The emergence of dynamic form through phase relations in dynamic systems

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RUNNING HEAD: Dynamic Form as Phase Relations

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Abstract. Theories of visual form have been plagued with the problem of the correspondence between aspects of the form across time and across spatial location. Following Bateson's idea that knowledge emerges from the relations among multiple flows of difference, our computational model illustrates how visual form can emerge from the phase relations between two such flows in a way that eliminates the correspondence problem. Computationally, the first flow of process in a Boolean network falls into one among many different attractor cycles each of which cycles at a given fundamental frequency. A second cyclic systemic flow, with its own frequency, is computationally necessary before a person can experience the patterns (transients, attractors) of the first flow on a computer monitor; and the frequency of this second flow is a control variable. Dynamic visual form, in this computational logic, emerges from the phase relations between the frequencies of the two flows. These dynamic forms exhibit, simultaneously, many kinds of apparent motion suggesting that the processes generating apparent motion are not merely illusions but are in the service of dynamic form perception. This model of perceptual organization and moving form is discussed in relation to other approaches.

KEYWORDS: Dynamic form perception, perceptual organization, correspondence problem, dynamical systems, phase relations, Boolean simulations, emergence

We propose a model for perceptual organization of visual form using one critical aspect of Gregory Bateson's ecological framework for learning and the nature of knowledge. While Bateson's approach has broad scope we focus on his description of knowledge as the flow of differences (see "Form, Substance, and Difference" in *Steps to an Ecology of Mind*, Bateson, 2000). In our approach visual form is inherently dynamic, that is, form changes over time. Thus our model will assume dynamic form is the general case and static snapshots of form are merely a special observational case that may loose the essence of the dynamics (e.g., Palmer 1999, p. 512). Within this context, mental process, and therefore dynamic form, can be broadly defined as the flow of differences and the transformation of differences in a richly connected network (e.g., Bateson, 2000, pp. 459-461; Bateson, 2002, pp. 85, 86). Stuart Kauffman's (1993, 1995) NK Boolean networks for studying biological processes in the evolution of biological form can model these flows of Batesonian difference. Malloy, Jensen and Song (2005) formalized Bateson's framework within Kauffman's evolutionary model using a simulation program, E42, using which we will exemplify the premises of our conception of dynamic visual form.

E42 as a Model of Batesonian Flows of Difference

E42 generates NK Boolean systems and outputs the behavior of those systems as visual forms. This formalization has three fundamental premises that distill Bateson's perspective. First, the map (what humans and other sentient beings know) is not the territory (that which is known); moreover, what gets onto maps from territories are differences in the territories. For Bateson, a "map" codes differences that occur in the "territory," whether these be "a difference in altitude, a difference in vegetation, a difference in population structure, difference in surface, or whatever… Differences are the things that get onto a map," (Bateson, 2000, p. 457). Therefore our computational model of dynamic form does not necessitate a close replication of neurons but only their abstract characteristics (fire/not fire).

Second, mental process can be abstractly described as a flow of differences in a richly connected network: "The transform of a difference traveling in a [system] is an elementary idea," (Bateson, 2000, p. 460). In Boolean terms, then, James' stream of consciousness becomes a stream of 0's and 1's which is necessarily highly abstracted but at least it is a stream which, as we will see, has a flow, standing waves, and eddies. This stream of differences, when modeled dynamically, can be construed to flow within the constraints of an adaptive landscape (Kauffman, 1993) consisting of many basins of attraction, each basin containing an attractor and, usually, many tributaries leading into the attractor. These attractors are, in effect, standing waves that are stable as process flows through them. They are the theoretical basis for one type of dynamic form (fundamental forms) that we will describe.

The mathematical description of these attractors is a theoretical alternative to the mathematical description of statistically relevant visual properties found in many models for visual form organization (e.g., Barlow, 2001; Elder & Sachs, 2004; Elder & Goldberg, 2002). The first two premises, (map/territory relations and the multiple flows of difference) are illustrated in the Map Territory Relations Flash Movie found at www.psych.utah.edu/onlinedata/malloy. The characteristics of these systemic flows (most particularly attractors, or, in a different language, standing waves) is what will constitute our conception of dynamic form.

The third premise of our model is that higher order knowledge emerges in the general process of finding differences among various flows of difference (Bateson, 2000, p. 454ff; Malloy, Bostic St Clair and Grinder, 2005; Malloy & Jensen, 2008). Particularly relevant here is Bateson's conjecture that knowledge emerges from the relationship between two or more flows of difference

(Bateson, 2002, chapter 3). We therefore argue that the perceptual organization of dynamic form can be modeled in terms of relations between multiple (at least two) flows. That the CNS has multiple flows is plausible; for example, Raffi and Siegel (2004) have shown such multiple cortical pathways in processing optical flow, and Merchant, Battaglia-Myer, and Georgopoulus (2004) report two populations of neurons responsive to apparent motion.

Correspondence Problem

Among Bateson's examples of double flows generating knowledge is binocular vision (2002, p. 64) where, in his terms, two flows of differences, one from each eye, must be put in relation to get the direct perception of space. This, of course, generates a difficult theoretical puzzle known as the correspondence problem (Palmer, 1999). To describe this problem we will use a static terminology (image, feature) that we will later abandon in our dynamic approach. The nervous system has two images one from the left eye and one from the right, and, with no *a priori* external knowledge about the ambient optical array that might have provoked these images, must discover which features in one image correspond to which features in the other. Spatial depth perception in binocular vision is one specific context in which the correspondence problem occurs and, thus, it is offered here as a specific example of a general issue addressed in our model. Depth perception *per se* is studied in many ways and this paper will not focus on the specifics of binocular vision. Nonetheless, in our model the dynamic activity of the left and right eyes would be or would provoke two flows of difference and, as noted above, multiple flows of difference are a prerequisite for knowledge (depth perception).

Moreover, our model will show that it is not the multiple flows alone that are important for visual form but the relations between them. More specifically, it is the phase relations between such flows that are critical. At the heart of what emerges from these phase relations will be a wide range of apparent motion phenomena; and it will be the same processes underlying apparent motion that will define the perceptual organization of dynamic form. As Kolers (1972), among others, pointed out "apparent motion speaks to the broad issue of the means by which man represents to himself the characteristics of the world outside his own skin." In this respect, our phase relation model bears upon the spatiotemporal issues described by Kubovy and Gepshtein (2003), particularly the question, p. 78, what is a Gestalt? From our answer to that question we will argue that defining the perceptual organization of moving form in terms of phase relations eliminates the correspondence problem in the motion of the form as it moves and changes from one moment to the next.

