Chaos, Self-Organization, and Psychology

Scott Barton

A variety of investigators in recent years have proposed models of psychological systems based on the concepts of chaos, nonlinear dynamics, and self-organization. Unfortunately, psychologists in general have little understanding of these important ideas. These terms are defined, and their relationships are discussed. The value of applying these concepts to psychological systems is demonstrated by exploring their utility in areas ranging from neuroscience to clinical psychology. Some of the difficulties in using nonlinear concepts and methodologies in empirical investigations are also discussed.

In recent years, a new paradigm for understanding systems has been gaining the attention of psychologists from a wide variety of specialty areas. This paradigm has no single name but has been described in terms of chaos, nonlinear dynamics (sometimes called nonlinear dynamical systems theory), and self-organization. Although these interrelated concepts have generated a great deal of interest in physics, chemistry, and biology (e.g., Gleick, 1987; Kauffman, 1993; Stewart, 1989), the majority of psychologists know very little about them. The purpose of this article is to define these concepts, clarify the types of issues they are applicable to, and discuss their significance for research and clinical practice.

Understanding Growth, Change, and Development in Psychological Systems

The dynamic behavior of complex psychological systems is often difficult to understand. Why, for instance, do groups of neurons often synchronize their firing patterns in a unique spatial manner (Freeman, 1991)? How can a person have two or more separate and distinct personalities (Putnam, 1988)? Why do various belief systems link up with one another to create family dysfunction (Elkaim, 1990)? The answers to these and many more questions about dynamic psychological systems can be explored using the concepts of chaos, nonlinear dynamics, and self-organization.

In neuroscience and psychophysiology, these concepts have been used to investigate the way memories are formed (Freeman, 1990, 1991; Kohonen, 1988), the way attention affects the dynamics of human electroencephalograms (EEGs; Basar, 1990a), the dynamic nature of sleep (Roschke & Aldenhoff, 1992), and the way connectionist models account for learning (Carpenter & Grossberg, 1987; Hanson & Olson, 1990). In experimental psychology, nonlinear dynamics have been used to model approach–avoidance conflicts (Abraham, Abraham, & Shaw, 1990), coordination (Turvey, 1990), and conditioning in animals (Hoyert, 1992). In clinical psychology, the concept of self-organization and nonlinear systems has been applied to models of family systems and marital therapy (Elkaim, 1990; Gottman, 1993), psychotherapy (Goudsmit, 1989; Reidbord & Redington, 1992), and the role of cognitive development in psychopathology (Guidano, 1991; Putnam, 1988). In addition, a number of authors have applied these concepts to core issues in the philosophy of science and systems theory. Their work has been helpful in understanding the processes of growth, change, and development among a broad range of biological and psychological systems (Jantsch, 1980; Levine & Fitzgerald, 1992; Odum, 1988; Sabelli & Carlson-Sabelli, 1989; Vandervert, 1991; Waldrop, 1992).

The level of technical understanding required to understand chaos, nonlinear dynamics, and self-organization from the perspective of mathematics or physics is generally not necessary for psychologists. However, a certain degree of familiarity with the mathematical and physical underpinnings is helpful. One of the most basic ideas is the concept of dynamics itself. Some of the principles involved in dynamics are described in the next section.

Dynamics in Nonlinear Systems

At the most basic level, dynamics is the study of the way in which systems change (Morrison, 1991). Dynamics explores the effect of various forces on the behavior of systems over time and the manner in which these systems seek optimal stable states. Dynamics may be used to explore a variety of systems. Some of these systems are relatively simple (e.g., a study of the forces acting on an apple that cause it to fall to a stable rest on the ground), whereas others are dauntingly complex (e.g., the forces that act on the fertilized human egg that lead to the development of a full-term infant).

From a mathematical perspective, dynamics can be thought of as linear or nonlinear. The basic assumption underlying linear dynamics is that the way a system changes can be most effectively modeled with two or more

Larry R. Vandervert served as action editor for this article.

I wish to thank Larry Vandervert for his extraordinary perseverance, patience, and enthusiasm while serving as action editor for this article. I also wish to thank Julian Libet, Charleston Veterans Administration Medical Center, for providing me with his generous support and feedback throughout the writing process. The input and assistance of Walter Freeman, William McCown, and Dana Redington were also invaluable, and I wish to acknowledge them as well.

Correspondence concerning this article should be addressed to Scott Barton, Department of Veterans Affairs, Ralph H. Johnson Medical Center, Rt 116B, 109 Bee Street, Charleston, SC 29401-5799.

Vol. 49, No. 1, 5–14

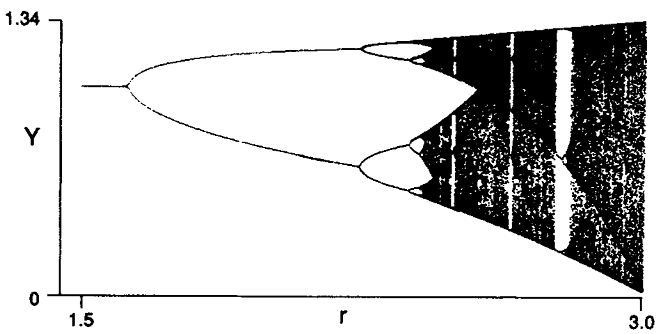
equations whose solutions can be combined to obtain another solution (Morrison, 1991; Stewart, 1989). Linear equations work quite well for a number of problems in the physical sciences. For instance, they are very useful if one wants to predict the orbit of the planets or understand the effects of wind resistance and gravity on the trajectory of a missile. Because they are additive, they also work well for a number of problems in psychology. They are, for instance, the cornerstone of statistics. When we perform an analysis of variance or enter data into a multiple regression equation, we are using linear equations to describe the relationships among variables.

