Atttention , Depth Perception, and Chaos in the Perception of Ambiguous Figures

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Ambiguous percepts have often been explained by simple satiation or fatiguing of neural circuitry coding the percept, while more recently some explanations involving nonlinear dynamics have appeared. The Necker Cube literature indicates that satiation is unlikely in early stages of the visual system, that the formation of depth Gestalts is a local process, and that there are correlations between attention, eye movements and the likelihood and residency times in the reversible states. It is conjectured that bifurcation parameter gradients in spatially distributed chaotic cell assemblies interact with motor and somatosensory systems to embody depth Gestalts. The gradients may be organized by intrinsic spatial flows resulting from forms which imply a perspective. Simulations exploring these conjecture are reported along with a brief review of relevant visual psychophysics.

1. INTRODUCTION

Gestalt psychology catalogued many fundamental psychophysical phenomena in vision and posited a qualitative field oriented model of perception, but to date no mathematical formulation explaining the rich behavior of gestalt formation has emerged. Since the Gestalt era, analytic or computational models in biological and machine vision have historically been dominated by treatments of early stages the visual system as a series of linear filter channels . Ambiguous or multistable percepts in depth perception (the Necker cube) and figure ground reversals (the Rubin vase/faces image) historically have inspired more theorists to consider nonlinear or computational models, as opposed to other visual phenomena more easily explained by linear systems theory. Models for multistability have ranged from straightforward circuits with some component which fatigued (Attneave 1971) to more sophisticated analyses based on catastrophe theory applied to psychophysical data (T'eed 1988) and a nonlinear model with attention parameters reset by coupling to order parameters, which might be considered a more richly elaborated fatigue mechanism (Haken 1988), (Ditzinger and Haken 1986). Analytical techniques from nonlinear dynamics for dimension estimation have recently been used to analyze time series of perceptual reversals, suggeting that low dimensional deterministic chaos could play a role in both depth interpretation and in the magnitude of sequential saccadic eye movements (Richards 1994). None of these studies to date have really addressed the full range of psychophysical data, or tried to integrate multistable phenomena into a theory of what the visual system is trying to do when it gets stuck in a multistable percept. For example, in the Haken models, we might ask what purpose is fulfilled by having the attention parameters reset?

The inherent dynamical complexity and instability which might lead to multistable behavior based on coupled chaotic oscillators have emerged in recent years based on observations from abstract network dynamics studies (Kaneko 1989) and as explicit models of perceptual and cognitive systems (Skarda & Freeman 1989; van Leeuwen and Styvers, this volume). In addition to the interest in chaotic oscillations, observations of synchronized gamma band oscillations have generated considerable attention in recent years and have been identified as possible signatures of attentional processes (Eckhorn 1992, Grossberg 1991).

The interaction of Gestalt formation with attention is fairly well documented in the case of reversible depth perception with the Necker cube. It is argued here that to depth perception and attention should be considered as a unified field which is computed from the interaction of visual forms with gradients in a spatially distributed bifurcation parameter. This formulation may provide insight into the complex interaction of switching and residency times with attention (as evidenced by eye fixation), depth gestalt, and spatial scale dependencies in multistable phenomena. The recently developed dynamics of coupled nonlinear oscillating systems may provide a rich enough dynamics foundation to model such systems.

This article will first introduce the range of psychophysical data associated with reversible depth percepts and some interactions between attention or fixation points and the perception of the Necker cube and the Muller Lyer size distortion illusion. Some historical theories treating the underlying processes of perspective decoding leading to illusions and the role of eye movements in memory formation are noted. The terminology and mathematical basis of coupled map lattices are described, including the extensions to anisotropic bifurcation fields mediated by the evolution of oscillations. Simulations of the evolution of the lattice dynamics with Necker cube initial conditions are presented, followed by a comparison to related models.

The ideas advanced here are in early stages of investigation and can only be considered as steps toward framework employing spatially extended nonlinear dynamics to applications in the computational perception of forms and to brain modeling. It was demonstrated in related work (DeMaris 1995) that the evolution of geometric patterns used as initial conditions in a chaotic coupled map lattice is useful in characterizing their shape. Initial oscillatory patterns, interacting in weakly chaotic regimes evolve to produce a unique state distribution which can characterize similarity of patterns via a Euclidean distance metric without explicit feature analysis or representation. The overall plan of my research is to extend this computation of oscillations derived from local geometric features to a final representation utilizing feature linking via intermittency, with the attentional and depth gestalt work introduced here serving to highlight regions of interest in a visual form and perhaps to modify shape determined oscillations to bind their location in space.