Assumptions of our Computational Model

Our simulation program, E42, derives from a long computational tradition (reviewed by Malloy, Bostic St Clair & Grinder, 2005). Early neural computation theories (McCulloch & Pitts, 1943; McCulloch, 1965) informed the work of Bateson through his collaborations with McCulloch (see M.C. Bateson, 1991). E42 returns the Batesonian epistemology to the computational realm by integrating it with the dynamic systems approach of Kauffman (Kauffman 1993). One of Kauffman's most profound insights was that even randomly generated Boolean systems (abstractly modeling genetics) produce "order for free;" that is, Boolean systems dynamically self-organize in ways that can model biological form akin to Turing's (1952) morphogenesis (the coming into being of biological form). E42 was designed to explore how these biological frameworks might apply to the genesis of visual form, particularly form that is moving. E42 presents these morphogenetic processes to a computer screen as visual forms that are dynamic Gestalts, and the program includes tools for manipulating the perception of such visual forms. These Gestalt phenomena, as we will generate them here, are perceptually immediately apparent. Kubovy and Gepshtein (2003) and

Malloy, Bostic St Clair, and Grinder (2005) have argued for methodologies that necessarily include the perceiver. Indeed Malloy, Bostic St. Clair, and Grinder (2005) argue for an epistemology in which the mapping of a formal model (e.g., E42 or Chomsky's recursive models) onto perceptual or linguistic phenomena must be grounded in the judgments of the person asked to perceive the Gestalt or linguistic phenomena. Without examining those arguments in detail, we ask the reader to examine her or his own judgments concerning the dynamic perceptual organizations presented by E42 as the pivotal evidence for dynamic form based on the phase relations between two flows of difference. Based on these Gestalt perceptual judgments we will theorize that the computational foundations underlying the tools for manipulating perceptually evident forms are parallel to the process of the perceptual organization of form in the central nervous system.

E42 makes no pretense that it is a replica of the nervous system (neural net models are more applicable for such purposes) nor does it act as a model of the learning process itself (parallel distributed processing models, as one approach, do that much better); rather, in this paper, the purpose of E42's simulation is to be a dynamic model of morphogenesis that formalizes visually dynamic form to two essential and abstracted characteristics—the flow difference in a complex network and the phase relations between two such flows. Phase relations are a general dynamic systems solution to understanding complexity (Baker & Gollub, 1996) dating back to Poincaré and his visualization of the dynamics of pendula and complex systems. Indeed, we are proposing that the mathematical description proposed by Poincaré for visualizing complex dynamics is deeply related to how the visual system solves the problems of visualizing complexity. Moreover, we will discuss how this approach side steps the correspondence problem in motion. Thus, while E42 is a highly abstracted level of neural computational modeling, with E42 simulations we can demonstrate a very general dynamic systems approach to the visualization of the complexity of the optical flow. This demonstration makes it clear that dynamic (including dynamically stable) visual form can be organized and re-organized by a single control parameter—the phase relations between two flows of neural process. And this control parameter does so, we will argue, in a way that eliminates the issue of correspondence.

Theoretical Hypotheses and Operationalization

We operationalize the two flows of neural process as the computational process in the CPU and the drawing of those computations on a computer screen. The computations in the CPU will create loops, or more technically attractor cycles, that are repeating patterns in time. The phase relationships between these attractor cycles and the process of presenting the attractors to the screen where a person can perceive them is the critical element of our model of the perceptual organization of dynamic forms. In terms of Bateson's flows of difference, phase relations between flows of difference becomes a crucial variable in perceptual experience.

In summary, first we focus on how visual form might emerge in dynamic relationships among flows of neural process abstractly modeled as Boolean flows. More specifically we will examine how the phase relations between two flows of Boolean differences generate interesting and varied perceptual phenomena in the area of dynamic form perception, including complex cases of apparent motion. Finally, given that we have well-defined simulations of complex phenomena in dynamic form perception, we explore how phase relations between flows of process can provide theoretical avenues for thinking about perceptual organization and form perception in general.

METHOD

The E42 methodology generates complex visual patterns that have the theoretical virtues of being both dynamic and systemic (Malloy, Bostic St Clair and Grinder, 2005). Malloy, Jensen and Song (2005) built E42 as an open-source NK Boolean simulation program, written in Java, to study how humans know the characteristics of dynamic systems. To use this software, users must enable Java in their web browsers. Moreover, web browsers on machines using Windows or Linux must have the Java plugin. Mac's with OS X and using the Safari web browser have Java is built-in; no plugin is necessary. Source code for the program is open and freely available.

NK Boolean networks (described in detail by Kauffman, 1993, p. 188ff; Kauffman, 1995, p. 75ff; Malloy, Jensen & Song, 2005) consist of an arbitrary number N of abstract entities called nodes. Since the model is Boolean, the nodes have two states: ON (state = 1) and OFF (state = 0). Each node takes input (0 or 1) from K nodes. Time flows in discrete iterations. On iteration T, each node takes the input (0 or 1) it receives from its K input nodes and uses a logical truth table to determine what its own value will be (either 0 or 1) on the next iteration, T+1. That is, the nodes are coupled; the output of one is input to others and visa versa. As a very simple example, suppose a node, call it Node A, receives input from K=2 other nodes. If Node A is using an AND operator then its state will equal 1 on iteration T+1 only if its two inputs are both equal to 1 on iteration T. Similarly if Node A is using an INCLUSIVE OR operator then its state will equal 1 on iteration T+1 if either its first input or its second input or both are equal to 1 on iteration T. So the relationship between a node's inputs at time T determines its state on the next iteration. This simple model can produce complex dynamic patterns. NK Boolean systems exhibit the usual characteristics of dynamic systems including attractor cycles which will be described below and which will play an important role in the perception of the dynamics of such systems.

Insert Figure 1 about here

State Vectors.

State vectors, S(T), are a convenient way to characterize a system's dynamics. A state vector is an ordered array indicating, for any given moment in time, which nodes are OFF (0) and which nodes are ON (1). Thus, for a 4-node system, S(T) = {1000} means the first node is ON and all other nodes are OFF. The state space is the list of all possible state vectors; for a small system with four nodes, the list of state vectors ranges from {0000} which indicates all nodes are OFF to {1111} which indicates all nodes are ON; this amounts to Boolean counting so there are only 32 possible state vectors in the state space of a 4-node system. In general, the number of state vectors is 2^N, so for any N that is large the state space is exponentially large. For purposes of exposition, suppose a system, call it 4-Node Standard, has only four nodes (N = 4). Suppose on some arbitrary first iteration T=1 the ON-OFF pattern for the four nodes from first node to last node is ON, OFF, OFF, OFF. This can be written as a state vector: S(1) ={1000}. The system is deterministic and one state vector leads to the next state vector. This deterministic derivation will not be included in this paper (see Malloy, Jensen & Song, 2005) but Figure 1 shows the results of that derivation where arrows indicate how one state vector flows into another. For our current example, examine Basin 2 in Figure 1b; if we start the sequence of state vectors with S(1) = {1000} that vector goes to S(2) = {0001} which goes to S(3) = {1100} which goes to S(4) = {0011} which goes to S(5) = {1000} which goes to S(6) = {0001} which goes to S(7) = {1100} etc… This sequence therefore describes the flow of states (or, alternatively, the behavior) of the system across time. Notice that there is a loop in state vectors.

Self-organized Landscape of Basins of Attraction.

