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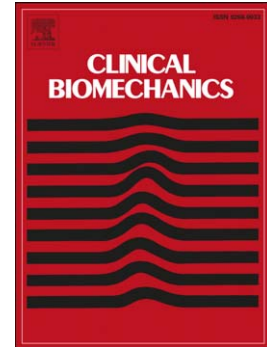
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On the use of continuous relative phase: Review of current approaches and outline for a new standard

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Abstract

In this paper we review applications of continuous relative phase and commonly reported methods for calculating the phase angle. Signals with known properties as well as empirical data were used to compare methods for calculating the phase angle. Our results suggest that the most valid, robust and intuitive results are obtained from the following steps: 1) centering the amplitude of the original signals around zero, 2) creating analytic signals from the original signals using the Hilbert transform, 3) calculating the phase angle using the analytic signal and 4) calculating the continuous relative phase. The resulting continuous relative phase values are free of frequency artifacts, a problem associated with most normalization techniques, and the interpretation remains intuitive. We propose these methods for future research using continuous relative phase in studies and analyses of human movement coordination.

Keywords: Phase angle, Continuous relative phase, Normalization, Gait data, Coordination, Movement variability

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1 **1. Introduction**

2 Within sports and health science, the biomechanical study of human move-
3 ment has many purposes; these include, but are not limited to, rehabilitation, in-
4 jury prevention and sports performance analysis. A common challenge for all of
5 these domains is simplifying the high-dimensional information available from 2D
6 video analysis, 3D motion capture systems or other modes of kinematic data col-
7 lection. Dynamical systems theory approaches to movement analysis have gained
8 support in recent years because it provides a theoretical framework for simplifying
9 and working with complex systems (see, e.g. Kelso, 1995). Dynamical systems
10 can be composed of many parts interacting and their behavior may often be de-
11 scribed by a single low-dimensional term or measure. Most human movements
12 involve a great number of moving parts, all coordinated together, explaining why
13 so many researchers and clinicians have put such effort into modeling the human
14 movement system as a dynamical system (e.g. Davids et al., 2003; Glazier &
15 Davids, 2009; Stergiou, 2004). For example, in locomotion the lower extremity
16 segments can be treated as a coupled system and the interaction of the segments
17 acts to effectively displace the body's position during locomotion. By treating the
18 musculoskeletal system as a system evolving over time, rather than focusing on
19 particular events, a much richer description of the interaction of the individual and
20 their environment can be achieved (Barela et al., 2000).

21 Rosen (1970) is often cited for suggesting that the behavior of a dynamical sys-
22 tem can be described by plotting a variable versus its first derivative – these plots
23 are commonly called phase portraits and provide qualitative utility in analyzing
24 human movement (Bartlett & Bussey, 2012; Beek & Beek, 1988). According to

25 Clark et al. (1993), the phase portraits of the shank and thigh are similar to a limit
26 cycle system – their coordination is cyclic and dissipative and therefore energy
27 must be supplied to continue the behavior. Accordingly, their relation in phase
28 space, or *relative phase*, can describe the dynamic coordination of these variables.
29 Continuous relative phase is a measure, which describes the phase space relation
30 between two segments (modeled as pendula) as it evolves throughout the move-
31 ment, which makes continuous relative phase an attractive and popular collective
32 variable for inter- and intra-limb coordination.

33 A central goal in dynamical systems theory is to identify the attractors, or sta-
34 ble states, of the system. Identifying stable states goes beyond simply identifying
35 the common coordinative states for a particular movement; analysis of the vari-
36 ability of continuous relative phase allows one to investigate the stability of the
37 system, or its resiliency to perturbation. Kelso (1995) noted that when coordina-
38 tion is perturbed beyond stability the relative phase pattern will fluctuate, indicated
39 by an increase in variability, before settling on a new stable pattern. Analyses of
40 the variability of continuous relative phase are insightful tools for understanding
41 the dynamics of higher order coordination. Therefore, the importance of a valid,
42 robust method for calculating phase angles, to be sure that the signal of interest
43 is measured without contamination from frequency artifacts, should be clear and
44 will be addressed in this paper.

45 Both the wide ranging applications of continuous relative phase as well as
46 the varying methods used in its calculation warrant an in-depth overview and dis-
47 cussion of its application, calculation and interpretation. This paper provides an
48 overview of the use of continuous relative phase in sport and health science before
49 comparing the approaches that have been taken in the literature for its calculation.

50 We demonstrate the prominent procedures in the literature using synthetic and em-
51 pirical data and outline what we suggest to be the new methodological standard
52 for continuous relative phase in sports and health science.

53 **2. Calculating Continuous Relative Phase**

54 Continuous relative phase is a new signal generated representing the difference
55 in phase angles of the two original signals. For the calculation of phase angles
56 two different methods have commonly been used in studies of human movement.
57 Firstly, continuous relative phase between two signals can be calculated based on
58 phase portraits (Burgess-Limerick et al., 1993; Hamill et al., 1999) and, secondly,
59 relative phase between two signals can be calculated using analytic signals gener-
60 ated by the Hilbert transform (Lamothe et al., 2009; Palut & Zanone, 2005). In the
61 following two subsections we describe these methods in detail.

62 *2.1. Phase Portraits*

63 Studies of human movement coordination are often grounded in dynamical
64 systems theory; therefore, system components can be assigned to a phase space in
65 which each state of the dynamical system is described by certain properties. Per-
66 taining to continuous relative phase analyses, the phase space usually consists of
67 the measured (time dependent) signal $x(t)$ and its velocity $\dot{x}(t)$, the first derivative
68 of the signal. The measured signal used in phase portraits is most often a segment
69 or joint angle, although others have used higher derivatives to construct the phase
70 space (Wagenaar & van Emmerik, 2000). To calculate the phase angle, frequency
71 effects of the phase portrait on the phase angle are reduced by normalization meth-
72 ods.

73 Before introducing normalization methods we should first distinguish between
 74 analyzing sinusoidal signals and non-sinusoidal signals. Sinusoidal (harmonic)
 75 signals are signals which can mathematically be described by a sine wave, for
 76 example, the signal

$$x(t) = A \sin(\omega t + \psi) + d, \quad (1)$$

77 where ω denotes the frequency, ψ denotes a constant shift along the x-axis, A is a
 78 constant describing the magnitude of the amplitude, and d is a constant which
 79 describes a shift along the y-axis. Non-sinusoidal (non-harmonic) signals are
 80 those which cannot be mathematically described by only a sine wave (such as
 81 in equation 1). For each of these types of signals there are some commonly used
 82 normalization techniques.