2. DEPTH PERCEPTION AND MULTISTABLE PERCEPTS

The *satiation* or *fatiguing* theory of multistable percepts is probably the most common in visual psychology texts today. This essentially states that the signal carrier of the percept becomes depleted, saturated, or otherwise enters a refractory period allowing the alternative percept to emerge. Prior to examining more complex dynamics the fundamental evidence against this simple explanation should be cited. The effects of luminance variation over three orders of magnitude on reversal rate, including scotopic (night vision) conditions in which cones were completely inactive, has been studied by Riani et al. (1984). Prior studies over smaller (twenty-fold) ranges had shown contradictory results, with some studies claiming no effect, others reporting effects up to 100% increase. The Riani et al. study, carefully designed to operate in the stable or plateau reversal regime[1], showed no effect on reversal rate. This was considered as strong evidence against a fatiguing effect in early levels of the visual system, up to area 17.

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[1] The time course of cube switching was shown by Brown (1955) to increase during an intial phase prior to reaching a relatively stable plateau, followed by a phase with greater variation in the switching time distribution.

2.1. EYE FIXATION IN VIEWING THE NECKER CUBE

In an attempt to resolve a long standing dispute on whether eye movements were an effect or cause of reversals, Ellis and Stark (1978) undertook a study of location and durations of fixations during reversals; subjects fixations were allowed to range freely over a fairly large (12 degrees) cube while recording fixation points, duration, and reversal times. They demonstrated that fixations are attracted along diagonals in the cube, had longer duration during reversal events (600-800 ms vs. 350-700 ms), and that fixations near (but not on) a central vertex forced its interpretation as part of the near face; they summarize scanning behavior as "back and forth between temporally changing externally appearing corners". Qualitatively described in their discussion are two motion effects apparently related to motion, fixation and attention: moving the cube, which intereres with fixation, can prevent reversals. The presence of a moving distractor bar in a large (visual angle 20 deg) cube also prevents reversals from occurring.

Two experiments indicating a strong causal relationship of fixation point on reversal are reported by Kawabata et al. (1978). In one experiment, subjects were instructed to fixate on one of the two central vertices which could be interpreted as the front face of a cube, and their fixation point was measured. The fixated vertex was perceived as part of the front face for roughly 70% of the time, and the reverse perception was held for 30%. When other vertices were fixated the residence times in each percept were nearly equal. In the second, subjects fixated on a target in a blank field prior to the cube being flashed for 200 ms in various positions; subjects then reported the perceived orientation. In this case, when the target point is near one of the possible front vertices it clearly induces the perception of that vertex in the near field, with probability of the alternative percept falling off with distance.

2.2. EFFECT OF VISUAL ANGLE SUBTENDED BY A NECKER CUBE

Size effects on reversal rate means and distributions have been studied over a wide range with careful control to measure the plateau reversal rate by Borsellino et al. (1982). They found a rapid decrease in the reversal rate for 0-5 degrees, a plateau between 5 and 30 degrees. Intriguingly two distributions of response are found at angles over 30 degrees: some subjects exhibited a strong trend of decreasing rate, others a much weaker trend. A model formulated to explain these results posited three component processes combining to produce the response - a constant term independent of angle, a retinal term, and a cortical term "interpreted as due to the spreading of excitation with the characteristic of a filling in pattern", with the perturbation which provokes spreading assumed to arise from different scanning strategies which come into play at larger angles.

Cognitive explanations, in which a spatially global percept enforces a top-down schema for perspective vied with fatigue theories prior to demonstrations involving multiple cubes which showed that multiple conflicting perceptions could exist in the same visual field (Long and Toppino 1981). Since then, evidence has accumulated for local processes; von Grunau et. al.(1984) estimate the effective spatial extent of the process at about 3 degrees of visual field, based on a series of experiments aimed at influencing the time during which the same or opposite orientations were perceived for two Necker cubes by a process of adaptation to a non-ambiguous perspective. Their predictions and findings seem to conform to a fatigue model of adaptation, as they report that adaptation to an unambiguous stimulus of orientation A decrease the proportion of time in percept A, and increase the time in orientation B; if fatigue is not involved, at least each stimulus seems to provoke the opposite. Adaptation effects were observed even when the unambiguous stimulus was rather dissimilar to the test in contrast, exact orientation and contours. However, no reference to slow adaptation effects such as Brown (1955) on reversal rate is mentioned in the study, making it difficult to separate adaptation effects with the establishment of plateaus, and the experimental design as reported seems problematic with respect to that effect.

