Geographical Vector Agent Modelling for Image Classification: Initial Development

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1.0 INTRODUCTION

Concomitant with the development of remote sensing imagery, image classification methods have added object-based image classification (OBC) to the prevailing pixel-based approach. The main distinctive characteristic of this method is to identify meaningful geographical objects, namely image objects, rather than individual pixels. At a primary level, image-objects are collections of contiguous pixels that are supposed to depict homogeneous thematic meaning, even if there is a variety of spectral values for the pixels within the object. Objects thus hold more information than pixel-based approaches, which only account for spectral content.

Despite the desirable and vast improvements that OBC has allowed, it still relies on a sequential process of segmentation of the image into objects followed by their classification. Nevertheless, this classical approach of OBC lacks the ability to complete the image segmentation by taking advantage of the thematic meaning of the object being created, as well as the procedural knowledge being generated during this process.

This limitation can be overcome by a dual approach which simultaneously runs the segmentation from pixels to interest objects, as well as the thematic classification of the objects being generated. Here we propose to implement this improved workflow by using geographical Vector Agents (VA). VAs are objects that have the ability to control and alter their shape and attributes in order to evolve in accordance with the nature of the phenomena being modelled. In this context, VA must support a dynamic geometry that can support both the segmentation and classification of the image in parallel.

2.0 VECTOR AGENTS

VA is a type of Geographic Automata in the sense that it is a processing mechanism characterized by states, transition rules, space and spatial behaviour (Benenson *et al.*, 2004). It addresses the limitations of Cellular Automata (CA) (Figure 1(1)) such as the assumption of regularity and the inability of movement of cells (Benenson *et al.*, 2004) by allowing a dynamic geometry (Figure. 1(4a)). VAs are geometric objects that can represent dynamic/static and regular/irregular vector boundaries with the potential to model a wide range of geospatial phenomena in the context of the geographic automata system (GAS) (Hammam *et al.*, 2007; Torrens *et al*., 2003).

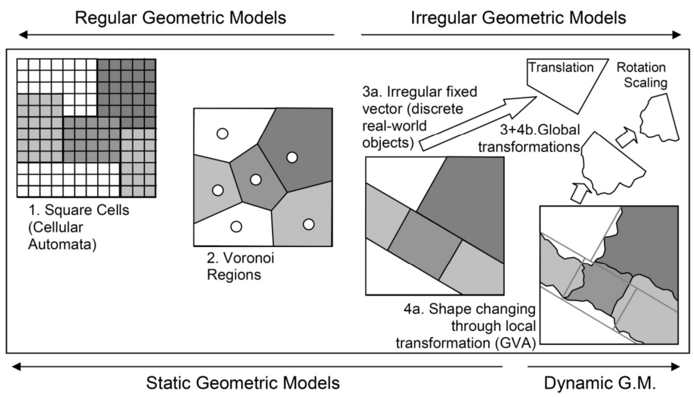

*Figure 1: Various methods of discrete spatial modelling, arranged on a continuum from regular to irregular geometry, and static to dynamic models (*Moore, 2011*).*

By enabling a state and spatial behaviour to be modelled based on geometric and contextual information, VA have the potential to model phenomena like image objects in a manner that approach better the parallelism of human interpretation, as opposed to the sequential processing of the OBC.

3.0 IMAGE OBJECT GEOMETRY IN THE CONTEXT OF THE VECTOR AGENT

An image object can be formed by aggregating pixels into a static irregular polygon (Figure. 2). To overcome the static geometry, the geometry of image objects is redefined in the context of the VA. In this sense, the image objects can be in point, line and polygon form and also they can change their geometry during the evolution process from point to the polygon. The points are a subset of the lattice points corresponding to the centre of pixels of the raster being classified. Furthermore, image objects can perceive and support the topological relationships, splitting and aggregation process, thus describing the geometry and topology in tandem.

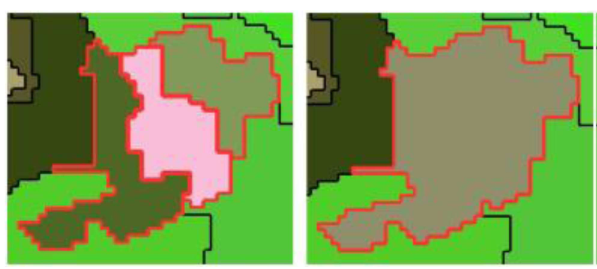

Figure 2: An irregular and static geometry of image objects representing (left) small scale and (right) large scale phenomena, respectively.

3.1 Image Objects Construction and Evolution

A winged-edge data structure represents an object by a set of faces, edges and vertices (Haidacher, 2011). The winged-edge is the central part of this data structure and is defined by a set of two vertices, two faces, and the successor and predecessor edges (Fig. 3). The use of the winged-edged data structure provides for a static irregular polygon so additional operations are required in order to support a dynamic geometry intended for the VA-based image objects classification (Figure. 4).