The problem with linear equations is that they cannot always describe what happens in natural systems. This failure is especially noticeable when continuous changes in certain control parameters lead to sudden jumps in behavior. Although linear equations are helpful in describing the smooth flow patterns of a liquid within a certain range of flow rates, for instance, nonlinear equations are necessary to describe these same patterns when that range is exceeded and the sudden jump to turbulence sets in (Gleick, 1987). This occurs in human psychophysiological systems as well. The speed of alternately tapping one's index fingers (antiphase tapping), for instance, can be adjusted in a linear manner within a certain range of tapping speeds. However, when the high limit of that range is exceeded, a sudden nonlinear jump to inphase finger tapping occurs (Kelso & Schoner, 1988).

To explore systemic change, nonlinear dynamics uses nonlinear equations (Abraham et al., 1990; Morrison, 1991). Nonlinear equations are not additive; therefore, they are often difficult to solve. Sometimes a single solution can be obtained, but often the answer involves a pattern of solutions. To find such an pattern, the data are generally run through a system of equations so that the results ultimately feed back into the system itself. If, for instance, one takes the equation $x' = x + rx\,(1 - x)$ and feeds the results back into the equation (so that what was x' for the first solution becomes x for the second), one can explore the behavior of a classic nonlinear equation (Tufillaro, Abbott, & Reilly, 1992). This process is called *iteration*. When x is set at 0.5000, the values of r are allowed to range between 1.5 and 3.0, and the results are plotted on the y axis; the peculiar pattern characteristic of bifurcations (the geometrical splitting of the solution) to chaos emerges (see Figure 1). These splits occur quite suddenly at certain values of r. Actually, the points in Figure 1 represent the solutions after they have had time to "settle down," in this case after 150 iterations for each value of r. Readers who have trouble making sense of this diagram might want to think of Figure 1 as a two-dimensional map of a time series. The only difference is that just enough numbers are plotted to show the repetitive pattern for each value of r. For those who are interested in exploring this pattern on their own, an extremely simple computer program in BASIC is available for studying a similar equation (Stewart, 1989).

As I have noted, nonlinear systems tend to settle down over time. This settling down, or convergence, tends

Figure 1
Bifurcation Diagram Arising From Iterations of the Equation $x' = x + rx\,(1 - x)$



Note. This diagram illustrates the way in which solutions to a very simple nonlinear equation can result in sudden jumps from one set of solutions to the next. Ultimately, they can jump to very complex chaotic behavior.

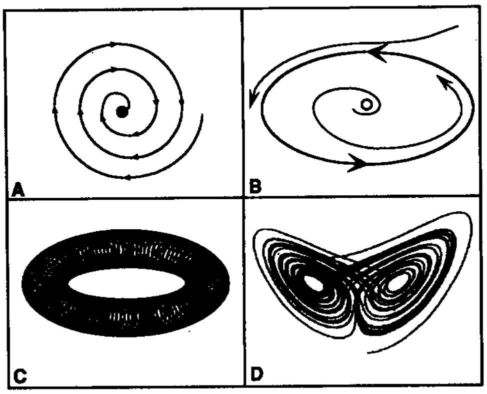
to result in one of four typical patterns (Abraham et al., 1990; Tufillaro et al., 1992). These patterns, when graphed in diagrams that show periodic changes in behavior, are called *attractors*. The trajectories of these attractors typically converge on a discrete point, a simple oscillating cycle, a quasiperiodic cycle, or a chaotic cycle (see Figure 2). The attractors in Figure 2 are portrayed in two dimensions.

The chaotic attractor requires a special explanation. The pattern in such an attractor is bounded, but after a certain number of repetitions within the system, it becomes very irregular. This irregularity results in unpredictability, despite the fact that it derives from a completely deterministic system. This unpredictability is associated with a property of chaotic systems known as *sensitive dependence on initial conditions*. This means that if two sets of initial conditions differ by any arbitrarily small amount at the outset, their specific solutions will diverge dramatically from one another over the long range. In the case of the pattern in Figure 1, for instance, if $x = 0.5000$ had been replaced with $x = 0.5001$, the solutions in the chaotic portion of the attractor would have been completely different, whereas the general chaotic pattern would be the same. Given that no measurement system is without some error, it becomes clear that if a system is chaotic, general patterns of future behavior may be predictable but specific behaviors over the long range will not.

It is possible to construct a chaotic attractor from a set of equations, as I have demonstrated here, or it can be reconstructed from a time series of observable repetitive behaviors. The latter solution is often the easiest way to map out the attractor associated with a complex psychophysiological system (e.g., Hoyert, 1992; Reidbord & Redington, 1992; Roschke & Aldenhoff, 1992).

Chaotic behavior is more than just a mathematical anomaly. It occurs in the real world as well. A wide range of physical, chemical, and biological systems are now

Figure 2
Types of Attractors Typically Found in Nonlinear Systems: (A) Point Attractor, (B) Cyclical or Oscillating Attractor, (C) Quasiperiodic Attractor, (D) Chaotic Attractor



known to exhibit deterministic chaos (Prigogine & Stengers, 1984; Stewart, 1989). The presence of chaos suggests that even if we are able to characterize all the variables in a nonlinear system completely, general patterns of future behaviors may be the best we can hope to predict. In an insightful treatment of this problem as it relates to behavior analysis, Hoyert (1992) explored the behavior of a hypothetical system designed to predict within-interval variability in a fixed-interval reinforcement schedule. He demonstrated that chaotic behavior can arise even when the variables in such a system are completely determined. Hoyert went on to note that the interdependence of variables in a nonlinear system, along with sensitivity to initial conditions, lead to the implication that studying each factor in isolation may not lead to useful knowledge about the behavior of the system as a whole. This concept, long a tenet of general systems theory, has now been unequivocally demonstrated in complex nonlinear systems.