2.3. ATTENTION, EYE MOVEMENTS, ILLUSIONS

Attention and monocular depth perception processes have been invoked in attempts to explain well known size illusions. B. Gillam elucidated a theory explaining such size distortion illusions as the Ponzo and Poggendorff illusions and foreshortening effects as part of a natural process of perspective decoding (Gillam 1980). She argued that the figures only seem illusory because of the removal of contextual details which reinforce a three dimensional interpretation, and provides a figure illustrating the imbedding of several illusions in a three dimensional scene where they appear well integrated. Such a depth Gestalt system could play an important role in conditions where contrast is inadequate to establish depth through texture gradients, for example.

In reviewing explanations of the origins of illusions, Gillam mentions activity theories which posit that illusions arise as a pretext for a behavioral response; in particular the *efferent readiness* theory due to Festinger (1967). Festinger and colleagues argued that the process by which the visual system prepares to initiate a saccade is the source of illusions. These are presumed to be strictly preparatory steps, not actual movements; that movements themselves do not play a determining role in most illusions is considered well established. It is also argued that some attentional foci are constructed by the visual system but may not actually initiate saccades; this should be contrasted with the earlier review of Necker cube reversal, where saccades and fixations are shown to correlate with reversals.

Festinger and colleagues noted that when subjects attempt to fixate on ends of Muller-Lyer figures, they fixate within the arrowheads rather than at the intersection points. He suggests that this has the result of lengthening the inward pointing arrows and shortening the outward pointing arrows. Perhaps the assignment of cause and effect should be inverted here; figure 17 below shows the lattice state after a quenching cycle is applied to the lattice initialized with a Muller-Lyer figure; we propose that these dynamics can compute attentional foci which serve as saccade targets, and which also serve to tune bifurcation gradients in the visual space.

Coran (1986) demonstrated that saccades to the fixation targets at the center of a Muller-Lyer figure systematically overshoot the actual target for the "lengthened" percept of an arrow pair. Another remarkable finding used a modified figure with color or linetype variations in a figure so that either the left or the right pair of lines could be perceived as longer if subjects were instructed to attend to the appropriate stimulus; saccades in this case, with the same visual stimulus present, were still subject to the overshoot effect corresponding to the attention mediated percept.

When attending to the topmost figure dashed or solid lines, the illusion is effectively interpreted like either of the situations above. This evidence argues against a low level mechanism based solely on early visual feature detection

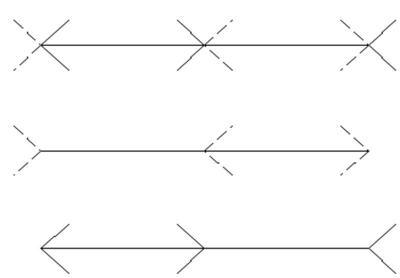

Figure The interaction of attention and size perception. Verbal instructions to attend to dashed lines or solid lines in the diagram can change the perception of the top figure to match the corresponding Muller Lyer illusion from the second or third row. After Coran and Porac (1983).

controlling saccades, and indicates that features distant from the target cooperate to distort either attentional foci or the resolutions with which saccades can achieve them.

Noton and Stark (1971) measured scan paths for subjects forced to look at pictures in the near visual field such that eye movements were required to view the whole picture, and developed a theory of object coding and recognition based on serial coding and matching. If a deterministic visitation order of features were required, scan paths should be repeatable for individual subjects viewing the same image; they found this to be generally the case, though there was some variation. They that when shifts of attention occur for objects subtending smaller angles in the visual field, such that no eye movements are required; they argue that a common attentional mechanism underlies both saccade and non-saccade attention processes. The variability in scan paths and the fact that in some recognition events no scan paths were observed were considered as problematic for the theory.

2.4. ATTENTION AND SIZE / DISTANCE PERCEPTS

Gillam's suggestion of perspective decoding seems to fit well with the inducing action of diagonal junctions and rotated Muller-Lyer like forms in the Necker cube where flows and gradients might emerge in the respnse of cell assmbies through lateral interactions. In this scenario, evolution and perceptual-motor actions during development combine to establish the system topology and parameter ranges, and the transducer projection topology (i.e. retinotopic mapping) to respond rapidly to such a stimulus by forming an attentional focus to guide visual behavior, such as scanning for junctions with vertical lines where stereo judgments can resolve ambiguous depth, or preparing for motor behavioral response to nearby objects in a particular region of the visual field. The emergence of oscillating "foreground" domains on such scene features in a field of large, incoherent "background" domains could serve to direct foveal attention and to tune visual / motor parameter gradients.