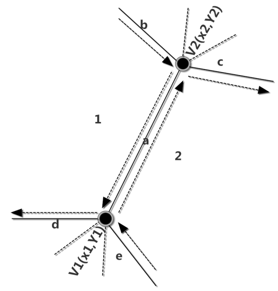

Figure 3: winged-edge data structure is a set of faces (1, 2), vertices (V1, V2), predecessor edges (b, e), and successor edges (c, d).

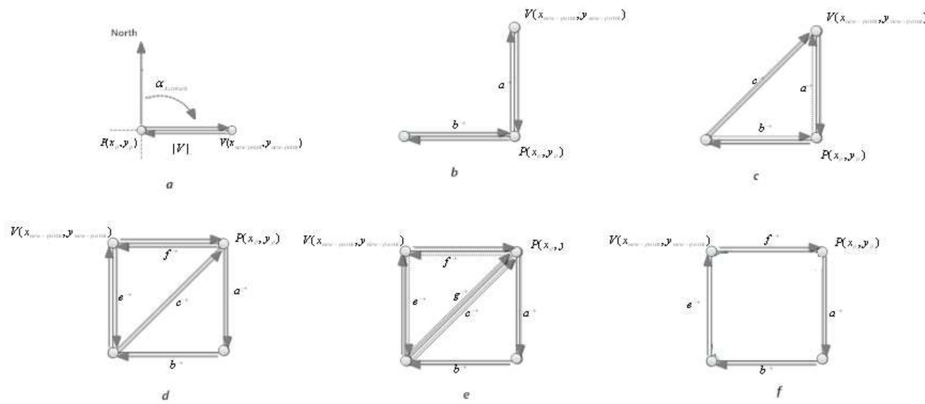

Figure 4: four elementary operations are required to change the image objects geometry: (a) vertex displacement, (b, c) edge joining, (d) edge displacement , and (e, f) edge remove.

Four elementary operations are defined to allow the geometry of vector agents to change dynamically:

1. Vertex displacement: this places a new vertex in the space image (Figure. 4a) and connect two vertices together by two half-edges.

2. Half-edge joining: this constructs a new edge based on a twin edge that is formed by two half-edges (Figure. 4b, c).

3. Edge remove: this forms a new polygon by the merging of two polygons (Figure. 4d, e).

4. Winged-edge displacement: a new edge is constructed based on two vertices (Figure. 4f), if there is a vertex in the effect neighbourhood of a new vertex.

To implement the above geometry in image space, we define a set of rules that consists of: (a) the initial geometry of image object is automatically formed as a point in the pixel centre; (b) each point can generate a new point along four cardinal directions by a constant distance that is specified by cell size r (c) the maximum length of each edge is equal to $r\sqrt{2}$; (d) each edge can be divided into two half- edges; (e) each new point has three reference points; and (f) an edge can be created if there is a point in the local neighbourhood of the new point, i.e., if the characteristics of the corresponding pixel meets some pre-defined criteria allowing it to belong to the VA.

Figures 5 & 6 illustrate how these rules are implemented by the image object, thus allowing its iterative evolution. First, a point is automatically initialized in space. Second, the first edge is randomly constructed by finding a second point in the local neighbourhood in space (Figure. 5a).The new edge being created consists of two half edges. Third, the first polygon is formed by finding the third and fourth point in image space. To do this, two half-edges (known as a twin edge) are combined to construct the first polygon (Figure. 5b). After the fifth point is placed in space, a new edge can be created where there is a point in the local neighbourhood of the new point (Figure. 5c, d). From here, the evolution process continues to reach a geometry that is associated with a homogeneous thematic class in the underlying raster image (Figure. 5e, f, g). An example of the evolutionary process of an image object is also illustrated from an initial square over one thousand iterations, in figure 6.

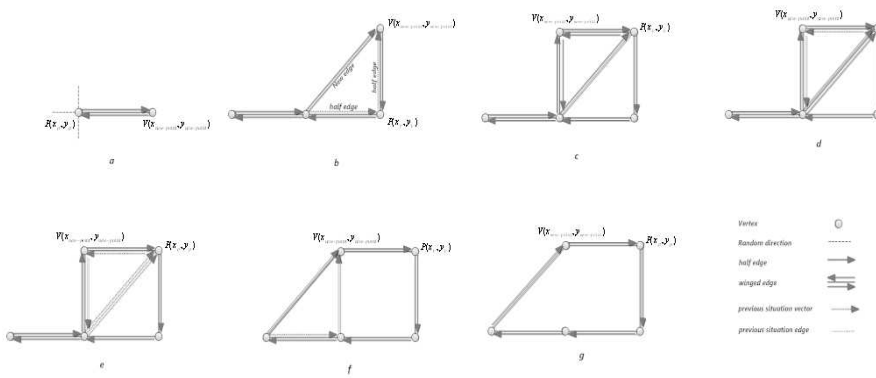

Figure 5: How an image object is born and evolves in the image space: (a) initializing by random point and construct the first edge, (b) to form the first polygon, and (c, d, e, f, g) to evolve an image object to reach interest the geometry of a thematic object.