Because the system is deterministic a given state vector, S(T), will always be followed by the same state vector S(T+1). Therefore the fact that in the above example S(5) is identical to S(1) means that S(6) must be identical S(2) and S(7) must be identical to S(3), and so on. That can be clearly seen in Figure 1b where starting with {1000} ==> {0001} ==> {1100} ==> {0011} ==> {1000}, the state vectors loop back upon themselves after four iterations. This indicates that the system is in an attractor cycle (in this case of length four, L=4) because there are four distinct state vectors, S(1) through S(4), repeating endlessly. The length of an attractor cycle, measured in the number of state vectors before it repeats, is the fundamental frequency of the attractor cycle (Baker & Gollub, 1996, call these natural frequencies). The system cannot escape this attractor cycle unless the system is perturbed. (Perturbation amounts to changing the state of one or more nodes.) A fuller discussion of the 4-Node Standard example is found in Malloy, Jensen, and Song (2005). The important points are (1) that an NK Boolean system is an abstract infrastructure (nodes, their connections, and their relational operators) and (2) that when this mathematical infrastructure "runs" its flow of process (described by a series of vectors indicating the states of each of the nodes) falls into a set of basins like those shown in Figure 1. Figure 1 can be described as an adaptive landscape (Kauffman 1993). That is, Figure 1 shows that from moment to moment the flow of process in our small Boolean system self-organizes into a landscape consisting of three basins of attraction much like mountains and valleys with lakes. The flow of the system's process is like water that flows via streams (tributaries) down mountain sides into the lakes (attractor cycles). Figure 1 shows a landscape that has three basins of attraction. Basin 1 has five tributaries, each of which flows into the attractor cycle (Attractor 1). Attractor 1 consists of four state vectors that cycle endlessly; since Attractor 1 repeats every fourth iteration its fundamental frequency is L=4. Basin 2 has only two tributaries and they both flow into Attractor 2 which also has a fundamental frequency L=4. Basin 3 has no tributaries and its attractor has only one state vector leading directly to itself; thus its fundamental frequency is L=1. Notice that all of the possible thirty-two state vectors for a 4-node system are present in Figure 1. The flow of process remains trapped in an attractor unless or until it is perturbed into another basin of attraction where it will run downhill along a tributary until it reaches the attractor cycle. The landscape describes fully all possible flows (from one moment to the next) that the system's process has available. Even as N increases even modestly ($7 < N < 50$) the state space and therefore the landscapes can be very complex with hundreds or thousands of attractors and tributaries that are very long strings. We emphasize that this landscape is an emergent characteristic of the system's infrastructure but is distinct from infrastructure (nodes, connections and operators). The attractor cycles, which we will discuss in terms of visual forms below, self-organize from the system's nodes, the connections among the nodes, and logical operators each node uses to decide to be either ON or OFF. In this sense an attractor cycle is related to but also distinct from the Boolean infrastructure in the same way that the perception of visual form is related to but distinct from neurology.

Static Snapshots of Dynamics

In order to understand how dynamic temporal forms emerge from the behavior of Boolean systems it is convenient to explain first how system dynamics can be portrayed statically. This is akin to taking a photo of the action in a team sport. Certain useful relations can be inferred from the frozen spatial relations among the players but the full dynamic pattern of a team playing together is lacking.

Historical Trace.

Consider the series of state vectors in the preceding discussion. Rotate the state vectors to be column vectors; then put these column vectors on a grid with 0's translated to white cells and 1's translated to black cells. The ordinate will then represent individual nodes from 1 (top) to N (bottom) and the abscissa will represent iterations from 1 to T. Figure 2a shows the state vectors of

Attractor 1 detailed above. The system has 4 nodes (ordinate) whose states vary across sixteen iterations (abscissa). Black cells translate as a 1 in a columnar state vector while white cells translate as a 0. Notice the visual form generated as the behavior of the system unfolds over time. Different attractor cycles generate different visual patterns; Figure 2b shows the form generated by Attractor 2 in 4-Node Standard. These patterns, generated in this way, are consistent with Turing's (1952) discussion of morphogenesis; for a fuller discussion see Malloy, Jensen, and Song (2005).

Insert Figure 2 about here

We now introduce an example with more complexity. Figure 3 shows a small Boolean system (N = 36 nodes) that has 126 known attractor cycles in its landscape; the fundamental frequencies of these attractor cycles include 2, 4, 5, 6, 7, 8, 10. Figure 3 shows three screen-captures for three different attractor cycles (panels a, b, and c) generated by this system. As noted above, the abscissa contains the node positions from the first (top) to the thirty-sixth (bottom). White cells correspond to a Boolean 0 and black cells to a 1. For each attractor (a, b, c) the ordinate shows discrete units of time (iterations) from T=1 to T=31. That is, Figure 3a shows a snapshot taken through a window into the dynamics of the system when the system is in one of its attractor cycles. The window is 31 iterations long. Similarly, panels' b and c show two other windows, each 31 iterations long, into two other attractor cycles. The length of the window, W, is a crucial variable once we move from a static picture to a dynamic flow.

Insert Figure 3 about here

Characteristics of Temporal Dynamics.

Cycles and Fundamental Frequencies.

In Figure 3a look at the first (left-most) column. The top cell is white, followed (downward) by another white cell then a black then another white then two blacks and so on to the bottom of the column which ends with a run of five white cells. You can think of the first column as the vertical state vector for the 36 nodes on the first iteration, S(1) = {0010110…}. Correspondingly, the second column is the vertical state vector for the second iteration, S(2) = {0010111…}. Thus Figure 3a shows the flow of state changes of all 36 nodes across 31 iterations. Notice the repetitive nature of the resulting pattern. Within the 31 iterations shown in Figure 3a, the vertical state vectors portrayed as white and black cells repeat themselves exactly every four iterations; this indicates that the system is in an attractor with a fundamental frequency L= 4 which is perceivable as a repetitive temporal pattern. The fundamental frequency of the system as it repeats across time is one defining aspect of what we mean by a temporal form. While we can perceive these characteristics of the system statically, the perception of such patterns from dynamic rather than static modality is the central focus of this paper; that is, printed pictures in figures on a page do not allow a person to perceive the dynamic phenomena that interest us here. Thus the Java applets are a necessary component of the results. Figure 3b shows a different attractor cycle which also has a fundamental frequency L = 4. Finally, Figure 3c shows the system in an attractor cycle with L =7.

As noted above, translating the flow of state vectors and keeping a visual record of that flow for some number of iterations (in this case 31) is what we call a historical trace of the system's behavior and in the static figures it can be seen through a finite window of time. Figure 3 makes apparent that a historical trace perceptual strategy allows different basins to be easily distinguished from each by a human observer; it is obvious that the system is in different attractors in the three panels of Figure 3. Moreover, if a person is willing to count carefully, the historical trace allows the fundamental frequency, L, to be determined.

Sub-cycles.