2.5. OSCILLATIONS, ATTENTION, FEATURE BINDING AND SALIENCY

Koch and Crick (1994) discuss a possible role for synchronized gamma band (40-80 Hz) oscillations such as those measured in cat visual cortex. They postulate that these oscillations are the mechanism for binding different temporal coded features into a unified percept. A detailed model is not proposed in that work, only that modulation of selected perceptual encodings would result in modification. of the temporal microstructure. The source of the attentional signal is postulated to come from an extra -cortical saliency map which regions containing features of interest for "binding" by temporal coding. How salient features are extracted from the visual field for a young organism with no ready made cognitive framework is not addressed, however.

Expanding on Freeman's chaotic oscillations paradigm, Baird has suggested that oscillations such as 40 Hz (gamma) might serve as a clock for averaging of local field potentials between cell assemblies during perceptual encoding (Baird 1991). Some investigators propose models in which 40 Hz is a natural resonance time in small networks or in a recurrent cortico-thalamic loop (Llinas 1994), (Mannion and Taylor 1991). If the native oscillation period of cell assemblies operating in the periodic phase regime were near 40 Hz, one can envision that the oscillations are modulated based on phase coherence between spatial regions when adjacent assemblies receive bursts of activity. This may allow inter-assembly lateral coupling (corresponding to an entrainment process) at a clocked interval, while inside each assembly coherent gamma oscillations might be a special state reached only under certain conditions by latteral interactions producing coherence in selected spatial locations in a retinotopically mapped area. Thus the control of binding as suggested by Koch and Crick still comes into play, but the saliency map and source of oscillatory control may, in the absence of search, emerge by the lateral interactions and recurrent feedback in an early visual area dedicated to that task. Oscillations inducing spatial bifurcations then appear to be the cortically determined *cause*, rather than than an effect, of the foreground interpretation, and could trigger activation or parameter changes in a layer or area dedicated to binding the oscillatory encodings of the surrounding larger regions. In the chaotic link scenario, the periodic synchronized oscillations might trigger parameter changes in a binding lattice to move the dynamics to an intermittency regime, linking oscillations of adjacent regions with rich spectral clusterings into a unified oscillation pattern. The basic dynamics of linking and binding via itermittent dynamics are described by Tsuda (1991).

3. NONLINEAR DYNAMICS AND NEURAL MODELING

Neural networks in which the global state vector evolves to a static condition might be termed convergent or equilibrium, in the sense that during recognition of learned categories they remain in the same convergent phase regime due to stationary parameters in the network dynamics. The Hopfield network with symmetric connections and multi-layer back propagation networks are examples of equilibrium networks in this sense, with the weights stabilized by training to a stationary state. To jump out of the equilibrium state which encodes a recognized memory to process continuing sensory input, such networks must be reset by some supervisory process. In contrast, biological networks exhibit continual non-stationary dynamical activity, with intrinsic resetting or cyclic behavior of dynamical control parameters governed by perception, attention, mood, and intrinsic cycles such as breathing (Elbert et. al. 1994). Even when dynamical control parameters are stationary, much of the work on what have been called dynamic pattern networks explores the chaotic and intermittent dynamical regimes to explain cognitive and perceptual phenomena.

Some basic concepts needed to understand the dynamical models are now introduced. For more detailed presentations of nonlinear dynamics emphasizing their application as a basis for cognition and learning the reader is referred to Mainzer (1994), and Abraham (1991).

3.1. ONE DIMENSIONAL NONLINEAR MAPS: DEFINITIONS AND TERMINOLOGY

A *map* is an iterated difference equation

$$S_{t+1} = f(S_t)$$

where S is a real valued state, f is some function mapping S within a subset of the real number domain R, and t is a discrete time step. Iteration implies that the result of applying the function at time t is fed back into the computation at time $t+1$. Nonlinear maps use some nonlinear function f, resulting in diverse asymptotic behaviors after transients periods which depend on the starting condition and parameters of the equation.

An *attractor* of a map is the asymptotic state or state sequence after many iterations. The *basin* of an attractor is the set of all states which converge to the same attractor after some number of iterations. This basin structure can be considered as an intrinsic categorization by partitioning the input states into categories corresponding to the attractors.

