chapter 3, an increase of wrist trajectory radii with increasing throwing distance was found with no such trend identified in Chapter 6, further investigation into this issue seems warranted.

Materials and Methods

Participants

Five males (Age=24±5, Height=183cm±8, Weight=80kg±4) participated in the study. Compared to Chapter 6 the participants were slightly younger and taller (Age_{Ch6}=27±5, $Height_{Ch6}$=175cm±16). Participants CR and CAL were semi-professional basketball players playing for the Otago-Nuggets (New Zealand national franchise). Participants LU and AN had played at club level whereas participant MI had no prior experience in playing basketball. All experimental procedures were approved by the University of Otago Ethics committee. All participants used their dominant right hand for throwing and had not experienced any injuries in the six months preceding the study.

Apparatus

A mobile basket fixed at a conventional height of 3.05m with a Plexiglas backboard and a standard sized basketball (Size 7, FIBA approved) was used for all shooting trials. Sampling frequency was set at 100 Hz during motion analysis with a three-dimensional motion capture system (Motion analysis corp.) using 12 digital-cameras. A DV-camera was synchronized with the motion analysis system in order to determine the time of ball release.

Participants were prepared using the same marker set-up as described in Chapter 6. Additionally, participants wore a wrist band on the right arm with a lightweight cord attached to it. A metal clip was attached to the loose end of the cord which could be attached to a weight of 2.5 Kg. The length of the cord was determined so that the cord would be taut when the thrower reached approximately the position just before ball release. This way a mechanical perturbation to the throwing arm could be applied which simulated other perturbation experiments (e.g., Button et al., 2000). Based on a pilot study the mass chosen resulted in a sudden jerk to the throwing arm which did not disrupt the overall movement for safety reasons but affected the movements of the throwing arm. This set-up was also chosen to simulate a foul made by a defender as might occur in an actual basketball game situation which mimics a perturbation effect.

Procedure

The procedure was the same as used in Chapter 6 with the addition of the mechanical perturbation. A metal clip was attached to the cord with the metal weight at predetermined random trials to create a perturbation for the throwing movement. In order to disguise the actual procedure of attaching the weight, the same sequence of operations was performed between every trial so that participants could not infer from pre-trial preparation whether the weight was being attached or not. Following the study from Scholz and Kelso (1989), participants were instructed to not anticipate the occurrence of the perturbation. Before data recording, participants performed a self-selected warm-up routine for 15 minutes with further instructions to perform a range of different shooting techniques. Subsequently, reflective markers were placed on key anatomical positions on the participants as well as the wrist band when they have indicated to the researcher that they are adequately warmed-up. Next, throwing instructions were given after which they performed five shots with and five shots without the perturbation each from 2m, 5m, and 7m to familiarize themselves with the procedure. All participants reported feeling comfortable with the wrist band on and reported that the cord did not interfere with their movement execution. Participants performed the same protocol starting with the INC condition followed by the DEC condition with ten shots per distance. Accordingly, τ_p was set at ten trials. This value was chosen ensure a large enough number of trials for the estimation of τ_{rel}. In between shots, 40 s recovery time was provided to prevent fatigue effects and to provide sufficient time for trial preparation by the experimenter. Perturbation trials were pre-determined using a random number generator with a special weighting of trials three to five. This ensured sufficient recording of trials following the perturbation as well as sufficient trials preceding the perturbation in order to decrease transient influences of throwing distance changes (see Scholz and Kelso, 1989). For each distance by condition, at least one trial was perturbed. Additionally two further trials were perturbed in order to make the weighting of trials three to five less obvious for the participants. Performance outcomes were recorded on a six-point nominal scale by an additional experimenter (see Chapter 6 for details).

Data processing

The same procedures used in Chapter 6 were applied in the current experiment.

Data analysis

Similarly, the same procedures used in Chapter 6 regarding performance score, mixed-modelling of joint angles, wrist displacement cluster analysis of continuous joint kinematics were performed. Based on movement times, angle time curves for all participant were normalised to 16 frames. In order to investigate critical slowing down, differences in kinematics in subsequent trials were calculated in the same way as the distance matrix for the cluster analysis set up (compare Chapter 6). To estimate τ_{rel} the dissimilarities were log transformed, then τ_{rel} values were estimated through a simple linear regression procedure:

$$\log(\mathit{fluctuation}) = \log(c * e^{\tau_{rel} * trial}) = \log(c) + \tau_{rel} * trial = a + \tau_{rel} * trial \quad (7.1)$$

Trials used for the regression included all trials from the perturbed trials to either the last trial of that particular trial block at that distance, or to the next perturbed trial within that condition, based on whichever occurred first. Accordingly, for each participant, sixteen coefficients together with confidence intervals using standard linear regression theory were obtained. In order to adjust for the possibility of type 1 errors due to the number of statistical tests, a Bonferroni correction was applied to the confidence intervals. The significance level was set at $p < 0.05$ and deemed highly significant if $p < 0.01$ for all statistical tests.

Results

The results section is divided into sub-sections on performance scores, investigation of critical slowing down and mixed-modelling of joint angles at ball release, wrist velocity, and wrist radius.

The results of the cluster analysis are presented in detail in Appendix A. For participants CR, AN, and MI the results of the cluster analysis provided clear support for a unimodal attractor layout where hysteresis but no critical fluctuations were observed. For participant LU, no clustering could be determined and all trials except one trial were grouped into one cluster. For participant CAL a unimodal scheme was identified, however, the distribution of movement clusters across throwing distances did not indicate hysteresis behaviour. In summary, none of the participants exhibited phase transition behaviour. Unfortunately, it was not possible to invite one of the participants who exhibited phase-transition behaviour from the previous studies again because of limited access to the motion capturing system.

Performance scores

In Figure 7-1 the rating of participants' performance according to their mean performance score is shown. The two most experienced players CR and CAL achieved the best and third best performance of this sample of basketball players, respectively. As expected participant MI, the novice performer, showed the least successful performance of all.

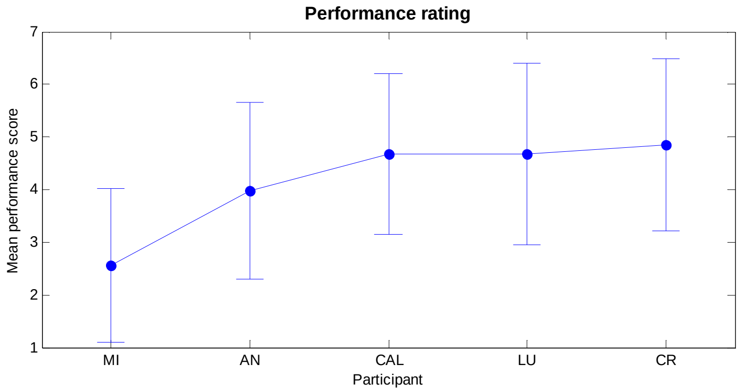

Figure 7-1: Mean performance and standard deviation for each participant.

In Figure 7-2 the mean performance scores per distance for each individual participant can be seen. Overall a general trend for decreasing performance with increasing distance could be viewed with some variation across participants.

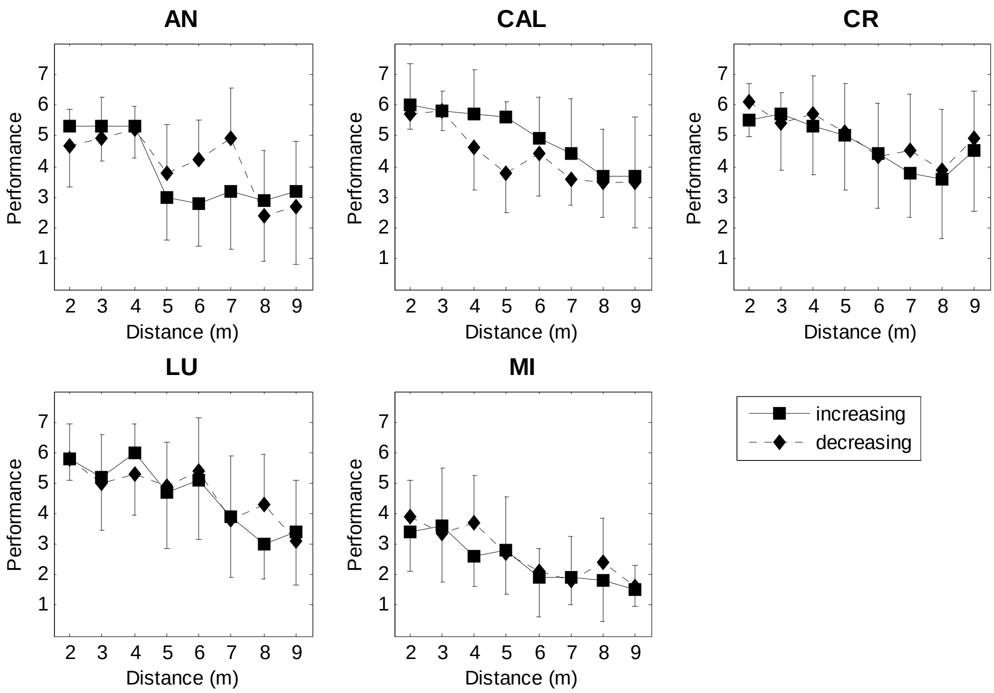

Figure 7-2: Mean performance scores and standard deviation for each participant at each throwing distance for increasing (■) and decreasing (♦) throwing distance.

Friedman-Rank sum tests indicated that the effect for distance almost attained conventional levels of statistical significance when blocked over condition $\chi^2_7 = 13.7$, $p < 0.06$, and a highly significant effect when blocked over participants, $\chi^2_7 = 28.79$, $p < 0.01$. Post-hoc tests yielded significant effects for distance between 5m and 9m and between 7m and 9m, which indicated deteriorating performance with increasing distance. For participants a significant effect was found when performance scores were blocked over distance $\chi^2_4 = 22.26$, $p < 0.01$. Post-hoc tests indicated significant differences between participants CAL-MI, CR-MI, and LU-MI. All remaining comparisons were statistically non-significant.

Critical slowing down

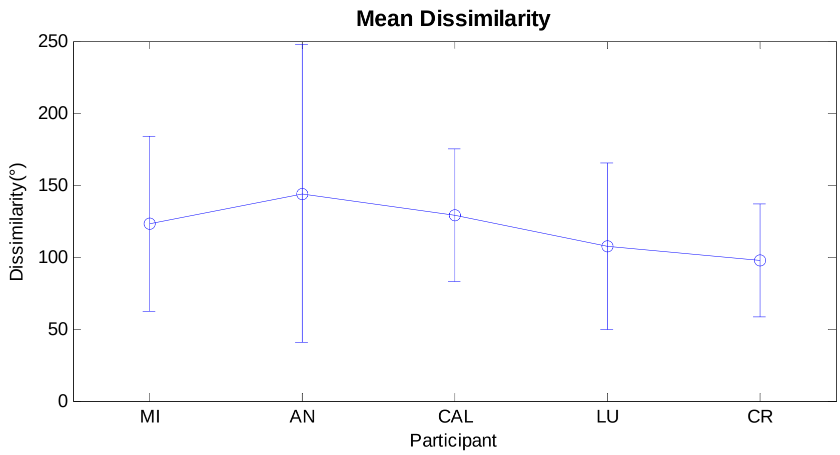

Figure 7-3: Mean dissimilarity scores and standard deviation for each participant (better throwers further to the right).

Figure 7-3 shows the mean dissimilarities of the subsequent trials for each participant in the order of actual performance during the experiment. The plot showed a slight tendency for decreasing trend with increasing performance. A Kruskal-Wallis Rank-sum test indicated a significant effect for participant, $\chi^2_4 = 99.24$, $p < 0.01$. Post-hoc tests indicated significant differences between AN and CR, LU, MI, and CR and between MI and CAL and CR which indicated that more successful participants showed smaller differences in movement execution between subsequent trials. Regarding the magnitude of the fluctuations, the obtained scores indicated relatively high differences of movement patterns between subsequent trials, as can be seen the differences ranged between 98° for participant CR and 144° for participant AN.

Based on the preceding cluster analysis results, no phase transitions were observed for any of the five participants. Therefore, no critical slowing down could be investigated and only behaviour of between-trial fluctuations after the application of the mechanical perturbation could be studied, which was postulated to follow an exponentially decreasing pattern.

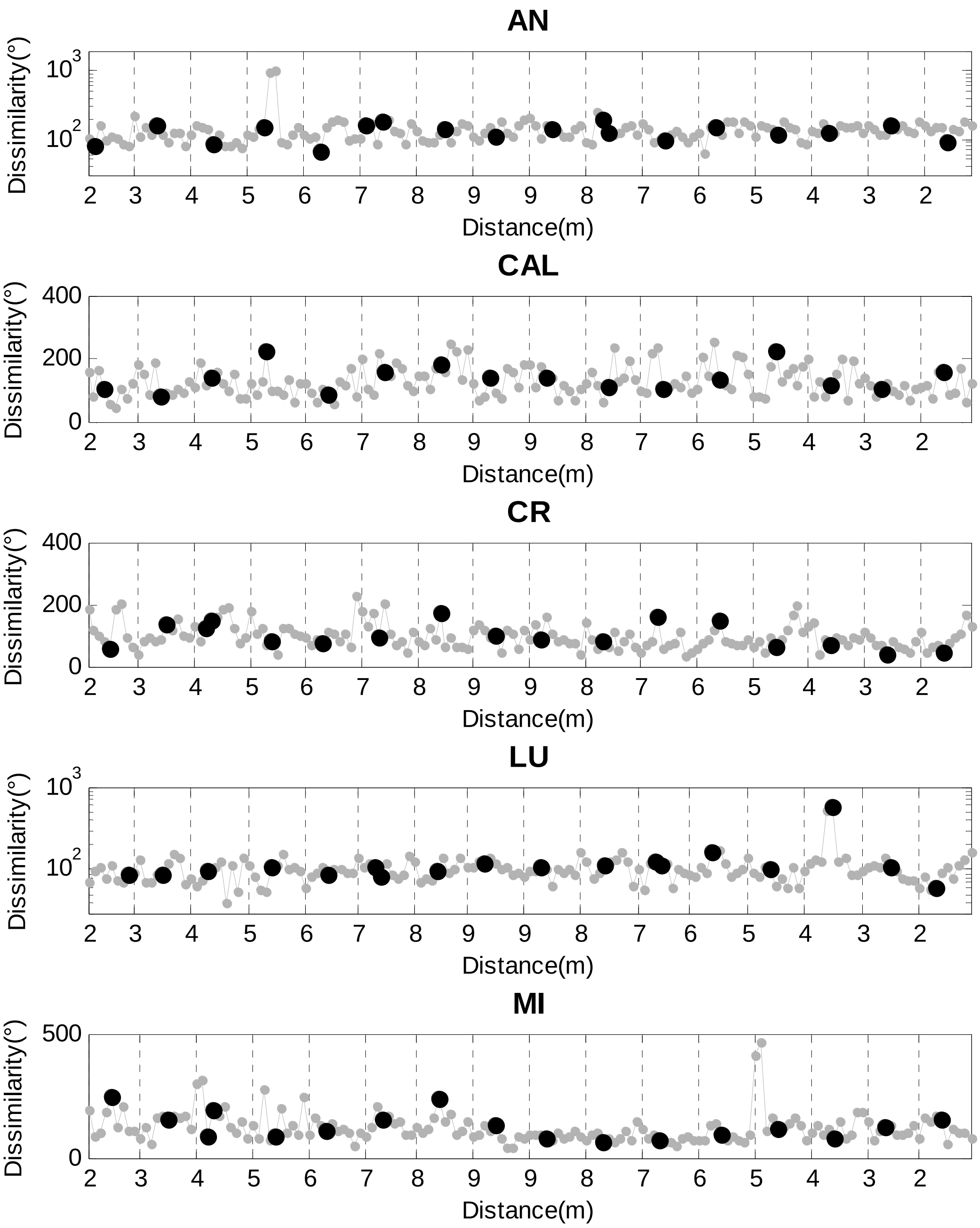

Figure 7-4: Individual plots of dissimilarity scores between subsequent trials in actual ordering of occurrence of unperturbed trials (●) and perturbed trials (●). For participants AN and LU a log-linear plot is shown in order to ease interpretation.

In Figure 7-4 the differences between successive trials were plotted against throwing distance in the actual sequence presented during the experiment. In general, the plots showed no distinct pattern and seemed to follow rather a random process. Regarding the behaviour after perturbed trials the plots gave no visual indication that dissimilarities after a perturbed trial followed an exponential trend. Hence, none of the plots resembled the proposed model plot showed earlier (compare Figure 2-5) and actual variations between trials showed high fluctuations for all participants at all times. Participants LU, AN and MI exhibited some high peaks in their respective plots which marked for participant AN the transition between two movement clusters whereas participants LU and MI seemed to exhibit rather outlying behaviour. For participant LU, the resulting trial marked a completely different movement pattern compared to the other trials. Yet, compared to the throwing movements observed in Chapter 6 (for example BR), this movement pattern appeared to resemble a valid hook shot (see also Appendix A). Accordingly, the movement could not be excluded. Further, as critical slowing down was estimated for each distance by condition block, maintaining this singular trial would not have influenced estimates for other throwing distances. With regards to differences between subsequent trials from different throwing distances the plots gave no clear indication that increasing or decreasing the distance by 1 m affected the differences more substantially compared to trials within a specific distance bin. Similarly, kinematics of the perturbed trials did not show any pronounced differences in relation to the unperturbed trials. For participant MI a small trend over the course of the experiment was visible where the fluctuations at the beginning of the experiment seemed to exhibit greater magnitudes compared to the later trials, apart from the singular peak at 5 m DEC. With regards to the magnitude of the dissimilarities, the plots supported the impression of Figure 7-3 and indicated relatively strong changes in movement execution between subsequent trials.

The estimated time scales for each participant for each distance by direction bin are presented in Figure 7-5. The estimates showed equally positive and negative values which indicated accordingly increasing and decreasing fluctuations after the perturbation. However, investigation of the confidence intervals showed that for each estimated slope coefficient a value of zero was included. Thus indicating high probability for non-significant slopes, therefore rejecting the hypothesis of an exponential decay pattern. Inspection of Figure 7-5 gave no indication for a systematic variation of the time scales with distance or switching between different movement clusters. The wide confidence interval for participant AN at 5 m INC was a result of the peak fluctuations mentioned earlier. For participant LU at 7 m DEC only 4 trials were available in order to estimate the fluctuations which resulted in the large confidence interval for this participant. Since the peak fluctuations for participant MI at 5 m

DEC occurred before the application of the perturbation, they did not influence the estimate of τ_{rel}.

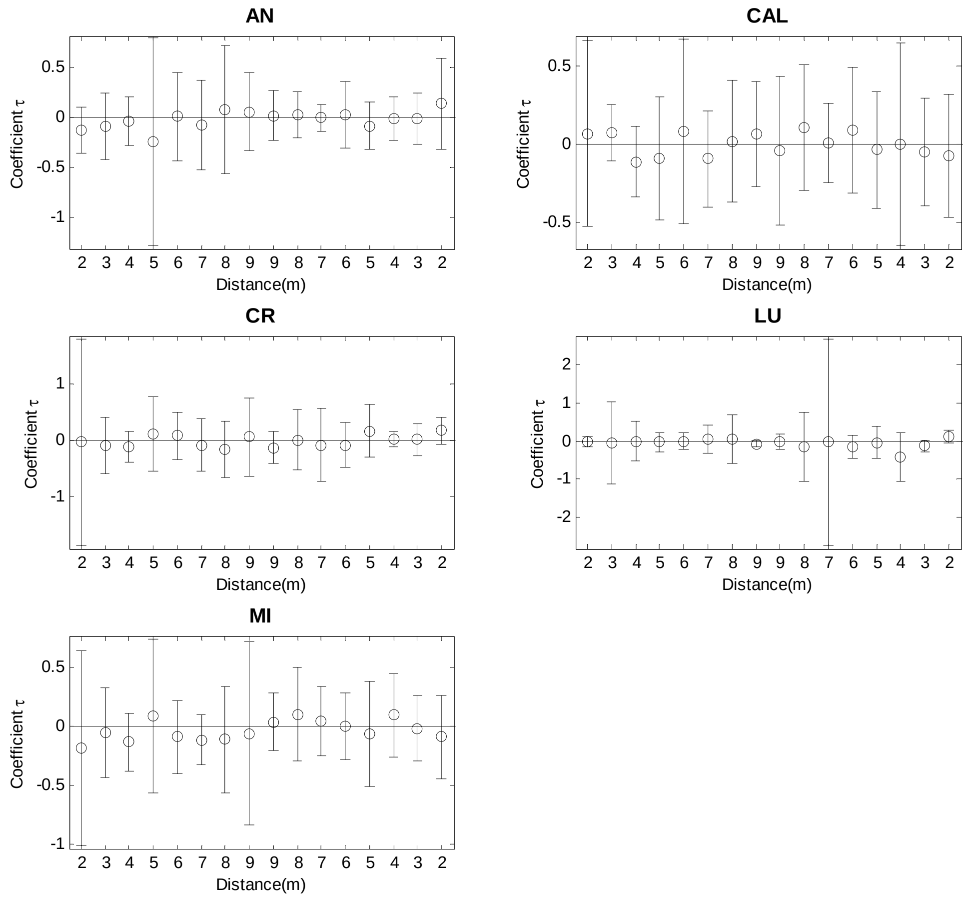

Figure 7-5: Individual plots of estimates of τ_{rel} with confidence intervals for each throwing distance in actual ordering of occurrence for each participants.

In summary, participants with better performance scores showed smaller differences between subsequent trials. There were no systematic changes in fluctuations between subsequent trials and no indication of relaxation behaviour, neither after changes of throwing distance, nor after a perturbation was identified.

Mixed-effect modelling

Investigation of the residuals obtained from application of the mixed-modelling to the right shoulder rotation angles, as in Chapter 6, showed strong deviations from normality which could not be remedied through different model-fits. Therefore, no mixed-effects analysis of the right shoulder rotation angles was undertaken.