While a dynamic system may be cycling as a whole at a fundamental frequency parts of it may be cycling at faster frequencies. In biological motion (Johansson, 1973) for example, a whole person walking may be a dynamically stable form, the arms may be cycling at a faster rate within the whole. Returning to Figure 3a, note that most of the nodes are repeating a pattern of states more frequently than every four iterations (the attractor's fundamental frequency). For example, Nodes 1, 2, and 3, at the top of Figure 3a have a sub-cycle frequency of 1, (subL=1); that is, they repeat the same state each iteration. Nodes 16, 17, 18 (among others) repeat the same state every other iteration and so have subL=2. Other nodes in Figure 3a, e.g., 11 and 12, repeat every fourth iteration and account for the system's fundamental frequency of four as a whole system. In other words, the system of nodes as a whole has a fundamental frequency of 4, but individual nodes in isolations may have shorter fundamental (sub) frequencies. We continue to call these sub-cycle lengths fundamental because they are intrinsic characteristics, akin to eddies, of the flow of the system's process. Similar results can be seen in Figure 3b. In contrast, Figure 3c shows a basin of L = 7. Since 7 is a prime number, the only subL to be found is equal to one (those nodes that remain always black or always white). All other nodes repeat their pattern every seven iterations (L). The perception of cycles and sub-cycles of dynamic systems is one focus of this paper.

Insert Figure 4 about here

Figure 4 shows another small dynamic system (N = 20), which will be called Exemplar 2 below. Note that the attractor cycle pattern is more complex; the fundamental frequency is L=50.

Figure 4 shows a window size, W, of 100 iterations (twice through the cycle length). There are no sub-cycles, although we will have to wait before we see convincing perceptual evidence of that assertion. As complex as this historical trace is, we will find both more complexity and more simplicity later when we present this system dynamically rather than statically.

Dynamic Presentations of Systemic Flows

Primary flow and Secondary flow.

Dynamic motion, such as biological motion (Palmer, 1999, p. 512), cannot be fully captured in snapshots. In Figures 1, 2 3 and 4 we have presented static images (a snap shot taken through a window) showing a historical trace of the states of the N nodes (abscissa) for some number, W, of iterations (ordinate). A simple way to think of what we are doing to generate dynamic presentations of a Boolean dynamic system is that we present a series of snapshots sequentially in real time. To create dynamic presentations on a computer screen the E42 program paints a series of state vectors to the screen; then the next series of vectors is painted over the previous series of state vectors, in rapid succession, much like the frames of a movie. More specifically, E42 tracks the flow of state vectors for W iterations, translates those state vectors into a N x W black and white image (similar to the figures above) and paints it to the screen; E42 then tracks the next W iterations and paints another N x W array to the screen, and so on. In more formal terms we can say that the screen painting process is cyclic and its frequency is W iterations. Indeed, while we use the term "window" and "snapshot" because they are a comprehensible way to describe what is going on, this language is misleading. Unlike cinema, which presents a series of slightly different snapshots, in our simulations there are only two flows of the same state vectors each cycling at a different frequency. We now describe the generation of dynamic form in terms of two cycling flows.

Phase relations.

In the simulations, the first of flow state vectors is continually calculated in a computer's CPU; it describes the status of system dynamics from moment to moment. To stay as theoretically neutral as possible, when we map this process to visual process, we will simply call this "primary flow." In all cases considered here, this primary flow of state vectors falls into cycles (attractors). The second flow is a cyclic process of painting the state vectors calculated in the CPU to the screen as columns of white and black squares. Again to be theoretically neutral we will call this secondary flow (because the first flow must exist before W iterations of the first flow can be calculated). The second flow cycles with frequency W. When the system is running dynamically, the frequency of the second flow, W, has interesting effects that can conveniently be described in terms of apparent motion phenomena. As in the wagon wheel illusion, when W = L, that is when W equals the fundamental frequency L of an attractor, the dynamics appear static (apparent stability) on the screen even though the dynamic system is running. This is because when the window is exactly one attractor cycle length long, each successive snapshot painted to the screen will be identical. Similarly, when W is longer than L, the dynamic patterns appear to move right to left and when W is shorter than L, the dynamic patterns appear to move left to right. More abstractly, we can describe the effects of changing the W variable as changing the phase relations between the cycles of the first flow and the cycles of the secondary flow.

While having two flows of system dynamics is theoretically justified as an operational consequence of Bateson's epistemology (that knowledge emerges in the relations between flows of mental process), it is also required in the logic of the simulation. In a computer simulation, to present the flow of a Boolean system's dynamics on a screen we must choose some window size, even if it is W=1. That is, we can paint each iteration as it occurs (W=1), or we can wait two iterations and paint them together (W=2) or wait three iterations and paint those together (W=3) and so on.

RESULTS

The primary results for this article cannot be printed on paper but are perceptual experiences of the reader while interaction dynamic systems simulations. These perceptual activities are found in a series of simulations named Exemplar 1, Exemplar 2 and Exemplar 3, all of which are archived at www.psych.utah.edu/onlinedata/malloy.

We will now turn to perceptual phenomena that result from manipulating the phase relations between the fundamental frequencies of a Boolean system (L and sub-L) and the frequency W, which is inherent in the process drawing the system on a monitor. Later we will speculate about the possibility that human perception of dynamic form might be modeled in terms of similar phase relations in the perceptual system.

Adjust frames per second.

If necessary, get the Java plugin at Java.com. Different computers run at different speeds; what matters perceptually is how many windows (frames) are painted to your screen every second. In all the following applets it is important first to press the “Use Delay” radio button and then to adjust the Delay slider until your particular computer is painting windows to the screen at about 25 to 35 frames per second (fps). The fps readout is to the right of the Stop/Play control bar. The number of fps is a potent variable and you may set it to any value you want by adjusting the delay between each painting of a window to the screen. We suggest the speed be between 25 fps and 35 fps as a useful range for apparent motion phenomena. Also, keep the fps below 65 since most monitors cannot paint accurately beyond about 65 fps. To adjust the delay between each screen-paint you may either drag the Delay Slider or, for finer adjustments, single-click on the Delay

Slider Bar either above or below the Slider. The Delay function is an important variable in perceptual organization and is part of our ongoing work, its consideration is beyond the scope of this paper.

Perceiving fundamental dynamics.

The Exemplar 1 applet allows the user to adjust the W variable in relation to attractor cycle length, L, and sub-cycle length, subL. Consistent with apparent motion effects, when the frequency of W equals fundamental frequencies (L or subL) the dynamic pattern (or part of it) freezes. The default attractor of Exemplar 1 has L=4; since the applet defaults to W=69 which is not divisible by 4, you will see apparent motion upon pressing Play. Only nodes that have sub-cycle length = 3 (or 1) will appear apparently stable. You will also find examples of ambiguous motion; simply drag your mouse back and forth across the parts of the display that are (apparently) moving and you will find that some of them will move either right or left. You can also see this ambiguity in motion just moving your eyes differently (without dragging a cursor). You may drag the Window Size Slider to change W which changes phase relations between the Boolean dynamics (first descriptions) and the screen paint process (second description). To get small increments or decrements in W you may click on the Slider Bar above or below the Slider. When you change W to 72 the whole display stops; the system is still running and what you see is apparent stability. When you change W to 71 the whole basin moves as a coherent whole. When you set W to 70 only those nodes with subL=2 will exhibit apparent stability. As noted above, setting W to any multiple of 3 results in apparent stability for those nodes with subL=3.

To change attractor cycles, you can perturb the system by clicking the Perturb button near the bottom of the control panel; this changes the values (from 0 to 1 or visa versa) of some fifty percent of the nodes. Typically, but not always, this will provoke the system into a different attractor basin. If the system does not change attractors, click Perturb again. While all the particulars change for the new dynamic pattern resulting from a new attractor cycle, the generalizations noted above remain perceptually evident.