Self-Organization

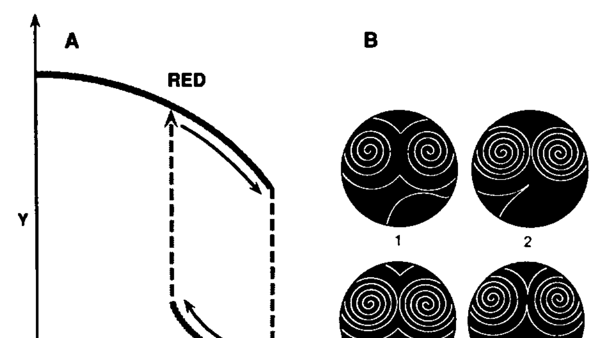
Fundamentals of Self-Organizing Systems

For any discussion of chaos to be linked meaningfully to psychological systems, it must be linked to the broader concept known as *self-organization* (Abraham et al., 1990; Kauffman, 1993; Prigogine & Stengers, 1984). Self-organization denotes a process by which a structure or pattern emerges in an open system without specifications from the outside environment. When a system of this type receives a sufficient amount of energy, it may become unstable. As a result of this instability, an originally uniform state can give rise to a variety of complicated temporal, spatial, and behavioral patterns (Prigogine & Stengers, 1984).

In this section, I focus primarily on self-organization in a chemical system known as the *Beluzhov-Zhabotinsky (BZ) reaction*. My goal is to help build an understanding of the fundamental characteristics of such systems, characteristics that are relevant to chemistry, biology, and psychology (Schore, 1981). The BZ reaction, discovered in Russia in the late 1950s, is often used to illustrate the concept of self-organization (Gleick, 1987; Prigogine & Stengers, 1984; Schore, 1981). Its behavior can be defined in terms of a cyclical or sometimes even chaotic attractor and can be modeled by a system of nonlinear differential equations (Epstein, Kustin, De Kepper, & Orban, 1983).

In the BZ reaction, the system has the potential to exist in two different states. Assuming that an iron catalyst is used, one state appears red and the other blue (Winfree, 1974). If the reaction is allowed to run in a continuously stirred beaker and the concentration of the reactants crosses a critical threshold, it will oscillate between the red state and the blue state at intervals of about 30 seconds. It first appears red and then blue. Unlike a "typical" chemical reaction, it does not move toward a static equilibrium point in a linear manner. Instead, it cycles in an obvious and dramatic fashion. The process of moving from red to blue or vice versa is sudden and discontinuous (see Figure 3A). This occurs because the chemical processes that result in the red state coming into existence become linked to the processes resulting in the blue state. When this happens, the two states codetermine one another in a cyclical, nonlinear fashion.

Figure 3
(A) Simplified Illustration of Oscillating States in the Beluzhov-Zhabotinsky Reaction; (B) Propagation of Spiral Waves in the Beluzhov-Zhabotinsky Reaction



Note. Substances X and Y are used generically to refer to any two substances that will support an oscillating chemical reaction. Note that when the solution is in the red state, the concentrations of Substances *X* and *Y* change slowly within a certain range. Beyond this range, however, the entire system switches suddenly to the blue state. After this, the concentration of reactants once again change slowly, although now in the opposite direction, until they reach a certain point. After this point, the whole system jumps suddenly into the red state. These linked processes occur repeatedly in a cyclical fashion.

B1–B4 illustrate spatiotemporal self-organization in a chemical system. Note the entrainment of the slower wave by the faster wave in the lower right-hand corner as the reaction progresses.

When the BZ solution is constantly stirred, only temporal oscillations will occur. However, if it is poured into a petri dish and allowed to sit quietly, a whole new type of organization emerges. Under these conditions, any small perturbation in the system, such as a piece of dust or a hot needle, will create a local region of instability. This instability then triggers the formation of spiral or circular waves that slowly propagate throughout the system (see Figure 3B). Thus, the system develops not only temporal self-organization but spatial self-organization as well. The waves propagate with a diverse set of frequencies, and a number of different waves can be created simultaneously. If a faster wave meets a slower one, it will overtake it, causing the slower one to disappear. This phenomenon is called *entrainment*. It can be observed in Figure 3B in the lower right-hand corner of the petri dish. In the stirred solution, the role of diffusion is nullified by constant stirring, so that only reaction-based temporal oscillations can occur. In the still of the petri dish, however, a linkage is established between reaction and diffusion, leading to both temporal and spatial oscillations (Winfree, 1974).

In discussing this reaction, Schore (1981) asked, "Where else do we find systems possessing a high degree of naturally generated organization that are highly sensitive to perturbations, switch rapidly from one state to another, and operate spontaneously (in response to minor fluctuations) as well as with external triggering?" (p. 454). His answer was, "in living systems." Specifically, he commented on how neural thresholds, states of consciousness, and various biological oscillators exhibit this type of behavior. The remainder of this article expands on this idea by focusing on the way in which these properties manifest in animal and human behavior.

The BZ reaction illustrates the general characteristics of self-organization that apply to psychological systems as surely as to chemical and biological systems. These include the readiness to exhibit (a) multiple stable states that can change suddenly from one to another when a parameter value crosses a critical threshold, (b) cyclical state changes, (c) the structural coupling of component processes, (d) temporal, spatial, and behavioral organization, (e) localized instabilities that can lead one part of the system to organize itself differently from another part of the system, (f) the ability of one unit to cause other units to oscillate at a harmonically related frequency (entrainment), and (g) behavior that can sometimes be modeled by a system of nonlinear equations.

Although chemical systems are valuable as metaphors, most biological and psychological systems are considerably more complex. Psychological systems lack the precise temporal or spatial symmetry seen in physical systems and instead involve complex neurological structures and behaviors. To understand these types of systems, it is important to realize that some self-organizing properties can only be found in living things. One of the most general of these properties involves the ability to develop stable yet flexible structures that serve important biological needs (Prigogine & Stengers, 1984). In the next section, I discuss the work of an investigator who has begun to explore such structures to understand the neural organization underlying perception, memory, and behavior.