Fixed-effects F-tests

Table 7-1: Wald-tests for fixed-effects structure for each joint angle.
*** = significant, ** = highly significant**

Angle	Distance	Distance^2	Direction
right elbow	2.76	2.52	0.23
right shoulder flexion	0.87	13.17**	22.13**
right shoulder abduction	41.84*	0.1	0.72
right wrist	1.55	1.31	17.66*
left elbow	16.31**	0.17	54.33**
left shoulder	0.23	0.5	7.49
right hip	0.05	3.31	12.13*
right knee	0.02	1.79	10.0*
left hip	24.32**	0.02	2.41
left knee	0.04	0.35	0.41
left ankle	4.6*	0.32	23.29**

In Table 7-1 the results for the fixed-effects are shown. No significant effects were found for the right elbow joint, the left shoulder joint, and the left knee joint. For the right shoulder joint flexion angle, significant main effects were found for the quadratic distance coefficient and direction (β_1 = -0.18 and β_2 = 5.36), resulting from decreasing flexion angles with increasing throwing distance and greater joint angles during the DEC condition compared to INC. The mixed-model analysis reported a significant effect for the right shoulder joint abduction angle with a coefficient of β_1 = 3.44 which indicated increasing abduction angles with increasing distance. Wrist joint angles, right hip joint angles, and right knee joint angles all showed significantly greater extension during the DEC condition (β_{3wrist} = 4.84, β_{3rhip} = -1.9, β_{3rknee} = 2.82). Similarly, the significant effects for the left elbow joint angle indicated greater joint extension at ball release during the DEC condition (β_3 = -9.93) as well as increasing extension angles with increasing distance (β_1 = -0.98). For the left leg, the hip joint displayed significantly greater extension angles with increasing throwing distance (β_1 = .56) and the ankle joint showed greater plantar flexion with greater throwing distance (β_1 = -0.61), as well as greater mean flexion during the DEC condition (β_2 = 2.45). In summary, fixed effects structure indicated common trends across participants for the kinematics of the supporting leg, the right shoulder joint and the left elbow joint.

Standard deviation of random effects

In Table 7-2, the estimated standard deviations for the random effects parameter for the different angles are shown. For the left shoulder joint a different random effects structure was indicated by the data where both linear and quadratic effects were nested in condition within participants. This model was applied based on the strong intra-individual differences exhibited by some participants between conditions. Through usage of this model, an additional variance term for the quadratic effect (σ_{cdd} = 0.44) was included. For the left elbow, the model-fits reported a very small intercept term for participants and likelihood-ratio test indicated that this term could be dropped. Therefore, for the left elbow joint a simpler model was used.

Table 7-2: Sample standard deviations of random effects for each joint angle. σ_s = sample standard deviation of participant-specific intercepts, σ_{sl} = sample standard deviation of participant-specific slopes, σ_{cd} = sample standard deviation of slopes between condition, σ = sample standard deviations of residuals

Angle	σ_s	σ_{sl}	σ_{cd}	σ
right elbow	13.93	1.57	0.47	3.31
right shoulder flexion	16.24	1.51	0.75	5.15
right shoulder abduction	30.96	1.14	0.52	7.29
right wrist	15.85	1.11	0.53	7.36
left elbow	19.51	NA	0.88	8.32
left shoulder	27.53	NA	4.41	6.92
right hip	12.93	0.36	0.45	7.1
right knee	28.49	1.35	0.48	12.34
left hip	14.03	0.18	0.16	4.77
left knee	12.63	0.55	0.12	3.24
left ankle	19.21	0.74	0.29	3.5

Comparison of residuals and participant standard deviations σ_s showed that the inter-individual variations were much greater compared to the intra-individual variation. The high inter-participant standard deviations were estimated for the right shoulder joint abduction angle, the left shoulder joint, and the right knee joint (all > 27°). The smallest values were found for the left knee joint and the right hip joint (< 13°). In contrast, for the general residuals, the greatest value was found for the right knee joint which was about 1.5 times higher than the second highest value of the left elbow joint. Across segments, small values were obtained for the left leg complex (<5°). With regards to the variation in participant specific linear slopes, the smallest variation was observed for the left leg complex and the right hip joint (<0.75). Similar trends could be observed for the standard deviations of the direction by slope interactions. The estimates for left elbow joint and the left shoulder joint were both influenced by the missing participant-specific slope, which resulted in the high values observed. However, for the left elbow joint, the magnitude of the standard deviation was only slightly higher compared to the remaining joint angles. This finding was interpreted as support for the chosen model-fit. In summary, the standard deviations indicated stronger differences between conditions for upper arm kinematics and higher similarities for the kinematics of the left leg.

Individual model coefficients

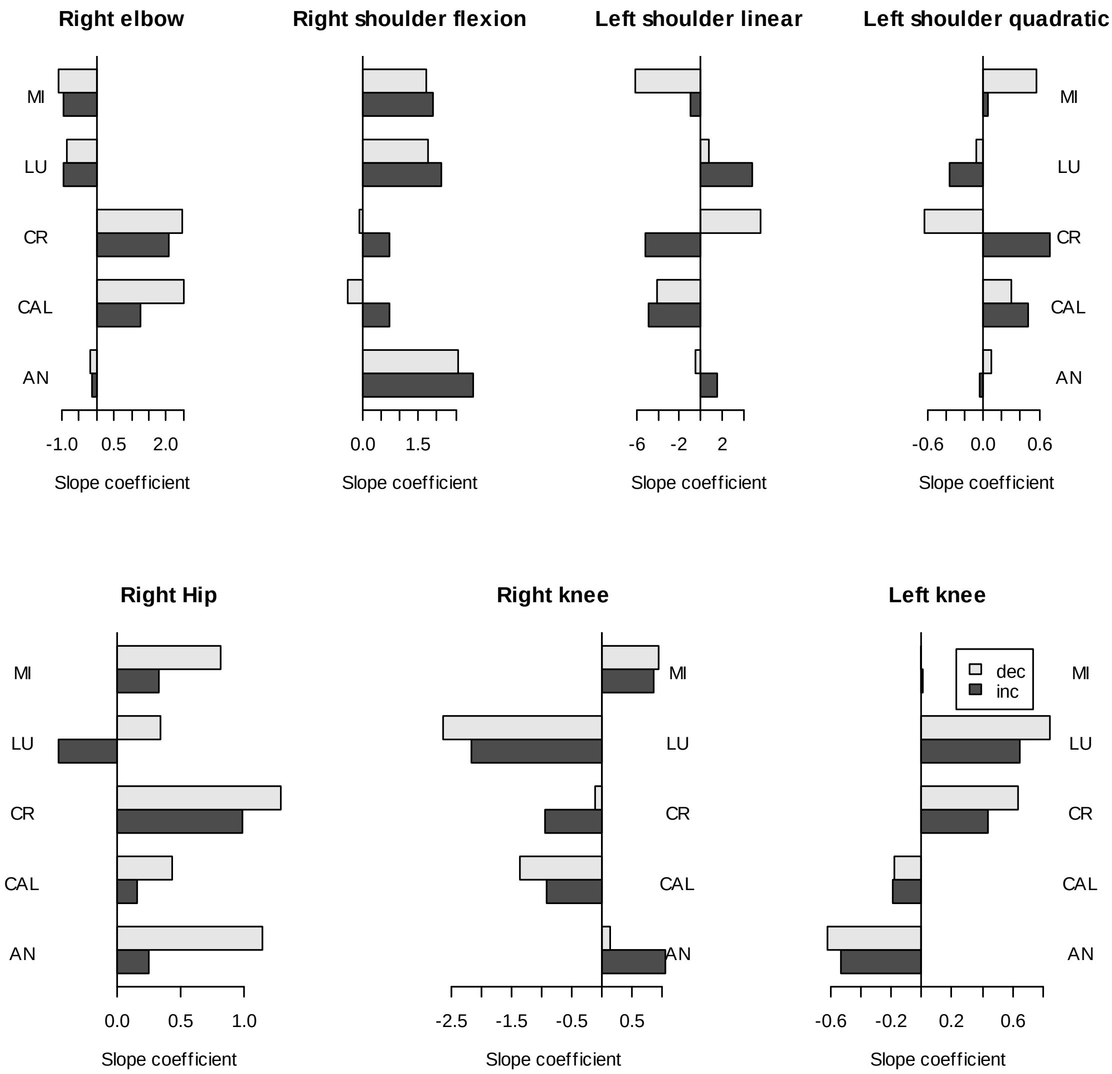

Figure 7-6: Best linear unbiased estimates of model coefficients for each participant for the right elbow joint, right shoulder joint flexion angle, left shoulder joint linear and quadratic coefficient, right hip joint, right knee joint, and left knee joint.

Investigation of the individual coefficients based on the estimated fixed-effects and BLUPs for the joint angles, which showed non-significant main-effects, displayed high inter-individual differences in response to changing throwing distance (compare Figure 7-1). For the right elbow joint the resulting coefficient could be separated into three different strategies. Whereas participants MI and LU showed greater flexion angles in the elbow joint with increasing throwing distance, participants CR and CAL adopted greater extension angles with increasing throwing distance and participant AN did not show any systematic variation in the elbow joint with throwing distance. A similar split of strategies was identified for the left shoulder joint for both linear and the quadratic trends. However, for this joint angle participants CR and AN even displayed opposite strategies between conditions which deviated in case of participant CR quite strongly. As a result, for participant CR, the combined effect of the estimated coefficient lead to increasing values for the INC condition and decreasing values for the DEC condition. These observations, when combined with the significant main effect for condition, lead to similar values for the higher distances (compare participant CA in Chapter 6). The right shoulder joint flexion angles showed similar positive coefficients for three participants and only small coefficients for two participants which also exhibited marginally different strategies between conditions. Similarly, for the right hip joint, all participants exhibited a similar positive trend except for participant LU who showed differences between conditions with opposite signs. The right knee joint again showed greater variations between conditions with values varying between -2.17 and 1.06, possibly bringing about the statistically non-significant population effects. Similarly, for the left knee joint, the variations between participants were much smaller with small estimates of absolute coefficients; nevertheless they exhibited different strategies between conditions. In summary, for the right shoulder joint flexion angles, the right hip joint and the left knee joint the non-significant fixed-effects were reflective of small individual changes, whereas for the remaining joint angles, potentially the different trends exhibited by participants influenced the overall sample effects.

Heteroscedasticity

Table 7-3: Ranking of estimated heteroscedasticity values for each participants for each joint angle and the ratio of highest residuals divided by smallest residuals for each joint angle.

Angle	AN	CAL	CR	LU	MI	Ratio
right elbow	5	1	2	4	3	2.14
right shoulder X	3	2	5	4	1	1.77
right shoulder Y	5	3	2	4	1	1.78
right wrist	3	1	2	5	4	2.19
left elbow	1	2	4	3	5	1.23
left shoulder	2	3	1	4	5	1.31
right hip	1	5	3	2	4	2.22
right knee	1	5	4	3	2	2.38
left hip	1	5	4	3	2	1.69
left knee	3	5	4	2	1	1.73
left ankle	4	5	2	3	1	2.58

In Table 7-3 the rankings of the inter-individual variance estimates and the ratio of the maximum to minimum variance for each angle are shown. The maximum ratio was observed for the left ankle joint. However, in comparison to the remaining ratios the value of 2.58 was not too different from the remaining ratios obtained, which were distributed around ratios of 2. The only exceptions were the left elbow joint and the left shoulder joint which showed ratios < 1.4 indicating that the residuals between participants were relatively similar. Regarding the distribution of the heteroscedasticity ranks across participants, no clear patterning could be identified which was confirmed by a non-significant Kruskal-Wallis rank-sum test.

Wrist velocity and trajectory radius

Application of the full model to the linear wrist velocity data indicated that a simpler model would already fit the data sufficiently. Using likelihood-ratio tests, a model without an interaction term for the direction and participant specific slope was chosen. Significant fixed-effects were found for all three coefficients ($F_{1,784} = 4403.58$, $F_{1,784} = 11.04$, $F_{1,784} = 4.41$, $\beta_1 = 0.64$, $\beta_2 = -0.01$, and $\beta_3 = -0.07$) which indicated that velocity increased with increasing distance, with slightly lower wrist velocity used by participants during the DEC condition. Residual standard deviations for the participant effect were threefold higher than residual variance ($\sigma_s = 1.15$, $\sigma = 0.37$).

For the wrist radius data, the model fit indicated that the random effects for direction could be dropped. The fixed-effects test indicated a significant effect for linear distance ($F_{1,784} = 6.32$, $p < 0.05$) and direction ($F_{1,784} = 5.78$, $p < 0.05$) with a small coefficient for both the linear trend of $\beta_1 = 0.02$ and direction of $\beta_3 = -0.02$. These data resulted in small increases of the trajectory radii with increasing distance and lower radii during the DEC condition compared to the INC condition. However, the actual difference between the radii at 2m and at 9m estimated by the fixed effects components was only 7cm. Residuals variance exhibited higher inter-individual variance ($\sigma_s = 0.10$m) compared to intra-individual variances ($\sigma = 0.08$m).

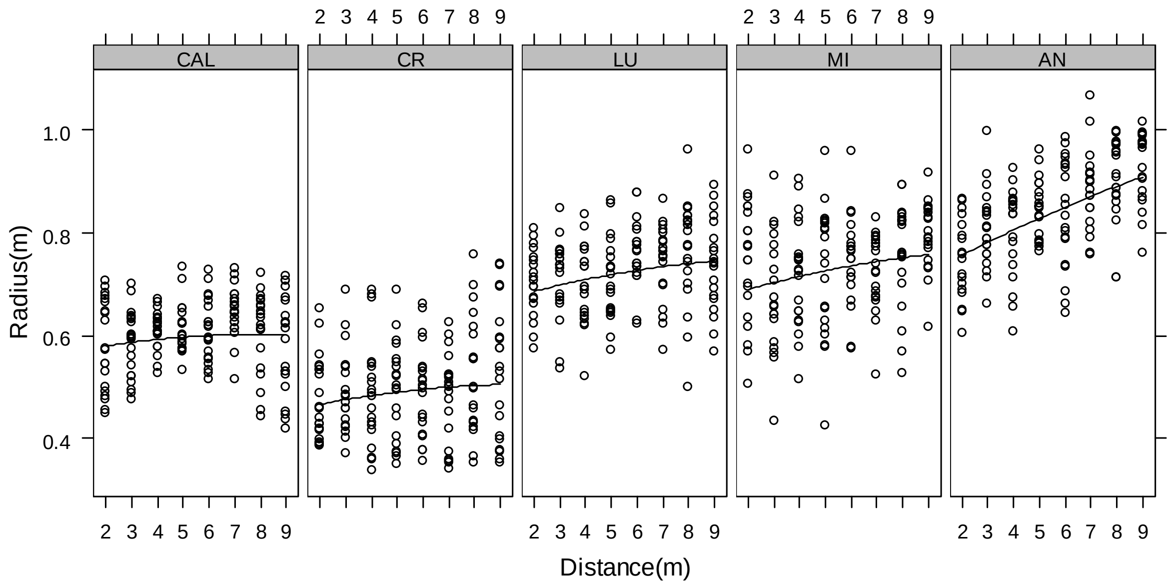

Figure 7-7: Estimates of wrist trajectory radii for each participant for each condition with superimposed model fit as estimated by the mixed-model.

Visual inspection of the radii against distance (see Figure 7-2) showed a clear trend only for participant AN, whereas for the remaining participants the changes were marginal.

Discussion

The present experiment investigated the effects of altering the throwing distance in a basketball hook shot movement through a scaling procedure. At random times the movement of the participants was disrupted using a mechanical perturbation. Investigation of fluctuations between subsequent trials provided no evidence for relaxation behaviour in the basketball hook due to the perturbation. Since none of the participants exhibited phase transition behaviour, critical slowing down could not be investigated.

Regarding the movement patterning strategies found in Chapter 3 and Chapter 6, the current study revealed somewhat different findings as none of the participants used the bimodal attractor strategy. All five participants exhibited behaviour indicative of a unimodal attractor where a single movement pattern was scaled according to throwing distance. With regards to the movement patterns, two different strategies across participants were apparent. In contrast, participants CR and CAL used a movement patterning involving synchronous movements in the shoulder joint and the arm, participants LU, MI and AN used a pattern with little movement in the elbow joint where ball acceleration was achieved by movements of the shoulder joint. Hence, the same two movement patterns, observed in Chapter 6 and Chapter 3, were also identified in the current study, strengthening support for the role of neurobiological degeneracy in performance of the basketball hook shot. Similarly, movement of the non-throwing arm showed greater variation compared to the throwing arm and kinematics of the supporting leg were similar across distances, with participants displaying the same pattern observed in previous studies. Since the unimodal patterns used by the participants showed hysteresis effects but no critical fluctuations, the results matched those obtained in Chapter 6, (except for participant CAL who did not show clear hysteresis behaviour). Participant CR showed a progression between qualitatively similar patterns, however, with different movement clusters at the beginning and the ending of the experiment. In conclusion, further support for more permanent adaptation of the attractor layout, similar to observations from participants DU, JA, and KE, in Chapter 6 was obtained.

Regarding the analysis of critical fluctuations in the current chapter, no investigation of critical slowing down was possible since none of the participants exhibited a bimodal attractor layout. Analysis of the fluctuations did not show any ordered behaviour and the fluctuations seemed to follow a random pattern. Hence, no exponential decay pattern could be identified for any of the participants. Investigation of τ_{rel} did not exhibit a negative coefficient which indicated that no relaxation behaviour was indicated by the data. The results can be interpreted from three different viewpoints. First, it is possible that the measurement used was not adequate to identify relaxation behaviour in this task. This experiment was the first study to investigate critical slowing down in discrete, multi-articular movement and this explanation seems reasonable. Second, it is possible that the applied perturbation simply was not strong enough in order to elicit the desired effects. Since the weight was determined based on pilot work no conclusive answer can be given. Hence, until further research of relaxation behaviour for discrete movement is available, based on both points interpretation of the data has to be treated with caution. Third, the measurement method was able to capture genuine behaviour after the perturbation and was solely a result of actual attractor dynamics. Adopting the latter position, and assuming that inter-trial differences provided information about τ_{rel} one can derive some properties of the underlying attractors.

Since the movement patterns showed relatively high fluctuations between subsequent trials, and relating this finding to the underlying attractor, the stability of the attractor potentially was not very strong. Thus, fluctuations inherent to movement systems could have lead to relatively greater 'natural' perturbations of the system. Translating this finding into an interpretation of a specific topological shape of the attractor, potentially this specific attractor exhibited a very shallow basin. Therefore, occurring fluctuations were not followed by immediate relaxation behaviour back to the prior state. Under this regime the additional mechanical perturbations would not be damped out immediately but could have just blended in with the general fluctuations inherent to the system. The great variation of the movement patterns individually used by the participants across throwing distances could be seen to support this view as shallow attractor layouts ease switching between different movement patterns (Carson et al., 1996; Schöner and Kelso, 1988b). As in Chapter 6, although the movement patterns for each participant showed similar qualitative appearances across distances, when comparing solely the trials from the smallest and the largest throwing distances, clear differences were visible (compare for example participant CR in the Appendix A). While the movements all belonged to the same attractor, the actual spread of the attractor needed to cover a broad area in attractor space. Potentially, this finding marks the difference between movements with greater and smaller numbers of biomechanical degrees of freedom, especially where movement segments interact with each other. Potentially for these highly interactive tasks, greater movement flexibility is necessary in order to overcome system inherent greater perturbations yielding a wide attractor area (Hang et al., 2001; Hirashima, Kudo, and Ohtsuki, 2003; Kudo et al., 2000). In contrast, for bimanual flexion-extension tasks where opportunities for perturbations are somewhat more limited, a tighter attractor regime might be more easily achievable. Regarding the relation of the height of the fluctuations and the performance attained during the fluctuations, there were some indications for decreasing fluctuations between subsequent trials with increasing performance similar to the results obtained by Button et al (2003). However, since only five participants were investigated in this study, no conclusions could be drawn on this point.

With regards to discrete kinematics, data in the current chapter provided further support for the findings reported in Chapter 3 and Chapter 5. As the throwing distance was increased, based on results from the previous chapters, an increase in the linear velocity of the wrist was expected and this was confirmed in the present chapter. Whereas in Chapter 3, a strong increase in the wrist radii was observed, this effect was not supported in Chapter 6, where only a marginal increase was reported. The present chapter confirmed the latter result and only small increases of wrist radii with increasing throwing distance were found. Investigation of individual plots showed great variations in the response patterns between participants. Therefore, the postulation of similarities between the basketball hook shot and uni-manual throwing movement (see Buchanan et al., 1997) could not be supported. The explanation of decreasing radii with increasing throwing distance following a transition from throwing for precision to throwing for distance (compare Kreighbaum and Barthels, 1996) could not be supported either.

The present data supported previous results regarding changes in throwing performance with increasing distance where a significant negative trend for this relationship was reported (see Chapters 3 and 5). Further, comparisons between participants noted significant differences between skill levels with post-hoc testing revealing significant differences only between the novice and the more skilled players. The rating of the participants performance followed, in general, expected differences based on prior playing experience.

With regards to the mixed-effects analysis in the present chapter, a significant main effect for right shoulder joint abduction angle for the linear trend could be observed with a coefficient of $\beta_1 = 3.44$, similar to the coefficient reported in Chapter 6 ($\beta_1 = 3.99$). In the latter, a significant effect for direction was noted which was not found in the present study. For the right shoulder flexion angle, a significant effect for the quadratic distance coefficient and for direction were observed, whereas in Chapter 6 only for direction a significant effect was reported. Estimated coefficients showed different signs ($\beta_2 = 5.36$, Chapter 6 $\beta_2 = -3.28$). The linear effect for the wrist joint could not be corroborated in the present chapter, but a direction effect was present as in the previous chapter ($\beta_2 = 4.84$, Chapter 6: $\beta_2 = 6.64$). For the left elbow, significant effects for linear throwing distance and condition were found which contrasted with previous findings. In Chapter 3 no effects on this joint were reported and in Chapter 6 a significant quadratic effects instead of linear effect was noted. In contrast, the differences between conditions were similar ($\beta_3 = -9.93$, chapter 6 $\beta_3 = -4.98$) where opposing trends were indicated with increasing distance. For the right leg, differences between all three chapters were observed. The present chapter displayed significant effects for the right hip and the right knee joint only for direction. In Chapter 6 significant effects were displayed for the quadratic term and between directions only for the right hip. In contrast, significant linear and quadratic trends in both hip and knee were reported but no significant differences between directions were determined in Chapter 3. The estimated coefficient also showed high variations between studies, e.g., the direction effect for the right hip joint was -0.16 in Chapter 3, 1.43 in Chapter 6, and -1.9 in the present chapter. For the left leg, the current chapter indicated increasing extension in both the hip and the ankle with increasing distance which confirmed the results obtained in Chapters 6 and 3. In relation to the fixed effects structure, the current experiment supported the hypothesis for stable sample effects with increasing throwing distance most notably in the kinematics of the left leg.