This applet demonstrates perceptually that shifting the phase relations between the fundamental system frequencies (L, subL) of the first flow and the second flow frequency produces changes in dynamic forms that highlight various fundamental characteristics of the system either by making them static or by changing their movement pattern. In other words a simple shift in the phase relations between intrinsic systemic dynamic characteristics and the process of screen painting can highlight fundamental characteristics of dynamic behavior by either freezing them in apparent stability or making them apparently move differently than the rest of the system.

Perceiving derivative dynamics.

We now examine how the phase relations between the two flow frequencies generate forms that are not fundamental to the system but are solely derivative of the interaction between the two flows. Let us look at a second example and then discuss this further. The Exemplar 2 applet demonstrates that system characteristics that are not fundamental frequencies of attractor cycles can pop out perceptually through manipulating the phase relations between the primary flow of system process (flow of state vectors in CPU) and the second flow of system process (screen paint), using W as a control variable.

Figure 4 shows a static version of the default basin for the Exemplar 2 applet; this system has two other known basins. Press Play and adjust the Delay so that fps is between 25 and 35. The applet loads with W = 75; at that setting islands of stability (that are not present in the static image of Figure 3) appear in the midst of a grey background (black and white cells alternating quickly). These islands are neither basins nor sub-basins. They are visual forms that have apparent stability and that emerge from the phase relations between the first and second flows. If these phase relations are changed, if W is set to 74 or 76 (click below or above the Slider on the slider bar), these islands will remain as coherent units but begin moving. Further changes in the relationship between first and second flows produce more complex perceptual results: At W = 77 other apparent forms emerge. These emergent forms are not found in static images of the system (e.g., Figure 4 nor are they found when the Stop button is pressed on the applet). The fundamental conceptual point is that the emergence of these dynamic patterns is a co-construction of two processes within the system's dynamic behavior.

Ambiguous motion.

In Exemplar 2 at W = 77, ambiguous motion also appears (as it did in Exemplar 1 at W=69). In Exemplar 2 ambiguous motion can be observed for Node 5 (fifth node from the top, lined up with a red hash mark). Move a pointer (the mouse arrow or a pen tip) horizontally along Node 5 from left to right and then right to left; the black squares will move with the direction of your pointer. (The user may have to change the horizontal speed of movement of the pointer to obtain this perceptual effect.) With a little practice users can provoke this change of direction of movement with their eyes alone. With W = 83, complex emergent forms with ambiguous motion can be perceived moving either right to left or left to right; once again, you may require a horizontally moving pointer to observe this phenomenon. Since the fundamental frequency of the default attractor cycle is L = 50, integer multiples of 50 will produce an apparently static pattern that looks like Figure 4, even though system is running. Additionally, as with other apparent motion phenomena, the speed of presentation in frames (windows) per second also affects perception and can be explored by manipulating the Delay Slider. Results at 50 fps can be strikingly different than at 25 fps.

Finally, explorations with Exemplar 3 will reveal similar phenomena to those found in Exemplar 2 but will have a resemblance to wave patterns like those in the flat area between a beach and waves that are breaking. At the default W = 91 and with the speed set to about 35 frames per second an ephemeral wave pattern moves from right to left while a choppy and more robust wave pattern moves more or less from left to right. Other window sizes produce strikingly different dynamic patterns. Once again, these patterns don't exist in the fundamental frequencies of the system itself but emerge in the phase relationships between the two descriptions of the system's dynamics.

DISCUSSION

The results demonstrate that window size, W, is a potent variable in a viewer's perception of dynamic visual forms that emerge from the phase relations among two distinct flows of the same state vectors calculated by a computer and painted onto a screen. So what does it mean that the window size (our manipulation of phase relations) is so influential? In painting CPU dynamics to a computer display, what appears on the screen is simply a copy of the ongoing dynamic flow in the CPU that happens to be converted from 0's and 1's to WHITE and BLACK. (But the conversion is not the important focus). The important focus is the necessary choice that the painting-to-the-screen process have some (however arbitrary) phase relation to the primary flow, as we noted just prior to the Results section above, and that dynamic form emerges from these phase relations.

Regarding the correspondence problem, notice that there is no issue of making 0's and 1's in the secondary (screen painting) flow correspond to 0's and 1's in the primary flow; the issue does not come up. Dynamic form simply is what emerges from phase relations. So the form itself corresponds to itself from moment to moment but this correspondence is intrinsic to the form (essentially phase relations) and is not a correspondence which is external to the perceptually organized form, it is not a correspondence of bits in one flow to bits in the other flow. The E42 simulation turns the correspondence process (e.g., Dawson, 1991) on its head and makes correspondence intrinsic to the form itself and dependent on a single control variable—phase relation.

The demonstration of the consequences of manipulating phase relations between the flow of E42's computational dynamics in a computer's CPU on one the hand and that same flow on the screen on the other hand is one kind of endeavor. The mapping of these simulation consequences to human perception is another, more speculative, endeavor; this endeavor is shared with any mapping in science from models and theories to results (or to observer-experiences in Gestalt-like cases such as ours); in this sense the scientific method never proves a theory but can argue for its ever greater plausibility or for its falsification. We have argued (Malloy, Bostic St Clair, and Grinder, 2005) that the mapping from theory to method to data is always a part of the scientific processes. Therefore, in agreement with Keller (2002, pp. 4,5) who grounds explanation in biology "in that which makes biologists say Aha!" we assume that the person who evaluates whether a scientific mapping is useful (or not) cannot be removed from scientific methodology. While such meta-arguments are particularly critical in Gestalt-like phenomena such as ours, they are a whole other issue that is beyond the scope of this paper. We assume the reader is willing to consider critically the following mapping.

Before we pursue the mapping of our model, we will be specific about what we are not doing. We don't propose that, in this study at least, E42 models any aspect of the universe such as the external ambient optical array. Nor are we proposing to build replicas of actual neural activity and pathways (neural nets and other models do that better). Rather, we are modeling Bateson's proposal that what gets onto maps from the territory are differences and his proposal that, of its nature, knowledge is a flow of transformed differences in a network; thus we suggest that E42 acts as an (extremely) idealized and abstracted model of the visual system's activity, in the Batesonian difference-based sense, when the visual system is coupled to the universe. We are also modeling Bateson's proposal that knowledge emerges from the relations among multiple descriptions defined as multiple flows of difference.

The Batesonian flow of differences is relevant to neural flows but acts as an examination of their more abstract characteristics rather than their replication. In that sense we don't specify which part of the visual system our model's two flows best map to; perhaps the first flow is dynamic retinal activity (which we use as one possibility in examples), perhaps both flows are post-retinal flows. Regarding the retina, it is plausible that retinal activity is dynamic and might be modeled by a dynamical system (Godfrey & Swindale, 2007) but, also, as noted above, there are at least two separate flows to two different populations of neurons that respond to apparent motion (Merchant, Battaglia-Mayer, & Georgopoulos, 2004). Our mapping primarily requires that there be two flows of neural activity whose phases could be put in relation to each other.