Self-Organization and Memory

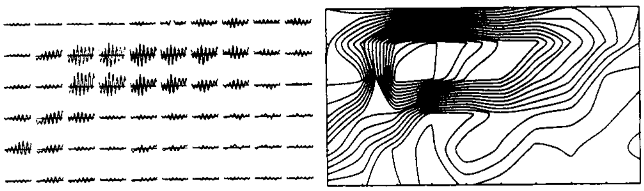
A variety of exciting approaches to exploring cognition and memory are arising from the perspective of chaos and self-organization. Some of the most fascinating studies have emerged from the laboratory of Walter Freeman (1990, 1991), one of the primary proponents of nonlinear models in the study of brain function. Freeman, a neurophysiologist at the University of California at Berkeley, has extensively explored the manner in which odors are remembered and represented in the olfactory system of rats. Using EEG measurements, the results he has obtained have given us new insight, not only into the mechanism of olfaction but into the general role of memory and nonlinear systems in the brain.

Understanding how odors are represented is a challenging task. One of the first approaches taken was to investigate the global EEG of the olfactory lobe itself. When a rat inhales an odor, it sets off a burst of electrical activity in the lobe. This burst is characterized by a waveform known as the *carrier wave*. The carrier wave is an aspect of the EEG that reflects the integrative actions of local pools of neurons in the brain. Its elicitation following exposure to an odor is a very reliable finding. However, the frequency and amplitude of the wave varies in an unreliable (functionally random) manner both between and within odorant exposures. Attempts at signal detection (e.g., signal averaging and detection of evoked potentials) have proved incapable of delineating a reliable differential response from one odor to the next when temporal patterns alone are investigated.

Freeman, however, knew that the information relayed to the brain by odorant exposure occurred in the form of a spatial pattern of pulse activity across neurons. He suspected that odors might therefore be represented on the lobe by some sort of spatial map. To explore this idea, he took a unique approach. Instead of placing a single electrode on the olfactory lobe, he placed an array of 60 electrodes on a representative portion of the bulb. The electrodes, arranged in a 6×10 array, allowed him to obtain EEGs at a far higher level of spatial resolution than he could previously obtain. When he did this, he found that each odor was indeed distinguishable by the spatial pattern of the amplitude of the wave (see Figure 4). In short, the message (e.g., "this is peppermint") was not in the waveform at all; it was in the spatial pattern of the amplitudes of the waveform. When animals learned a response to an odor, each odor was shown to have a specific spatial amplitude pattern. In the process of exploring this area, Freeman found clear-cut evidence of biologically significant self-organization: stable spatiotemporal structures in olfactory EEGs triggered by a small perturbation (the odor).

If the spatial structure of odor representations had been all that Freeman had found, it would have been an important contribution in and of itself. The full signifi-

Figure 4
Left Side: 60 Electroencephalograms Recorded Simultaneously From the Olfactory Cortex of a Rabbit as It Recognizes a Scent; Right Side: Contour Plot Corresponding to the Amplitudes



Note. The electrodes are arranged in a 6 × 10 rectangular array. The carrier wave is nearly the same in each recording, except that the amplitude varies. The shape of the wave, however, does not indicate the identity of the scent. Information about identity is contained in the spatial pattern of the amplitudes. The differences between amplitudes are represented in a manner analogous to the differences in elevation on a topographic map. From "Spatial Properties of an EEG Event in the Olfactory Bulb and Cortex" by W. Freeman, 1978, *Electroencephalography and Clinical Neurophysiology, 44*, p. 589–590. Copyright 1978 by Elsevier Scientific Publishers, Ireland Ltd. Reprinted by permission.

cance of his discovery, however, depended on more details about the process of learning. He continued to investigate this phenomenon and found a multitude of fascinating qualities.

After making this initial discovery, Freeman asked an interesting question. "What happens to the original spatial pattern associated with the first odor when a second odor is learned?" If the original representation is truly stable (like the stimulus response connection it is associated with), it should not be changed by new learning. To illustrate this metaphorically, assume that one had learned to associate peppermint with some behavior. After the learning was completed, one's spatial EEG pattern for peppermint was determined. Subsequently, one learned to associate cinnamon with another behavior. After this, one's pattern for cinnamon was assessed as well. If one once again smelled peppermint and were tested again, one might expect the pattern associated with peppermint to look the same as it did before. When Freeman ran an analogous experiment with animals, however, he found that just the opposite occurred. The pattern for peppermint changed when it was tested again. He was forced to conclude that the neural representation of an odor is not fixed like a photograph. Instead, the structure of old learnings reform in the context of more recent learnings. This reorganization of the nervous system is not consistent with the view that discrete categories of experience are stored away in fixed physiological patterns in the brain. It is also additional evidence of self-organization: spatiotemporal structures that have some degree of stability but that can reconstruct themselves when destabilized by new information.

Freeman (personal communication, July 8, 1993) noted that it is important to be aware that the structures he discovered reflect the meaning of the stimulus, not merely its presence. The spatial structure of peppermint associated with positive reinforcement, for instance, is completely different from the structure associated with punishment.

These findings throw light on what, historically, has been one of the core problems in understanding memory: its extraordinary flexibility as a function of changes in mental state, emotional needs, more recent learnings, and external cues. Bartlett (1932) was keenly aware of this problem. He noted that "some widely held views [of memory] have to be completely discarded, and none more completely than that which treats recall as the reexcitement in some way of fixed and changeless traces" (Bartlett, 1932, p. vi). Bartlett went on to note that

> A new incoming impulse must become not merely a cue setting up a series of reactions in a fixed temporal order, but a stimulus which enables us to go directly to that portion of the organized setting of past responses which is most relevant to the needs of the moment. . . . There is one way in which an organism could learn to do this. . . . It may be the only way. . . . An organism has to somehow acquire the capacity to turn round upon its own "schemata" and construct them afresh. (p. 206)

Freeman's work, along with that of others, is now allowing us to confirm that this "reconstruction" of memory actually occurs at an objective physiological level.