83 In order to analyze a sinusoidal signal, Fuchs et al. (1996) showed that the
 84 phase portrait should be normalized so that the resulting trajectory in phase space
 85 is circular and centered around the origin of the phase space. To achieve the cir-
 86 cularity they showed that the $\dot{x}(t)$ axis of the signals should be normalized by
 87 multiplying the $\dot{x}(t)$ axis by the factor $\frac{1}{\omega}$: the inverse of the signal's frequency.
 88 Furthermore, in case a sinusoidal oscillator is described by equation 1 with $d \neq 0$
 89 the oscillator must be shifted by $-d$, so that the phase portrait is centered around
 90 the origin of the $x\dot{x}$ phase space. This ensures that phase portraits of different si-
 91 nusoidal signals $x_1(t)$ and $x_2(t)$ are comparable and hence avoid artifacts caused
 92 by frequencies and/or different shifts d_1 and d_2 . To calculate phase angles, the
 93 displacement of sinusoidal data does not need to be normalized because the phase
 94 angle ϕ of a sinusoidal oscillator (for simplicity we assume $d = 0$) does not influ-

95 ence the calculation of ϕ

$$\begin{aligned}
 96 \quad \phi &= \arctan\left(\frac{\dot{x}(t)}{x(t)}\right) \\
 97 \quad &= \arctan\left(\frac{\omega A \cos(\omega t + \psi)}{A \sin(\omega t + \psi)}\right) \\
 98 \quad &= \arctan\left(\frac{\omega \cos(\omega t + \psi)}{\sin(\omega t + \psi)}\right) \quad (2) \\
 99
 \end{aligned}$$

100 To analyze non-sinusoidal signals, different normalization methods have been
 101 used. The goal of normalizing the data has been to transform the phase portraits in
 102 such a way that both displacement of the signal and its first derivative are limited
 103 to the range between -1 and 1. In this paper we used the two most frequently used
 104 methods (similar to those reported by Kurz & Stergiou (2002)). First, normaliza-
 105 tion is accomplished for any input signal $y(t)$ by the function

$$f(y(t_i)) = \frac{y(t_i)}{\max(|y(t)|)}. \quad (3)$$

106 This technique limits the input signal of the function to either -1 or 1 depending on
 107 the maximum absolute value of $y(t)$. This method is often used for velocity nor-
 108 malization because the zero value has qualitative meaning and, arguably, should
 109 be preserved. In other words, after normalization the zero value represents the
 110 zero value in the original signal. A second normalization technique is based on
 111 the function

$$g(y(t_i)) = 2 \left(\frac{y(t_i) - \min(y(t))}{\max(y(t)) - \min(y(t))} \right) - 1. \quad (4)$$

112 This function transforms the original values $y(t)$ in such a way that the minimum
 113 value of $g(y(t))$ equals -1 and the maximum value of $g(y(t))$ equals 1. Here the

114 zero value is midway between the maximum and minimum and can, therefore,
 115 be arbitrary. Since angle definitions can be arbitrary, the method in equation 4
 116 has often been used for normalizing joint or segment angles. We summarize the
 117 normalization methods found in the literature as follows:

- 118 • **Method A** uses equation 4 to normalize the joint angular displacement and
 119 equation 3 to normalize the angular velocities (Barela et al., 2000; Burgess-
 120 Limerick et al., 1993; Dierks & Davis, 2007; Hamill et al., 1999; Heider-
 121 scheit et al., 1999; Hein et al., 2012; Li et al., 1999; Miller et al., 2008, 2010;
 122 Stergiou et al., 2001a,b; Yen et al., 2009).
- 123 • **Method B** uses equation 4 for both angular displacement and angular ve-
 124 locity normalization (Figueiredo et al., 2012; Haddad et al., 2010; Kwakkel
 125 & Wagenaar, 2002; Lamothe et al., 2002; Meyns et al., 2013; Selles et al.,
 126 2001; van Emmerik & Wagenaar, 1996).

127 After normalization, the phase angle of the signal at time t_i is calculated based
 128 on the normalized phase portrait (Barela et al., 2000; Li et al., 1999; Peters et al.,
 129 2003)

$$\phi(t_i) = \arctan\left(\frac{\dot{x}_{\text{norm}}(t_i)}{x_{\text{norm}}(t_i)}\right). \quad (5)$$

130 Finally, the continuous relative phase, $\text{crp}(t_i)$, at time t_i between two signals $x_1(t)$
 131 and $x_2(t)$ is calculated as

$$\begin{aligned} \text{crp}(t_i) &= \phi_1(t_i) - \phi_2(t_i) \\ &= \arctan\left(\frac{\dot{x}_{1,\text{norm}}(t_i)x_{2,\text{norm}}(t_i) - \dot{x}_{2,\text{norm}}(t_i)x_{1,\text{norm}}(t_i)}{x_{1,\text{norm}}(t_i)x_{2,\text{norm}}(t_i) + \dot{x}_{1,\text{norm}}(t_i)\dot{x}_{2,\text{norm}}(t_i)}\right). \end{aligned} \quad (6)$$

135 2.2. *The Hilbert transform*

136 Phase angles can also be calculated based on a measured signal $x(t)$ and its
 137 Hilbert transform $H(t) = H(x(t))$. The Hilbert transform allows the transforma-
 138 tion of any real signal into a complex, analytic signal $\zeta(t)$ Gabor (1946) defined
 139 as

$$\zeta(t) = x(t) + iH(t) \quad (7)$$

140 where the Hilbert transform $H(t)$ of $x(t)$ serves as the imaginary part of the an-
 141 alytic signal¹. Based on the complex signal the phase angle at time t_i can be
 142 calculated by

$$\phi(t_i) = \arctan\left(\frac{H(t_i)}{x(t_i)}\right). \quad (8)$$

143 The continuous relative phase $\text{crp}(t)$ between two signals $x_1(t)$ and $x_2(t)$ can
 144 be computed, first by transforming these signals into analytic signals using the
 145 Hilbert transform, then by subtracting the phase angles from each other. For ex-
 146 ample, the continuous relative phase for the two signals at time t_i is

$$\begin{aligned} \text{crp}(t_i) &= \phi_1(t_i) - \phi_2(t_i) \\ &= \arctan\left(\frac{H_1(t_i)x_2(t_i) - H_2(t_i)x_1(t_i)}{x_1(t_i)x_2(t_i) + H_1(t_i)H_2(t_i)}\right), \end{aligned} \quad (9)$$

150 where $H_1(t)$ and $H_2(t)$ denote the Hilbert transform of each signal, respectively.

151 In the next section we demonstrate with simulated data as well as kinematic

¹In general, the Hilbert transform is considered a convolution of a function (signal) in the time domain. The Hilbert transform needs to be defined using the Cauchy principle value so that the integral converges and thus exists. As an integral, the Hilbert transform can be solved in the time domain. There are many methods for calculating the Hilbert transform; many software applications, such as MATLAB, calculate the Hilbert transform in the frequency domain using the (Fast) Fourier transform and its inverse.