With regards to the standard deviation of the random effects, the present chapter reported similar results, as obtained in the previous two chapters, with high inter-participant variation in the left shoulder joint and the right knee joint common to all three studies. Regarding the magnitude of the estimated inter-participant standard deviations, the levels were comparable between the studies ranging from 5° (Chapter 3) for the lowest variations to 39° (Chapter 6) for the highest variations. However, the data from the present chapter differed from the previous ones, in that the lowest values were only around 12°, somewhat greater compared to the values reported in other chapters. The effect of higher inter-participant variation compared to intra-participant variation, however, was corroborated. Regarding the estimated standard deviations of slopes, the preceding studies found higher variation of slopes between participants compared to the variations within participants between conditions which was supported by the current study. Lowest variations were indicated by the left leg angles across all three studies. In summary, the current study also showed high variation for the upper arm kinematics between participants paired with low inter-personal variation for the left leg. Investigation of individual strategies in the right elbow joint showed a similar response as present in Chapter 3 where all potential changes were realized by different participants. Comparison of the individual trends in the right shoulder joint flexion angle at ball release showed some differences between the current study and Chapter 6 where again all three adaptations strategies were present. In the current chapter only either very small or positive increases in flexion angles were observed. For the left shoulder joint, the results were similar between Chapter 6 and the present study with both studies containing one participant showing clear hysteresis behaviour across distance. The left knee joint which was investigated on an individual basis in all three studies showed similar small changes with increasing distance for either direction. The results for heteroscedasticity estimates confirmed the previous findings that there is no clear participant or skill related distribution.

In summary, for all three studies, the most robust adaptations across distances and participants were found for the discrete kinematics at ball release for the supporting leg. The general adaptation strategy consisted of increasing extension of the supporting leg with increasing throwing distance by greater plantar flexion of the ankle joint. This is further combined with greater extension angles in the hip joint, which kept knee angles constant across throwing distances and conditions. Overall sample effects showed greater variation between the chapters and across participants, which highlights the need for more individual based approaches. Standard deviations of estimates in all three studies indicated high inter-individual differences in absolute magnitude of chosen joint angles, suggesting inter-individual differences in neurobiological constraints and skill levels. Based on the heteroscedasticity analysis, all three chapters showed no clear relation to performance level which was different from previous results obtained for basketball free throws (Button et al., 2003). However, it has to be noted that continuous movement kinematics were used in this chapter.

Conclusion

The aim of the present study was to identify critical slowing down in a discrete multi-articular action. However, as none of the participants showed phase transitions, it was not possible to investigate critical slowing down but only relaxation behaviour after application of the mechanical perturbation. Investigation of kinematic differences between subsequent trials did not support the postulated relaxation behaviour for the basketball hook shot. Thus, based on the results obtained in the current chapter, it appears unlikely that critical slowing down would have been identified even for participants exhibiting phase transition behaviour.

According to the results from the cluster analysis approach, all five participants used a unimodal attractor scheme and scaled a single movement pattern according to the throwing distance. Thus, the results of the cluster analysis and the findings from the discrete kinematics at ball release supported the findings from Chapter 3 and Chapter 5. Analysis of the discrete kinematics at ball release confirmed the previous results where high similarity in the trends for the supporting leg across participants were observed and this was concurrent with greater individual trends for the upper body kinematics.

8 Chapter Eight : Epilogue

Introduction

The purpose of this chapter is to summarise the main findings from this programme of work and to highlight the implications for future research on discrete, multi-articular actions from a dynamical systems perspective. The following sub-sections group together some of the main issues which emerged from the experiments reported in Chapters 3, 5, 6, and 7 and the reviews of the relevant literature from Chapters 1 and 4. In the first section of this chapter, problems related to the investigation of discrete, multi-articular actions from a dynamical systems perspective which emerged purely from a theoretical point of view will be reiterated. The following section focuses on the description of a suitable movement model, the basketball hook shot, and the related study which was presented in Chapter 3. The important issue of data analysis has surfaced frequently in this programme of work, as acknowledged in the subsequent section covering cluster analysis and the findings from Chapter 5. Accordingly, the next section focuses on the application of the dynamical systems theoretical paradigm to the basketball hook shot and the implications which resulted from the studies presented in Chapter 6 and Chapter 7. Finally, the last sections will address the implications emerging from the findings of this programme of work, followed by a discussion of limitations and future research directions.

Discrete, multi-articular actions

The dynamical systems theoretical framework for studying movement coordination was introduced through concepts derived from the theory of synergetics (Haken, 1983; Kelso, 1995). Synergetics, based on insights from inanimate physical systems, provided the necessary experimental apparatus, which made investigation of neurobiological movement coordination from a dynamical systems perspective possible. As shown in the overview of the literature, the dynamical systems framework has been able to provide answers to some of the fundamental problems on movement coordination. However, as Chapter 2 highlighted, the theoretical principles of the dynamical systems approach have generally been derived from studies of rhythmical movements mainly incorporating a limited number of biomechanical degrees of freedom. Hitherto, these principles had been tested to a large extent only with these specific movement models. An interesting question concerned whether the application of dynamical systems theory is appropriate for the study of discrete and/or functional movements which vary from the prevalent movement models (Hossner, 2000; Obhi, 2004; Walter, 1998).

Potentially discrete movements pose some conceptual problems for the dynamical systems framework. For instance, there may be fundamental differences in phase transitional behaviour between discrete and rhythmical movements. Since transitions between attractors can be represented by a trajectory in phase space, for neurobiological systems this trajectory follows a continuous function since discontinuities would present instances where infinite acceleration would be needed. This is not possible for neurobiological systems (Newell et al., 2001). This property is readily present in the rhythmical case, and accordingly when transitions occur they are accompanied by the appearance of several intermediate movement patterns (demarcated by critical fluctuations). However, for a discrete movement this is not necessarily the case because in principle different attractors are accessible in successive movement executions. When performing discrete movements, it is possible for the actor to evaluate feedback from the previous trial and reflect upon his performance. Accordingly, he/she can revise his/her intentions leading to changes in movement behaviour. For example, regarding the movement model used by Sorensen et al (2001), it is reasonable that changing from a forehand table tennis stroke to a backhand stroke in subsequent trials is readily possible. Therefore, modelling discrete movement may be feasible on a single trial basis, as demonstrated by Schöner (1990), Saltzman and Kelso (1987) and Jirsa and Kelso (2005). Yet, the transition to repetitive movement execution has not been sufficiently addressed in the literature. This issue is perhaps conceptual in nature and may require further modelling to address it.

Another problem, more methodological in nature, arises with discrete movements in regards to the identification of critical slowing down. Following Schöner's (1990) proposition on modelling of discrete movements, it was argued that critical slowing cannot be investigated within a single trial since typically, the execution time is not sufficient for the movement to relax back to the unperturbed movement trajectory. Schöner (1990) proposed the inter-trial fluctuations as a surrogate measure of pattern stability. However, this suggestion has not been fully investigated in the literature and therefore no knowledge about critical slowing down in discrete movements is currently available.

The issue of discrete movements and their relation to rhythmical movements gained further momentum based on evidence for significant differences in regards to kinematics

(Button et al., 1998; van Mourik and Beek, 2004; Wei et al., 2003) and brain activation (Miall and Ivry, 2004; Schaal et al., 2004). Accordingly, the review of the literature in this thesis pointed out that more research using discrete movement models is necessary, as repeatedly formulated in the dynamical systems literature (see for example Beek et al., 1995; Kelso and Schöner, 1988; Schöner, 2002; Summers, 1998; Walter, 1998).

Classification of movement models according to a three-tier scheme developed by Newell et al. (2001) made apparent the issue of task degeneracy related to prevalent movement models. The model describes three coupled levels of movement organization. The highest level describes the spatial-temporal outcomes of behaviour, the middle level describes the dynamics of the segments kinematics, and the lowest level describes behaviour of underlying subsystems (Newell et al., 2001). In the majority of DST studies, the spatial-temporal outcome of the movement prescribed the segment kinematics, which in effect results in equality of the two-upper levels. This collapsing of the upper levels raised the issue: to what extent was the observed behaviour a result of unrestricted self-organization and not of the specific task constraints? (Bongaardt, 1996; Hong and Newell, 2006). This issue can be closely allied with the concept of degeneracy (Edelman, 1987). Related to movement patterning, degeneracy describes the fact that the same task outcomes can be achieved with different movement patterning. Accordingly, it seems plausible that when degeneracy is available to the actor, behavioural responses to a specific task could show much richer dynamics compared to relatively constrained movements as shown in a study using a ski-simulator task (Hong and Newell, 2006).

Regarding the biomechanical degrees of freedom involved in the majority of studies conducted from a dynamical systems perspective, a disproportionate number of studies involved movements incorporating only very limited biomechanical degrees of freedom (Cordo and Gurfinkel, 2004). Based on the definition of coordination formulated by Bernstein (1967) which emphasized the redundancy problem in relation to neurobiological degrees of freedom, these movement models could arguably be regarded as a special case of movement coordination. Accordingly, it may not be appropriate to transfer findings to other movement models where some of these constraints are relaxed (Cordo and Gurfinkel, 2004; Heise and Cornwell, 1997; Swinnen and Carson, 2002). Review of studies which investigated movements involving a higher number of biomechanical degrees in freedom present in Chapter 2 suggested much more complex behaviour compared to the bimanual and unimanual case (see for example Jeka et al., 1993; Kelso and Jeka, 1992; Limerick et al., 2001).

In summary, three main issues with regards to prevalent movement models could be identified: (i) the dichotomy between discrete and rhythmical movement models (ii) low vs. high biomechanical degrees of freedom (iii) degenerate vs. task determined movement models.

In order to investigate these issues further, a suitable movement model has to be identified and adopted within this programme of work..

The basketball hook shot, a suitable movement model

During the review of the literature on dynamical systems theory, several applications to ballistic throwing movement were discussed (Liu and Burton, 1999; Southard, 1998, 2002). Unfortunately, each of these studies showed some serious limitations, although it was argued that they provided a good starting point for the development of a suitable movement model in this programme of work. Following the suggestions by Davids et al. (2006; , 2005) and the approach of Liu and Burton (1999), a basketball throwing movement was investigated as a potential candidate movement model. Assessment on the literature of basketball set-shots and jump shots gave some indication that the throwing distance might represent a control parameter, but also that standard basketball shots exhibited only relatively small variations with distance, which would hamper the identification of different movement patterns and therefore possible attractors. In search for a throwing movement which potentially shows greater adaptations due to changes in throwing distance, the basketball hook shot was identified. On analysis, the basketball hook shot per-se did not prescribe a determined movement model but rather a class of movements which shared a common characteristic (see distinction between shy hook shot and jump hook shot according to Martin, 1992). It was noted that by using a basketball hook shot the restrictions for movement patterning should be less severe compared to a standard basketball shot (e.g., a free-throw), thereby facilitating possible degenerate behaviours. As the basketball hook shot belongs to the domain of ballistic throwing movements, its execution is discrete and involves whole body movements using large numbers of biomechanical degrees of freedom. In addition, since the hook shot is an airborne throwing movement it was assumed that changes in movement patterning would be attenuated because of inertial interactions between body segment movements (Hang et al., 2001). Therefore, it was expected that different movement patterns would be relatively straightforward to identify. Hence, the basketball hook shot appeared well suited in order to investigate some of the theoretical issues formulated earlier. Another argument in favour of the basketball hook shot was based on the fact that the hook shot resembled quite a specialized movement with very little application outside of basketball playing. Therefore, the amount of behavioural information serving to guide movement adaptations could readily be influenced by the instructions given to potential participants by the experimenter.

In Chapter 3 movement patterning in the basketball hook shot due to changes in throwing distance was investigated. The basketball hook shot is an emergent action dependent on specific task constraints, especially the presence of a defender and, therefore, another question tailored to applied settings was addressed. As the review of the basketball literature highlighted, very little knowledge is currently available for investigating movement adaptations in the presence of a defender. Since an approaching defender presents additional spatial and visual constraints, some differential adaptation could be postulated based upon investigations of perceptual phenomena in bimanual movements (Byblow et al., 1999; Schmidt et al., 1990). Accordingly, in addition to the throwing distance, defender and no-defender conditions were introduced.

In order to provide better linkage between the proposed movement model and pre-existing movement models, it is important to investigate if studies of unimanual movements and the basketball hook shot could be related to each other. Based on the anticipated trajectory of the wrist a potential link between the basketball hook shot and studies with unimanual shoulder-arm-wrist movement was identified (Buchanan et al., 1997; DeGuzman et al., 1997). Accordingly, decreasing radii for the trajectory of the throwing arm were expected as shown in the unimanual case with increasing movement speed.

The results presented in Chapter 3 indicated that throwing distance constrained the movement patterning. They provided further support for the candidacy of throwing distance as a control parameter. The participants in that study had different amounts of experience, with one participant being a professional basketball player and one participant being a complete novice. There were strong differences in movement kinematics across throwing distances and between participants. Surprisingly, the presence of the defender showed only minor influences on movement patterning and only for the novice player. It was argued that this finding could have been a result of the specific movement execution of the basketball hook shot by the more experienced participants, where their body positioning during the shot constrained possible interference by the defender unlike during a basketball set shot. Regarding sample trends across movement kinematics, analysis of discrete and time-continuous measures indicated high similarity across participants and distance for the lower limb segments and greater differences for upper body kinematics. Therefore, a mixed-modelling approach was adopted which made detailed investigations of within-individual effects possible.

Investigation of angle-angle plots showed a clear distinction for two different movement patterns across throwing distances for the expert performer. One movement pattern was used at smaller distances and the other pattern at greater throwing distances. Observed differences were based on qualitatively different coordination patterns for both upper limb segments. It was argued that the two different movement patterns resembled attractors and accordingly, for this participant, a bimodal attractor layout potentially was present. For the remaining participants differences across throwing distances were less pronounced with high consistency for the throwing-arm and the supporting leg paired with some greater variability of the movement kinematics of the non-throwing arm. Hence, for these participants the results tended to support the use of a single attractor which was transiently adapted in order to satisfy the task constraints (Kostrubiec et al., 2006). Together the findings neatly expressed the notion of morphological structures introduced earlier (Bernstein, 1967). Comparison of the movement patterns across participants highlighted that, although some commonalities were found in gross movement kinematics, the investigation of detailed kinematics showed some significant differences between the participants which highlighted the degenerate nature of the task. For the second unimodal group, unlike the bimanual case where attractors generalized across participants (one-to-one mapping between attractor and in-phase/anti-phase movements), for the basketball hook shot the attractor appeared to follow rather a one-to-many mapping (one attractor maps to several different movement patterns across participants). Hence, the results indicated some potentially significant differences in attractor properties between discrete, multi-articular actions and more confined rhythmical movement models.

Regarding the hypothesized similarities between the movement exhibited by the trajectory of the wrist of the throwing arm and findings from unimanual movements, the results indicated exact opposite trends. Whereas for the unimanual movements an increase of the curvature was observed (Kelso et al., 1991b), for the basketball hook shot the curvature decreased with increasing movement velocity. Accordingly, further investigation was necessary.

Analysis of discrete, multi-articular actions

Although the experiment in Chapter 3 showed how the concepts and tools of dynamical systems theory could be applied to studying the basketball hook shot, the results also highlighted the necessity for the development of a more comprehensive analysis tool, since identification of different movement patterns was mainly based on visual inspection. Development of an analysis tool would thereby enable the systematic identification of distinct movement patterns. Therefore, in Chapter 4 the necessary prerequisites for a suitable analysis apparatus were derived and several existing tools were assessed according to these criteria. The results indicated that, at present, none of the existing tools that were investigated fulfilled all the necessary prerequisites. However, cluster analysis was identified as providing the closest proximity. Therefore, it was decided to further develop the cluster analysis approach already used in the literature to incorporate the required properties.

In Chapter 5, the extended cluster analysis approach was developed using a bootstrapping procedure together with another validity measure to extract movement clusters based on the kinematics of an action. Further, it was explained how the cluster analysis could be combined with a scaling methodology to facilitate identification of hallmark characteristics of dynamical systems in distinct movement patterns, including critical fluctuations, hysteresis, and critical slowing down. Subsequently the cluster analysis method was tested using three different movement models. Application of the cluster analysis method to a bimanual movement (wrist pronation-supination task) showed not only identical results to traditional analysis methods (i.e., calculation of discrete relative phase), but was able to show more in-depth information not accessible to traditional methods. Hence, using a bimanual movement model, the cluster analysis approach could be successfully linked to the existing body of literature utilising the dynamical systems perspective.

In a second experiment, three different basketball throwing techniques (free throw; three point jump shot; hook shot) executed by experts performers were individually analysed using the cluster analysis approach. The results matched the a-priori known differences between the shooting techniques which supported the application of the cluster analysis approach to discrete, multi-articular actions. Finally, an experiment was specifically conducted with the basketball hook shot. Applying a scaling methodology common to investigations from a dynamical systems perspective, throwing distance was first increased between 2m and 9m and subsequently decreased from 9m back to 2m. To facilitate different movement patterning between smaller and greater throwing distances, the experiment was performed in a gym with a low building ceiling. As was argued, this set-up should have prevented the participants from simply up scaling their movement patterns according to the throwing distance. The results obtained from the cluster analysis approach indicated for both participants a distinction into two different movement patterns in relation to the throwing distance. One pattern was more prevalent at smaller throwing distances and the other at greater throwing distances. For one participant, the transition between movement patterns showed critical fluctuations identified by the cluster analysis approach, whereas for the other participant, no such increases in movement fluctuations were found. However, in both cases the transitions between the movement patterns were accompanied by hysteresis effects. Accordingly, it was argued that for one participant the movement patterning followed a bimodal attractor layout, whereas for the other participant, only a single attractor was used which supported the findings from Chapter 3. In summary, the results further strengthened the feasibility of the programme of work. Together, the results obtained in Chapter 3 and Chapter 5 provided the necessary requirements in order to perform a scaling experiment with the basketball hook shot.

Scaling and perturbation of the basketball hook shot

In Chapter 6 the scaling methodology developed in Chapter 5 was again applied to basketball hook shots without the constraint of a low ceiling building. Eight randomly chosen participants representing a variety of different skill levels participated in the study. The results of the cluster analysis identified throwing distance-related changes in movement patterning for all participants. However, the investigation of angle-angle plots, critical fluctuations and hysteresis provided evidence for phase-transition behaviour only for two participants. In both cases, a bimodal attractor layout was identified corroborating the findings from Chapter 3 and Chapter 5. Adaptations in the movement kinematics were mainly based on the upper limb segments, whereas movement kinematics of the supporting leg showed high stability across distances as well as across all participants. For the remaining six participants a single movement pattern was adapted to throwing distance, again exhibiting greater variation in the kinematics of the non-throwing arm. These results also corroborated the findings from Chapter 3 and Chapter 5. For these participants no critical fluctuations were found but all participants exhibited hysteresis effects. It was argued that, for these participants, the movement patterning was the result of a single attractor which was adapted to the throwing distance.

Comparison of the individual coordination patterns across participants revealed considerable differences between individually chosen movement patterns. With regards to the movement strategies (bimodal vs. unimodal), no relation to prior experience level or actual performance of the participant was found during the experiment. Investigation of the discrete kinematics at ball release using the mixed-effects modelling approach corroborated the findings from Chapter 3. The results again indicated greater differences between participants for the upper limb kinematics as opposed to greater similarity in the kinematics of the supporting leg. Together, the results from the discrete, as well as continuous, analysis revealed insights into the degenerate properties of the basketball hook shot. The results highlighted great inter-individual differences in movement patterning for this task and it was argued that differences in intrinsic dynamics were responsible for the great variety of task solutions.

Regarding differences between discrete and rhythmical movement models, the distribution of movement clusters provided evidence that participants were able to alternate between movement patterns in subsequent trials. As this behaviour is not possible for rhythmical movements, this finding marked a significant deviation from previous modelling schemes and served to further highlight specific differences between discrete and rhythmical movements. Further, as explained during the literature review, a potential source of constraint responsible for altering movement between subsequent trials could have been task success, i.e. the scoring of a basket. However, the lack of a clear relationship between obtained performance scores and the differences in movement patterning in subsequent trials did not support this hypothesis.

Since phase transitions behaviour for the basketball hook shot could be established in Chapter 6, the next step consisted of testing the stability properties of the underlying attractors by means of critical slowing down. Hence, in Chapter 7 a perturbation study with the basketball hook shot was conducted. Using a paradigm adapted from previous research (Button et al., 2000; Haggard, 1994; Scholz and Kelso, 1989) a mechanical perturbation was introduced during execution of the throwing movements. Since in Chapter 6 it did not become clear what the defining property for the chosen adaptations scheme (bimodal vs. unimodal) was, performers from a range of different skill levels were again chosen to participate in the study. Following the proposition made by Schöner (1990) the differences between subsequent trials was chosen as a potential measurement for relaxation behaviour and accordingly critical slowing down. However, as the cluster analysis showed, all five participants exhibited an unimodal attractor layout and therefore no phase transition behaviour was found. Therefore, the investigation of critical slowing down was not possible. The results indicated that the fluctuations between subsequent trials did not follow the expected pattern. Fluctuations showed high levels for all participants and remained uninfluenced by the mechanical perturbation and changes in throwing distance, which appeared somewhat counterintuitive.

Implications

With regards to phase transition behaviour it can be concluded from the combined results that phase transition behaviour is less likely to occur in the basketball hook shot compared to bimanual anti-phase/in-phase movements (see Chapters 3, 5, 6, and 7). Out of 21 participants only 4 showed clear phase transitions between two qualitatively different movement patterns, whereas the remaining participants all used a single type of movement strategy across all distances and conditions. As the differences between single and multi-pattern behaviour were not related to skill level, it can only be assumed to be a result based on the individual intrinsic dynamics of the actors. Nevertheless, for participants where phase transitions could be identified, the results confirmed the basic predictions of the dynamical systems theoretical framework. For example, a loss of stability, exemplified by critical fluctuations, was necessary in order to switch between the different movement attractors. Further, since switching between attractors was accompanied by hysteresis effects, the evidence in support of phase transition behaviour was further strengthened.