That phase relations between processes produce complex patterns is quite general in nature and includes the dynamics of musical instruments as they produce sonic forms and biological morphogenesis (Abraham & Shaw, 1984, chapter3). Baker and Gollub (1996) detail how phase relations are a critically useful way of visualizing complex, even chaotic, dynamics. If someone asks what is the shape of the moon in the night sky we would surely have to ask about its phase before replying. The fundamental point is that we can visualize the phase relations between any two flows and that such visualization is one theoretical approach to how a visual system might organize form as form morphs over time.

Indeed the phase relation model is one kind of answer to Kubovy & Gepshtein's (2003, p. 78) question: What is a Gestalt? Our primary and secondary processes generate, through their phase relations, the emergent Gestalt. Moreover, there is no need for a separate, *a priori*, specification of correspondence between elements (0's and 1's) in the two generating flows; the fact that the 0's and 1's in the two flows do not correspond (in the general case) is the basis for the emergence of the variety and complexity of forms in the Exemplars. The changes over time in the forms are fully described by the phase relations and, while various points in a given form do correspond from moment to moment, this correspondence is part of what emerges from phase relations. In Holland's (1998) terms, primary and secondary flows are the constrained generating procedures from which form emerges. The primary and secondary generating processes are fully coupled with the emergence of form much like the interactions of water molecules are coupled with the appearance of standing waves in a stream.

Meta-Theoretical Issues

In perceptual organization how might the phase relation control variable work? What controls this control variable? The answer to that question is, of course, meta to the model we are describing but it is plausible to assume that phase relations could be adjusted by larger feedback systems. The perceptual system would not require a homunculus; instead it would merely need some feedback system that adjusts the phase relations between the primary and secondary flows of process based on the utility of interacting with the environment using one emergent percept versus another emergent percept. As is perceptually evident in Exemplar 3, this feedback-based adjustment would allow the emergence of a great variety of dynamic forms in relation to the optical flow that results from (motor initiated) movement, shifts of attention, and other ongoing visual and cognitive processes (see Turvey & Carello, 1986, and Kugler & Turvey, 1987, for a dynamic systems update of a Gibsonian ecological approach relevant to these meta issues, and particularly Van Orden, Moreno, & Holden, 2003, for how the real time emergence of dynamic form might, like word pronunciation, "attend on larger relations" for the control of phase relations among lower order processes). Ultimately, since these phase relations can literally freeze or pop out dynamic forms, there is no need for a homunculus for recognizing forms.

In terms of human development and perceptual learning, the ability to shift and stabilize these phase relations would depend on the utility of the emergent forms for a particular sentient being relative to specific contexts; for example, higher-order kinds of feedback (reward, punishment, social group coherence, etc.) would determine the utility of one adjustment of phase relations over another. Humans would learn, for reasons of pragmatic and cultural feedback, to organize and therefore perceive certain visual forms by adjustments in the phase relations between the two flows. Thus perceptual and social learning would occur at the level of phase relation adjustments while the forms themselves emerge from the learning-dependent phase-relation adjustments. This is parallel to Kauffman's idea, modeled with Boolean systems, that, in evolution, biological form self-organizes (in our terms from the flow of genetic code) and that natural selections act to favor one form over another. In this theoretical framework, both learning and natural selection are thus relieved of the burden of how form, in all its complexity, comes into being; they are given only the function of answering the question, which form specifically continues to be present?

A second important issue that is intrinsically related to our model (or any model of perception) is the issue of map-territory relations. This model assumes at least two flows of visual process; and for perceptual organization that is all that is necessary in the model. Meta to this model is the issue of how the nervous system relates to the world around it. As mentioned in the introduction, following Bateson, we assume that what "gets onto maps" (into the visual system) is differences in the territory. We also assume that the territory itself is a dynamic system, that, as it were, the mountain creek we are gazing at is a flow of water molecules and that these molecules by the logic of fluid forces self-organize into complex standing waves, eddies and in general what we call current. This happens in much the same way a Boolean flow self-organizes into attractor cycles; indeed that is the heart of Bateson's computational point—that a difference-based dynamic system is sufficiently rich to constitute a map of the territory.

We assume that the visual neurology (say for example the retina) is entrained with this dynamic environment. Allow for the moment that our "primary flow" is mapped to retinal flow, entrained as it is to the dynamically stable patterns in the environment, and that the retina itself falls into attractor cycles. The perceptual organization of perceived form, then, is what is generated by the phase relations between this primary flow and the secondary flow. The perceived forms that emerge, of course, would have no need to resemble the forms in the territory; indeed, they must surely be what, in logic, is called a different "kind" of form. Our complex percepts of the waves in the stream's current have no requirement to be anything like the waves in the current itself. What matters is that we have the control variables necessary to adjust our perceptual forms to be ones that are useful in, say, navigating that current. In our model this is a simple adjustment of phase relations. That humans make such adjustments is clearly the case; when someone says, do you see that cloud that looks like a camel, it may take some adjustment before we can say, oh yes, there it is; I "see" it.

Theoretical Consequences of a Phase Relations Model

Fundamental forms.

In the Exemplar 1 results we see that manipulating phase relations between a primary flow and a secondary flow of systemic dynamics produced (dynamically) static visual forms that reflected fundamental characteristics of the system (L and sub-L). The primary flow and the secondary flow are both still running, thus forms that are static (not moving) are only apparently static. To the degree that, say, the retina, is entrained with fundamental frequencies of the attractors that the territory has fallen into (the actual standing waves in the mountain stream), then these dynamically static percepts do, while of a logically different kind, reflect veridically the dynamics of the environment. Evolutionary morphogenesis alone produces many visual regularities, including camouflage and aposematism (e.g., the black-yellow striped coloration of the bumblebee meant to signal predators that is unpalatable) that, when combined with eye and body movement, are cyclic and describable as attractors.

Derivative Forms.

A (model of a) visual system should be able to reflect the constraints in the environment (Marr, 1982), particularly dynamic ones. In Exemplar 2 and Exemplar 3 we see the emergence of dynamic forms that are not fundamentals of the system's attractor cycles (and therefore not reflective of the fundamental frequencies that are constraints in the environment), rather, they are solely derivative of the phase relations between the primary and secondary flows within the visual system. This is intriguingly parallel to the idea that sentient beings, particularly mammals, primates, and humans don't simply extract "that which exists" in the territory (environment) but rather that their perceptual process interacts with "that which exists" in ways that actively co-construct or "enact" their experience going beyond the information given (Varela, Thompson, & Rosch, 1993). Indeed, while our results do not resolve the issues currently debated around "representation" (e.g., Schvaneveldt & Van Orden, 2002), they are consistent with approaches that argue against the necessity of the concept of representation; these approaches instead emphasize dynamic co-constructions of which our emergent dynamic forms could be an example.