Although the findings showing changes in spatial patterns as new odors were learned were exciting, Freeman (1990) also wondered about dynamic processes in the more classical sense of the word. He was especially interested in the rate at which neural information spread from the sensory receptors to the bulb itself and the shape of that spread. When he explored this, he discovered that once an odor had been learned, its recognition could begin anywhere among the sensory receptors on the bulb and spread rapidly and coherently throughout the entire bulbar structure in the manner of a two-dimensional spreading wave. He noted that this type of spreading response was necessary to account for the bulb's ability to rapidly create the same psychological meaning from a variety of spatial points on the sensory receptors. As noted in the last section, the property by which information necessary for creating a spatiotemporal structure is "stored" in a nascent form throughout the system and in which a perturbation can generate this structure through a wavelike response is a hallmark of self-organization in chemical and biological systems (Goldbeter & Segel, 1977; Prigogine & Stengers, 1984; Winfree & Strogatz, 1984).

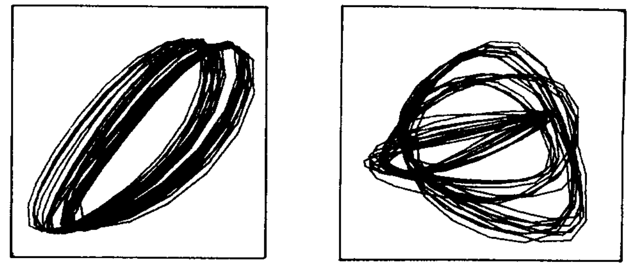
With every new finding adding further evidence that he was dealing with a complex nonlinear system, Freeman finally attempted to model the behavior of the bulb using a system of nonlinear differential equations. He wanted a model that allowed him to mimic many of the properties he observed naturally in the bulb, including the ability to suddenly "turn on" a state of odor recognition associated with an appropriate activity pattern and the ability to learn new information about an odor without losing all information about previous odors. Freeman was able to create such a model. Two examples of chaotic attractors his equations formed are illustrated in the phase portraits appearing in Figure 5.

Despite the success of Freeman's approach in understanding the dynamics of the olfactory system, it has its limitations. One limitation is that his model, although it accounts quite well for a number of observed properties, does not correspond with the actual EEG patterns in the olfactory lobe. By comparison, the real patterns seem impossibly complicated and noisy. This discontinuity between model and reality is a common problem in investigating natural nonlinear systems. Not only are investigators rarely able to completely characterize all the variables that affect a complex system, but they must isolate a system well enough to cut through what Morrison (1991) called a "sea of noise" (p. 271). Achieving the necessary degree of isolation is a difficult task, even in very simple physical systems (e.g., see Gleick, 1987). In neural systems, the problem is compounded by an even greater degree of complexity and interconnectedness. Freeman (1990) noted that many of the better known tests for nonlinearity in mathematics, physics, and chemistry are inadequate in neuroscience because of this complexity. The initial conditions of the brain shift irreversibly every time something new is learned.

It is because of this irreversible process of growth and pattern development in psychological systems that I stress the characteristics and dynamics of self-organizing systems rather than their mathematics. In Freeman's work, these properties include sudden state changes, spatiotemporal organization of odor representations, a wavelike spread of information, and stable yet flexible structures associated with learning. What is truly extraordinary is that the processes by which the brain creates memories can be similar in so many ways to the processes driving an oscillating chemical system. It is the common base of nonlinear dynamic processes that connect the two systems.

Through nonlinear dynamics and a growing understanding of self-organization, a whole new way of thinking about brain function is beginning to emerge. Basar (1990b) has edited an entire book of contributions in this area. Edelman (1992) has devised an ambitious theory using the concept of self-organization and evolution to explain brain function and development. Milton, Longtin, Beuter, Mackey, and Glass (1989) have reviewed the role of nonlinear dynamics in clinical neurology. There is little doubt that the growth and development of nonlinear dynamic models in neuroscience will continue into the foreseeable future.

Figure 5
Phase Portrait of Two Chaotic Attractors Modeled by Nonlinear Differential Equations to Represent Odorant Responses



Note. Observe the geometric similarities to the chaotic attractor in Figure 2D. From "Simulation of Chaotic EEG Patterns With a Dynamic Model of the Olfactory System" by W. Freeman, 1987, *Biological Cybernetics, 56,* p. 143. Copyright 1987 by Springer-Verlag. Reprinted by permission.

Self-Organization and Clinical Psychology

There is perhaps no other area in which chaos theory, nonlinear dynamics, and self-organizing systems are so intuitively appealing yet so analytically difficult as in clinical psychology. With a few notable exceptions, their application to clinical issues are metaphorical and qualitative in nature. This is due to the inherent complexity of the clinical realm and the difficulty measuring behavior with the reliability necessary for mathematical modeling (Maturana & Varela, 1987). Individuals and family systems must be taken as they come, with all their complexity and unreliability. They cannot be manufactured in the laboratory for the convenience of the investigator. Therefore, they are fundamentally more difficult to quantitatively model than the systems described in the section on self-organization in chemical systems. Many investigators are working on the development of quantitative methods, but their efforts are in the early stages at the present time (e.g., Levine & Fitzgerald, 1992; Reidbord & Redington, 1992).