Investigation of the kinematics showed that for both adaptation schemes the attractors represented a wide range of different movement patterns. Especially for the unimodal case, comparison of movement patterns from the smallest and the greatest throwing distances showed strong differences in segment kinematics. Accordingly, a potential attractor responsible for generating these movements had to cover a broad area incorporating highly different movement patterns. This result stands in contrast to investigations using bimanual movements where the actual movement patterns were more strongly restricted and showed for example, only small changes in movement amplitudes (Haken et al., 1985). Relating the present finding to previous studies of motor learning conducted from a dynamical systems perspective, potentially for this discrete, multi-articular task, movement patterning was altered using the cooperative strategy described earlier (Kelso and Zanone, 2002; Zanone and Kelso, 1992). Hence, in order to meet the task requirements, the participants chose instead to adapt an existing attractor layout rather than switching between different attractors. This behaviour was also identified by Kostrubiec et al. (2006) as a flexible strategy for adapting behaviour to specific contexts. With regards to movement patterning, such a strategy is assumed to preserve the topological structure of the movement (Zanone and Kostrubiec, 2004) as indicated by the movement kinematics in the current studies. Hence, the same strategy typically utilized for persistent learning effects during skill acquisition potentially could also have been used for immediate adaptations occurring on much smaller time scales. In support of this view were results obtained for participants JA and DU in Chapter 6 and participant CR in Chapter 7. These data showed that a similar movement pattern (unimodal scheme) was used over the course of the whole experiment, but that the movement patterns at the end of the experiment differed from the initial patterns, indicative of a learning effect. This finding seemed especially counterintuitive since two of these participants stemmed from the group of most experienced players and also demonstrated the best performance in their respective studies. Therefore, one would assume the least changes for these actors. Adopting this interpretation it becomes possible to explain the great differences between the movement patterns at the smallest and the greatest throwing distances found in all studies. Since the attractor was continually shifted further away from the initial position, the resulting movement behaviour followed this shift. Hence, through continual changes in throwing distance, and the accumulation of differences in movement execution, the great variations between movement patterns could have emerged. Thereby, the differences between similar throwing distances would also exhibit relatively similar movement patterns as shown in the presented studies.

Relating this notion to those participants who showed a bimodal scheme, potentially the second attractor was in close proximity to the initial attractor, and therefore the movement systems ‘preferred’ a phase transition to satisfy the changing task constraints, as opposed to an attractor shift. In contrast, for the unimodal scheme, either no second attractor was available, or the distance between attractors in the layout was too large to trigger a phase-transition. Accordingly, responsibility for the existence of a unimodal or bimodal adaptation strategy would largely fall upon the individual intrinsic dynamics of the performers. Interestingly, results obtained from participant CA in Chapter 6, who exhibited a phase transition, indicated the same shifting process for the usage of movement cluster 6 as did participants using the unimodal scheme. Potentially, the shifting vs. phase-transition approach does not resemble a non-overlapping dichotomy but can be used in combination as the data from participant CA indicated.

With regards to the process which drives the shifting of the attractor it is likely that intentional dynamics played a major role. Since, intentional dynamics can be used in order to stabilize different regions in attractor space, similar to the process of re-learning, a similar strategy could be applied for these more transient changes (Schöner and Kelso, 1988b; Zanone and Kelso, 1992). Therefore, the observed movement patterning (bimodal vs. unimodal) are likely the result of the interactions of intrinsic and intentional dynamics (Carson et al., 1996; Lee, 2004). Since, in the case of discrete movements, intentions explicitly seem to play a stronger role compared rhythmical movements (Schöner, 1990), this view receives some support. This notion of shifting attractors according to the task requirement also provides a possible explanation for the identified hysteresis effects in the unimodal adaptation scheme. As the attractor is shifted only by a small amount, a small residual of the previous attractor could always be maintained. This residual could contribute an attracting force which pulls the current attractor back to the previous position and accordingly leads to a movement pattern which exhibits some characteristics of the previously used one (Zanone and Kostrubiec, 2004). Hence, this type of behaviour would resemble small residual (e.g., ‘memory’ or ‘positive transfer’) effects on a short time-scale. A study in support of this view was conducted by Classen, Liepert, Wise, Hallet and Cohen (1998). Participants received transcranial magnetic stimulation (TMS) which resulted in thumb movements in specific individual directions. Subsequently, thumb movement in the opposite direction were trained with varying time intervals (5 min – 30 min). Follow-up application of TMS resulted in thumb movement in the trained direction, but not in the initial direction. However, after individually different time intervals, the movement direction returned to the initial direction. A similar effect could be responsible for the hysteresis behaviour found in the current studies.

Incorporating into this model the results obtained from Chapter 7 regarding the relaxation behaviour, not only is the attractor shifted according to specific requirements of the task, but it also shows a relatively shallower basin of attraction compared to bimanual movements. As the fluctuations indicated no influence due to either the mechanical perturbation or to changes in throwing distance, the ‘natural’ level of perturbations for this specific task could show greater magnitude, thereby masking these external perturbations. Possibly, this effect resulted from the multi-articular nature of this specific movement model. As the basketball hook shot incorporated greater biomechanical degrees of freedom, it seems intuitive to assume that the movement is exposed to greater perturbations inherent within the movement system. Accordingly, when the attractors underlying this system are tightly constrained, potentially it could be difficult for the system to adapt to these perturbations. Hence, a less stable attractor possibly could be more easily adapted due to unforeseen changes. Further, as shown on several occasions, the participants were able to switch between highly different movement patterns in subsequent trials. This finding might indicate that it was relatively easy for participants to modify the attractor layout in between trials. As shown in experiments using bimanual movements that intentionally switching between attractors is limited by the inherent stability of the attractors (Carson et al., 1996; Serrien and Swinnen, 1999), using an attractor with a flat bottom layout could support fast adaptations in small amounts of time, since no great regions of instability and stability have to be negotiated and breached.

Referring to the initial definition of coordination in overcoming redundant degrees of freedom, the studies highlighted that once redundant or degenerate degrees of freedom are available to the performer, these can be readily exploited. Although the movement generation shared similar characteristics across the different actors, the individual appearances showed considerable differences in movement execution. It is arguably in this feature that the strongest differences between the traditional movement models from the bimanual rhythmical domain and discrete, multi-articular actions were found. Whereas an attractor in a bimanual experiment could be generalized as anti-phase or in-phase across actors and even across tasks (for example finger movement and wrist movement Carson, 1995; Haken et al., 1985), in the case of the basketball hook shot the exhibited movement patterns showed much stronger individual differences. Hence, once degeneracy is available it seems likely that actors individually will make use of it.

Since the predictions of dynamical systems theory were not met in total, one possibility to be explored is that the findings could be explained with an alternative theoretical approach favouring, for example, the concept of motor programmes. Since the Schema model (Schmidt, 1975) was initially established using discrete movement models (Schmidt, 2003), it may provide an appropriate theoretical model for explaining some of the data in this programme of work. At first glance, the fact that most of the participants across the four experiments used a scaling strategy could be seen as evidence in favour of a generalized motor program (GMP). Each participant could simply have used a single GMP and scaled it according to the throwing distance. Since, the Schema theory allows for individually different GMPs across participants (Carter and Shapiro, 1984) the inter-individual variability can also be explained by the GMP theory. However, as pointed out in the discussions of each chapter, even for the participants exhibiting a scaling strategy, the movement patterns at the smallest and greatest throwing distances showed significant topological differences in movement patterns. Thus, the movement patterns at the greatest distances did not represent simply an 'up scaled' version of the movement patterns at the smallest distance. Therefore, it seems unlikely that linear changes of Schema parameters, whilst maintaining the relative timing components of the movement (Schmidt, 2003), were used. This notion is further rejected by the results of the cluster analysis. Since, the calculation of the distance measures were based on normalized angle curves, if a simple scaling, leaving the relative timing unchanged, would have occurred, the result would have been observations of identical curves for all trials yielding no clustering at all. This observation occurred for only for two out of fifteen participants in the programme of work and it is unlikely that these individuals were using a schema to regulate movements, while other participants were not. Further, except for three cases, all participants exhibited a hysteresis effect, implying that a specific "recall schema" (Schmidt, 1975, p.236) was maintained for a longer time depending on the direction of distance change. However, GMP theory does not predict differences in program execution depending on the previous action and therefore, in its current definition, cannot accommodate for the observed hysteresis effects.

Regarding those participants where clear phase transitions were observed, it is even more difficult to find an explanation using GMPs. In all three cases the two movement patterns adopted by the participants showed completely different topological characteristics. Hence, two different GMPs would have been necessary to accommodate for the different classes of the observed movement patterns (Morris, Summers, Matyas, and Iansek, 1994). Again, since hysteresis effects were present during all transitions, it is not clear how to accommodate these findings using a GMP framework. For example, Participant CA used several similar movement patterns during the initial trials and switched to a complete different pattern at higher distances, which he maintained until the end of the experiment. It is not clear why this participant would use one GMP at small throwing distances whilst increasing distance and another GMP when decreasing throwing distance, especially since performance scores exhibited no obvious differences between the conditions (compare Figure 6-2) and he was able to switch between GMP's in subsequent trials. Hence, it seems difficult to explain the present findings using generalized motor programmes.

In conclusion, whether the observed effects and proposed attractor shifting observed in this programme of work represent typical features for discrete, multi-articular movement models more generally cannot be derived based on the results obtained in studying this specific movement model. Potentially, the results observed were merely a result of the basketball hook shot and cannot be further generalized to other movement domains, which leads to the limitations of the present work and potential applications for further research in the future.

Limitations and Future directions

The main limitations in the current programme work rested on the dependence on the cluster analysis approach for identifying movement patterns. A systematic method of identifying different movement patterns was needed to subsequently link specific movement patterns to attractors. This dependence stemmed from the required departure from the pre-existing movement model in using a discrete multi-articular movement model as the object of investigation. However, as pointed out earlier, in order to overcome some of the major criticisms of the dynamical systems theoretical framework this departure seemed necessary. To attempt to bridge the gap between discrete multi-articular actions and typical bimanual rhythmical movements, this novel movement model was developed from previous work on the throwing task. Similar, the cluster analysis approach was tested with a typical bimanual movement model first, in order to show its validity and the potential transition for its use with the novel movement model (see Chapter 5).

In general, this problem highlights the issue of how movements can be modelled as attractors and how an attractor can be identified when no obvious distinctions are available like in the case of anti-phase and in-phase movements. As pointed out, typically the justification for a valid distinction into different movement patterns is based on intuitive reasoning or prior experience. Hence, when using movement models remote from pre-existing experiments it is not easily possible to apply any a priori justification. The main motivation for the development of the cluster analysis method was that this approach would ease the problems involved when addressing novel movement models and to facilitate further research. Possibly, the steps taken in the present programme were too bold and maybe a simpler movement either only discrete or degenerate could have been enough in order to highlight further issues. The results of the current programme work therefore only provide preliminary statements about the properties of discrete multi-articular actions, and can be viewed as a potential departure point for further research. The data reported in this programme of work reveal that further research investigating the properties of discrete/multi-articular/degenerate actions is needed.

The second limitation was related to the estimation of critical slowing in Chapter 7. Again, since no previous work was available to guide the application of the perturbation paradigm to discrete, multi-articular actions, a relatively conservative standpoint, based on the existing literature, was adopted. Similarly, the study described in Chapter 7 can be seen as a first necessary step in order to develop an appropriate methodology for probing the stability of attractors in discrete movements. Further research is needed to conclusively state whether the results obtained represented genuine attractor stability properties or were merely a result of the measurement method chosen. Perhaps the selected mechanical perturbation was sufficient in order to disturb the stability of the pattern. Since it was difficult to control the exact timing of the perturbation, potentially the magnitude of the perturbation varied in between trials and therefore influenced subsequent movement behaviour. However, this variation would have added random rather than systematic noise to the data and, therefore, the results may represent clear trends. Similarly, perhaps the weight was not sufficient in order to trigger the desired effects although it was determined in extensive pilot work. In conclusion, these issues highlight the need for further research using discrete movements in order to further develop and refine the perturbation paradigm for this class of actions.

In general it can be said, that compared to critical fluctuations and hysteresis, the topic of critical slowing down has drawn much less attention in the literature. This is even true for rhythmical movement models. Accordingly, many questions can be formulated which have not been addressed so far. How general are critical fluctuations across different movement models, for example, cannot be derived from the current literature. Another issue which has also not been addressed concerns the relation of critical slowing and motor learning. For example, in the learning studies performed by Kelso, Zanone and colleagues (Kostrubiec et al., 2006; Kostrubiec and Zanone, 2002; Temprado, Monno, Zanone, and Kelso, 2002; Zanone and Kelso, 1992, 1997; Zanone and Kostrubiec, 2004), changes in attractor layout and the related stability of attractors were found. However, none of the studies investigated the stability of the attractor using a perturbation paradigm but rather relied on measurement of standard deviations of relative phase measurements in order to estimate attractor stability. Accordingly, whether and how critical slowing down is also a function of motor learning has not been investigated at all and further research seems necessary. In summary, it seems desirable to devote more research resources to the investigation of critical slowing down, especially as it deals with one of the fundamental properties of attractors, their stability, which in turn constitutes one of the corner stones of the dynamical systems framework.

Regarding the application of the mixed-modelling approach to discrete ball release data in chapter 3, 5, and 6 it can be said that some interesting results were obtained using this approach, which would not be obtained through the classical ANOVA. As the mixed-modelling approach is widely used in other research domains (Boyle and Willms, 2001; Brown and Prescott, 1999; Pinheiro and Bates, 2000; Sullivan et al., 1999; Verbeke and Molenberghs, 2000; Ware, 1985; Weiss, 2005), it is hoped that the present programme of work on movement coordination might facilitate further applications of these methods, which provide much richer information combining adaptation on a sample and individual level. As this problem is not tied to the dynamical systems perspective, the potential field of applications for this approach are vast and further application seems desirable. Hence, as the software tools are readily available and widely accessible, it is hoped that more research will take on this approach.

The present study also highlighted the importance of individualized analysis schemes (Button, Davids, and Schöllhorn, 2006). With recent advances in recording techniques, experimenters are now in the unique position that extensive behavioural data from individuals can be collected and analysed. In this regards the current study tried also to overcome some of the limitation of previous studies concerned with basketball throws. For example in Chapter 2, the total throws investigated in the reviewed basketball literature consisted of only 1073 throws, whereas in the present thesis a total of over 2600 basketball throws, using full body kinematics, were analyzed. It is important for this approach to gain further support in the literature as potentially much more detailed behavioural data can be obtained with its implementation.

Finally, in relation to the two different adaptation schemes found in this research programme, it is still not clear what reasons exist for the adoption of different schemes to satisfy task constraints, and further research is necessary. Potentially initial differences in arm or body segment strength could have influenced the preference for a particular scheme. This issue highlights that, at present, is not clear how to establish intrinsic dynamics for tasks other than anti-phase/in-phase movements. For example, an interesting question concerns whether it is possible to probe stability characteristics for different types of throwing movements and infer from these analyses preferences for different adaptation strategies.

In conclusion, the present programme of work highlighted some of the issues the dynamical systems theoretical framework is currently facing. The studies described throughout the thesis aimed at providing some ideas of how to address these issues. Overall, the present programme of work supported the basic tenets of the dynamical systems theoretical framework to movement coordination. Investigation of the basketball hook shot showed some surprising features with regards to the obtained attractor layout and further corroborated DST as a valid theoretical framework for the investigation of neurobiological behaviour across several movement domains. With regards to the novel movement model, some clear indication on how to model discrete multi-articular actions could be obtained. The novel cluster analysis approach should facilitate further research using discrete multi-articular actions and ease the identification of the attractor dynamics in new domains. It is hoped that further research into the issue of degeneracy can be stimulated as this emerged as one of the main themes in the present work.

In the end, as noted at the very beginning, the current programme of work could not answer the question of how we are able to move from point A to point B. But it highlighted that, whereas some actors may choose to walk through a gate, others may jump over a fence instead. Nevertheless, both will be able to meet the task requirements of transiting from points A to B in their own individual way.

> *If people do not believe that mathematics is simple, it is only because they do not realize how complicated life is.* John von Neumann (1903-1957).

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10 Appendix A – Individual results of cluster analysis from Chapter 7

In Table 10-1 the results of the bootstrapping procedure and the according number of trials contained in each identified cluster are shown.

Table 10-1: Results of multi-scale bootstrapping procedure (p-values) for each cluster for each participant and number (no.) of trials contained in each cluster.

Participant	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 5		Cluster 6	
	p	no	p	no	p	no	p	no	p	no	p	no	p	no
AN	87	63	90	93	NA	1	NA	1						
CAL	83	12	99	70	98	78								
CR	86	76	78	33	91	51								
LU	NA	1	99	155										
MI	95	96	97	33	NA	1	94	4	NA	1	89	22	NA	1

The number of identified clusters varied between 6 clusters for participant MI and 2 clusters for participant LU and in general the obtained p-values supported the results of the cluster analysis quite strongly. For LU cluster 1 contained only a singular trial which was identified as an outlier and no clear clustering structure could be recovered from the cluster analysis of the remaining trials. The bootstrapping procedure indicated higher stability for lower grouping. However, these were not supported by the Hubert-Γ scores, therefore no further separation into different clusters was applied (compare Figure 9-1). For the complete results from the cluster analysis compare Appendix C.

A.

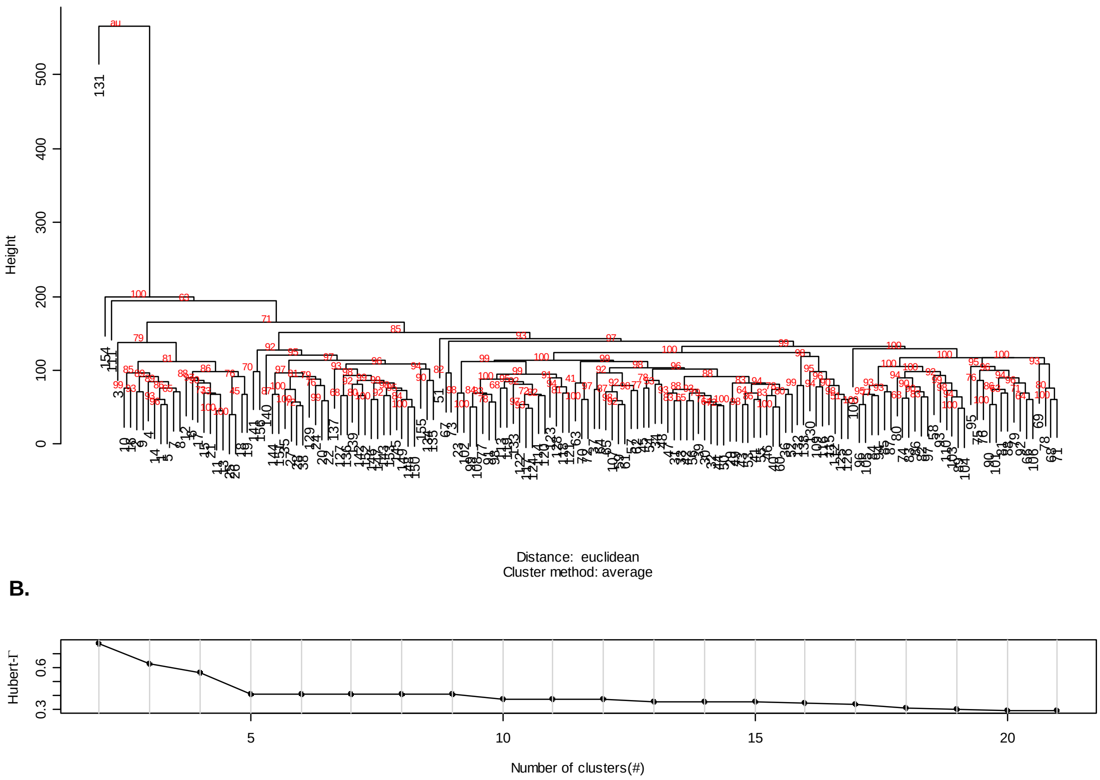


Figure 10-1: (A) Results of bootstrapping procedure for participant LU (B) Plot of Hubert-Γ scores against number of clusters for participant LU.

For the remaining participants the identified clusters were well supported by both the bootstrapping procedure and the Hubert- Γ scores. The individual results will be presented in the order of the performance starting with the most successful participants and ending with the least successful.

Participant CR

For participant CR a three cluster solution was obtained with relatively equal spread of trials across the clusters. Investigation of the angle-angle plot for the right arm indicated that the movement was initiated by abduction of the shoulder joint followed by synchronous flexion and abduction in the elbow joint and the shoulder joint (see Figure 9-2.a). Comparison of the movement clusters indicated differences especially between movement clusters 2 and 3 and movement cluster 1. For movement cluster 1 mean starting angles were -76°±4° STD, whereas for cluster 2 and 3 angles of -92°±7° STD and -89°±6° STD accordingly were found. For the starting angles of the right elbow joint, movement clusters showed values of 86°±3° STD for movement cluster 1, 84°±5° STD for movement cluster 2, and 78°±8° STD for movement cluster 3. Investigation of the left arm kinematics made the differences between the movement clusters apparent. Especially kinematic differences between movement cluster 3 and movement clusters 1 and 2 were clearly visible (see Figure 9-2.b). These differences stemmed from both joints, where for movement cluster 3 the elbow joint showed greater flexion paired with greater abduction angles in the shoulder joint compared to movement clusters 1 and 2. With regards to differences between movement clusters 1 and 2, the plots gave also some indication based on the starting flexion angles of the elbow joint which were slightly greater for movement cluster 2 (97°±5° STD) compared to cluster 1 (89°±7° STD). Hence, relating these findings to the somewhat lower p-values obtained during the bootstrapping procedure which indicated that movement clusters 1 and 2 showed lower stability, this finding could have been a result of the considerable overlap between the two movement patterns. Kinematics of the left leg showed no peculiar differences between the movement clusters and were marked by high stability across all trials and movement clusters (compare Figure 9-2.c). Plots followed a diagonal pattern with a negative slope of 45°.