A dynamical system with attractors can be used as a model for perceptual and memory processes. Training a supervised neural network consists of shaping the dynamics of a network so that the attractor basins map input states into the categories (attractors) desired. While learning and memory capacity in attractor networks is a major area of research, here the emphasis is on pattern formation and spatial computations which modify the dynamics prior to learning episodes.

A well studied map used as a network node (cell, neuron unit, site) in the models described later in this chapter is the logistic map[2]:

[2] This variant of the logistic map is used by Kaneko, Perez, and Varela. Another and perhaps more common formulation with the range constrained to lie between 0 and 1 is

The equation for the logistic map is

$$S_{t+1} = 1 - bS_t^2 \quad \text{subject to the constraints } -1 < S < 1,\ 0 < b < 2;$$

where b is a bifurcation parameter; changing the parameter forces a structured transition between phases following the sequence {fixed point : limit cycles: intermittency (unstable quasi-periodic motion): chaos}. Typically the transition points between phase regimes are visualized by bifurcation trees for systems with one bifurcation parameter, or phase space plots for spatially extended systems with multiple parameters.

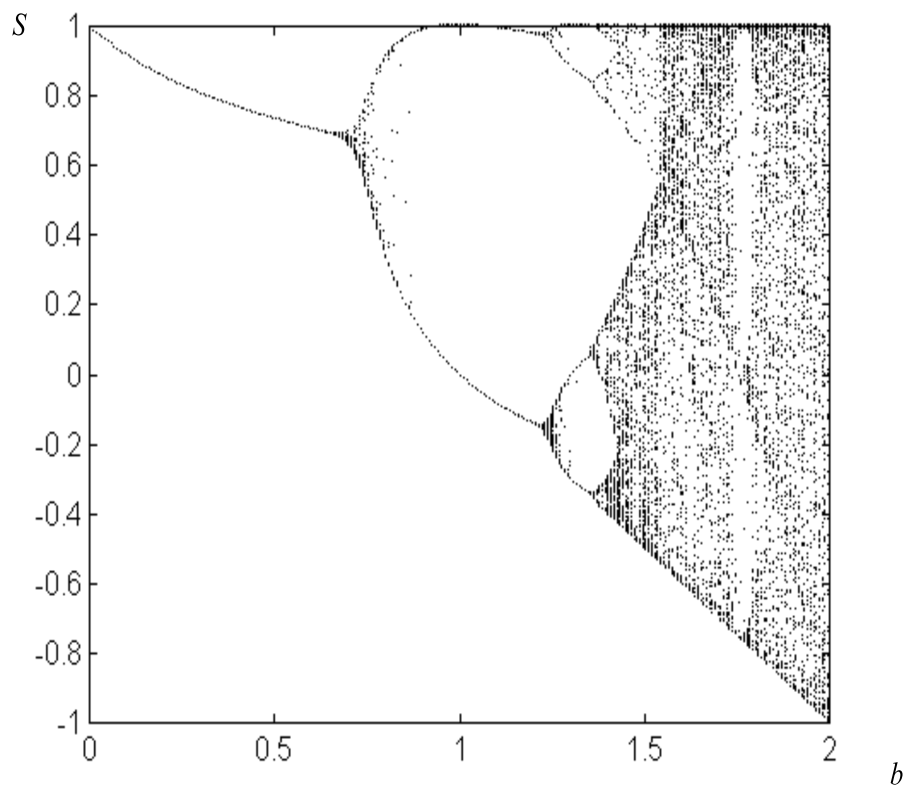

Figure 1 Bifurcation tree showing asymptotic states of attractors as the parameter b is increased. Random initial points are chosen and the system is run for 100 time steps. Where multiple state s points exist for the given b, a periodic, intermittent or chaotic attractor exists; the actual state values are cycling as shown in the time series.

$S_{t+1} = bS_t(1 - S_t)$. The qualitative dynamics of the two formulations are very similar.

Depending on the bifurcation control parameter *b* , the attractor state sequence may be a single state (fixed point), periodic oscillation between a few states (limit cycle), or a pseudo-random visitation of the state space points but within a bounded area (strange attractor, chaotic attractor). Each of the attractor types can be considered as a *phase* or *phase regime* of the dynamics, analogous to thermodynamic phase in classical physical systems. These phase regimes are bounded by critical values of the control parameters. When a control parameter is modulated to cross a point where attractors appear or disappear the crossing event is known as *bifurcation*. Bifurcations between qualitatively different regions of phase space, such as crossing the transition from limit cycles to chaotic behavior, are termed *phase transitions*.

