EMERGENT SHAPE GENERATION IN DESIGN USING THE BOUNDARY CONTOUR SYSTEM

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Abstract.
This paper discusses the boundary contour system as the basis of a computational model of emergent recognition applicable in design. Details of this system which make it appealing as a computational approach for emergent recognition are introduced. The performance of a system implementation is covered and an extension to improve its performance is discussed.

1. Introduction

In the field of design computing, emergent recognition is defined as,

emergent recognition (ER):
the process of seeing properties, features, functions not originally intended in a designed artefact.

The ability to recognize and complete without difficulty incomplete emergent shapes is an important aspect of human visual perception. There has been increasing interest in producing computational analogs of shape emergence. Part of the reason for this interest is based on the hypothesis that emergence can play a role in design in the visual domain and in creative designing in particular. Thus, a computational system capable of shape emergence could play a role in computer-supported creative designing.

1.1. COMPUTATIONAL MODELS OF EMERGENT RECOGNITION

From this interest in ER, various computational models of emergent perception have been investigated (Gero and Damski 1994, Gero and Jun 1997, Gero and Yan 1994, Liu

1994). These recent works have generally approached the problem in a symbolic, rule based, depth first search manner. The concepts involved (infinite maximal lines and shape correspondence) are largely derived from the vector representation of shapes while the ER was defined as the identification of isomorphisms with schemas after perturbing in characteristic ways the vector representation. Henceforth, this approach is referred to as the CS (conceptual schema) approach.

A different approach has been developed in the domain of real-time neural networks and has been labelled the Boundary Contour (BC) system by its co-developers Grossberg and Mingolla (1985). It is differentiated from the CS approaches in a number of significant ways.

1.1.1. *Non-Schema Based*

Previous computational models of shape emergence have largely been of two kinds: symbolic systems based on schemas and sub-symbolic systems also based on (teaching the system) schemas. The effect of these models is that not all emergent shapes can be found computationally because they need to be recognised a priori by the system developer.

The BC system does not rely on schemas. Instead it uses a small number of rules applied at all locations and orientations of a two and a half dimensional matrix which represents the scene. Application of the rules occurs in parallel and in real time (Grossberg 1987a, 1987b) such that Gestalt effects can result from the computation. It would seem that this approach may provide a richness not found in previous ER systems.

1.1.2. *Illusory Reality*

The BC system was developed as a cognitive theory used to analyse and explain a variety of perceptual grouping and segmentation phenomena. The theory was approached from the perspective that the perceptual system faces a major problem in the ambiguous nature of the input data available to perceive from. This ambiguity comes from several sources which include:

- imperfections in the human perceptual system, such as the veins and blindspots in the lens which tend to mask real input data and create illusory input data. These imperfections also result from the discreteness of the visual system and the problems associated with discrete edge detection.

- noise, a uniform level of activation across a visual field, which can be the result of differences in lighting conditions.

- and the Gestalt nature of perception where

  "it has been widely recognised that local feature of a scene, such as edge positions, disparities, lengths, orientations, and contrast, are perceptually ambiguous but that combinations of these features can be quickly grouped by a perceiver to generate a

clear separation between figures and between figures and ground." (Grossberg and Mingolla 1985)

Starting from this condition, the theory offers the explanation that the processes required to perceive reality from illusory and ambiguous input data also can provide the perception of illusory shapes from real data. ER is not an anomaly of normal perception but an emergent effect itself. To design computing, this suggests that the BC system does not require precision vector based drawings as input. Instead, fuzzy hand drawn sketches are valid input. This positions ER as a potential tool at the early stage of designing.

1.1.3. *Preattentive*

The boundary contour system is not a recognition system but rather a stage of image preprocessing whose output is theoretically an input to the recognition system. The output is an activation pattern of the same computational representation as the input. It is not a representation which could be efficiently generalised from and as such is not directly considered recognition. The input-output transformation carries little knowledge, learns no knowledge of particular shapes and is recurrent. Without such knowledge the resulting performance of the system is unpredictable.

1.1.4. *Selective*

Unlike the CS systems, the BC system is selective. The selected output is a pattern which best satisfies a small number of competing constraints applied at each location in the input data matrix. Mathematically described in terms of differential equations among neurons of the matrix, the BC system is a dynamic non-linear system which approaches an attractor defined by both the input data and the constraints imposed by the input-output transformational rules.