152 data, the effect of the normalization methods A and B and the Hilbert transform
153 on continuous relative phase values. To aid interpretation, whenever possible, we
154 use modeled data which has been reported previously in the literature.

155 **3. Modeled Data**

156 *3.1. Sinusoidal oscillators*

157 In this section we begin with simple sinusoidal examples to demonstrate the
158 effect of various normalization techniques. Therefore, we calculated the continu-
159 ous relative phase for all testing cases using phase angles which were calculated
160 based on: a) not normalizing the original data at all, b) normalizing velocity using
161 the technique shown by Fuchs et al. (1996), and c) creating analytic signals using
162 the Hilbert transform. These procedures are approximate reproductions of those
163 shown in Peters et al. (2003), with the addition of the Hilbert transform method.

164 *3.1.1. Example 1: two sinusoidal signals with the same frequency, shifted hori- 165 zontally*

166 Figure 1 illustrates a sinusoidal oscillator $x(t) = \sin(2t)$, $t \in [0, 2\pi]$, and the
167 same sinusoidal oscillator shifted by 18° , the corresponding $x\dot{x}$ phase portraits,
168 and a plot visualizing the continuous relative phase between these two oscillators
169 calculated using different techniques. In this example the velocity of the two os-
170 cillators was normalized with respect to the frequency, $\omega = 2$, of the sinusoidal
171 oscillator through the factor $\frac{1}{2}$. Note that in the right panel of Figure 1 the Hilbert
172 transform is not shown because the transformed values lie in the complex plane
173 rather than the phase plane in which the original and normalized values are lo-
174 cated.

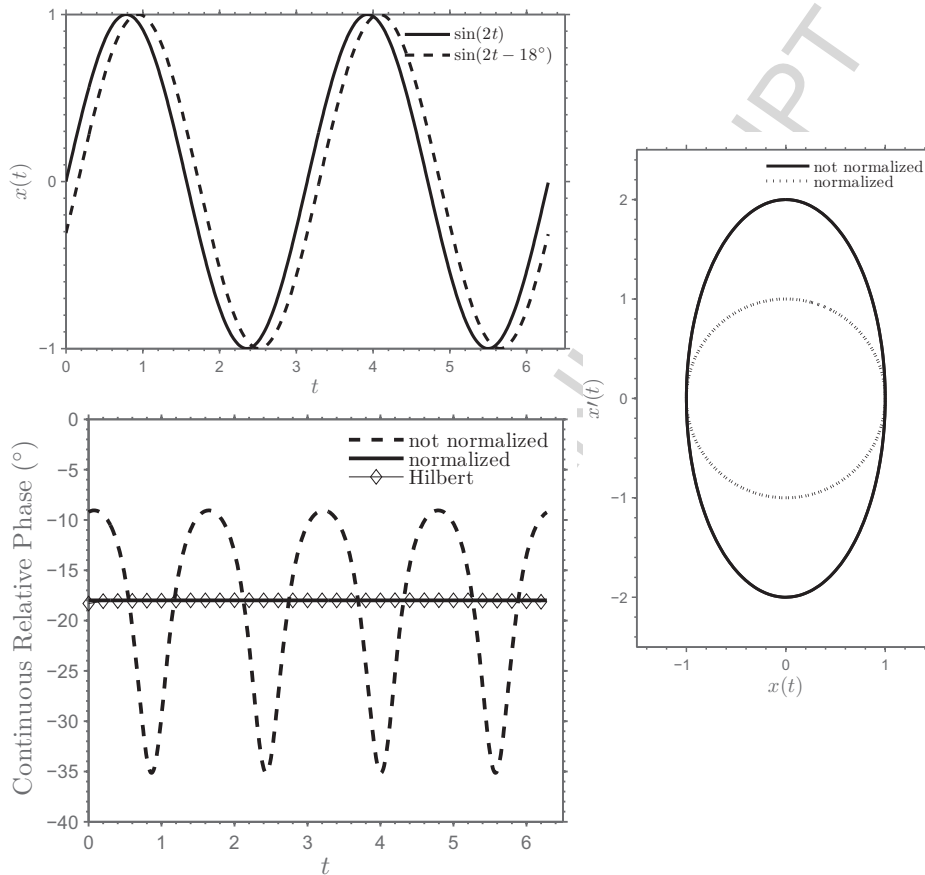


Figure 1: Two sinusoidal signals, one phase shifted by 18° (top left), the phase portraits for both signals (right) and the corresponding continuous relative phase calculated with: no normalization, with frequency normalization and the Hilbert transform (bottom left).

175 The continuous relative phase calculated based on non-normalized data (Fig. 1,
 176 bottom left, dashed line) shows oscillating behavior about a constant continuous
 177 relative phase, even though the two oscillators behave equally only phase shifted
 178 by 18° . One would expect the continuous relative phase of these two oscillators
 179 to be constant and equal to 18° ; the oscillating behavior of the continuous rela-
 180 tive phase of the non-normalized data represent frequency artifacts (Fuchs et al.,
 181 1996; Peters et al., 2003). This is made clear by the continuous relative phase

182 values which were calculated based on frequency normalized velocities. The re-
 183 sulting continuous relative phase is constant and shows exactly the 18° difference
 184 between the two oscillators. Finally, we calculated continuous relative phase us-
 185 ing the Hilbert transform based on the raw sinusoidal data. The resulting plot
 186 (Fig. 1, bottom left) also shows the expected constant difference of 18° between
 187 the two oscillators.