3.2. HIGHER DIMENSIONAL SYSTEMS: SPATIOTEMPORAL CHAOS

While the map introduced above illustrates a dynamical system containing a single state variable, the definitions can be extended to networks of coupled reak valued nodes, known as *coupled map lattices*.[3] The network attractor is then a vector or array of the states of all nodes. In such networks, a spatial bifurcation behavior at the level of the entire network is evident, emerging from the interaction of excitatory and inhibitory connections between the elements. This network-level bifurcation may be tuned by controlling the phase regime of the individual nodes, the number of connections between nodes (neighborhood size), the ratio of excitatory to inhibitory connections, or the coupling strength between nodes.

Various network topologies have been explored for spatio-temporal chaotic systems. Network nodes may be *locally coupled* to adjacent nodes, *diffusively coupled* to a small region of the lattice, *globally coupled* to every node, coupled to a random set of neighbors, or some blending of these conditions.

Each variable (site or unit) in a field (the lattice) represent a quantity associated with an aggregate of microscopic units. This kind of representation, common in statistical mechanics or fluid dynamics, is known as a *macrostate* variable. Temperature or instantaneous velocity of a fluid, for example, might be macrostate variables in a CML fluid dynamics study. Here the macrostate variable S is associated with the ensemble activation (average spike train frequency of a connected ensemble). Modeling of network details with spiking activation functions and membrane transfers via numerical solutions of ordinary differential equations

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[3] Kaneko (1983) introduced the term; other authors have referred to similar discrete time, discrete space systems as cellular neural networks (Chua 1988), fractal chaos networks (Peréz 1987) and cellular dynamata (Abraham 1991).

has been employed by Kowalski et. al. (1992) and Chapeau-Bondeau and Chauvet (1992) to demonstrate oscillating, chaotic, and sometimes synchronized chaotic behavior. Such oscillations in small networks have been subsumed in the macrostate variables in the coupled map models and simulations described here.

When a physical system is simulated with a coupled map model, a sequence of processes is decomposed into simple parallel dynamics at each lattice point, with each process carried out succesively. In the present model, this means that at each iteration, a diffusion step is performed modeling lateral entrainment of cell assemblies, then a reaction step representing local evolution within each assembly. The bifurcation parameter for the logistic map at each site is also a variable parameter in this system and is updated at a slower rate based on the local neighborhood evolution.

The entire diffusion step can be expressed as:

$$S_d(x,y) = (1-c)S_t(x,y) + \frac{c}{4}\left[S_t(x,y+1) + S_t(x,y-1) + S_t(x+1,y) + S_t(x-1,y)\right]$$

where S_d is the intermediate diffusion array, t is the current time step, x, y are the spatial indices of the pixel array S at the center of the diffusion neighborhood, S is the state variable at each pixel of the array, and c is the coupling constant restricted to the range (0.0 to 1.0). (1-*c*) scales the state at each node prior to summing the neighbor states, to insure that the states remain within bounds. In practice the step is implemented by a diffusion / scaling step followed by the application of the map.

The second computational unit applied in each time step is the logistic map:

$$S_{t+1}(x,y) = 1 - b_t(x,y)S_d(x,y)^2$$

where *S, t, x,* and *y* are as above and where b is the bifurcation parameter, restricted to the range (0.0 < b < 2.0). S is restricted to the range (-1.0 < S < 1.0).

In Kaneko's studies the lattice dynamics are characterized in the space of bifurcation and coupling, but with each held constant in a particular simulation. In the model here b is itself allowed to vary anisotropically in space, computed from the local evolution of the map and with some influence from a global field according to the following equation:

4. SIMULATION EXPERIMENTS

Experiments are underway in the authors map lattice simulator to test some of the reasoning outlined here. Initial results are shown in the figures below. While the results are still inconclusive, the reader should at least get a feeling for the style of investigation. No attempts to reproduce and understand the dynamics of all of the Necker cube psychophysical parameters has been made yet. Two cubes of different sizes are evolved in the lattice with an initial gradient established to simulate a depth organization biases or such that the bottom of the visual field is nearer the viewer by default.

In what are described as the *autobifurcation* scenarios shown, it should be noted that the bifurcation parameters are updated every four steps, following suggestions by Baird (1991), that the framing rate of parameter changes should be slower than the diffusion / entrainment interactions. If gamma band (40-80 Hz) frequencies correspond to the fundamental lattice time steps, allowing the b parameter lattice to be updated every 4 steps correspond to changes in the alpha (10 Hz) frequency band of the EEG.