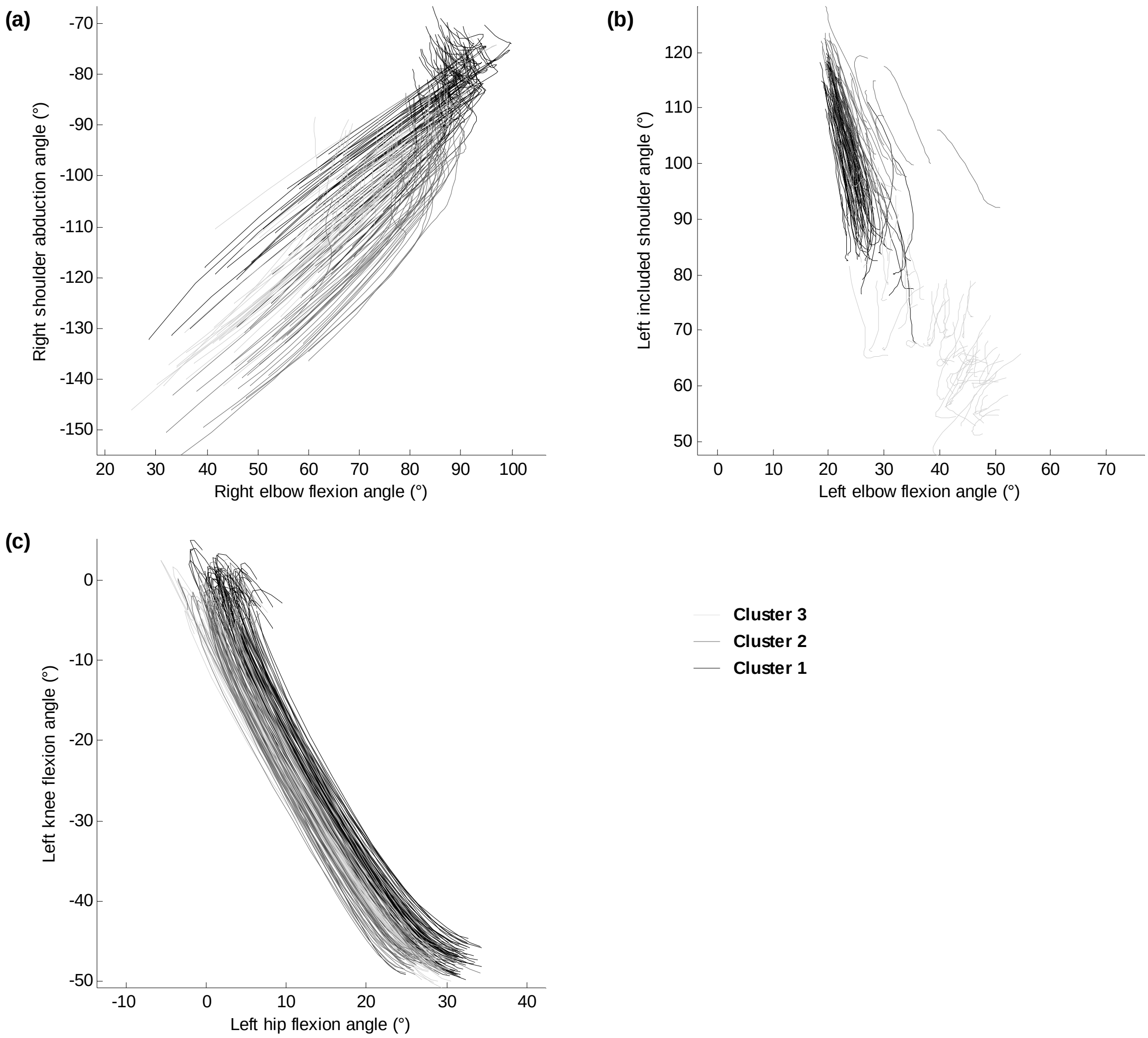


Figure 10-2: Angle-angle plots for all movement clusters of participant CR. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

Investigation of the cluster distribution across throwing distances and conditions for participant CR revealed a progression between the three movement clusters. Cluster selection was marked by high stability with few alternations between the different movement clusters. Movement clusters 2 and 3 were present mainly at smaller throwing distances, whereas movement cluster 1 represented trials from greater throwing distances. During the INC condition CR started with movement cluster 3, which was used until 7m distance, where a switch to cluster 1 occurred. Subsequently movement cluster 1 was maintained until 4m, where the participant switched to movement cluster 2. Switches between clusters were always initiated by changes in the throwing distances, where each time the first movement clusters at a new throwing distance belonged to the subsequently stabilized movement cluster. With regards to the progression of the movement (3→1→2), the distribution clearly resembled a hysteresis effect. Relating the cluster progression to the movement kinematics, since the initial movement cluster (cluster 3) showed quite peculiar differences to movement clusters 1 and 2, potentially the execution of shots from higher throwing distance influenced the subsequent execution of throws from lower distances. This finding could have lead to a greater similarity between the later movement clusters and resembling some sort of learning effect and more in reminiscence of a movement scaling approach.

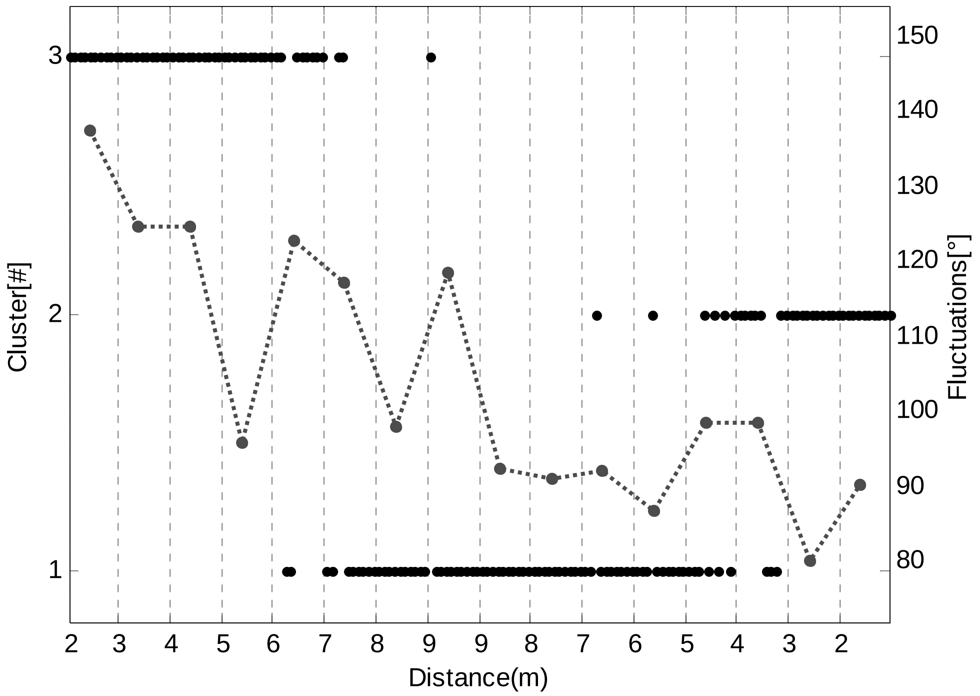


Figure 10-3 : Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant CR. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

The fluctuations showed in general a decreasing trend over the course of the experiment with some slight peaks at 6m during INC (95°→123°) and at 5m during DEC (87°→98°), which accompanied the occurrences of switches between movement clusters.

In summary, for participant CR the results obtained from the cluster analysis indicated the adaptation of a single unimodal attractor landscape to the throwing distance. The movement patterning showed a clear hysteresis effect but gave little support for the presence of critical fluctuations. Regarding the differences between the movement patterns at the end and the beginning of the experiment, movement kinematics of the non-throwing arm showed strong significant differences potentially suggestive of a learning effect.

Participant LU

As pointed out earlier, for Participant LU no true clustering could be identified, and therefore, only a general overview over the kinematics will be given. Regarding the coordination of the right arm participant LU used a movement pattern with small ranges of motion in the right elbow joint (11°±4° STD, compare Figure 9-4.a). The plots appeared very similar across trials supporting the conclusion of no true clustering. Interestingly, the single trial which deviated completely from the remaining trials showed a coordination pattern resembling the pattern found for participants BR, JA, and NI in Chapter 6. The coordination of the left arm showed considerable variation but no clear patterning across trials between the left shoulder joint and left elbow joint was visible (compare Figure 9-4.b). The kinematics of the left leg again showed a trend similar to the right arm with very little inter-trial variation also exhibiting the -45° degree pattern shown by the previous participants and in the other studies (see Figure 9-4.c).

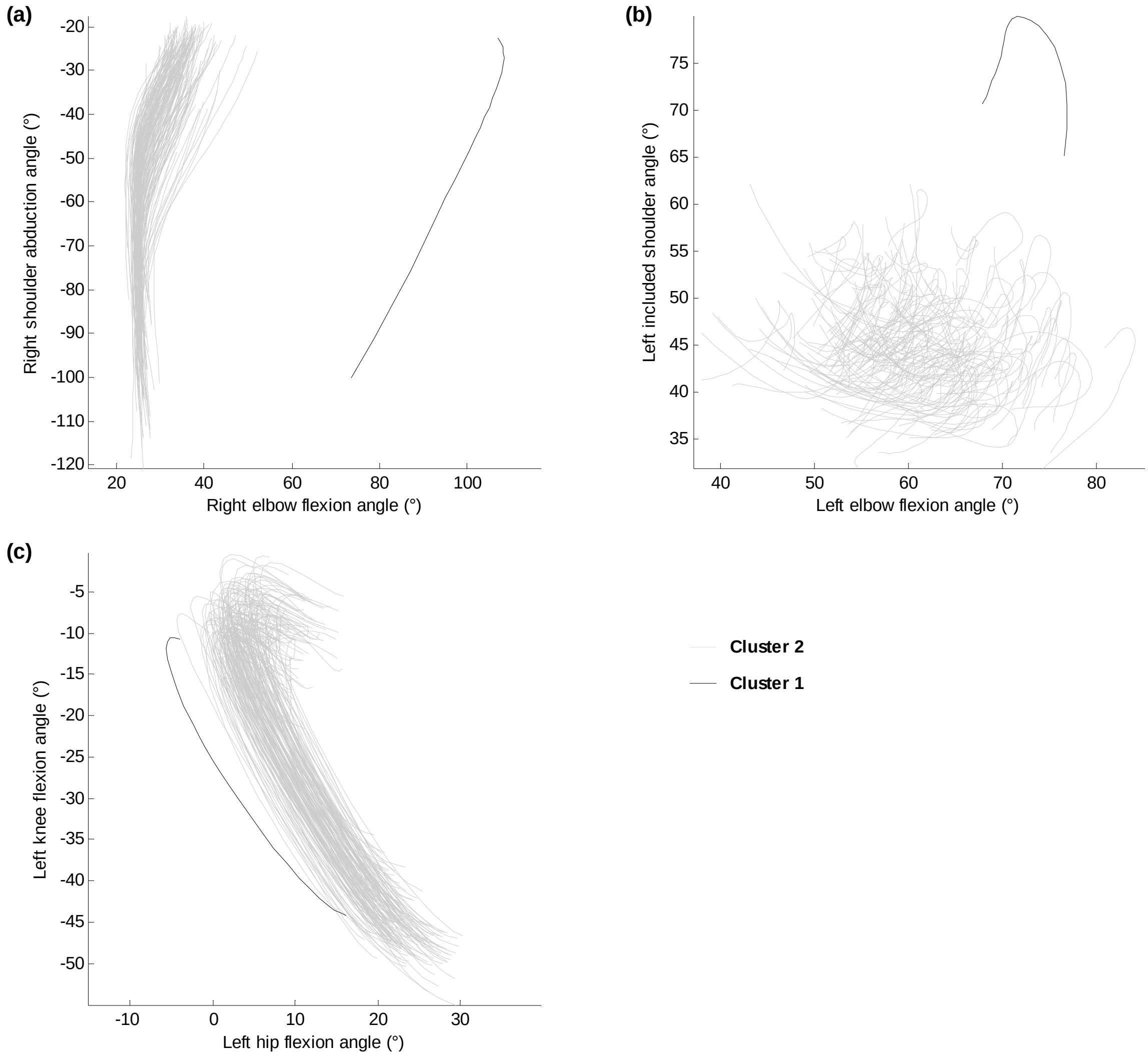


Figure 10-4 : Angle-angle plots for all movement clusters of participant LU. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The fluctuations showed only one peculiar peak which seemed to be mostly influenced by the outlying trial. Regarding the obvious differences between the singular trial and the remaining trials, this effect can be seen as an example where in subsequent trials transitions between movement patterns could be achieved in discrete movement which, as pointed out earlier, is not possible for continuous movements (see Figure 9-5).

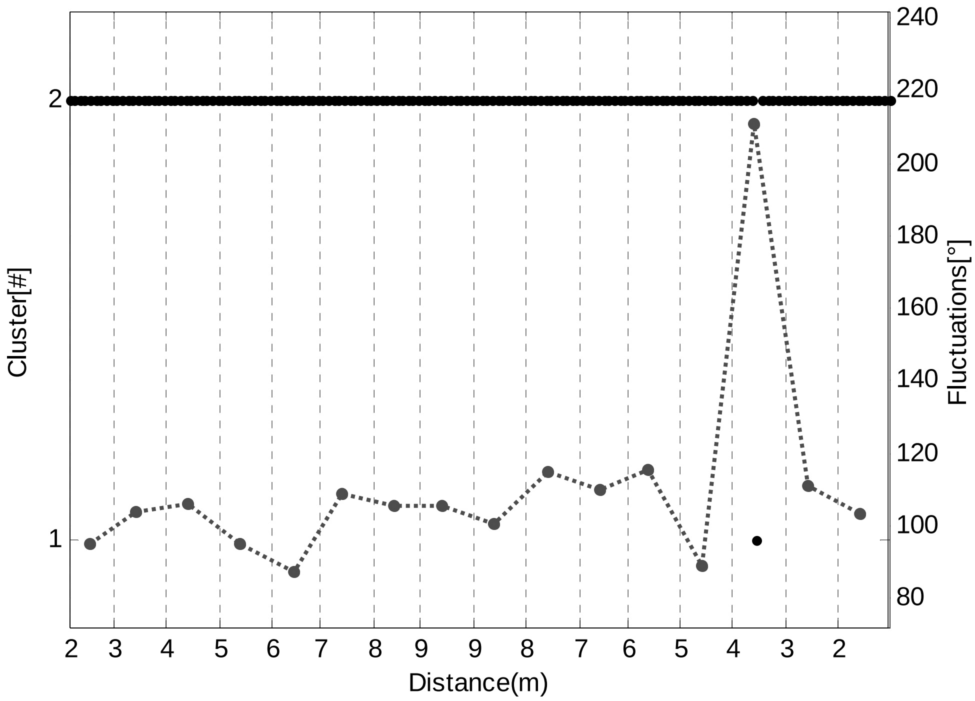


Figure 10-5 : Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant LU. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

Participant CAL

Although three clusters were identified by the cluster analysis for participant CAL the majority of trials were represented by cluster 2 and 3 and the additional smaller cluster 1 contained only a small number of trials. Investigation of angle-angle plots for the right arm suggested no clear differences between the different movement clusters (see Figure 9-6.a). However, whereas the three movement clusters showed very similar starting angles, there were some differences in the joint angles at ball release. Especially trials from movement cluster 1 showed much smaller mean shoulder joint angles (103°±7° STD) at ball release compared to movement clusters 2 (-132°±8° STD) and 3 (147°±4° STD). Accordingly, ranges of motion deviated in both joint angles. Overall, the coordination patterns of the right arm exhibited high stability across trials and indicated no qualitative differences between the movement clusters (see Figure 9-6.b). The coordination of the left arm showed somewhat more variation across trials but still lacked clear qualitative differences between the different movement clusters. The coordination pattern was marked by initial abduction of the left shoulder joint paired with constant elbow joint angles. Subsequently, the pattern changed into synchronous extension of the elbow joint and adduction of the shoulder joint. Kinematics of the left leg showed no variations between movement clusters and exhibited high stability across trials with a near 45° directed plot (see Figure 9-6.c).

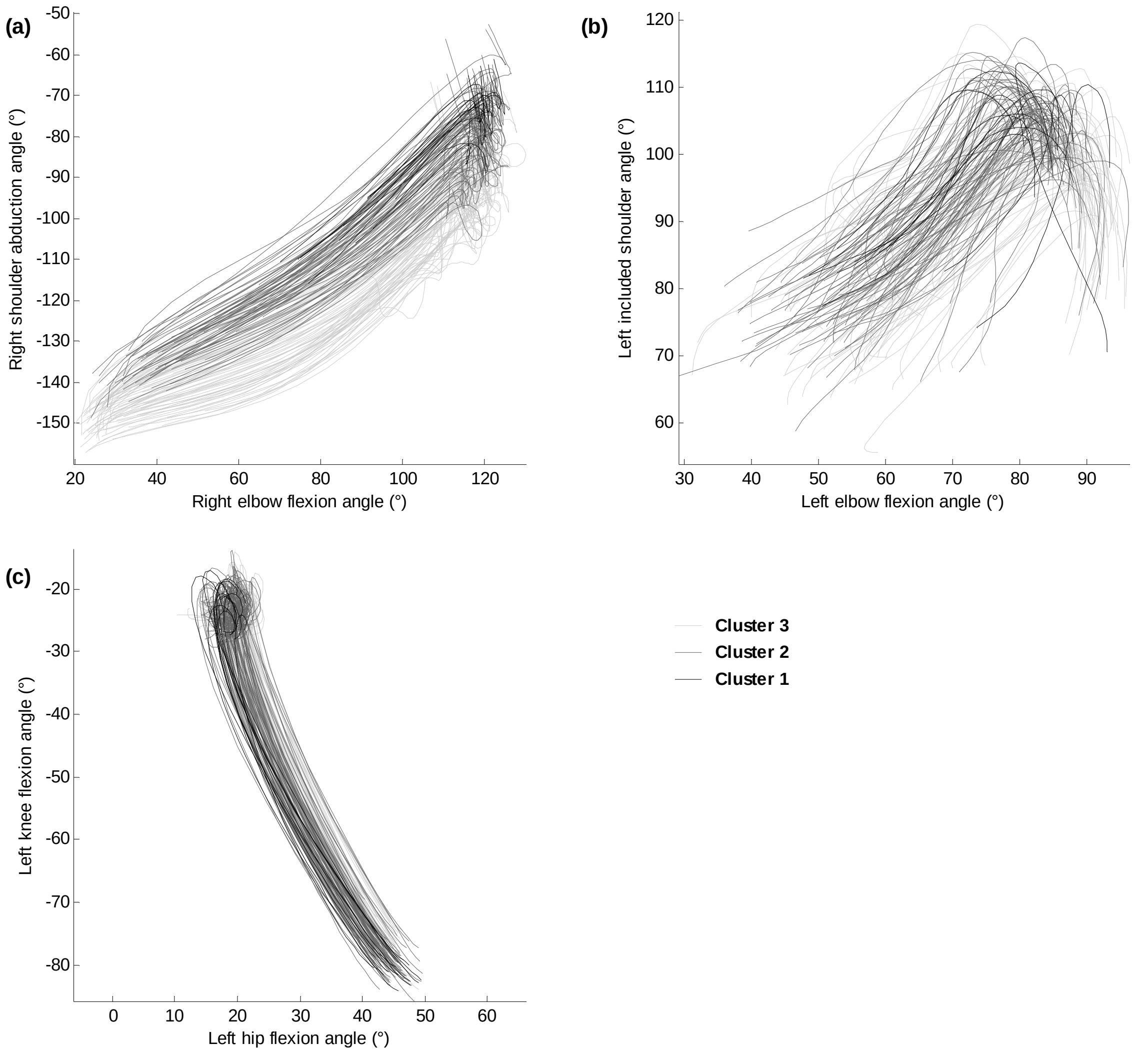


Figure 10-6 : Angle-angle plots for all movement clusters of participant CAL. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

When plotting the clusters against the trial sequence the movement cluster distribution showed a relation to the throwing distance (see Figure 9-7). Movement cluster 3 was mainly used during the lower distances whereas movement clusters 1 and 2 were distributed over the higher distances. During the INC condition movement cluster 3 was used up to 5m where a switch to movement cluster 2 occurred. Afterwards movement cluster 2 was prominent until 9m DEC with some singular occurrences of movement cluster 3. At 9m a switch to movement cluster 1 occurred but only to become immediately unstable again during the following throwing distances and movement cluster 2 became again the preferred movement pattern. Subsequently, movement cluster 2 was used only for one more distance bin and at 6m distance the final switch back to movement cluster 3 occurred. Between 6m and 4m the participant exhibited some alternations between clusters 2 and 3 until 3m from where onwards only cluster 1 was used. Regarding the distribution of the movement cluster, no clear indication of hysteresis effects were found. Regarding the differences between INC and DEC, the transitions were made at 5m and 6m accordingly. Especially during DEC, some alternations were present where the participant revisited movement cluster 2 although the majority of throws were performed using movement cluster 3. The fluctuations showed a pattern with three smaller peaks which did not coincide with switching behaviour and only the third peak occurred in the vicinity of a switch between clusters. Both the transitions (3→2) and (2→1) were accompanied by low values of mean dissimilarity scores.

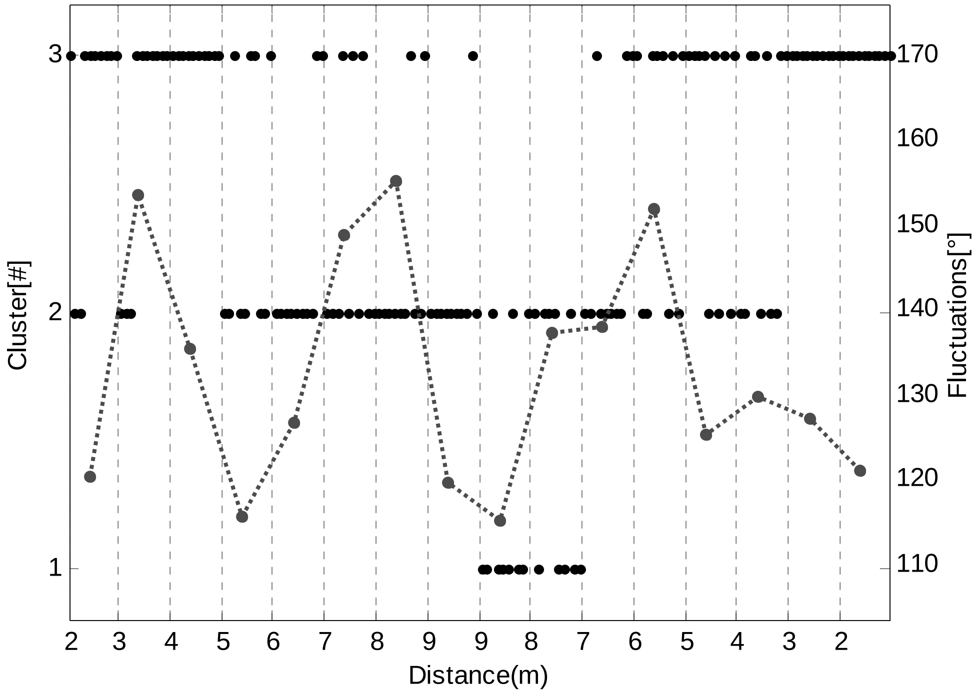


Figure 10-7: : Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant CAL. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In conclusion, for participant CAL a unimodal attractor layout was present and no indications neither of critical fluctuations nor of hysteresis behaviour were found.