188 3.1.2. Example 2: two sinusoidal signals with different frequencies

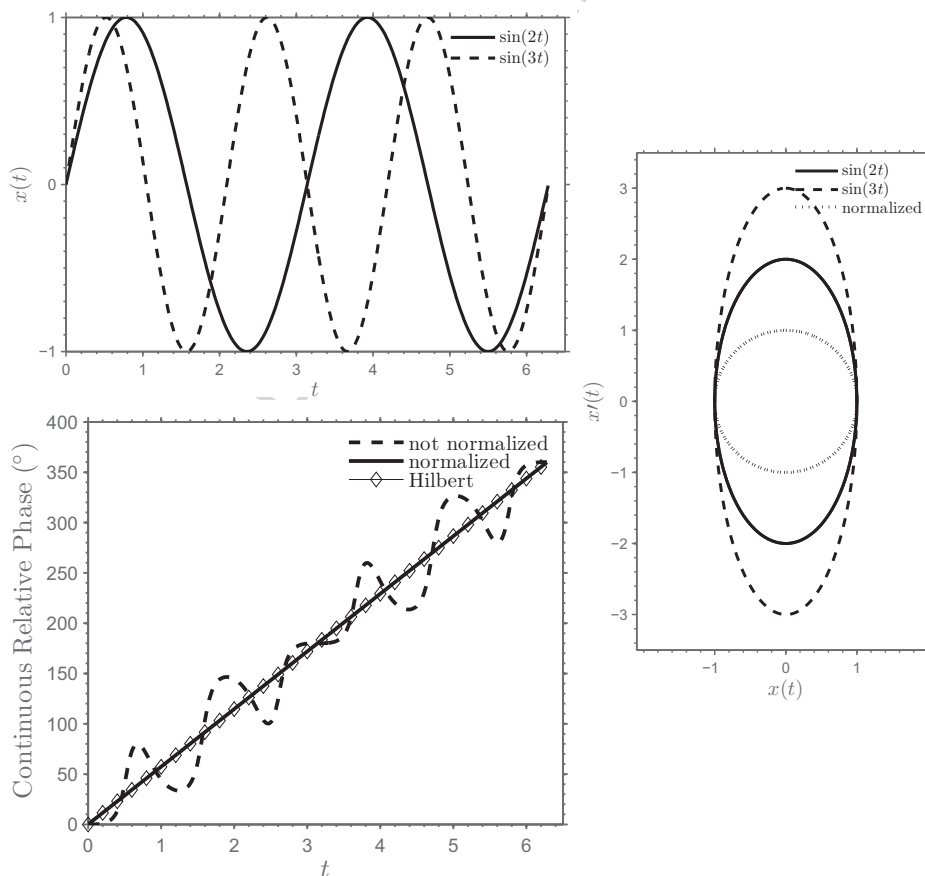


Figure 2: Two sinusoidal signals with different frequencies (top left), the phase portraits for both signals (right) and the corresponding continuous relative phase calculated with: no normalization, with frequency normalization and Hilbert transformation (bottom left).

189 Here we compare continuous relative phase calculations between two sinu-
190 soidal oscillators with different frequencies. The two oscillators are represented
191 by $x_1(t) = \sin(2t)$ and $x_2(t) = \sin(3t)$, respectively. Figure 2 shows the two os-
192 cillators each within the interval $t \in [0, 2\pi]$, their respective phase portraits, and
193 a plot containing continuous relative phase values. The velocities of the two os-
194 cillators were normalized each by the inverse of the respective frequency $\frac{1}{\omega}$ (as in
195 the previous example (Fuchs et al., 1996)).

196 As already shown by Peters et al. (2003), continuous relative phase calculated
197 based on non-normalized data shows a fluctuating pattern (Fig. 2, bottom left,
198 dashed line); this can again be explained by frequency artifacts (Fuchs et al., 1996;
199 Peters et al., 2003). After normalizing the velocities of the two oscillators, each
200 with respect to its frequency, the continuous relative phase shows the expected
201 pattern. The oscillators move linearly from in-phase to anti-phase and eventually
202 back into in-phase during the respective time period $[0, 2\pi]$. Finally, we calculated
203 continuous relative phase values using Hilbert transform based on the raw data.
204 The resulting continuous relative phase values show the same linear pattern as the
205 continuous relative phase values calculated based on normalized phase portraits.

206 3.2. *Non-sinusoidal signals*

207 In this section we compare the different methods for calculating continuous
208 relative phase with respect to non-sinusoidal signals. The term non-sinusoidal can
209 describe different kinds of data; thus we first distinguish between non-sinusoidal
210 signals which are based on a mathematical description and empirical data. A
211 mathematical description of a signal usually relies on a modeling process. The
212 models are either the combination of basic functions like the signal in equation 10
213 or can be systems of differential equations (c.f. HKB model; Haken et al., 1985;

214 Kelso, 1984). Empirical data representing human movement is not mathemati-
 215 cally described by functions, they are most often time series data, for example,
 216 kinematic joint angles (see section 4.1).

217 We compared continuous relative phase calculations using different techniques
 218 for both functional and experimental non-sinusoidal data. Continuous relative
 219 phase values were calculated and compared to each other based on phase angles
 220 calculated based on a) not normalizing the original data at all, b) normalizing data
 221 using the normalization methods A and B, and c) creating analytic signals using
 222 the Hilbert transform.

223 3.2.1. Example 4: two non-sinusoidal signals

224 This example is based on non-sinusoidal data which are represented by the
 225 function

$$x(t) = \frac{\cos(t - 0.25\pi)}{\sqrt{1 + 0.41418^2 - 2 \times 0.41418 \sin(t - 0.25\pi)}} \quad (10)$$

226 which is similar to the non-sinusoidal signal in Peters et al. (2003). In this section,
 227 continuous relative phase values between a signal modeled by equation 10 for
 228 $t \in [0, 2\pi]$ and the same signal shifted by 126° are compared. Figure 3 shows the
 229 two signals, their respective phase portraits, and continuous relative phase values
 230 calculated using the different techniques mentioned above.

231 Since the signals in Figure 3 are shifted but have the same frequency, nei-
 232 ther signal will ever *catch up* to the other so that they are in-phase. In section
 233 3.1.1 the two shifted sine waves had a constant continuous relative phase once
 234 the frequency artifacts were removed. Because the signals in Figure 3 are non-
 235 sinusoidal they are constantly increasing and decreasing their phase shift of 126° ;
 236 therefore, the expected behavior of their continuous relative phase should fluctu-