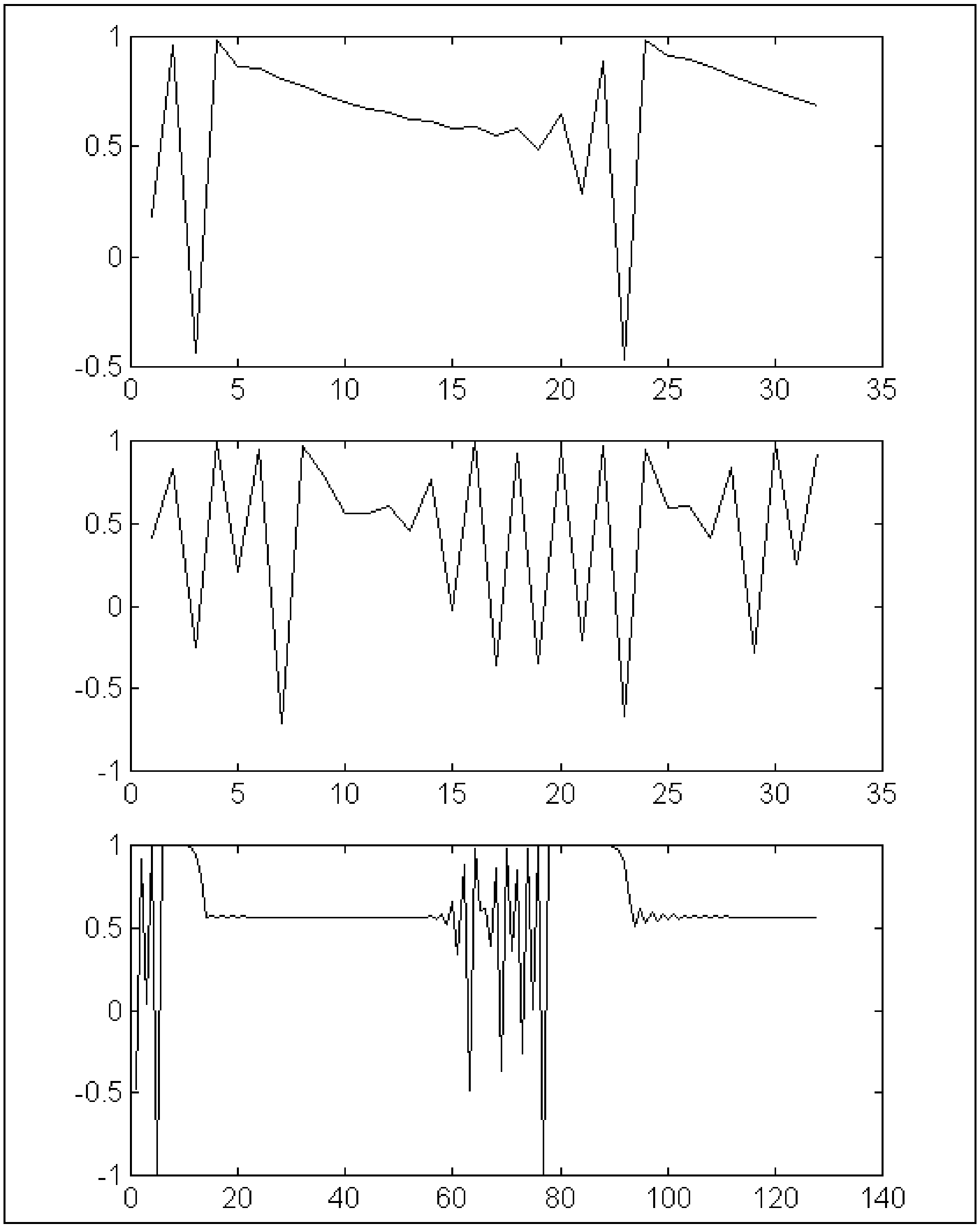

Figure 2 Auto-bifurcation cycles induced in a single uncoupled logistic map by evolving *b* parameter at each step according to b= b* (a + .5) (top graph), or b=b * (a+1) * (2-b) (center, bottom). Initial b is 1.544, random initial conditions. The oscillation period varies with initial state value. In this illustration the bifurcation frame rate is the same as reaction diffusion time step; in contrast to the spatially extended simulations shown below.