2. BC System in Design Computing – The ER Interface

Beyond being simply an alternative computational approach, it is conceivable that the differences described above have value in the performance of an ER system. To consider this, it is first necessary to state the current vision of utility and operation of an ER system in practice. From the perspective of visual design computing, the BC system appeals, first and foremost, as a computational approach to emergent recognition. As such, it was envisaged that the process could be used as a background image processing algorithm which modifies a drawn/sketched scene. This process is expected to have value if it provides alternative shapes which are in some non-conventional way derived from the initially drawn shape. As an alternative to prior ER systems, the BC system would present a single recognition for the input scene that is consistent across the entire scene. Without knowledge of any particular shapes, it was expected that the BC system would be a good ER system for it would not rely on recognising the known.

3. The BC System Implementation – Providing the Interface

The operating principle of the BC system is simple. Input and output data exist as patterns of activation on a two and a half dimensional matrix of activations in a neural network. The activation patterns are transformed through sequential and recurrent sets of filters which implement simple rules designed to reduce the ambiguity in local information.

An example of this input output transformation of a (non-emergent) shape is shown in Figure 1.

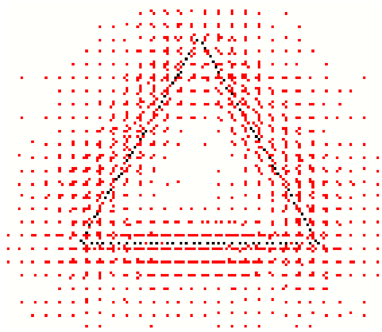

Figure 1. Input scene to the BC system and edge detection.

The overall transformation occurs through the individual transformations which make up the BC system. First the input scene is edge detected via a contrast sensitive mask. This identifies the edges of the scene but in doing so creates considerable ambiguity. An example of the edge detector output is shown in Figure 1. As can be seen the process has a side effect that line ends, edges and corners are fuzzified (cannot be determined by local evidence). It is just this type of input which begins to justify why alternative shapes can appear at all. Figure 2 shows the output scene from the BC system.

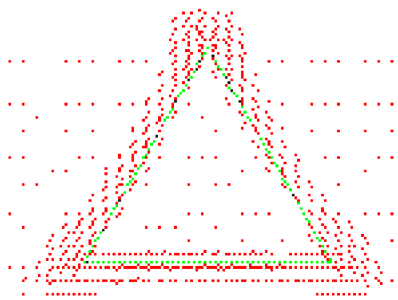

Figure 2. Output scene from the BC system.

The remaining transformations seek to disambiguate the border of the scene. A number of rules are utilised whose effect is to combine non-local and local evidence to infer local evidence.

Heuristically these rules are:

Rule 1 Edge Location Rule: An edge cannot exist at one direction and orientation and at the same direction and a location orthogonally nearby.

Rule 2 Edge Direction Rule: A region edge cannot go in two directions at the same location.

Rule 3 Edges As Populations Of Edgelets: An edgelet cannot remain active without receiving long range feedback from other edgelets on the same edge.

That these rules can be specified in terms that are computable by a neuron and a small neighbourhood makes the BC system computationally plausible. They are expressed in the BC systems in terms of several On-Centre Off-Surround competitive processes and a cooperative feedback process (Grossberg 1987a, Grossberg 1987b, Carpenter and Grossberg 1991). Individually these processes can be linked together in a computational loop, giving the overall view of the image processing as shown in Figure 3.

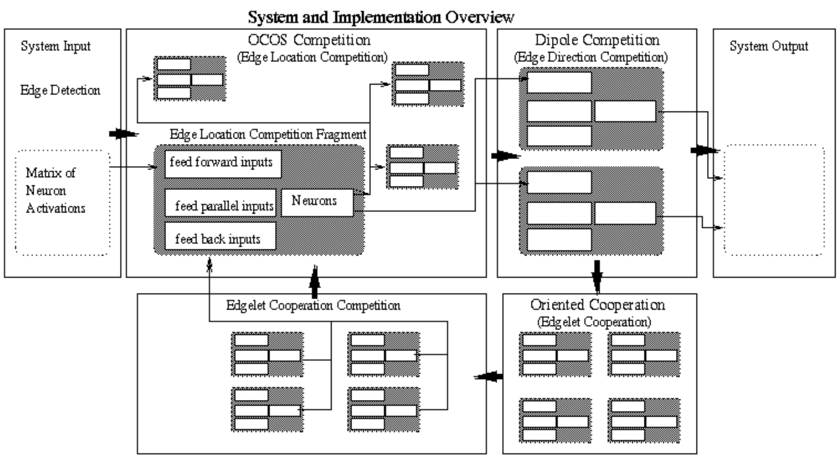

Figure 3. BC system overview

4. BC System Performance

The capability of the BC system to produce emergent recognitions has been verified through a reimplementation of the original system and testing examples provided in the original literature (Grossberg 1987b). Though important, this verification lead to an