Participant AN

For participant AN the cluster analysis identified four different clusters were cluster 3 and 4 contained only one trial each. The angle-angle plot of the right elbow joint and right shoulder joint abduction angles showed some differences between the two identified movement clusters (compare Figure 9-8.a). For movement cluster 2 shoulder joint abduction angles at the beginning of the movement (top) were somewhat smaller compared to cluster 1 (mean$_{cluster1}$ = -65°±7° STD, mean$_{cluster2}$ = -65°±7° STD). A similar trend was visible for the shoulder joint angle at ball release where mean angles for the movement cluster 1 were -121°±6° STD and -104°±9° STD for cluster 2. No such differences were found for the right elbow joint angles. The kinematics of the left shoulder joint and left elbow joint did not show any strong differences between the two movement clusters and, with the exception of a few trials, exhibited quite similar behaviour across all trials (see Figure 9-8.b). Movement kinematics of the left leg showed minimal variation between the movement clusters. The plots were marked by initial synchronous extension in both joints with the hip joint starting from a flexed position, which went into a extended position. Subsequently, the knee joint angles stayed nearly constant at the end and the hip joint flexed back into a neutral position (see Figure 9-9.c).

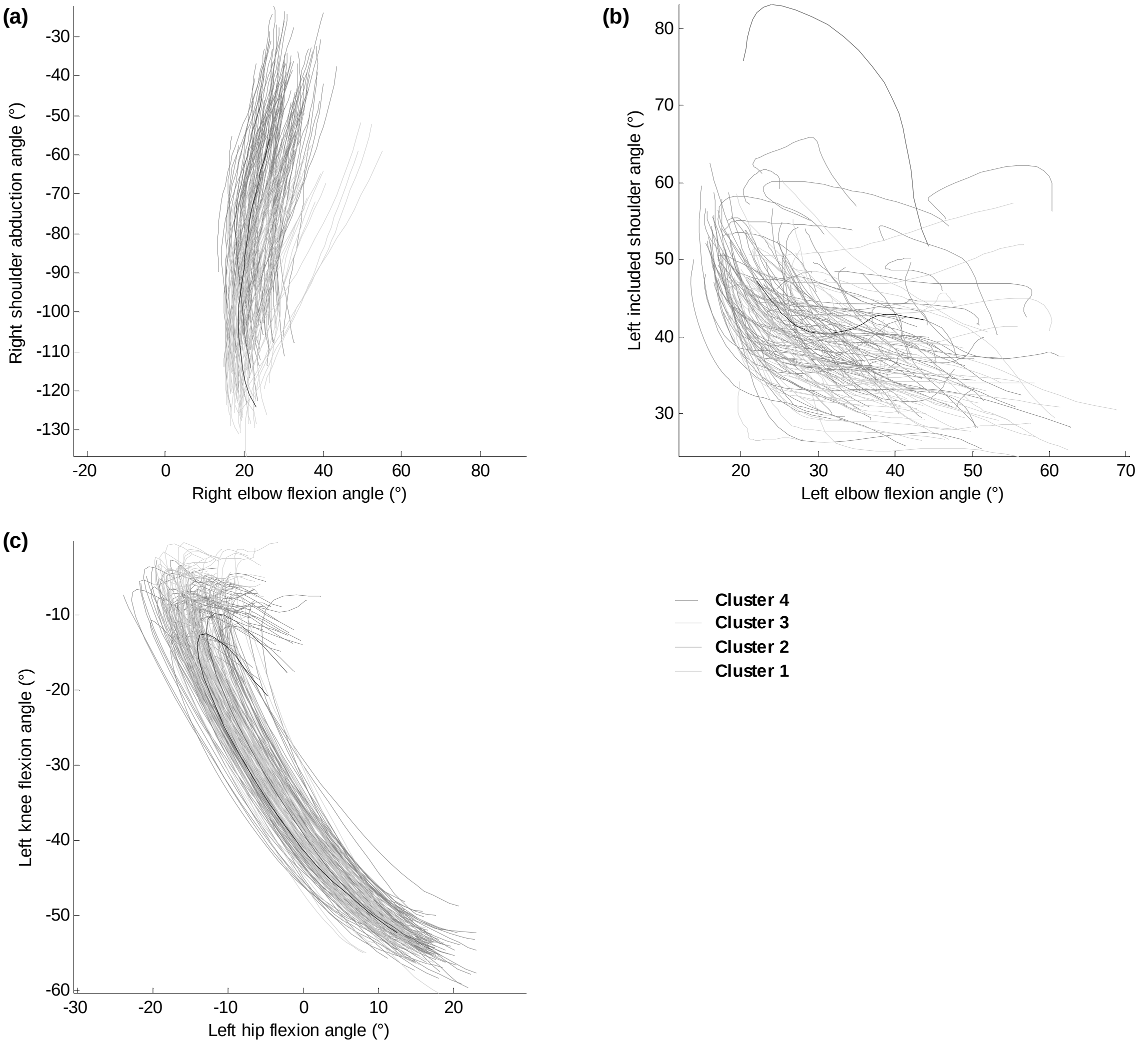


Figure 10-8 : Angle-angle plots for all movement clusters of participant AN. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The cluster distribution indicated that the two main clusters were related to throwing distance with movement cluster 1 being more prominent at the smaller throwing distances and movement cluster 2 mainly utilized during greater throwing distances (see Figure 9-9). During the INC condition movement cluster 1 was used from 2m up to 5m with a switch at 6m to movement cluster 2, which was maintained until 4m DEC where the switch back to movement cluster 1 occurred. The switches between the different movement clusters followed in both cases very closely the jumps of the throwing distances, occurring during the first trial in the subsequent new distance. Since the switch during DEC from movement cluster 2 to 1 occurred at a smaller throwing distance compared to the INC, the plot provided clear indication for hysteresis behaviour.

The fluctuations scores showed a sudden increase only at 5m (118°→294°) which preceded the switch to the new cluster but no such rise in the dissimilarity scores was observed during the DEC condition, where the transition between the two clusters was not accompanied by a pronounced increase in dissimilarity scores (130°→150°). Rather the fluctuations were similar in magnitude, potentially indicating that loss of stability used only for the first transition but not for the second.

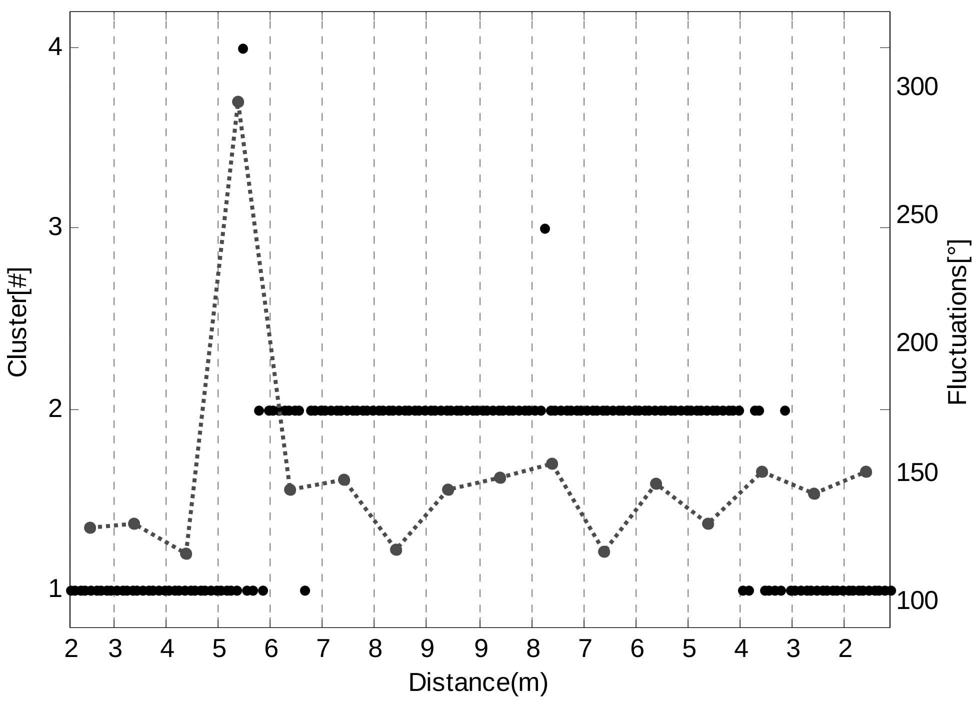


Figure 10-9: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant AN. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In summary, for participant AN the results indicated a unimodal attractor layout where a single movement pattern was scaled according to the throwing distance. Distribution of movement clusters clearly supported hysteresis effects but also critical fluctuations for one instance of the switches between movement clusters.

Participant MI

For participant MI the greatest number of movement clusters in this chapter were identified. However, the majority of the trials were contained in clusters 1, 2, and 6. Angle-angle plots of the right arm did not show any clear differences between the different movement clusters except for movement cluster 6 which showed the greatest range of motion in the right shoulder joint (see Figure 9-10). All remaining trials showed similar ranges of motion with small differences for the starting angles for the right elbow joint. In general the range of motion of the elbow joint for individual trials was very limited and the motion in the throwing arm was mainly accomplished by the shoulder joint. Movement cluster 7 showed a clearly different movement pattern from the remaining trials. For the left arm the outlying behaviour for cluster 4 and 3 could be confirmed with the distinction between the remaining trials remaining somewhat elusive (compare Figure 9-10.b). Ranges of motion for both joints of the left arm were in general quite small ($mean_{left\_elbow}$= 4°±5° STD, $mean_{left\_shoulder}$ = 3°±5° STD). For the left leg the plots of the angle-angle kinematics gave no clear indications for differences between the movement clusters and exhibited considerable overlap (see Figure 9-10.c). In general, the typical pattern shown by all participants was present. Coordination between the two segments was kept constant by participant MI only the location of the plots was somewhat shifted between trials.

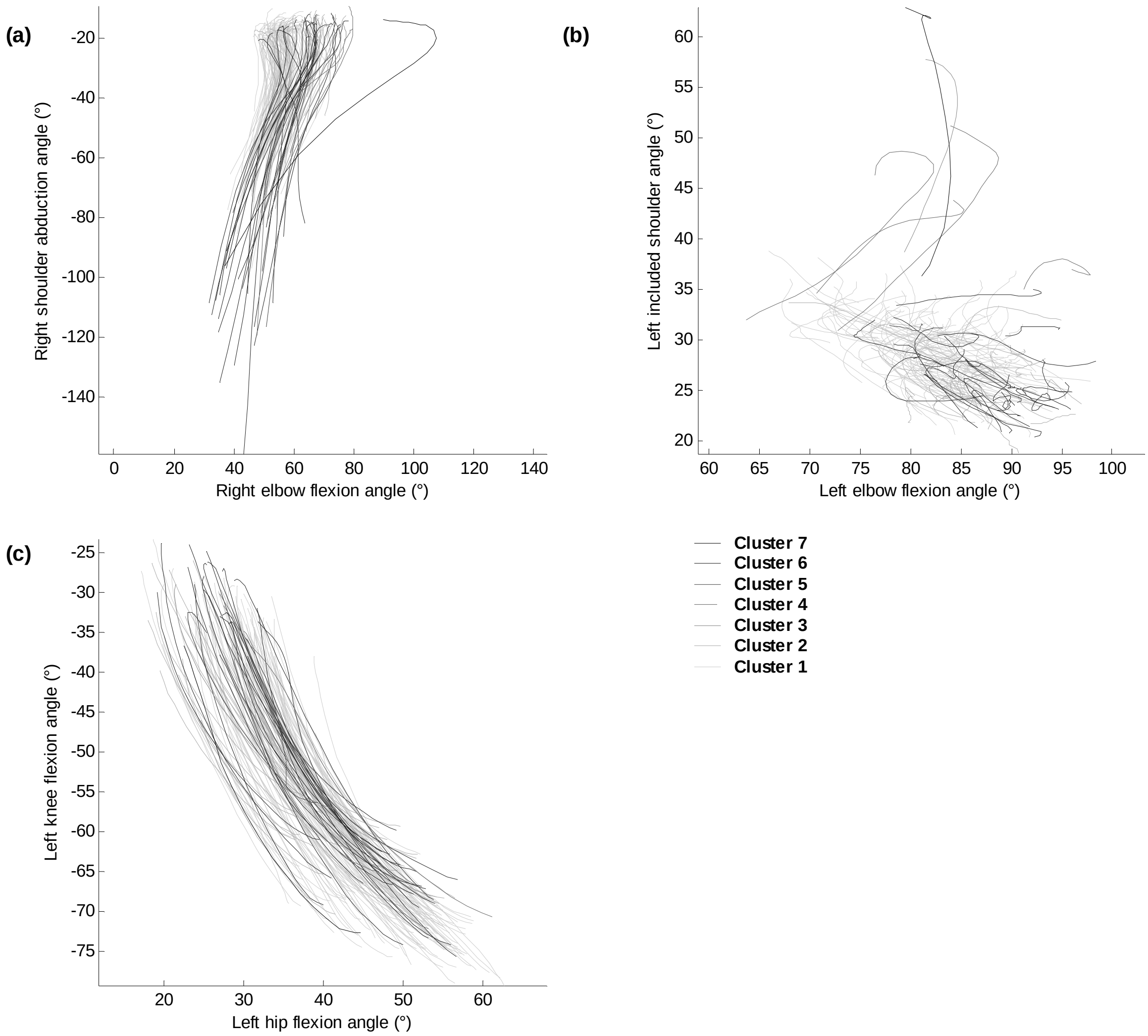


Figure 10-10 : Angle-angle plots for all movement clusters of participant MI. (a) Angle-angle plot of right shoulder joint abduction angles against right elbow joint flexion angles. (b) Angle-angle plot of left included shoulder joint angle against left elbow joint flexion angle. (c) Angle-angle plot of left knee joint flexion angle against left hip join flexion angle.

The distribution of the movement clusters showed some greater variability during the smaller distances of the INC condition, where a mixture of movement clusters 2, 4, and 6 was used with movement cluster 2 potentially having the highest stability (see Figure 9-10). This alternating pattern strategy was maintained until 6m distance where movement cluster 1 was stabilized. Subsequently this cluster was used until the final distance of 2m during the DEC condition where again some greater fluctuations were visible and some preference for movement cluster 2 was indicated. The fluctuations showed a decreasing trend for the INC conditions from 2m to 9m (182°→97°) with smaller values for the subsequent distances until 5m DEC which accompanied the occurrences of trials using movement cluster 2. At 5m a sharp rise (94°→200°) occurred which was followed by somewhat higher fluctuations for the remaining distances. The distribution of movement clusters gave some indication of hysteresis behaviour where especially movement cluster1 was used much longer during the DEC condition compared to the INC condition. However, participant MI finished the experiment using similar movement compared to the beginning (cluster 2).

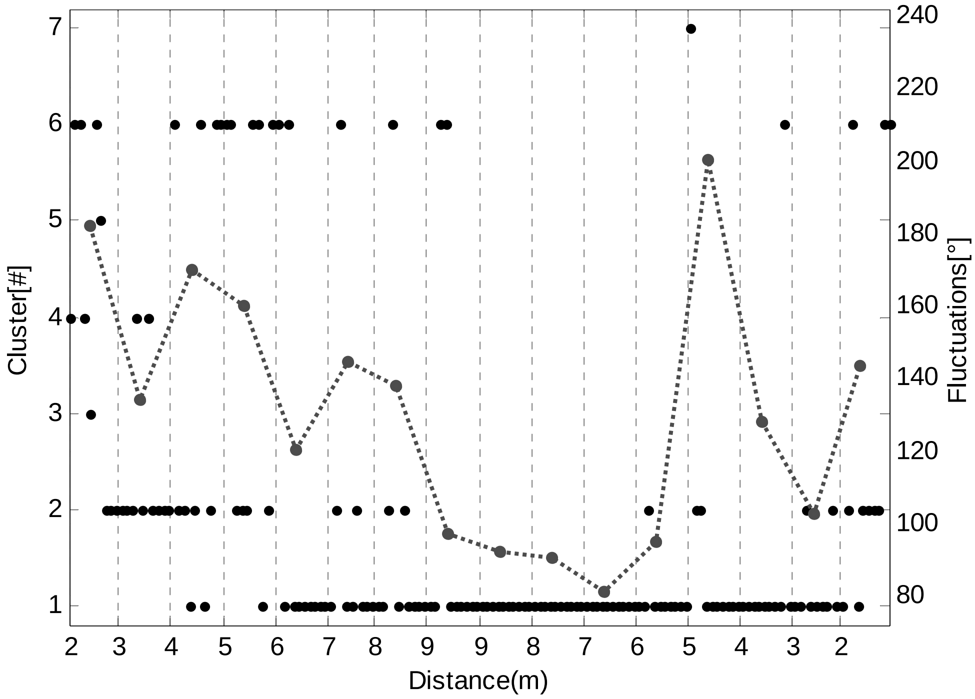


Figure 10-11: Distribution of movement clusters (●) against trials grouped by distance in ordering of actual occurrence for participant MI. Mean dissimilarity scores at each according throwing distance by direction are superimposed (-●-).

In summary, participant MI seemed to use a single movement pattern across all distances and, in regards to the initial trials, where often movement cluster 6 was used, potentially some exploratory behaviour was present which lead to learning. This view is also supported by the observation of decreasing fluctuations scores and the subsequent main usage of a single movement cluster.

11 Appendix B – Matlab code

```
function res = npoints(mat, no, type)
% npoints(mat, no, type)
% RETURNS A MATRIX WITH no NUMBER OF ROWS WHERE THE COLUMS
% CONSIST OF THE INTERPOLATED POINTS OF MAT BASED ON A
% TYPE (LINEAR, CUBIC, SPLINE) FIT
if nargin==2
    type = 'spline';
end
[m,n] = size(mat);          % DETERMINE SIZE OF MATRIX
x = 0:m-1;                  % ORIGINAL NODES
xx = linspace(0,m-1,no);    % INTERPOLATED NODES
res = zeros(no,n);          % RESULT MATRIX
for i=1:n
    res(:,i) = interp1(x,mat(:,i),xx,type)';
end


function y = dist_fluct(data_n,index)
%dist_fluct(data_n,index)
% CALCULATES THE FLUCTUATIONS IN MOVEMENT PATTERNING PER DISTANCE
% ON ALL TRIALS WITHIN A DISTANCE-BY-DIRECTION COMBINATION
% data_n SHOULD BE A 3D MATRIX WHERE THE FIRST DIMENSION REPRESENTS TRIALS,
% THE SECOND DIMENSION REPRESENTS A TIME SERIES, THE THIRD DIMENSION
REPRESENT
% DIFFERENT JOINT ANGLES. index SHOULD CONSIST OF MATRIX WITH THREE COLUMNS
% EQUALLING [DISTANCE, TRIAL, CONDITION] AND ROWS REPRESENT TRIALS
[no_trials,no_ts,no_ang] = size(data_n);
dmat =
squareform(pdist(reshape(data_n,no_trials,no_ts*no_ang),'euclidean'));
y = zeros(8,2);
for dist = 2:9
    for cond = 1:2
        i       = find(index(:,1)== dist & index(:,3) == cond);
        smat    = dmat(i,i);
        y(dist-1,cond) = mean(smat(triu(smat)~=0));
    end
end


function tdiff = su_trials(data_n)
%SU_TRIAL(NDATA)
% CALCULATES THE DIFFERENCES BETWEEN SUCCESSIVE TRIALS
% data_n IS A 3D MATRIX WHERE THE FIRST DIMENSION REPRESENTS TRIALS, THE
% SECOND DIMENSION REPRESENTS TIME SERIES, THE THIRD DIMENSION REPRESENT
% DIFFERENT ANGLES
[no_trials,no_ts,no_angles] = size(data_n);
tdiff   = diag(squareform(...
    pdist(reshape(data_n,no_trials,no_ts*no_angles),'euclidean')),1);
```

12 Appendix C – Detailed cluster analysis results

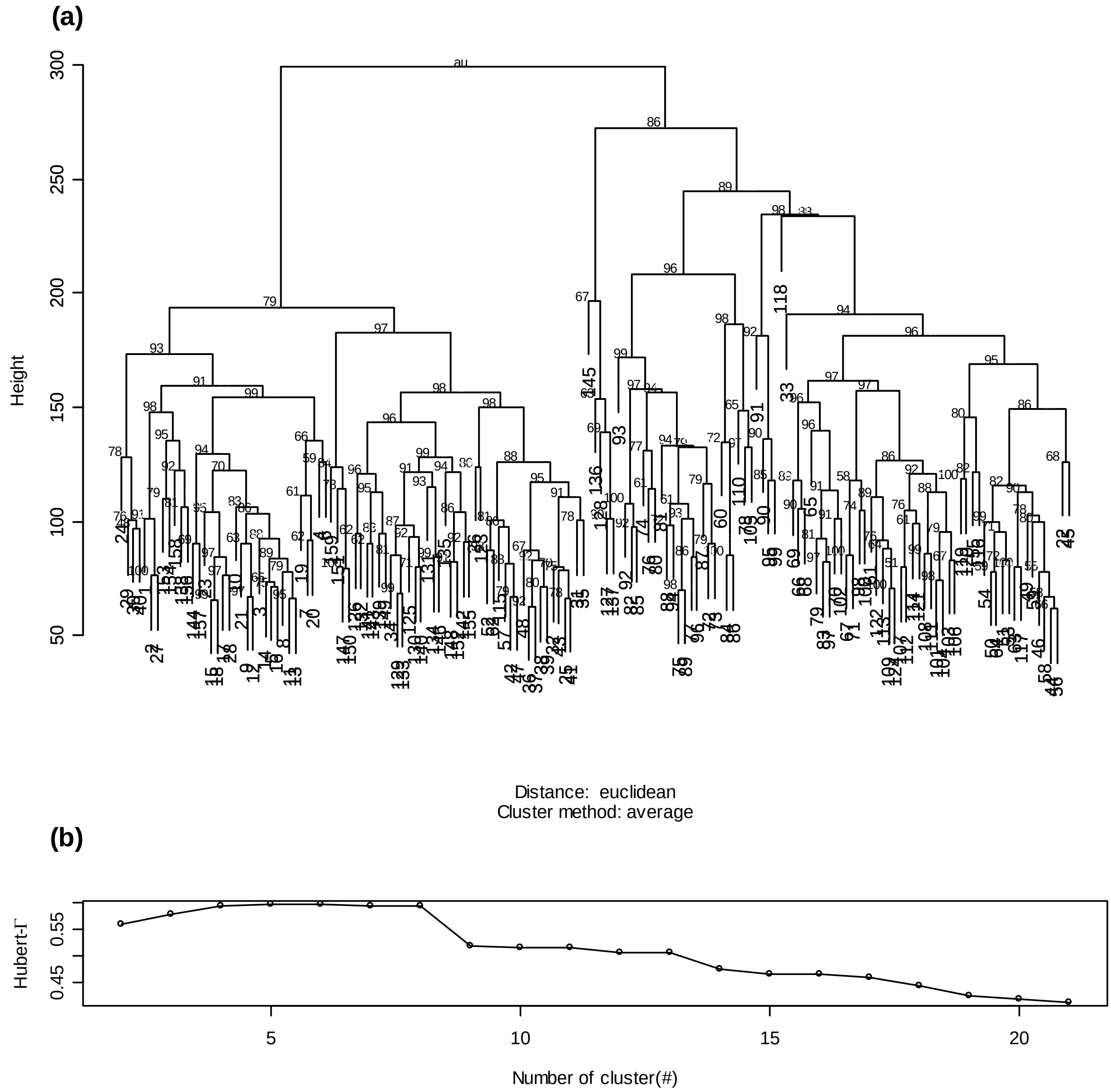


Figure 12-1: (a) Results of bootstrapping procedure for participant BR. (b) Hubert-Γ scores of clustering for participant BR.