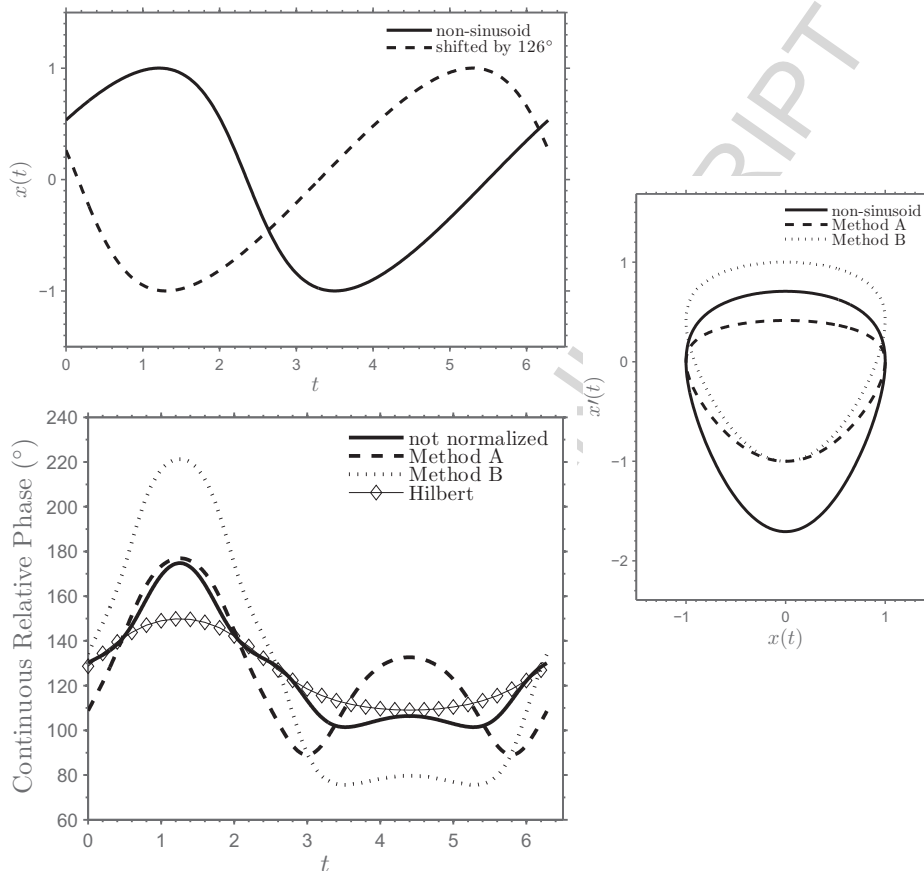


Figure 3: Two non-sinusoidal signals, one phase shifted by 126° (top left), the phase portraits for using different normalization methods (right) and the corresponding continuous relative phase diagrams (bottom left).

237 ate around 126° . The Hilbert transformed data show this behavior exactly, the
 238 non-normalized continuous relative phase values resemble those of the Hilbert
 239 transform most closely, although artifacts of the non-circular phase portrait are
 240 evident. The normalized continuous relative phase values show the greatest devi-
 241 ation from the Hilbert transformed values. This is because normalizing introduces
 242 artifacts when the original signal is non-sinusoidal (Kurz & Stergiou, 2002).

243 **4. Empirical Data**

244 *4.1. Example 5: kinematic data*

245 In this section the various methods for calculating phase angles are demon-
 246 strated using kinematic data representing hip-knee coupling during three strides
 247 of treadmill running.

248 The ranges of motion in Figure 4, on which the continuous relative phase cal-
 249 culations are based, were roughly between 152° and 195° for the hip and between
 250 66° and 164° for the knee. Since the joint angles are located in the top right quad-
 251 rant of the time domain plot (Fig. 4, top left), the analytic signals created by the
 252 Hilbert transform may only have positive real values. Hence, the two respective
 253 analytic signals are located in the right half of the complex plane. Consequently,
 254 the phase angles of these two signals are limited to the range $[-90^\circ, 90^\circ]$ at the
 255 most.

256 For this reason the trajectory of the signal should be transformed in such a way
 257 that it winds around the origin of the complex plane. Whereas Rosenblum et al.
 258 (2001) suggest transforming the signal by subtracting the mean value of the signal
 259 from the signal, we suggest centering the range of a signal's amplitude around
 260 zero by

$$x_{centered}(t_i) = x(t_i) - \min(x(t)) - (\max(x(t)) - \min(x(t)))/2, \quad (11)$$

261 and eventually calculating the analytic signal using the Hilbert transform based on
 262 $x_{centered}(t)$.

263 The resulting analytic signal will have the same imaginary component, which

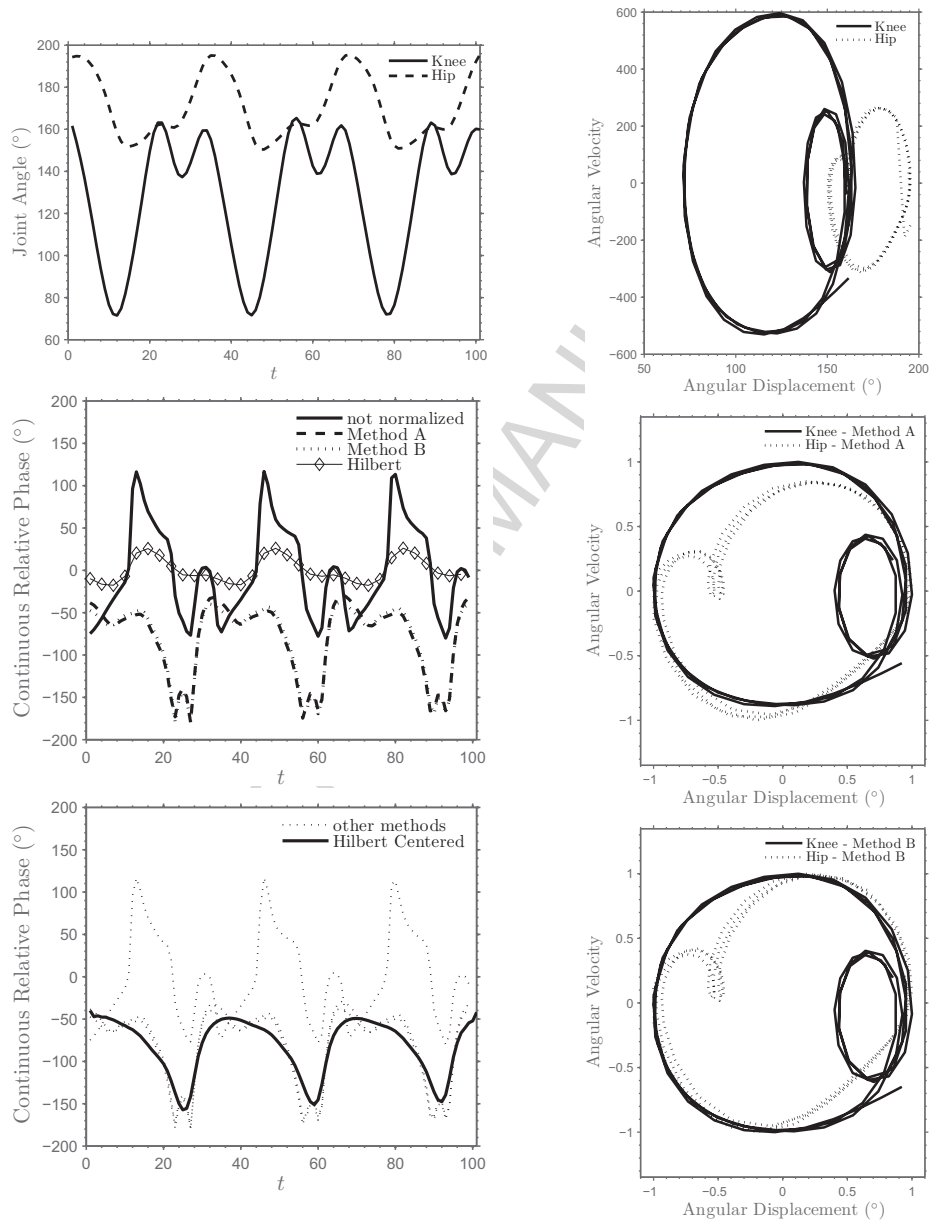


Figure 4: In the left panels, time domain plots of hip and knee joint angles for treadmill running (top), continuous relative phase values (middle) and the continuous relative phase values using the centered Hilbert transform (bottom; methods from the plot above are also included for reference). In the right panels, phase portraits for hip-knee coupling in treadmill running: without normalization (top), normalized according to Method A (middle) and Method B (bottom).