appreciation of the BC system as something of an incomplete system for the purpose of ER in design computing.
The BC system as an approach towards a design computing tool theoretically provides the capability to select both embedded shapes and to produce illusory shapes. In the former no new lines or boundaries are constructed, only new interpretations of existing boundaries are formed. In the latter the new shapes are bounded by some or even all boundaries that did not exist in the initial shapes. In illusory shape emergence we draw a further distinction between those emergent shapes which have boundaries which are linear extensions of existing boundaries, those which have boundaries which include intersections and those whose boundaries are not extensions of preexisting shapes, Figure 4.

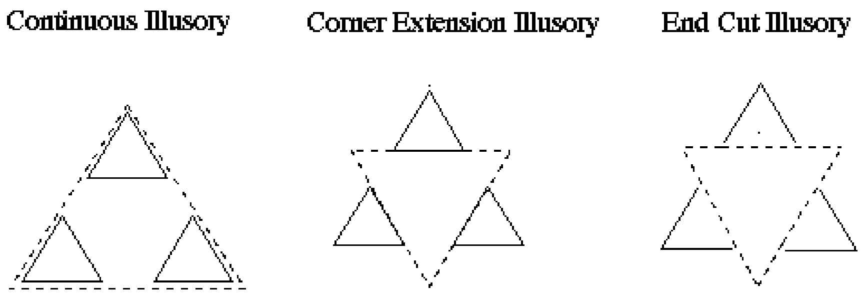

Figure 4. Classes of emergent recognitions

Demonstrated in the literature and verified through our implementation is the capability of the BC system to produce recognitions derived from the linear continuous extensions of pre-existing boundaries. This capability to select embedded shapes has been provided by other computational approaches to emergent recognition through it is conceivable that the BC system approach would facilitate it. The BC system as originally designed was demonstrated not to be capable of corner extension illusory ER. As this is a limitation in its utility for designers, an extension of the BC system to provide corner extension illusory ER was investigated and is described below.

The end cut illusory extension requires some consideration, for the BC system does suggest a capability to provide such ER. As the edge detection ambiguates the end of lines, the competitive processes of Rules 1 and 2 serve to reinforce orthogonal and near orthogonal end cuts to boundaries (Grossberg 1987b). This in turn provides the starting point for illusory shape emergence using the same principles as will be described below to provide continuous extension ER. As the only computational approach theoretically capable of providing such a capability, the BC system deserves further consideration.

4.1 ORIENTED COOPERATIVE FIELDS

To appreciate the BC system and its capability to produce emergent recognitions, it is necessary to specifically consider one stage of the system: the oriented cooperative feedback process (Rule 3 above) of the BC system which both facilitates continuous illusory extension ER and prohibits corner extension illusory ER. Oriented cooperation takes the form of positive feedback from the activation of an intermediate neighbourhood of a neuron back to the single neuron. It is a top down reinforcing filter which was designed to enforce the rule that evidence for an edge should be reinforced by extensions of this edge (Rule 3). Feeding back the reinforcement requires the input from the edge extension and in the original BC system description such neighbourhoods were lobed fields as shown in Figure 5.

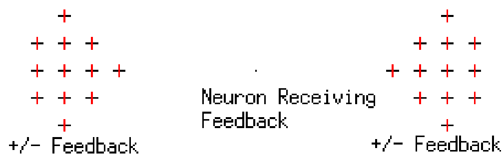

Figure 5. A cooperative field

Cooperative fields, as originally proposed, were two opposing lobed regions. Quite obviously these are limited to linear boundary completion. Grossberg and Mingolla (1985) hinted at curved boundary completion using a slightly curved cooperative field. However, the logical extension of this idea to corners does not work. The BC system was run with angular cooperative fields of the form shown in Figure 6 in an attempt to achieve illusory corner extensions recognition.

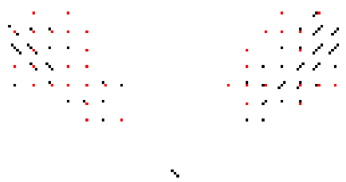

Figure 6. Angular cooperative field receiving positive feedback and no negative feedback

Simple use of such angular cooperative fields has a disastrous side effect in that the feedback from orthogonal cooperative fields is equal. This feedback is mutually annihilating in the dipole competitive stage of Rule 2 as can be seen in Figure 7.