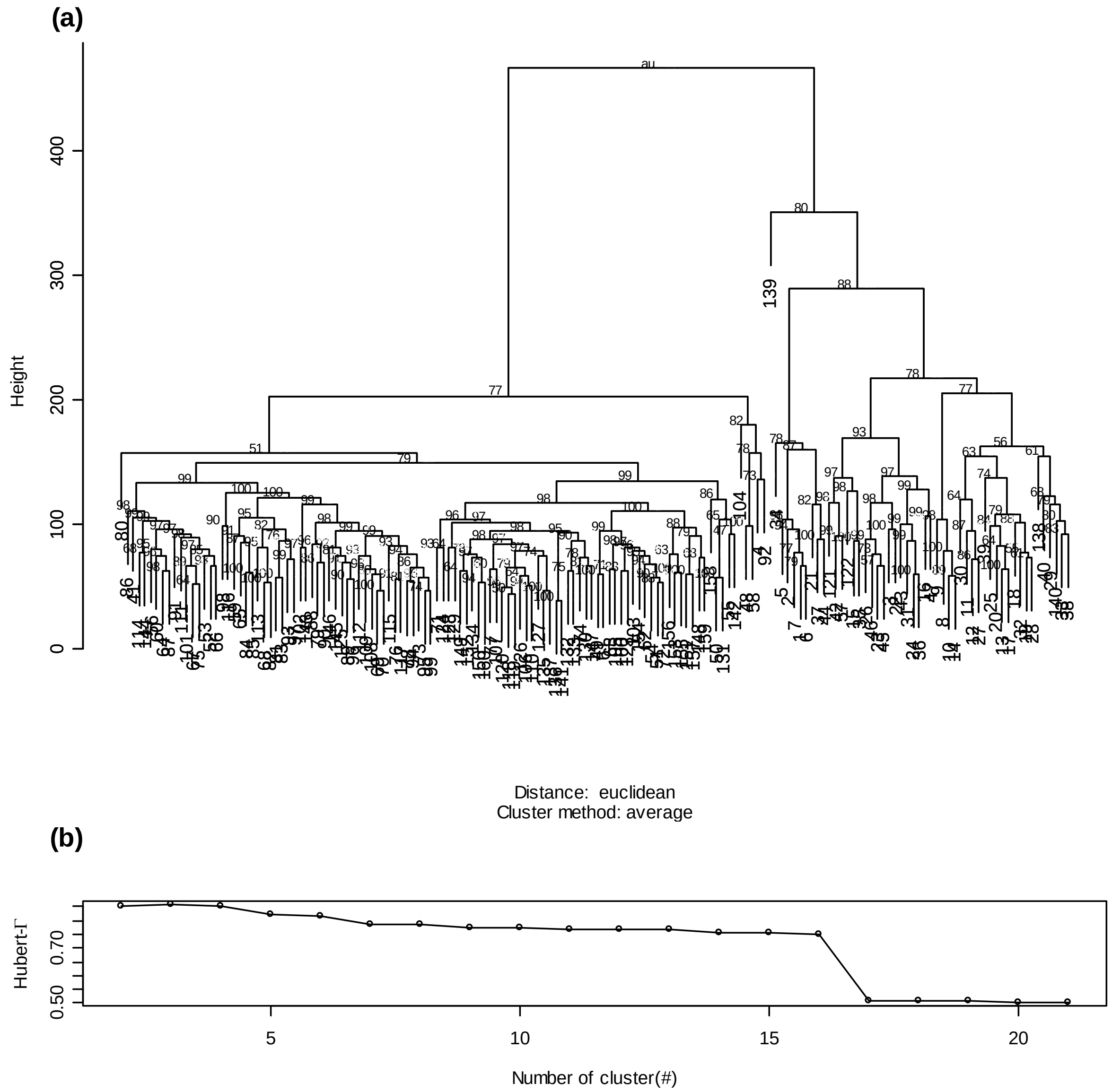


Figure 12-2: (a) Results of bootstrapping procedure for participant CA. (b) Hubert-Γ scores of clustering for participant CA.

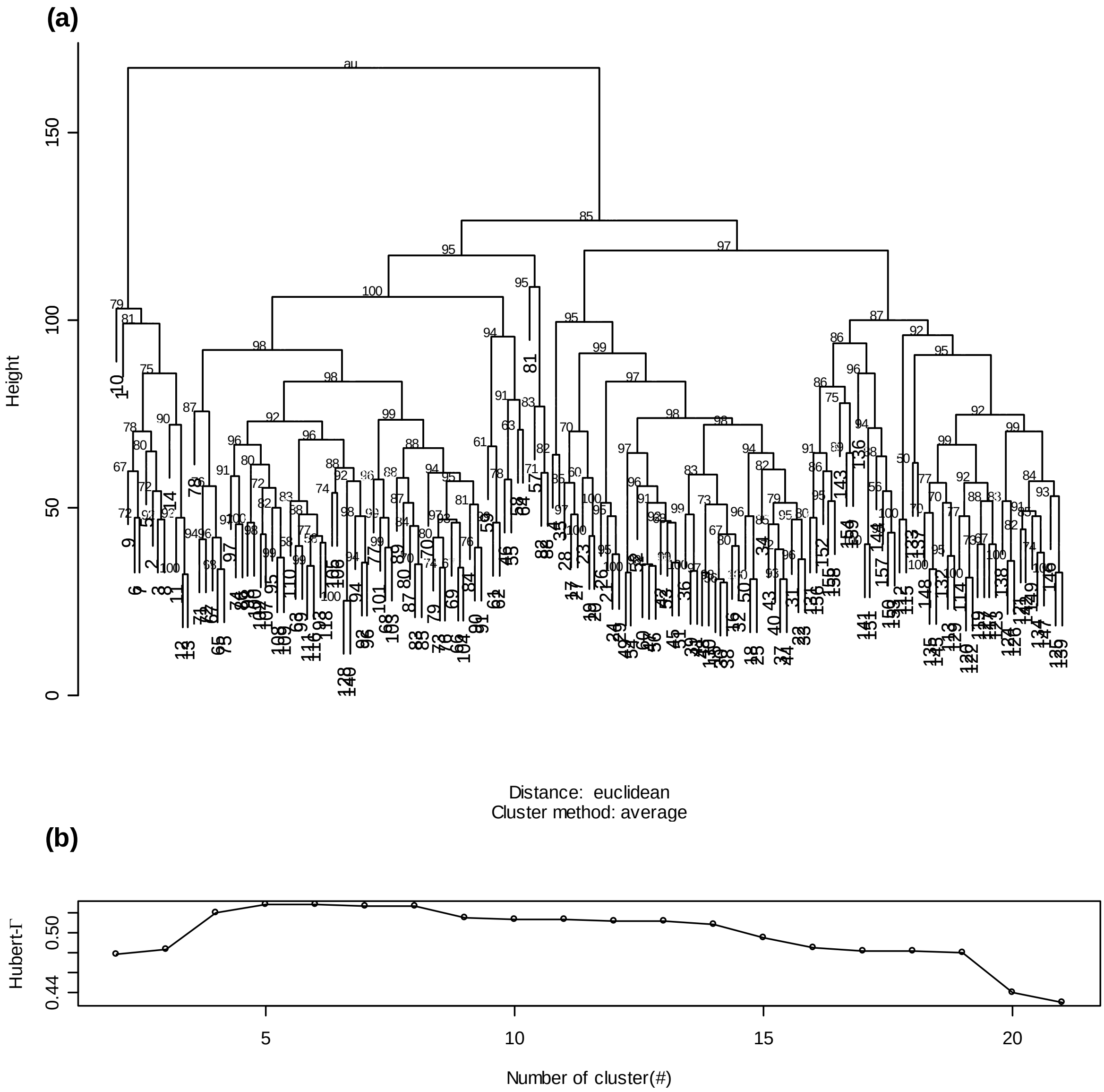


Figure 12-3: (a) Results of bootstrapping procedure for participant DU. (b) Hubert-Γ scores of clustering for participant DU.

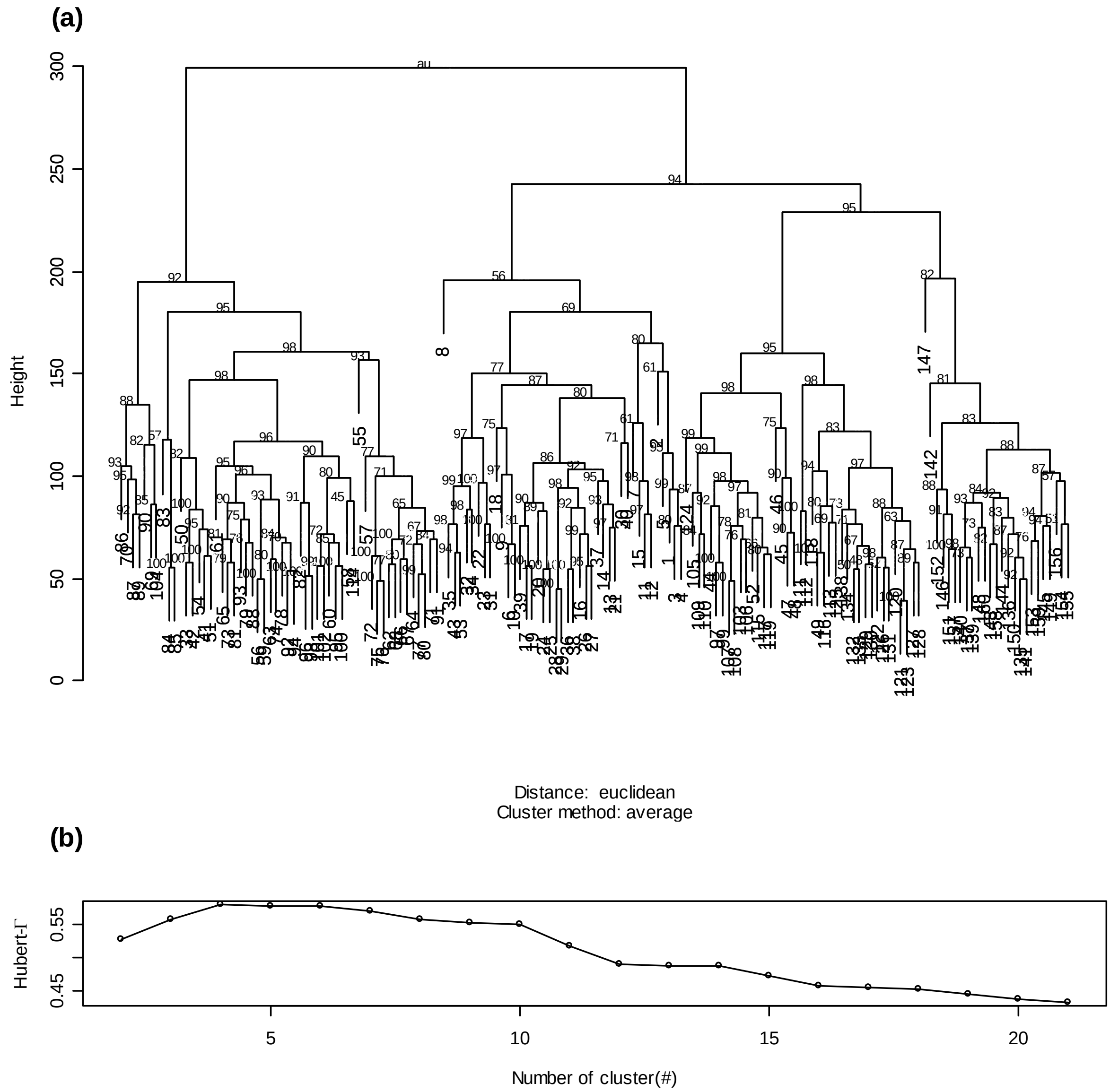


Figure 12-4: (a) Results of bootstrapping procedure for participant JA. (b) Hubert-Γ scores of clustering for participant JA.

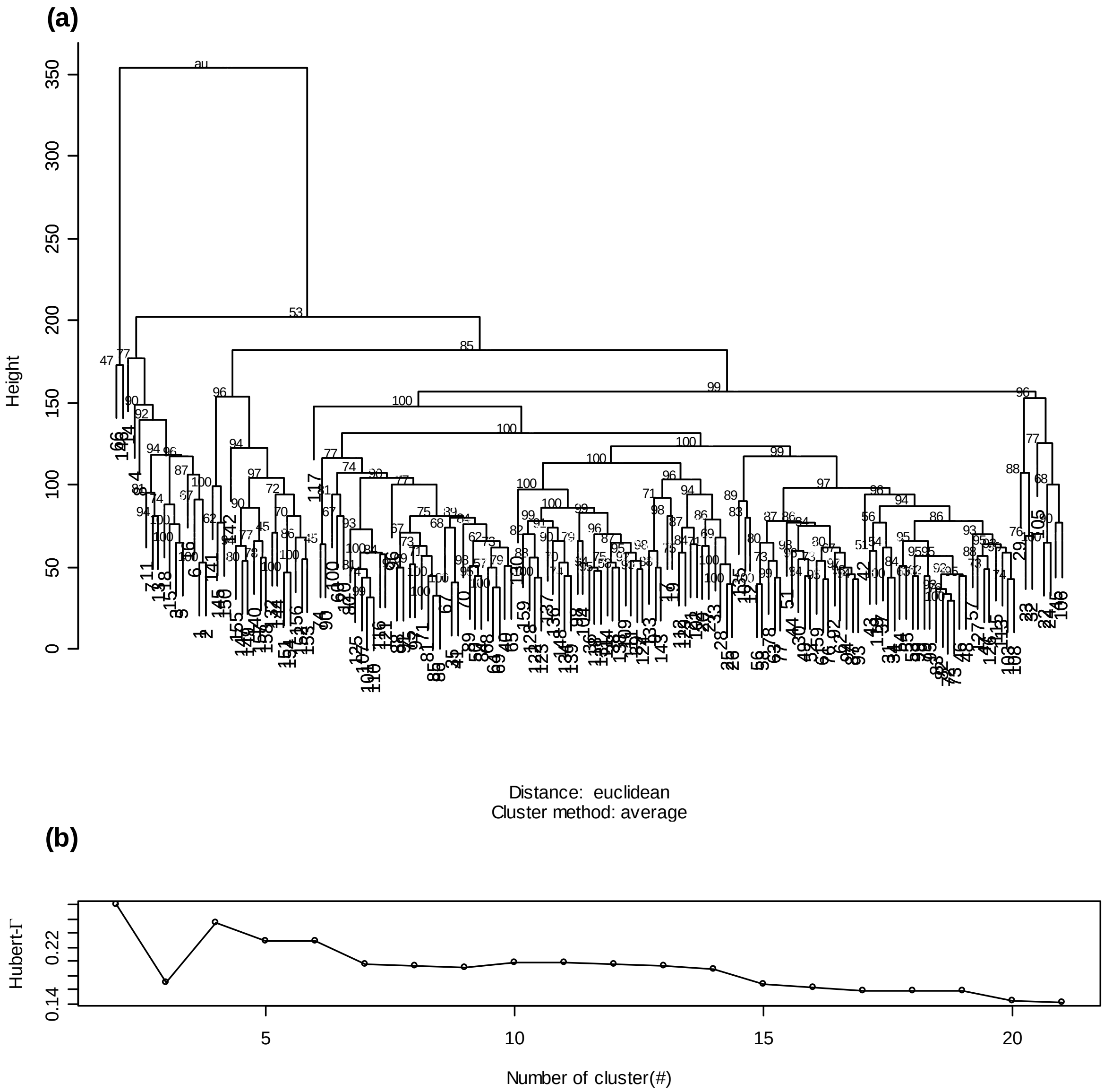


Figure 12-5: (a) Results of bootstrapping procedure for participant KE. (b) Hubert-Γ scores of clustering for participant KE.

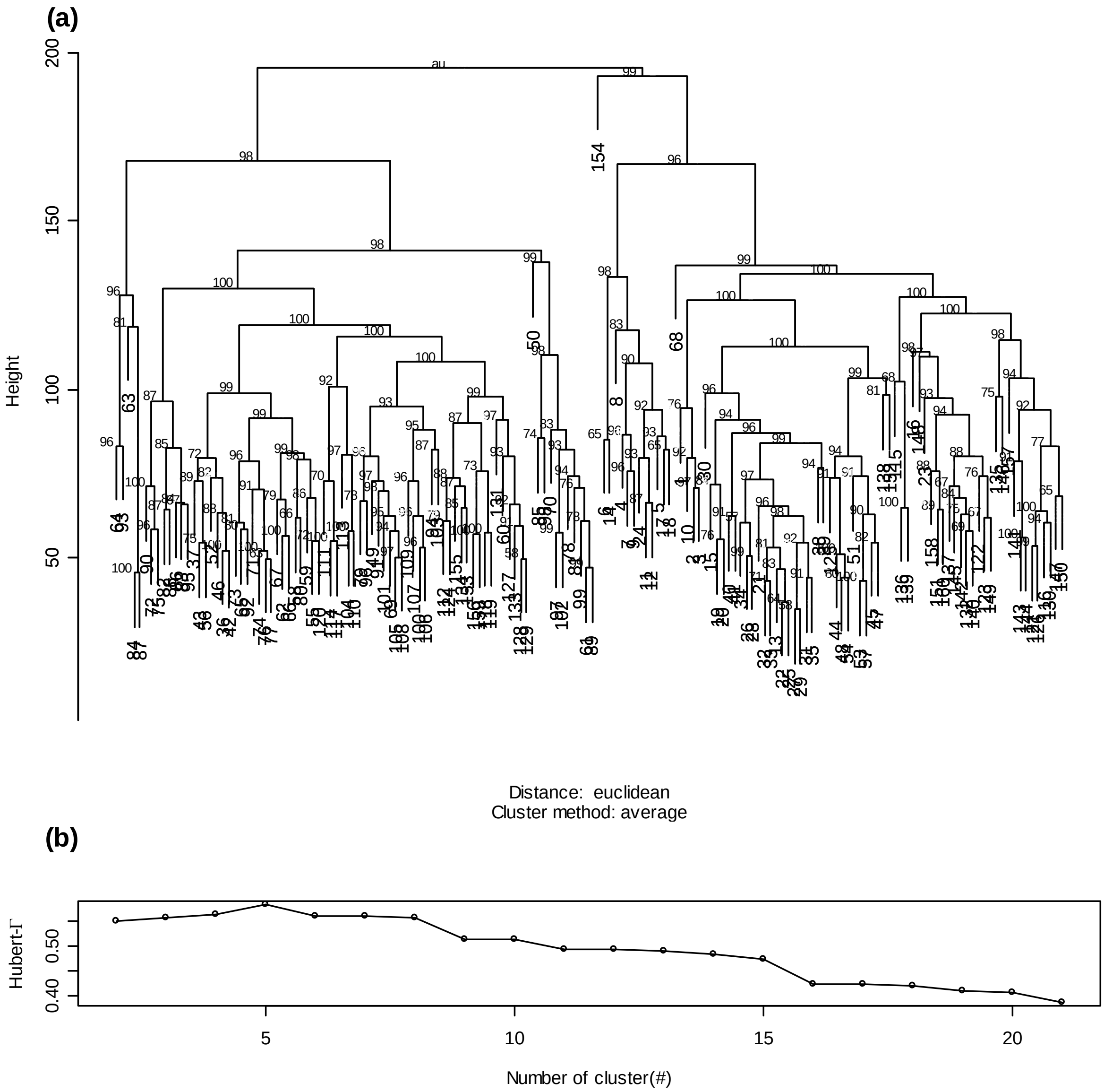
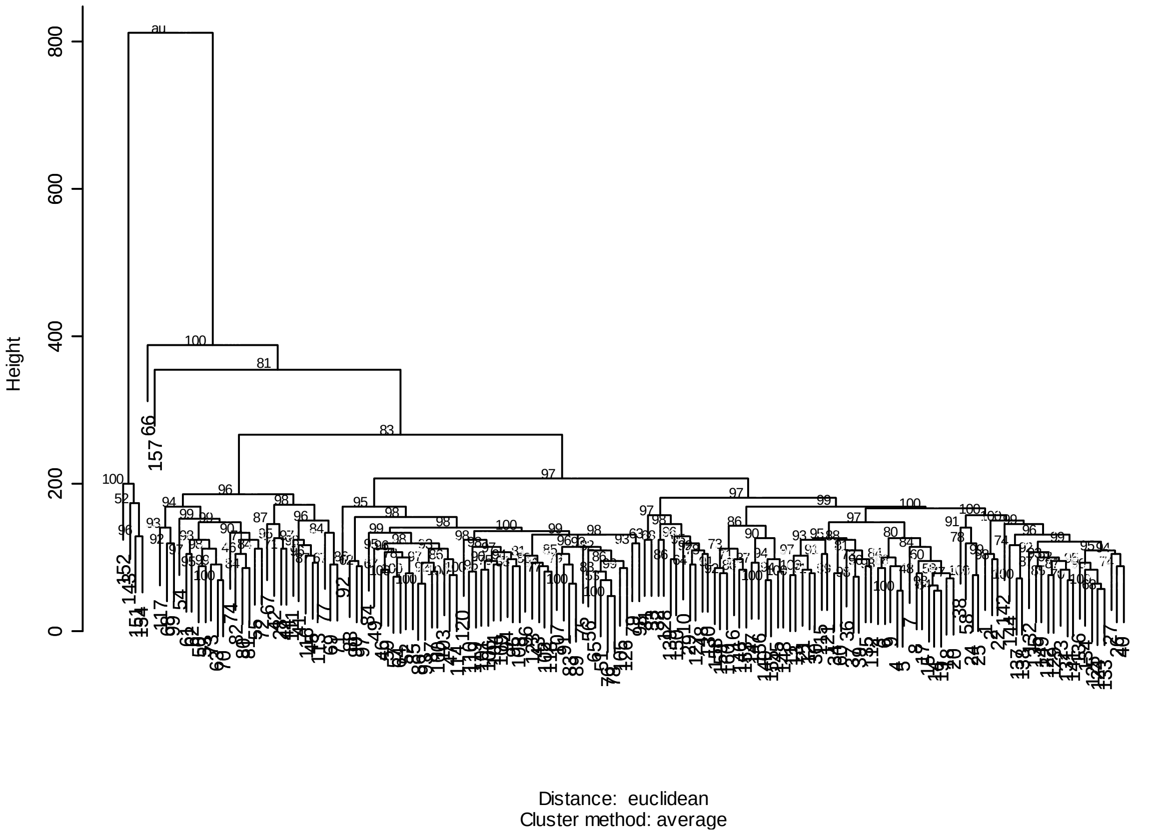


Figure 12-6: (a) Results of bootstrapping procedure for participant NI. (b) Hubert-Γ scores of clustering for participant NI.