264 is determined by the Hilbert transform, as that of the raw data since

$$H(x(t) + c) = H(x(t)), \quad (12)$$

265 where c denotes a constant shift of the signal's amplitude (see appendix Appendix
266 A). This approach allows the resulting phase angle to have values in the range
267 $(-180^\circ, 180^\circ)$ (Fig. 4, bottom left).

268 5. Discussion

269 The purpose of this paper was to review applications of continuous relative
270 phase and commonly used methods for calculating the phase angle, address im-
271 portant points which have been discussed in the relevant literature and, based on
272 the results of our analyses, to propose a valid and robust method for calculating
273 the phase angle applicable to most research questions in sports and health science.
274 We have demonstrated the effect of different normalization techniques on the re-
275 sulting continuous relative phase values. Several other issues pertaining to the
276 interpretation of continuous relative phase are discussed in the following section.

277 5.1. Phase angle vs. continuous relative phase

278 Some debate has developed concerning the range used for continuous relative
279 phase and the phase angle (Hamill et al., 1999; Kurz & Stergiou, 2002; Wheat
280 et al., 2003). The arctan function outputs values in the range $(-\frac{\pi}{2}, \frac{\pi}{2})$, or in de-
281 grees, $(-180^\circ, 180^\circ)$. In terms of relative phase, for the range $[-180^\circ, 180^\circ]$ a
282 continuous relative phase value of 0° represents in-phase behavior and values of
283 -180° and 180° represent anti-phase behavior (Scholz & Kelso, 1989). Some
284 authors have chosen to use the absolute value of continuous relative phase values

285 (Hamill et al., 1999; Heiderscheit et al., 1999; van Emmerik & Wagenaar, 1996),
286 since the values -180° and 180° both indicate anti-phase behavior and by do-
287 ing so, the necessity for using directional statistics is alleviated (Sparto & Schor,
288 2004). Conversely, others have suggested that the positive and negative values
289 have qualitative meaning and should be preserved. If the phase angle of the prox-
290 imal segment is subtracted from the phase angle of the distal segment, then pos-
291 itive continuous relative phase values indicate that the distal segment is ahead of
292 the proximal segment in phase space (Barela et al., 2000; Clark & Phillips, 1993;
293 Hamill et al., 2000; Kao et al., 2003; Kiefer et al., 2011; Kurz & Stergiou, 2002;
294 Yen et al., 2009), or the complex plane, and vice versa.

295 This seems to have highlighted a point of misunderstanding between the terms
296 *phase angle* and *continuous relative phase*. While continuous relative phase val-
297 ues may be manipulated into the range $[0^\circ, 180^\circ]$ for reasons mentioned above,
298 this should not be confused with defining the phase angle in the range $(0^\circ, 180^\circ)$
299 (Hamill et al., 1999; van Emmerik & Wagenaar, 1996) or even $[-90^\circ, 90^\circ] \setminus \{0^\circ\}$
300 (Kurz & Stergiou, 2002).

301 Wheat et al. (2003) showed that by defining the phase angle in a 180° range,
302 in their case $(0^\circ, 180^\circ)$, the subsequent continuous relative phase values are non-
303 intuitive. Therefore, we suggest defining the phase angle as that which is natu-
304 rally produced by the arctan function. For this reason we feel the need to em-
305 phasize that the phase angle and continuous relative phase cannot be used inter-
306 changeably. Phase angles should always be in the ranges $(-180^\circ, 180^\circ) \setminus \{0^\circ\}$
307 or $(0^\circ, 360^\circ) \setminus \{180^\circ\}$, while continuous relative phase may be expressed in the
308 ranges $[0^\circ, 180^\circ]$ or $[-180^\circ, 180^\circ]$ or $[0^\circ, 360^\circ]$.

309 *5.2. Joint vs. segment angles*

310 Many studies which have used continuous relative phase have used joint an-
311 gles as the original signals. The use of joint angles, however, is contradictory to
312 modelling the segments as pendula. Consider, for example, adjacent joint rela-
313 tionships such as the coupling of the hip and knee. To calculate phase angles from
314 the hip and knee joint angles, the thigh segment is included in both angles, and
315 consequently influences the phase angles for each joint. Calculating phase an-
316 gles in this way goes against the original interpretation under the dynamical sys-
317 tems framework, notably by Kugler et al. (1980) and by Clark & Phillips (1993)
318 specifically to gait. Only segment angles measured relative to an external refer-
319 ence frame allow meaningful and interpretable results that can be used to describe
320 phase relationships properly from a dynamical systems perspective.

321 *5.3. Maximum and minimum values*

322 Different methods for obtaining the maximum and minimum values used in
323 the normalization procedures (equations 3 and 4) have also been reported. This
324 pertains to whether the maximum value for each trial is used to normalize the
325 respective trial or whether the maximum value among a group of trials (e.g. a sin-
326 gles testing session) is used to normalize each trial (Hamill et al., 2000). Authors
327 seldom report exactly how they obtain the maximum and minimum values. As
328 Hamill et al. (2000) showed, when using phase space to calculate the phase angle,
329 the method for determining maximum and minimum values affects the contin-
330 uous relative phase calculation. One advantage of using the grouped approach
331 (i.e. maximum or minimum value from a group of trials) for normalizing is that
332 the trials being compared are scaled by a constant factor. However, rather than
333 discussing this issue further, as we have shown thus far, the (centered) analytic

334 signal based on the Hilbert transform provides the correct phase angle and, there-
335 fore, removes the need for normalization in order to fit the data into a unit phase
336 space.