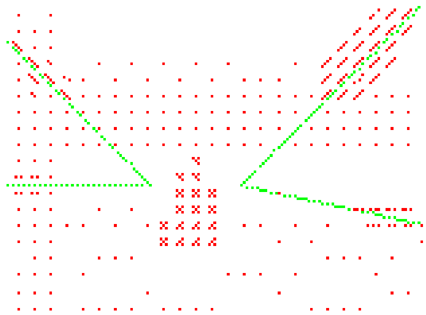

Figure 7. Feedback from angular cooperative field which is equal and orthogonal and hence eliminated by the edge direction rule (Rule 2)

4.2 LOCATION/ORIENTATION SPECIFIC ANGULAR COOPERATIVE FIELDS

To overcome this problem the definition and use of cooperative fields which distinguish their location relative to a corner was tried. These cooperative fields are consequently referred to as location/specific cooperative fields. Specifically, with standard fully lobed cooperative fields the field would be activated independently of its root orientation and root position relative to the corner, Figure 8. With the semi-lobed fields it is possible to choose configurations which feed back orientation only when the lobe root is on one side of a corner.

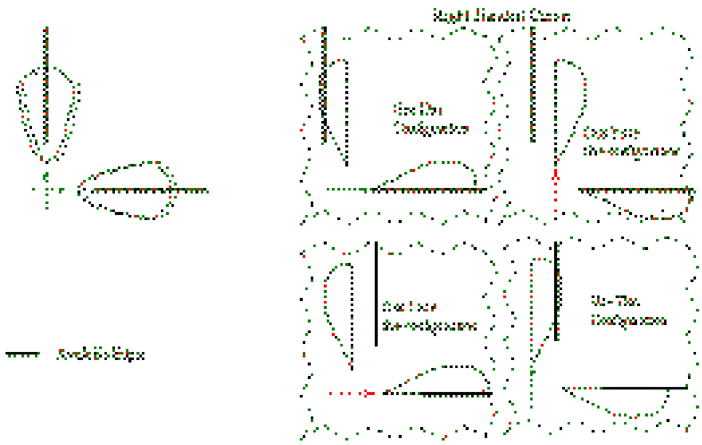

Figure 8. Location/orientation specific angular cooperative field

Using these lobes, it became possible to achieve corner illusory extensions, Figures 9 and 10.

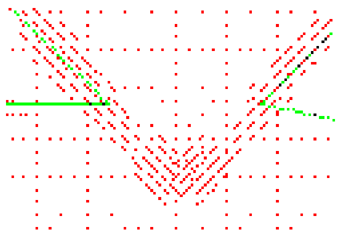

Figure 9. Example of corner extension illusory recognition

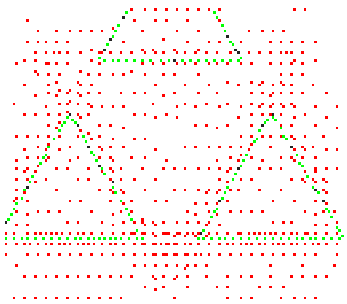

Figure 10. Example of corner extension illusory recognition

5. Conclusions

These investigations into the BC system as a computational model of emergent recognition for use in visual designing have yielded the following observations.

The performance of the BC system was disappointing in its robustness. The system is extremely sensitive to the correspondence of cooperative field parameters to the scale of possible boundary completions. To obtain the emergent results which are presented above, the system required extensive fine tuning. Essentially the problem here is that not enough computational power could be brought to bear in this exercise to simultaneously allow the system a variety of parameter settings. The BC system requires a lot of computational power for it is computing concurrently a large number of parallel constraints. To proceed towards the use of the BC system or a variant as a viable design support tool, much optimization or better, significant parallelization of the computation is required.

The BC system is also disappointing in that the output often remains locally quite ambiguous. By no means does the system approach a definite and precise edge definition. Often the competitive and cooperative processes are not able to produce a winner and maintain the ambiguity present in the edge detected data. As such it would seem the BC system is suited towards a human design aid rather than input to a following recognition system.

In spite of these disappointments, the appeal of the BC system or a variant of it as an alternate to previous computational models remains valid. Systems characterized by selective, non-schema based approaches operating from imprecise drawings do offer an alternative.

Acknowledgments

This work is supported by a grant from the Australian Research Council. Computational resources are provided by the Key Centre of Design Computing.

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This paper is a copy of: Tomlinson, P. and Gero, J. S. (1997). Emergent shape generation via the boundary contour system, *in* R. Junge (ed.), *CAAD Futures 1997,* Kluwer, Dordrecht, pp. 865-874.