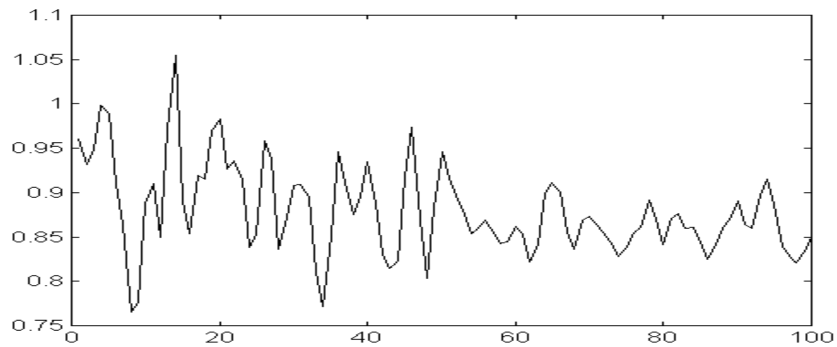

Figure 3 Two step running average mean *b* value of 6x6 window around top left "possible front corner", under auto-bifurcation cycle with initial b = 1.6561, gradient to 1.5561 to bottom of image, c=.3. 400 time steps are shown. Minima of *b* should correspond to greater local coherence. Note second minima around step 35.

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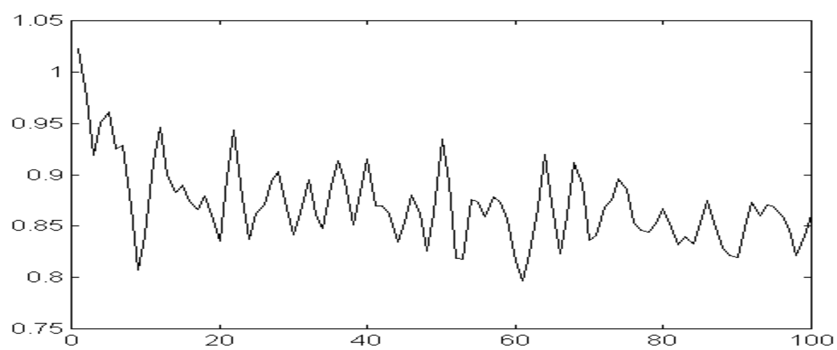

Figure 4. Two step running average mean *b* value of 6x6 window around bottom right "possible front corner", under auto-bifurcation cycle with initial *b* = 1.6551, gradient to 1.5551 to bottom of image, c=.3. 400 time steps.

5. DISCUSSION

The approach here is similar in some respects to that advanced in the Ditzinger and Haken model for figure ground reversal, but attempts to introduce a spatial dimension and focus to account for the known size effects and the apparent links to depth organization and eye movement biasing effects

The multistable effects of binding via synchronized chaotic oscillations in the model of van Leeuwen and Styvers are argued to model the strong fluctuations in residency time in Gestalt grouping phenomena, but do not seem to account for effects of scale on the switching times and distributions or the regularities associated with eye movements; these aspects of the Necker Cube reversal motivate the search for a dynamics involving local diffusion and self organized bifurcation fields for attention as a control mechanism for binding through intermittency dynamics.

In the formulation of Ditzinger and Haken, relationships between attention parameters and an order parameter are defined such that there is a saturation nonlinearity of an attention parameter when an order parameter (corresponding to a particular percept of figure) increases, forcing a "reset" in the attention state variable. This in turn triggers a dynamical reorganization and emergence of the alternate attractor in the order parameter. Haken notes that a time constant in the equation linking order parameters and attention control the reversal times between percepts. The simulation of a single map in an auto-bifurcation scenario suggests that reversal times may be governed by the initial state, rather than needing to add any time constant. The extension here in which the bifurcation state is continually updated by the local oscillations toward a quasi stable fluctuation around the transition to chaos might better account for the association of transition time and fluctuations with the spatial scale of the cube.

Kaneko (1990) suggests that *globally coupled maps* may provide a good model for switching between ambiguous figure-ground percepts. The phenomenon of cluster switching is offered as a mechanism. Input on a single site can induce reorganization of the entire cluster. (Cluster refers to lattice sites synchronized in the same attractor.) No experiments along these lines have been undertaken to date in my investigation, but the combination of reaction diffusion in a locally coupled map such as explored here with a global map storing the gradients corresponding to a depth gestalt may be more realistic than the tuning of the single lattice bifurcation field used in the experiments described in the previous section.

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