337 *5.4. Inter- and intralimb couplings and normalization*

338 Initially, continuous relative phase was used as a higher resolution form of
339 discrete relative phase for assessing the coordination between two oscillating seg-
340 ments: often representing contralateral or interlimb coordination. For interlimb
341 coordination one might expect that the limb being compared could oscillate in
342 a near sinusoidal manner. For these situations the methods described by Fuchs
343 et al. (1996) may satisfy the assumption that the phase space spanned by the two
344 oscillators is circular and that the two oscillators are simply phase shifted. Fur-
345 thermore Varlet & Richardson (2011) demonstrated a method for dealing with
346 changes in frequency in interlimb coordination assumed to be sinusoidal (also
347 based on the Hilbert transform). However, the current paper focuses on whole-
348 body movements, for which continuous relative phase is most often used to repre-
349 sent intralimb coupling – or the coupling between adjacent joints. For questions
350 of intralimb coordination, one can safely assume that the time-series of joint an-
351 gles being compared are always non-sinusoidal (possibly with the exception of
352 isokinetic exercises). To be clear, if two joints both oscillate sinusoidally, their
353 continuous relative phase values throughout the measurement must be linear. If
354 the two signals have the same frequency, the continuous relative phase values
355 must be constant and equal to the phase shift (Fig. 1), and if the signals have
356 different frequencies, the continuous relative phase values must be linearly in-
357 creasing or decreasing depending on the frequency difference (Fig. 2). There can
358 be no way for continuous relative phase to fluctuate throughout the movement if

359 the joints oscillate sinusoidally and frequency artifacts have been removed. There-
360 fore, for research into intralimb coordination using continuous relative phase we
361 suggest using the amplitude centered Hilbert transform (as shown in Fig. 4) so
362 that changes in coordination throughout the movement may be exposed.

363 5.5. Normalization

364 We have identified two main methods for normalization, which have been used
365 to scale data to the unit phase space (Burgess-Limerick et al., 1993; Hamill et al.,
366 1999). Others have argued for no normalization in favor of maintaining the origi-
367 nal topology or aspect ratio of the data (Clark & Phillips, 1993; Kurz & Stergiou,
368 2002). While others have employed the Hilbert transform to create an analytic
369 signal (Lamoth et al., 2009; Palut & Zanone, 2005). In Section 3.1 we showed
370 that the scaling method of Fuchs et al. (1996) adequately transforms the data,
371 thus removing frequency artifacts from the continuous relative phase calculation.
372 However, since sinusoidal data does not arise from empirical measurements of hu-
373 man movement, the method will have limited use with such data. Understandably,
374 many have used sinusoidal signals to demonstrate the effects of various normaliza-
375 tion methods and phase angle definitions (Hamill et al., 1999; Kurz & Stergiou,
376 2002; Peters et al., 2003) – including the current paper – because of the simple
377 characteristics of sine waves. However, the validity of transferring the demon-
378 strated methods from sinusoidal to empirical data have not always been made
379 clear.

380 Sinusoidal data often have their amplitude centered around zero, possibly for
381 this reason the necessary shift of d when $d \neq 0$ has not been discussed. When
382 dealing with empirical data, one should expect the data to be non-sinusoidal and
383 have the amplitude not centered around zero. Therefore, we suggest that the data

384 first be centered, so that zero represents the midpoint between the maximum and
385 minimum values (Rosenblum et al., 2001). The amplitude centering is analogous
386 to the shift of d for sinusoidal signals. However, for non-sinusoidal empirical data
387 the Hilbert transform should be used to remove frequency effects.

388 *5.6. Discrete and cyclic movements*

389 In keeping with the resemblance of human movement to the limit cycle, most
390 studies involving continuous relative phase as a measure of coordination have
391 applied it to cyclic movements. Running (Dierks & Davis, 2007; Hamill et al.,
392 1999; Hein et al., 2012; Miller et al., 2010, 2008; Kurz et al., 2005; Trezise et al.,
393 2011) and walking (Barela et al., 2000; Clark & Phillips, 1993; Haddad et al.,
394 2010; Kwakkel & Wagenaar, 2002; Lamoth et al., 2002; Li et al., 1999; Meyns
395 et al., 2013; Wagenaar & van Emmerik, 2000; Wu et al., 2004), the transition
396 between gait modes (Kao et al., 2003; Lamoth et al., 2009; Seay et al., 2006;
397 van Emmerik & Wagenaar, 1996) and swimming (Figueiredo et al., 2012; Seifert
398 et al., 2010, 2011) constitute the most common cyclic human activities studied
399 (note that we only consider whole-body movements in this review). These types of
400 movements closely correspond with the concept of phase analysis, which allows
401 unique characteristics of the movement to be exposed qualitatively, because of
402 the shape of the phase space trajectories. For example, a damped oscillator will
403 show, in phase space, convergence to the origin as it loses energy. Accordingly,
404 some have argued that studying cyclic movements (modeled as pendula) in terms
405 of energy transfer with the environment can provide important insight into the
406 changing state of the modeled system (Clark et al., 1993; Kurz & Stergiou, 2004).

407 However, central to dynamical systems theory is the continuous interaction
408 between the many constraints (performer, the environment and the task (Newell,

409 1986)), which give rise to coordinated movement on the biomechanical level
410 through self-organization. Furthermore, these interactions can influence perfor-
411 mance of a task on different time scales (Schöllhorn et al., 2009). For exam-
412 ple, fatigue can cause sprinters to make coordinative compensations for changing
413 availability of energy resources (Trezise et al., 2011). On the other hand, for dis-
414 crete tasks requiring precision, variability can also be managed throughout execu-
415 tion of the task to aid performance (Bootsma & van Wieringen, 1990). Therefore,
416 although only a few studies have used continuous relative phase to study discrete
417 movements (Burgess-Limerick et al., 1993; Robins et al., 2006), it seems reason-
418 able to do so in order to reflect the changing constraints affecting the performance
419 of the task, given a few caveats. The time scales between repetitions of discrete
420 tasks are different from those of cyclic movements and should be acknowledged
421 by authors using continuous relative phase for analyzing coordination variability
422 in discrete tasks. Additionally, time continuous concepts such as relaxation time,
423 the amount of time required after the system is perturbed to return to its original
424 stable state (Scholz & Kelso, 1989), may not yet be meaningful for discrete tasks.

425 5.7. *Interpretation*

426 So far we have proposed that continuous relative phase should be calculated
427 based on amplitude centered Hilbert transform values rather than phase angles ob-
428 tained through plotting phase portraits when the original signals are non-sinusoidal.
429 Yet to be discussed is the interpretation of the continuous relative phase using the
430 Hilbert transform. As shown in Figure 4 (bottom left), the centered Hilbert trans-
431 form gives similar continuous relative phase to those gained from normalizing the
432 phase portraits; however, with the frequency artifacts removed. Therefore, the
433 interpretation of the continuous relative phase values using the Hilbert transform

434 should not change compared to the interpretation of continuous relative phase
435 based on phase portraits (Hamill et al., 1999; Li et al., 1999). Furthermore, when
436 using continuous relative phase for measures of variability such as an ensemble
437 curve representing multiple trials or variability at each time point (Stergiou et al.,
438 2001a,b; Yen et al., 2009) care should be taken to remove frequency artifacts as
439 they could have significant influence on these measures.