In the past, a number of prominent psychotherapists and researchers speculated briefly about the role of chaos and nonlinear systems in psychotherapy (e.g., Meehl, 1978; Minuchin & Fishman, 1981). Although they suspected it might have some utility, they did not develop their ideas to any significant degree. In recent years, the number of interested model makers has increased dramatically. Various aspects of nonlinear dynamics have been applied to Jungian therapy (Abraham et al., 1990; Bütz, 1992; Eenwyk, 1991), psychoanalysis (Langs, 1992), posttraumatic stress disorder (Glover, 1992), psychic development and individual psychopathology (Guidano, 1991), family systems (Elkaim, 1990), the genesis and treatment of multiple personality disorder (Putnam, 1988, 1989), schizophrenia (Schmid, 1991), and psychiatric disorders in general (Sabelli & Carlson-Sabelli, 1989). These models are notable for their general reference to topics and features derived from nonlinear dynamics, but otherwise are remarkably heterogeneous. In general, these authors have used these concepts to model process, change, and development in psychological systems. A great deal of the impetus for this work originated in Europe, driven by the perspectives of Maturana and Varela (1980) in neuroscience, and Prigogine (Prigogine & Stengers, 1984) in nonequilibrium thermodynamics.

The concept of nonlinear transitions in mental states is one of the most common themes among clinicians writing about nonlinear dynamics. In keeping with Emde, Gaensbaur, and Harmon (1976), a mental state is defined as "a constellation of certain patterns of physiological variables and/or behaviors which seem to repeat themselves and appear to be relatively stable" (p. 29). This general concept of mental states can be applied to a wide range of problems in clinical and experimental work.

Wolff (1987) was one of the first to apply concepts derived from nonlinear dynamics to the development of mental states in infants. He explored a wide range of phenomena, including waking, smiling, sleeping, and crying behaviors. Wolff demonstrated how some states, such as waking, are very unstable in newborn infants. As infants mature, however, they develop longer and longer uninterrupted periods of wakefulness, indicating increased stability. Wolff's concern with understanding the stability of states and the change in stability with the passage of time is very much in the tradition of nonlinear dynamics.

Building on the work of Wolff (1987), Putnam (1988, 1989) began to explore change in a very different domain: state transitions in adults with multiple personality disorder. He proposed that children naturally develop various mental states, each imbued with a different sense of self. Normally, with the passage of time and the presence of emotional support, these states are consolidated into a more or less coherent self. However, when a child is severely and repetitively traumatized, he or she may enter these states defensively to avoid emotional or physical pain. When this occurs over a long period, the sense of self fails to consolidate. The various states become elaborated and develop a different set of memories, affective qualities, and identities. They also become unstable and discontinuous, predisposing the individual to sudden jumps between one state and another. Recall from the discussion of the BZ reaction that one part of a self-organizing system can organize itself separately from another. In this case, memories and perceptions become organized so differently in each state that communication between one state and another is blocked. Unfortunately, this communication is the very thing that is needed to develop a coherent sense of self. Putnam (1989) described how the process of developing coherence involves opening channels of communication between states. This occurs through discouraging pathological dissociation and encouraging the integration of dissociated states, memories, and affects.

State oscillations following trauma have been described in areas other than identity. Horowitz (1986), for instance, noted that the oscillation of intrusive memories (e.g., nightmares and flashbacks) with the avoidance of situations associated with the trauma (e.g., phobias and withdrawal) is typical of the pathology following a traumatic event. He explained how an appreciation of the oscillatory nature of these symptoms can help prevent their misinterpretation and assist in treatment.

In a very different approach to exploring nonlinear dynamics and mental states, Reidbord and Redington (1992) looked at the relationship between the phase portraits of a patient's heart rate and their behavioral state during psychotherapy. They reconstructed a variety of chaotic attractors associated with the patient's mental states from heart rate data (see Figure 6). Although the utility of this approach to the solution of clinical problems has yet to be determined, it is an important advance in basic research. Roschke and Aldenhoff (1992) reported an analogous investigation of the correspondence between chaotic attractors reconstructed from EEGs and various stages of sleep.

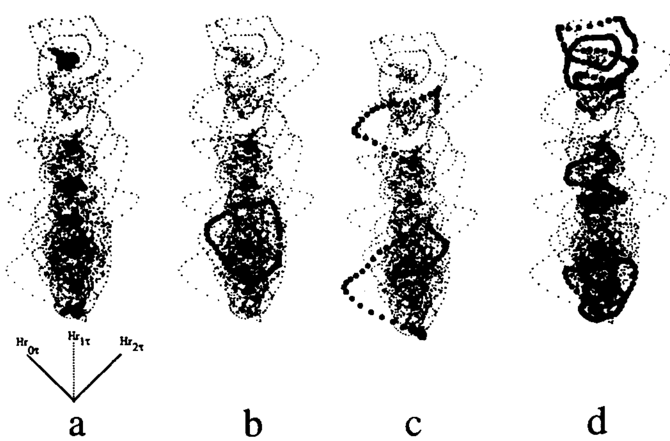
Difficulties With This Paradigm

Despite the many advantages of nonlinear dynamics and self-organization in expanding the description and analysis of psychological systems, these concepts have numerous problems in their application to both basic and applied research. The problem of not knowing the factors involved and separating the signal from the noise was discussed in the section on memory, but a number of other problems deserve discussion as well.

Confusion of Concepts and Techniques Among Different Fields

Varela (1989) issued an important warning to those who would compare neuroscience to family therapy in the context of self-organization: "Circulation of concepts between diverse approaches is reciprocal, but we cannot simply and directly export or import such notions.