The model, simple as it is, makes a important distinction between emergent forms based on the fundamental frequencies of retinal dynamics (Exemplar 1) on the one hand and emergent forms derived solely from the phase relations between the two flows (Exemplar 2 and Exemplar 3). In contrast to fundamental forms, derivative forms emerge solely from the relations between the two flows; this does not mean that they cannot be stable and useful. Given that the retinal image is entrained with a particular environmental context whose dynamics are stable across time, these derivative forms would then emerge reliably for each visit to that context. It matters less for the organization of behavior that our percepts are reflective of fundamental frequencies in the environment (versus derived from those frequencies) than that the percepts be reliable across successive interactions.

Complex Movement of Complex Forms.

The complexity of form and movement (including bistability) exhibited by the exemplars, while derived from and described by a phase relation model based on Bateson's idea of multiple flows of difference, has the virtue of being the movement of complete wholes. While it would be theoretically acceptable to describe the perceptual organization of moving forms in terms of a single control parameter, phase, it would also be interesting to relate the phase model to the many models of organization and motion, particularly apparent motion. This leads directly into the limitations of E42 in its current version.

Limitations of the Model and Future Directions

The simulation program was originally designed to explore how dynamic systems frameworks about the morphogenesis of biological form might shed light on the perceptual organization of visual form; it was not designed to study apparent motion. Yet when we observe the model's generation of visual form it is clear that apparent motion plays a central role in the organization of form in the model. From our perspective it is sensible, then, to take the view that apparent motion in its many kinds is in the service of the perceptual organization of dynamic form since dynamic form perception would be of critical importance in evolution. If the model is one of both apparent and real motion of form, then the cyclic attractors the retina falls into can result from actual motion or from an experiment in apparent motion; it make no difference to the emergence of form due to phase relations between two flows.

While one of the strengths of our simulations is that our displays integrate many kinds of apparent motion into perceptually organized moving forms; this strength is also a limitation. The current version of E42 presented here does not allow analysis of the forms into differing kinds of motions. Thus, while our findings are deeply sympathetic to the idea that form emerges in time-space (Gepshtein & Kuboby, 2000), without the ability to analyze the motions in our exemplars we cannot provide results that build upon and clarify the distinctions developed by their motion-lattice methodology. Moreover, it is difficult to directly relate our results to apparent motion phenomena. Examination of Exemplar 1, Exemplar 2 and Exemplar 3 reveals many apparent motion phenomena including second order motion (in the waves in Exemplar 3), complex plaid motions (in Exemplar 3 set at W=59 and fps = 25), kinetic depth (subtly at many settings for Exemplar 3 waves and strikingly in Exemplar 1 for the row of columns moving together ambiguously right or left), and transformational motion (in Exemplar 1 where the sets of three square-arches appear or disappear depending on the settings Delay and W). Our displays also share some aspects, at least, of random dot kineograms, but they are generated in different ways and for profoundly different reasons.

These examples of the kinds of apparent motions found in our displays are not meant, at present, to analytically sort various kinds of apparent motion that have been found (Anstis, 2005; Cavanagh & Anstis, 2002, Ramachandran & Anstis, 1986). In fact, it is difficult to extract with certainty any one of these types of motion from the exemplars for description and analysis. As an example, direction repulsion (Hiris & Blake, 1995) most likely is ongoing in our complex displays but it is difficult to say how specifically.

This means many questions about how the kinds of apparent motion contribute to the overall organization of form seen in our exemplars can't be answered directly with our methodology. Quite simply, our approach is currently not useful for answering many questions about apparent motion; to be fair, the method is aimed at the genesis and organization of whole visual forms based on evolutionary distinctions made by Kauffman (1995). But the questions about apparent motion are interesting and most likely relevant to the further elaboration of our approach to form perception. For example, Cavanagh and Mather's (1989) proposal that first-order and second-order motion are generated by the same kind of operation is consistent with our findings but we cannot support or disconfirm their proposal (and therefore strengthen or weaken ours) with detailed follow-up analysis using E42. The boogie-woogie illusion (Cavanagh & Anstis, 2002), as another example, has descriptive power in relation to some of the waves that ephemerally drift upwards in Exemplar 3 but that illusion is not analyzable from our current displays.

Because of the limitations in the previous paragraphs we are building a motion vector tool to analyze the motions that are present in the various self-organized forms shown in the exemplars. Such a tool is aimed at exploring motion vector analyses such as those by Gepshtein and Kubovy (2000), particularly in their motion lattices (Kubovy & Gepshtein, 2003), but in the context of our complex dynamics. In our framework their motion lattices, flipping between frame 1 and frame 2, constitute an attractor with L=2; thus their findings (e.g., 2000) that spatial variables affect element motion but not group motion begin to add insight into how our derived forms might come about. Such an integration of our holistic forms that emerge from phase relations and the analytic processes of motion lattices could shed light on the question (Kubovy & Gepshtein, 2003, p. 78): Where is the Gestalt? We have created an early version of the motion vector tool but at this time we cannot say how useful that analysis will be for addressing the larger issues in apparent motion or in separating specific models.

A further limitation of this study is that, for the moment, we are ignoring E42's Delay variable which is tantamount to ignoring the importance of timing variables in apparent motion (e.g., Giaschi & Anstis, 1989). From our experience we know that this is a second potent variable, along with phase relations, for determining dynamic form. The Delay variable on our displays, while globally manipulating timing variables, does not make basic distinctions such as that between stimulus interval and inter stimulus interval. It is only designed to manipulate frames presented per second in a way that allows adjustment for differing processing speeds on different computers. Thus our current tools do not address the manipulation of important timing variables. This lack, of course, does not change the importance of phase relations in dynamic form but rather indicates that our model is incomplete; any complete theory on dynamic form must consider the manipulation that we operationalize as the Delay variable along with other relations among timing intervals. In fact Gepshtein and Kubovy (2000) point out a methodological advantage of holding timing variables constant in examining models (sequential versus interactive) of perceptual organization; in their case the choice was principled. The advantages of fixing timing variables may still apply, however, when examining the exemplars.

In addition to the motion vector tool mentioned above, and in line with the work of others (e.g., Hock, Gilroy, & Harnett, 2002; Hock, Schöner, & Giese, 2003), our current and future work focuses on using complexity (Dubuc & Zucker, 1995) and dynamic systems mathematics, particularly on the mathematics of potential wells (Chantal & Zucker, 1990), to describe how, out of all the potential motions available, a specific derived form emerges. The second direction for future research is based on symmetry theory; this assumes that symmetry deeply imbues the natural world (Stewart & Golubitsky, 1992) and so it follows that symmetrical information imbues the primary flow that is entrained with symmetrical information in the territory. Symmetry and therefore group theory provide conceptual tools not only for explaining how the retina might be dynamically entrained to the dynamics of the universe but also how a visual system might easily move among different perceptual organizations which are contained in symmetry groups (Malloy, Butner, Cooper, Smith, & Dickerson, 2007).

CONCLUSION

We have presented a model of the perceptual organization of dynamic visual form derived from an evolutionary theory (Kauffman, 1995) in which self-organization is a key element of biological morphogenesis and derived from the ecological epistemology of Gregory Bateson (2000). Some primary visual process (say the retina) is construed to be a dynamic flow that is coupled to the dynamics present in the environment. Assuming such a coupling exists, the retina is modeled as an NK Boolean system that has characteristics typical of dynamic systems such as attractor cycles. These systemic characteristics are assumed to be related to dynamically systemic characteristics in the environment.