(a)



(b)

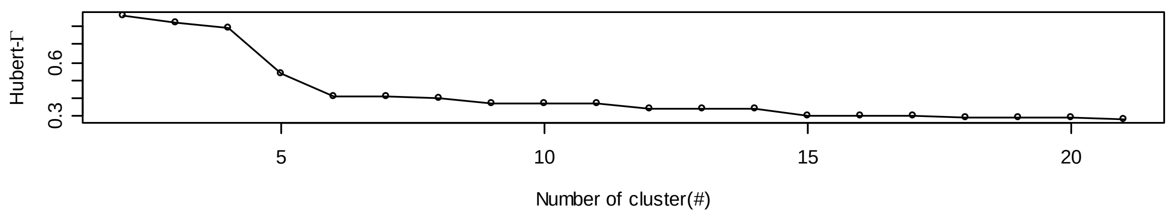


Figure 12-7: (a) Results of bootstrapping procedure for participant RY. (b) Hubert-Γ scores of clustering for participant RY.

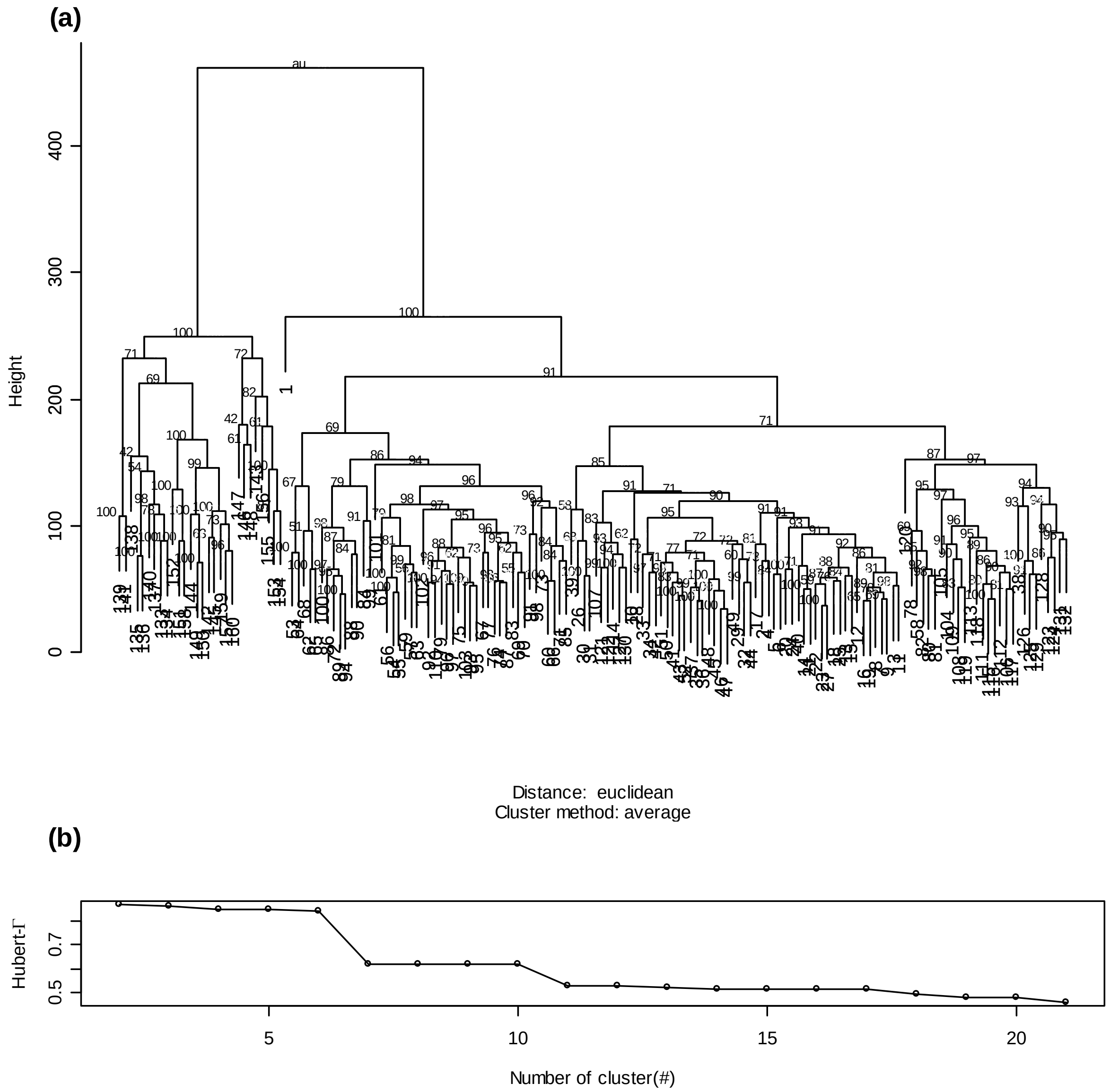


Figure 12-8: (a) Results of bootstrapping procedure for participant SH. (b) Hubert-Γ scores of clustering for participant SH.

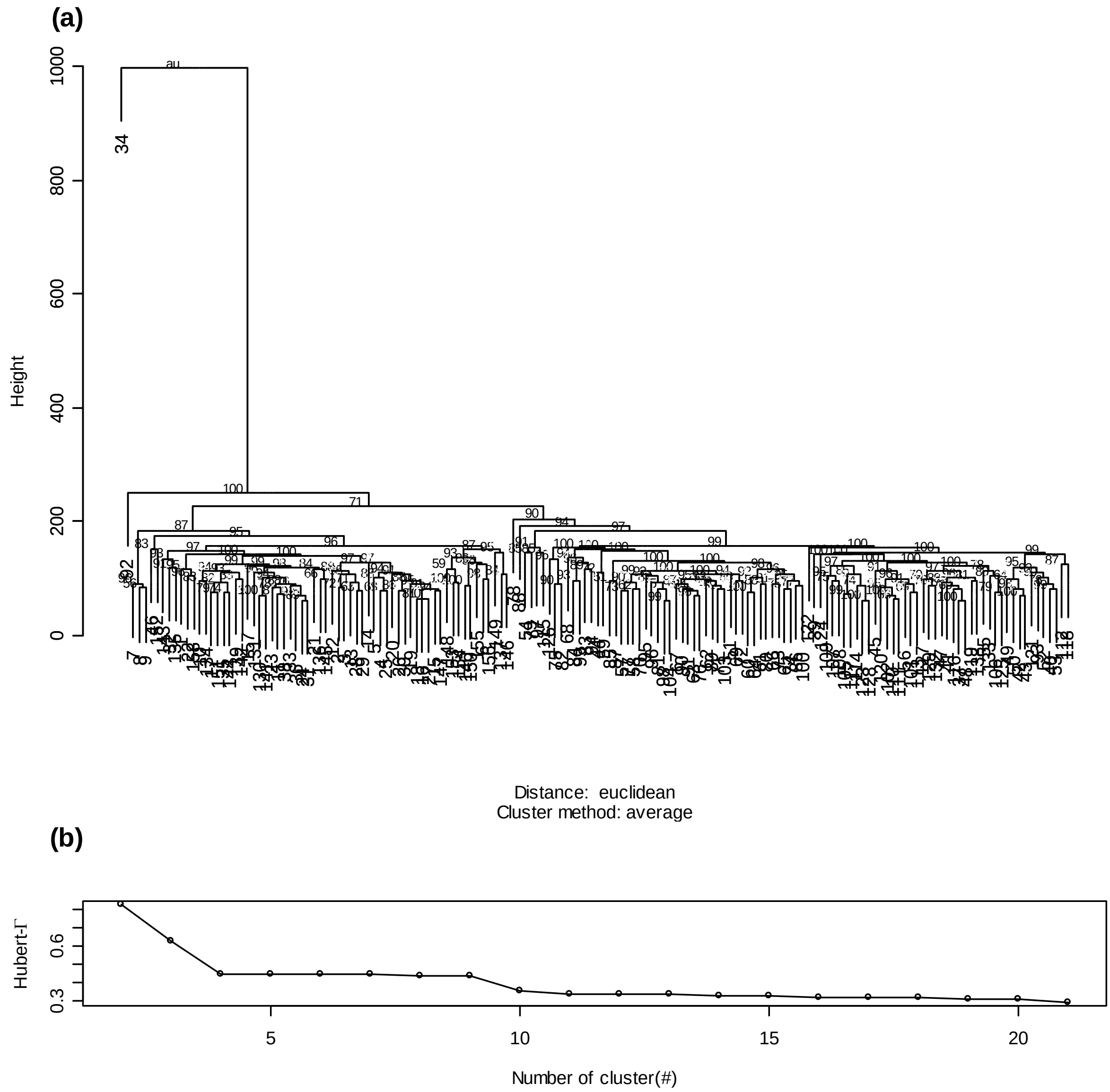


Figure 12-9: (a) Results of bootstrapping procedure for participant AN. (b) Hubert-Γ scores of clustering for participant AN.

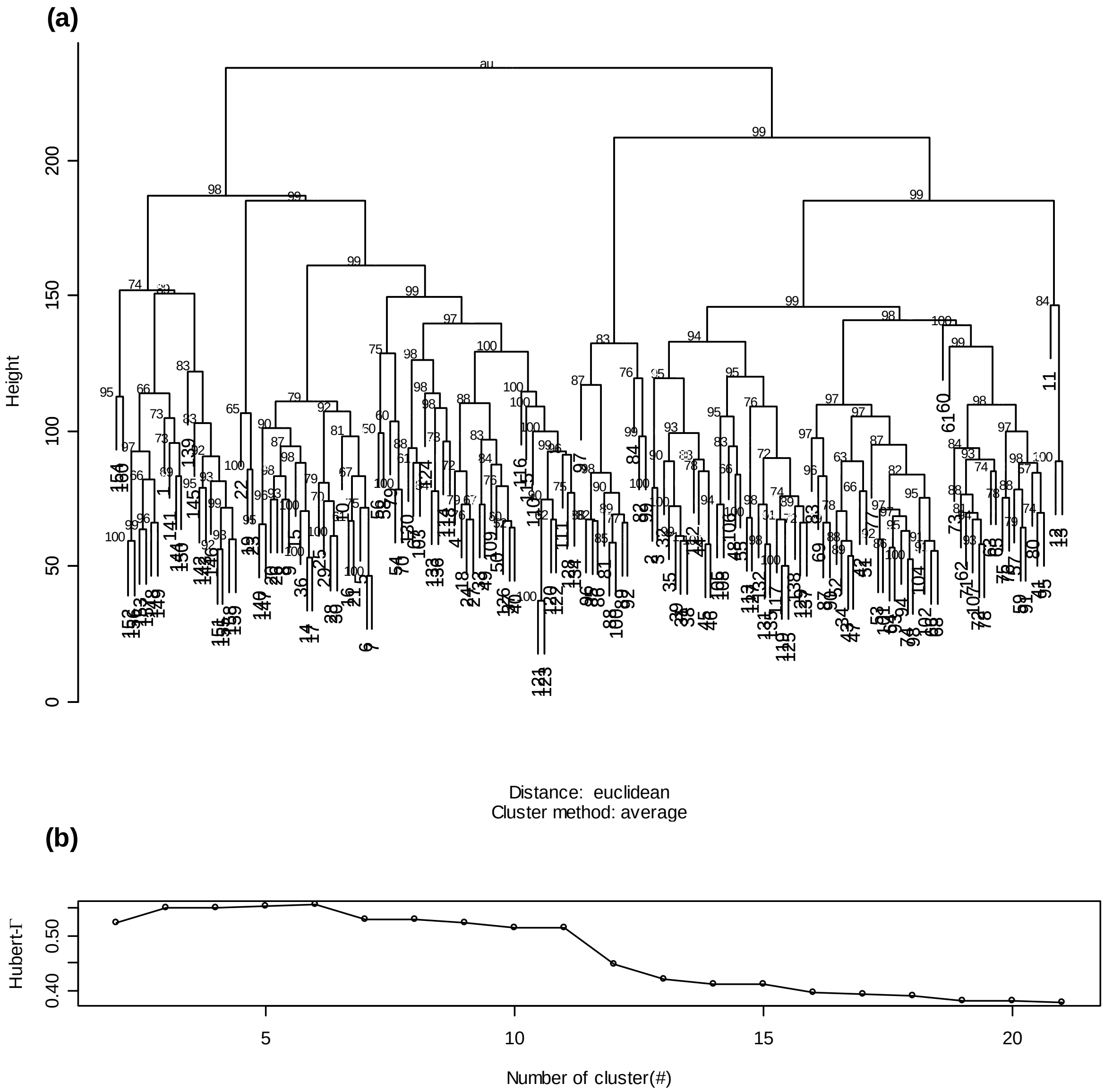


Figure 12-10: (a) Results of bootstrapping procedure for participant CAL. (b) Hubert-Γ scores of clustering for participant CAL.

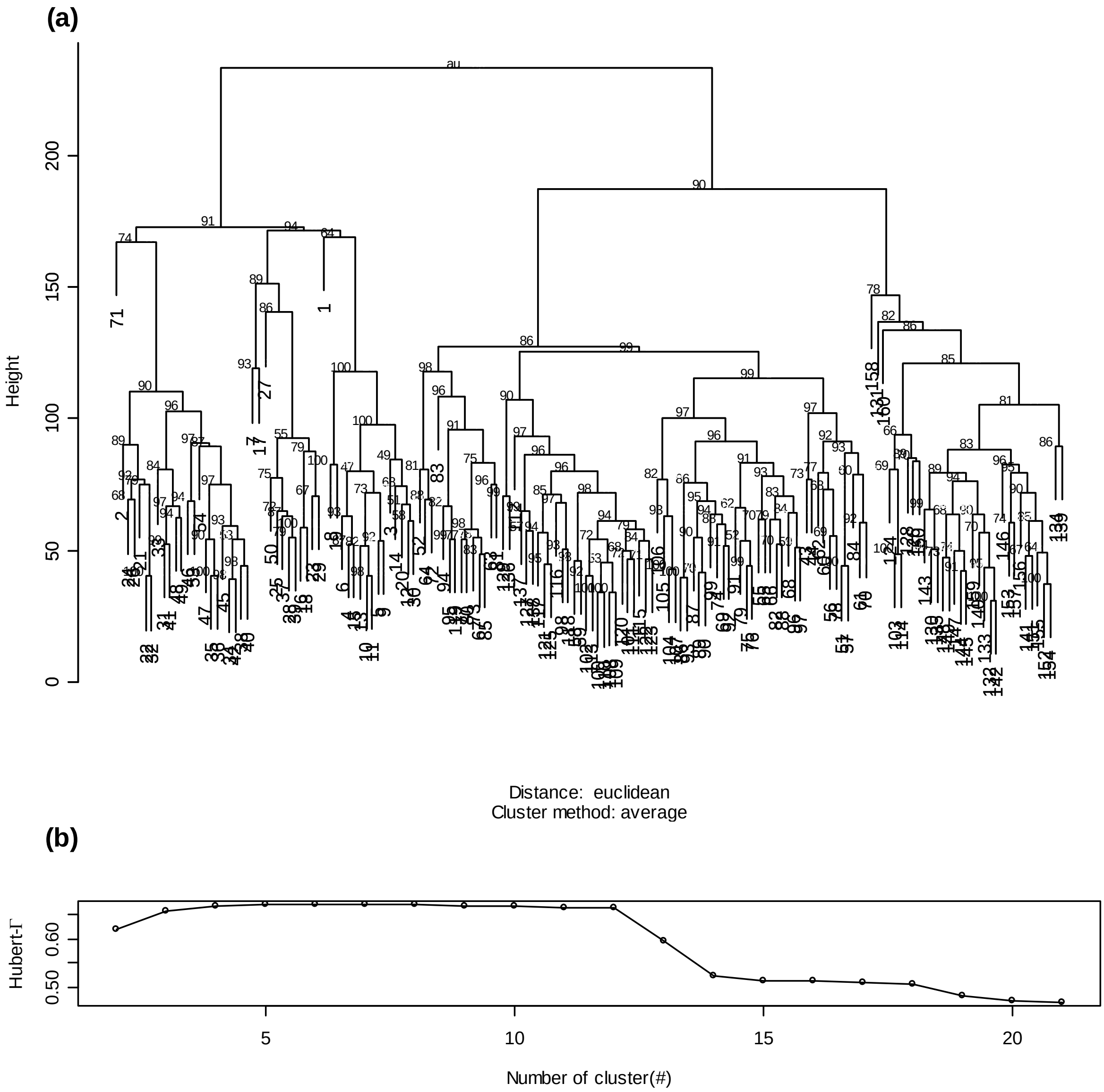
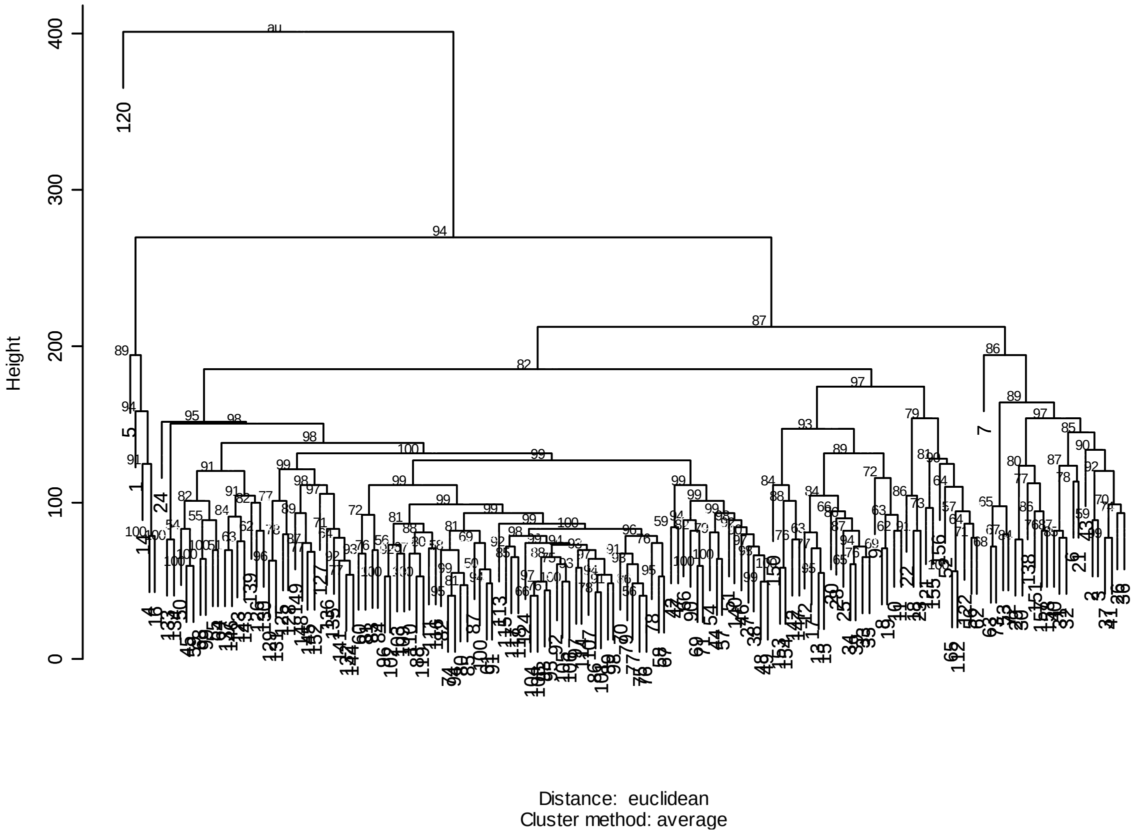


Figure 12-11: (a) Results of bootstrapping procedure for participant CR. (b) Hubert-Γ scores of clustering for participant CR.

(a)



(b)

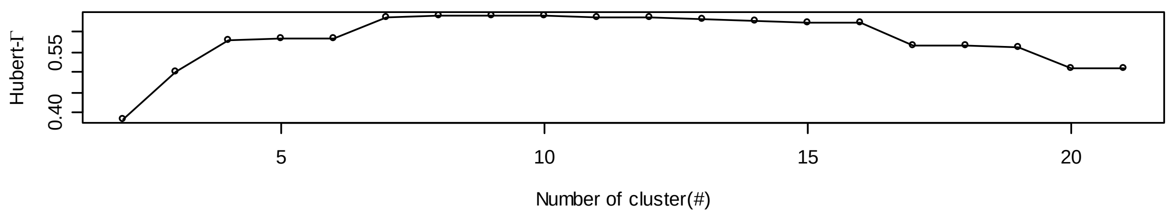


Figure 12-12: (a) Results of bootstrapping procedure for participant MI. (b) Hubert-Γ scores of clustering for participant MI.