Figure 6
Four Phase Plots Constructed From a Time Series of Heart Rate Data



Note. All correspond with different clinical states observed during a single session of psychotherapy. The three axes used to construct these plots are listed in the lower left-hand corner. The darker portions of the plots show the paths that the trajectories were most likely to settle into. For the sake of clarity, a varying number of phase plots were superimposed on one another in Types a, c, and d. In Type a trajectories, the patient's behavior tended to be avoidant and overcontrolled. In Type b trajectories, the characteristic behavioral pattern had a narrative quality but was somewhat less avoidant. In Type c trajectories, the patient's pattern showed the highest level of affect. These trajectories were the most clinically variable overall. In Type d trajectories, the patient was more likely to discuss the focal topic in therapy and their conversation flowed more easily between topics and emotions. From "Psychophysiological Processes During Insight Oriented Psychotherapy" by S. Reidbord and D. Redington, 1992, *The Journal of Nervous and Mental Disease, 180*, p. 652. Copyright 1992 by Williams & Wilkins. Reprinted by permission.

. . . stable patterns in natural systems . . . have a clear resonance with the establishment of human institutions, but the differences between them are profound" (p. 24). The wisdom of this statement should be obvious. The dynamics of a propagating wave are a poor model for therapists wishing to understand dysfunctional family relationships. On the other hand, therapists might be very interested in the linkage of attributions, beliefs, and coping skills that underlie and maintain a family's pathology. A major problem in the psychological literature on chaos, nonlinear dynamics, and self-organizing systems is that this important distinction is often ignored.

One way that the distinction between fields is set aside is when authors use rigorous terminology from nonlinear dynamics to refer to psychological variables that are multidimensional and difficult to quantify. Bütz (1992), for instance, defined chaos as "overwhelming anxiety," whereas Sabelli, Carlson-Sabelli, and Javaid (1990) conceptualized creativity and destructiveness as "chaotic attractors." These definitions, although clearly metaphorical, bear little resemblance to the definition of *chaos* in the physical sciences. Terms that refer to specific and limited ideas in mathematics and physics should not be confused with the broader characteristics of self-organizing psychological systems. Using these terms as metaphors may be acceptable as a heuristic device, but the two are not the same. Although useful at times, all metaphors eventually break down or lose their validity when more and more exacting parallels are drawn between them and reality (Chubb, 1990).

Another common and related source of confusion involves taking a perfectly good hypotheses about a psychological process and pitching it as if we could measure that process precisely. Jung (1946/1969), for instance, posited that the more one represses a particular feeling or belief, the more likely it is to get converted to its opposite. The more an individual represses the belief "I am worthless," for instance, the more likely he or she will be to express it as "You are worthless." Jung's is a perfectly reasonable hypothesis. However, to model such a process with a phase diagram based on a system of differential equations (e.g., Abraham et al., 1990) is to imply a level of measurement precision we don't have in clinical psychology. This type of analogy may create a sort of "halo effect" that makes the targeted construct seem more easily and accurately assessed than it really is.

The confusion of techniques appropriate at one level of analysis to those appropriate at another can also be seen when the wide variety of variables observed in the real world are collapsed into a few simple dimensions. Callahan and Sashin (1990), for instance, developed a dynamic model based on the factors of feelings, thoughts, and actions to predict what they call *affect–response*. Using an ordinal scale, they divided each dimension into low, medium, and high and plotted them on a three-dimensional state plot. However, to describe feelings, actions, and thoughts only as low, medium, and high would, for most therapists, reduce them beyond recognition. When the qualitative features of these dimensions are ignored, their meaning becomes too hard to discern. Although all modelers must ignore some features of a complex system, little is gained by ignoring them to the point of making the model impractical.

Confusion Over How to Test Hypotheses

Testing hypotheses may seem problematic when the notion of linear causality no longer applies and correlation seems irrelevant. Although much work remains to be done to develop good nonlinear methodologies (see Basar, 1990a; Levine & Fitzgerald, 1992), this realization need not pose an insurmountable problem for investigators. The primary thing to remember is that the fundamental goal of modeling or analyzing a self-organizing system is to understand a *pattern* of dynamic behavior. Hypotheses must be built around such a pattern. Freeman (1990), for instance, explored the hypotheses that the spatial pattern of olfactory EEGs was related to specific odors. Reidbord and Redington (1992) explored the hypotheses that dynamic flow patterns deriving from heart rate data were related to mental states. In both cases, the unit of analysis was a dynamic pattern of observed behavior. Testing hypotheses about the difference between mean values of individual variables before identifying the dynamic pattern of interest may obscure a focus on the patterns that are naturally present in the system (Prigogine & Stengers, 1984).

In regard to data analysis, the following three approaches are worth considering:

1. If it is feasible to model a self-organizing system with various nonlinear equations, then modelers should by all means attempt such strategies. Nonlinear differential equations are especially useful in modeling neural sytems (e.g., Carpenter & Grossberg, 1987; Freeman, 1990). In modeling social systems, a system dynamics approach has often proved productive (Levine & Fitzgerald, 1992).

2. If it is possible to reconstruct a nonlinear attractor from a time series, then modelers should try this as well. This approach has proved helpful in behavior analysis (Hoyert, 1992), and in studying psychophysiological systems (e.g., Reidbord & Redington, 1992; Roschke & Aldenhoff, 1992). Taking this approach, however, is a function of one's ability to get reliable and meaningful data out of an experiment in which stable, clearly delineated cycles of behavior are apparent.

3. If it seems unlikely that mathematical techniques that focus on the analysis of repetitive cycles alone will prove helpful or practical (e.g., when exploring developmental changes with maturity), the properties of self-organizing systems can be subsumed in one's model and various aspects of the model tested using standard statistical techniques. Wolff (1987), for instance, was able to demonstrate increasing stability in the sleep–wake cycle of infants using statistical methods alone. His focus, however, remained on dynamic phenomena.

The various methodologies, both linear and nonlinear, are mutually compatible, not contradictory. They can be used to study different aspects of a system, depending on which is most appropriate for addressing the specific question at hand. The coherence of alpha waves in attentional tasks, for instance, has been explored both with linear correlation coefficients and nonlinear correlation dimensions (Basar, 1990a). Similarly, the mechanism underlying the wavelike spread of olfactory information has been studied by fitting the sums of cosine waves (a linear approach), whereas the pattern of olfactory EEGs has been modeled by a system of nonlinear differential equations (Freeman, 1990).