Bateson proposes that the emergence of new, useful knowledge requires, as a minimum, a double flow of process and that new knowledge will emerge from the relations between or among flows. In that framework we have described two flows, a primary flow (the retina or one neural path streaming from the retina) and a secondary flow (perhaps another visual pathway); the phase relations between these two flows allow the perceiver to pop out forms that, while of a profoundly different kind, are entrained with systemic frequencies (attractors and sub-attractors) of the ambient optical array. Such fundamental forms are proposed to be the theoretical basis for aspects of perception that have high consensus across observers and would be validated by different systems such as scientific instruments.

In contrast the phase relations between these two flows can also pop out forms that are not systemic characteristics of primary flow (e.g., retinal) dynamics; they solely derive from the phase relations between primary dynamics and some secondary dynamical flow. Such derived forms might be the theoretical basis for aspects of perception that are more subjective, such as forms people perceive in clouds that may not be immediately apparent to other people but can be perceived after some sort of perceptual adjustment. Such derived forms could still have strong correlations with the dynamics of the environment.

In either case, fundamental or derivative, the perceptual organization of moving form is entwined with multiple kinds of apparent motion. The description of dynamic form in terms of phase relations makes the correspondence of points on the form from one moment to the next an artifact of the phase relations and eliminates the need for an *a priori* specification of point correspondence. The adjustment of phase relations between a primary visual process and a secondary process is considered to be controlled, without homunculus, by feedback from other parts of the CNS which are responsive to the utility of one way of organizing form versus other ways of organizing form for acting in the world.

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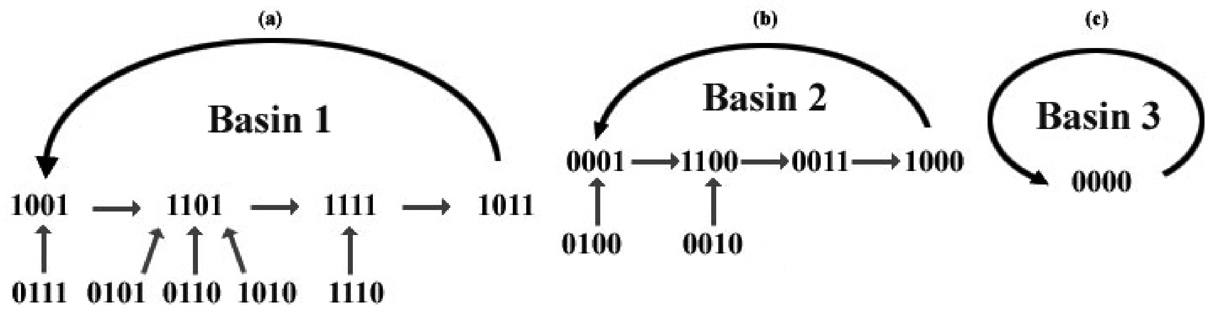
Figure Captions

Figure 1. The Boolean Landscape for a small dynamic system, 4-Node Standard.

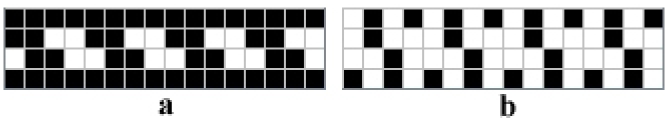
Figure 2. Sixteen iterations (abscissa) of an N=4 node (ordinate) NK Boolean system showing four cycles through two different attractor cycles. Attractor 1 is shown in a and Attractor 2 is shown in b.

Figure 3. Three snapshots of the flow of differences in three attractor cycles into which a small Boolean system falls. This system has 126 known attractor cycles. Attractors a and b each have a length of 4 iterations while attractor c has L = 7. Attractor cycle length is the fundamental frequency of the system when it in a particular attractor.

Figure 4. A static snapshot of the flow of differences for one attractor cycle for a small Boolean system with N = 20 nodes (ordinate). The fundamental frequency of the attractor is L=50 iterations and the snapshot shows two passes through the cycle. When this attractor is viewed dynamically a large number of different forms emerge that cannot be perceived in this static snapshot.



f i g u r e 1



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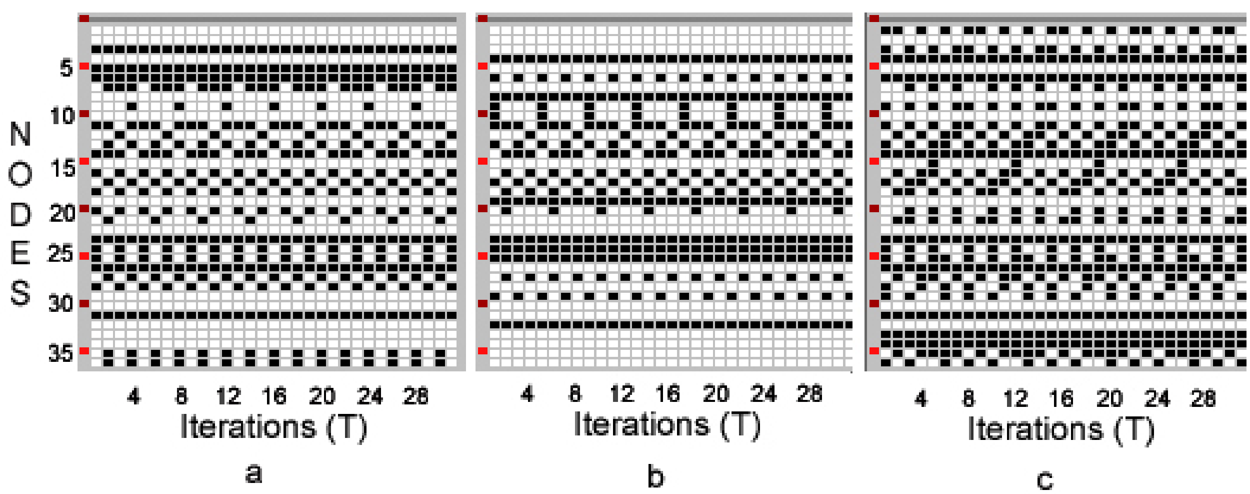

f i g u r e 3

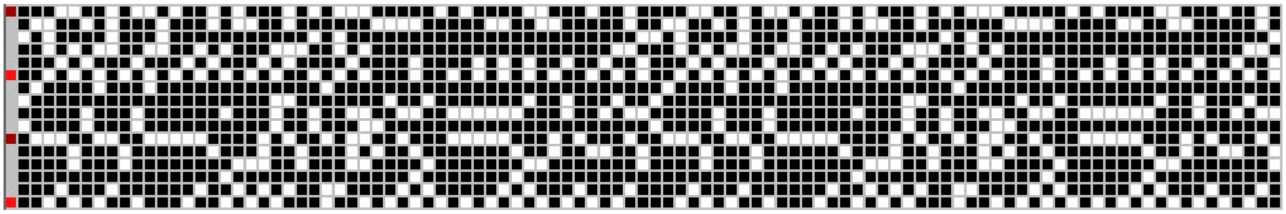

figure 4