440 Some have suggested, that continuous relative phase does not allow one to
441 make inferences on the original signals (Miller et al., 2010; Peters et al., 2003).
442 In-phase coordination simply means that the two joints occupy the same phase
443 angle at the same time in the movement, whether the phase angle is measured
444 in phase space or in the complex plane. Peters et al. (2003) stated that the non-
445 intuitive result was generated when the original signals had the same slope in the
446 time domain but were not *in-phase* according to continuous relative phase. It
447 seems that the authors interpreted continuous relative phase with respect to direc-
448 tion (joint angle is increasing or decreasing) and velocity rather than displacement
449 and velocity. Peters et al. (2003) highlighted two points on two lines with the same
450 slope but obviously different displacement values and it is confusing that they sug-
451 gest these should correspond with in-phase coordination according to continuous
452 relative phase. That interpreting a joint angle's movement direction and velocity
453 should predict its relative phase is a misinterpretation of relative phase, but may
454 provide the basis for a new form of dynamic analysis of coordination – one which
455 is more descriptive than discrete relative phase and simpler, or possibly more in-
456 tuitive, than continuous relative phase.

457 *5.8. Recommendations for future use*

458 We have demonstrated the effects of normalization on various sinusoidal sig-
459 nals as well as on non-sinusoidal signals. Although normalizing sinusoidal sig-
460 nals adequately removes frequency effects, since sinusoidal signals will not be
461 obtained from experimental data, we suggest that the normalization method pro-
462 vided by Fuchs et al. (1996) is irrelevant for studying multi-articular or whole
463 body movements. Others have suggested different normalization methods, or in
464 fact no normalization at all, to account for the frequency or amplitude of empir-
465 ical data, but as we have shown, these methods either do not remove frequency
466 artifacts from the calculated continuous relative phase values or do not allow the
467 full range of phase angles on which continuous relative phase is based. In place
468 of a) sinusoidal normalization, b) normalization methods A and B, or c) no nor-
469 malization we propose the following steps:

- 470 1. centering the amplitude of the data around zero (equation 11)
- 471 2. transform each signal into an analytic signal using the Hilbert transform
472 (equation 7)
- 473 3. calculate the phase angles for each signal (equation 8)
- 474 4. calculate the continuous relative phase (equation 9)

475 The Hilbert transform creates an analytic signal from non-sinusoidal signals, thereby
476 removing frequency artifacts and making it appropriate for studying inter- and
477 intralimb coordination in human movement. We should also mention that ana-
478 lytic signals can be created for any real signal but the phase angle only has a real
479 physical meaning if the real signal is a narrow-band signal. Of course, kinematic
480 data representing human movement satisfy this condition (Meng et al., 2006), but

481 we bring attention to this in case researchers of human physiological or behav-
482 ioral data encounter signals which do not have a narrow-band frequency spectrum
483 (Boashash, 1992).

484 Applying the methods in this paper to other types of human movement data
485 was out of the scope of this paper, but we will highlight one particular point of
486 interest for researchers in other domains of human movement science seeking
487 to use continuous relative phase. We have suggested the signal's amplitude be
488 centered around zero; this is true for kinematic joint angles because the joint angle
489 values are relatively arbitrary – they depend on how the joint angle is defined.
490 However, if the values have qualitative meaning then another form of centering
491 the data may be more appropriate. For example, Palut & Zanone (2005) looked
492 at the lateral coordination of two tennis players on the court. The authors argued
493 that the players could be modeled as a paired oscillator, which oscillates about
494 the center line. In this case, the centerline (assigned as zero displacement) on
495 the tennis court has qualitative meaning and should be preserved. For studies of
496 player positional data, new methods for calculating the phase angle, such as those
497 for tennis (Palut & Zanone, 2005), should be investigated.

498 **6. Conclusions**

499 In this paper we identified and compared commonly reported methods for cal-
500 culating the phase angle for use in continuous relative phase analyses. Using syn-
501 thetic and real data we compared the commonly reported normalization methods
502 and showed that, after centering the signals' amplitudes around zero, the con-
503 tinuous relative phase values obtained from the analytic signal created using the
504 Hilbert transform in all test cases gave the intuitive answer. We therefore suggest

505 that future research adopt the amplitude centered Hilbert transform to remove fre-
506 quency artifacts of the non-sinusoidal signals being studied.

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 671 6.

672 **Appendix A. Invariance of the Hilbert transform with respect to a constant**
 673 **amplitude shift of the signal**

674 According to Gabor (1946) the Hilbert transform of a real signal (time depen-
 675 dent) $x(t)$ is defined as

$$H(x(t)) = \frac{1}{\pi} \text{P.V.} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau, \quad (\text{A.1})$$

where P.V. means that the integral is taken in the sense of the Cauchy principal value. The Hilbert transform of a signal $x(t)$ with respect to a constant shift c of

the signal's amplitude is

$$\begin{aligned}
 H(x(t) + c) &= \frac{1}{\pi} \text{P.V.} \int_{-\infty}^{\infty} \frac{x(\tau) + c}{t - \tau} d\tau \\
 &= \frac{1}{\pi} \left(\text{P.V.} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau + \underbrace{\text{P.V.} \int_{-\infty}^{\infty} \frac{c}{t - \tau} d\tau}_{\stackrel{A.3}{=} 0} \right) \\
 &= \frac{1}{\pi} \text{P.V.} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau \\
 &= H(x(t))
 \end{aligned} \tag{A.2}$$

because

$$\begin{aligned}
 \text{P.V.} \int_{-\infty}^{\infty} \frac{c}{t - \tau} d\tau &= \lim_{a \rightarrow -\infty} \lim_{b \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \left(\text{P.V.} \int_a^{t-\varepsilon} \frac{c}{t - \tau} d\tau + \text{P.V.} \int_{t+\varepsilon}^b \frac{c}{t - \tau} d\tau \right) \\
 &= \lim_{a \rightarrow -\infty} \lim_{b \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \left([-c \ln |t - \tau|]_a^{t-\varepsilon} + [-c \ln |t - \tau|]_{t+\varepsilon}^b \right) \\
 &= \lim_{a \rightarrow -\infty} \lim_{b \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \left(c (-\ln |\varepsilon| + \ln |a| - \ln |b| + \ln |\varepsilon|) \right) \\
 &= \lim_{a \rightarrow -\infty} \lim_{b \rightarrow \infty} \left(c \underbrace{(\ln |a|)}_{\rightarrow 0} - \underbrace{(\ln |b|)}_{\rightarrow 0} \right) \\
 &= 0.
 \end{aligned} \tag{A.3}$$

676 Hence, the Hilbert transform of a signal $x(t)$ is invariant with respect to a constant
 677 shift of the amplitude of $x(t)$.

Conflict of Interest Statement

The authors declare there no are conflicts of interest relevant to the content of this manuscript. No sources of external funding were used to support the preparation of this manuscript.

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