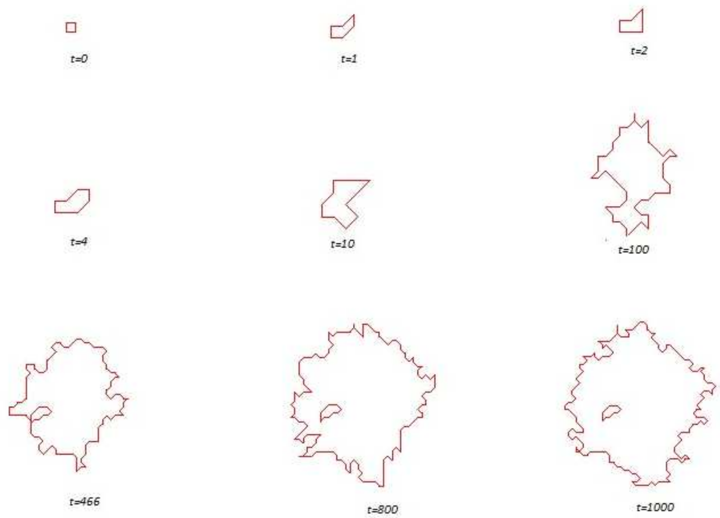

Figure 6: Simulation result for first 1000 time steps in the agent modelling shell Repast Simphony representing how an image object uses the four aforementioned operations to transform its geometry.

4.0 IMPLEMENTATION BASED ON A SYNTHETIC IMAGE

Many real world problems involve multiple measures of performance, or objectives, which should be optimized simultaneously (Fonseca et al, 1995). Classical OBC associates image objects from an initially fully segmented image into meaningful thematic classes. The proposed methodology simultaneously supports image segmentation and classification in tandem.

To implement this approach, we defined an initial simple scenario in which possible VA attributes are limited to the pixel value of a synthetic image formed by pixels of only 4 different values (Figure. 7). Three agents are initialized in image space and evolve according to the above-mentioned set of rules. Figure 8 illustrates this evolution and how VA aggregate themselves depending on the geometry and contextual properties, here the pixel value of the underlying raster image. VA evaluates how best to grow and merge until reaching an acceptable model of the image object's class (Figure. 8). Although simplistic at the moment, this approach provides many opportunities for refinements that can address the problem of image classification in a profoundly innovative way.

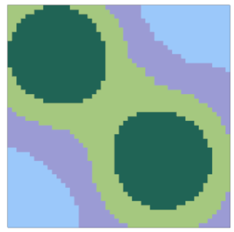

Figure 7: the synthetic image.

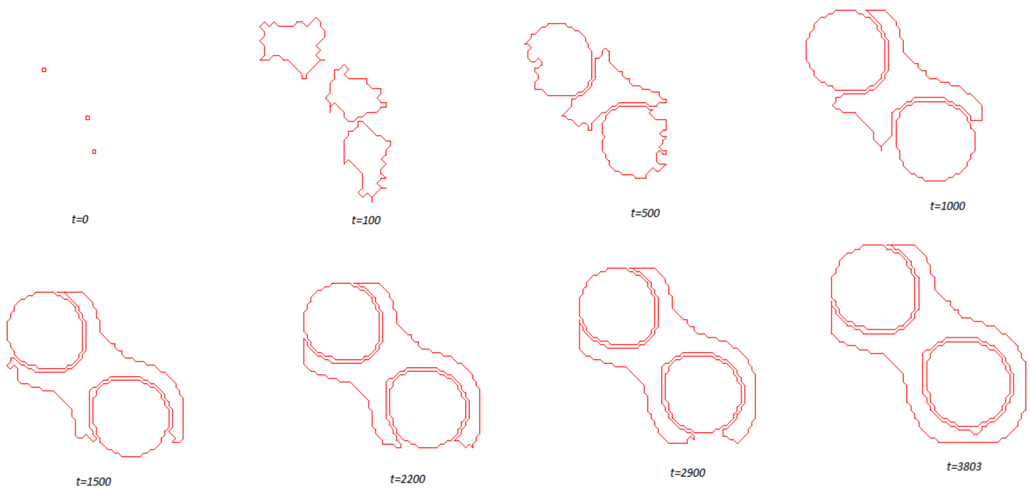

Figure 8: Simulation result for two classes, namely dark and light green colour to illustrate how the VA evolves under the constraint of the underlying raster image.

5.0 SUMMARY

The main concept of an innovative VA-based classification method was proposed, in order to execute simultaneously the process of image segmentation and classification. This research has highlighted some abilities of the VA to support a dynamic geometry for image objects. Further investigation should be performed to deal with issues of interaction between image objects, identification of initial classes, implementation of sophisticated feature space criteria to support classification, and the dynamic evolution of VA attributes during the iterative process.

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