In regard to research and design issues in general, it is important to note that this paradigm, although new and exciting, offers no cure for the profound difficulties psychologists face in establishing reliability and validity in all of their research. Instead, it provides a new way of thinking about psychological systems. Ultimately, its value to psychology will be a function of its ability to solve problems and understand phenomena more effectively than competing paradigms. As with all new paradigms, investigators need the latitude to be speculative at first. Following the generation of new ideas and models, they must then subject their speculations to empirical tests. When the problems, generic principles, and research methodologies are all chosen carefully, however, the concepts of chaos, nonlinear dynamics, and self-organizing systems can allow investigators to explore a variety of areas from new and promising angles, ones that many may have never before considered.

Conclusion

In this article, I have presented some of the basics of chaos, nonlinear dynamics, and self-organizing systems. I propose that these revolutionary ideas, which are beginning to prove productive for investigators in the physical sciences, deserve more attention among psychologists. By applying them to specific fields of research, our understanding of complex systems may be broadened and new ways found to view old problems. I hope that more investigators and clinicians will take them up and use them to explore systems in their own areas of interest.

REFERENCES

Abraham, F. D., Abraham, R. H., & Shaw, C. D. (1990). *A visual introduction to dynamical systems theory for psychology.* Santa Cruz, CA: Aerial Press.

Bartlett, F. C. (1932). *Remembering: An experimental and social study.* Cambridge, England: Cambridge University Press.

Basar, E. (1990a). Chaotic dynamics and resonance phenomena in brain function: Progress, perspectives, and thoughts. In E. Basar (Ed.), *Chaos in brain function* (pp. 1–27). New York: Springer-Verlag.

Basar, E. (Ed.). (1990b). *Chaos in brain function.* New York: Springer-Verlag.

Bütz, M. R. (1992). The fractal nature of the development of the self. *Psychological Reports, 71,* 1043–1063.

Callahan, J., & Sashin, J. I. (1990). Predictive models in psychoanalysis. *Behavioral Science, 35,* 60–76.

Carpenter, G. A., & Grossberg, S. (1987). Discovering order in chaos: Stable self-organization in neural recognition codes. *Annals of the New York Academy of Sciences, 504,* 33–51.

Chubb, H. (1990). Looking at systems as process. *Family Process, 29,* 1669–1675.

Edelman, G. M. (1992). *Bright air, brilliant fire: On the matter of the mind.* New York: Basic Books.

Eenwyk, J. R. (1991). Archetypes: The strange attractors of the psyche. *Journal of Analytical Psychology, 36,* 1–25.

Elkaim, M. (1990). *If you love me, don't love me: Constructions of reality and change in family therapy.* New York: Basic Books.

Emde, R. N., Gaensbaur, T. J., & Harmon, R. J. (1976). Emotional expression in infancy: A biobehavioral study. *Psychological Issues, 10* (Monograph 37). New York: International Universities Press.

Epstein, I. R., Kustin, K., De Kepper, P., & Orban, M. (1983, March). Oscillating chemical reactions. *Scientific American, 248,* 112–123.

Freeman, W. (1978). Spatial properties of an EEG event in the olfactory bulb and cortex. *Electroencephalography and Clinical Neurophysiology, 44,* 586–605.

Freeman, W. (1987). Simulation of chaotic EEG patterns with a dynamic model of the olfactory system. *Biological Cybernetics, 56,* 139–150.

Freeman, W. (1990). Searching for signal and noise in the chaos of brain waves. In S. Krasner (Ed.), *The ubiquity of chaos* (pp. 47–55). Washington, DC: American Association for the Advancement of Science.

Freeman, W. (1991, February). The physiology of perception. *Scientific American, 264,* 78–85.

Gleick, J. (1987). *Chaos: Making a new science.* New York: Viking Penguin.

Glover, H. (1992). Emotional numbing: A possible endorphin-mediated phenomenon associated with post-traumatic stress disorders and other allied psychopathological states. *Journal of Traumatic Stress, 5,* 643–675.

Goldbeter, A., & Segel, L. A. (1977). Unified mechanism for relay and oscillation of cyclic AMP in Dicytostelium Discoideum. *Proceedings of the National Academy of Sciences, 74,* 1543–1547.

Gottman, J. M. (1993). The roles of conflict engagement, escalation, and avoidance in marital interaction: A longitudinal view of five types of couples. *Journal of Consulting and Clinical Psychology, 61,* 6–15.

Goudsmit, A. L. (Ed). (1989). *Self-organization in psychotherapy.* New York: Springer-Verlag.

Guidano, V. F. (1991). *The self in process.* New York: Guilford Press.

Hanson, S. J., & Olson, C. R. (1990). *Connectionist modeling and brain function: The developing interface.* Cambridge, MA: MIT Press.

Horowitz, M. J. (1986). *Stress response syndromes.* New York: Jason Aronson.

Hoyert, M. S. (1992). Order and chaos in fixed interval schedules of reinforcement. *Journal of the Experimental Analysis of Behavior, 57,* 339–363.

Jantsch, E. (1980). *The self-organizing universe.* Elmsford, NY: Pergamon Press.

Jung, C. G. (1969). *The structure and dynamics of the psyche: Vol 8. The collected works of C. G. Jung* (2nd ed.). (R. F. C. Hull, Trans.). Princeton, NJ: Princeton University Press. (Original work published 1946)

Kauffman, S. A. (1993). *The origins of order.* New York: Oxford University Press.

Kelso, J. A. S., & Schoner, G. (1988). Self-organization of coordinative movement patterns. *Human Movement Science, 7,* 27–46.

Kohonen, T. (1988). *Self-organization and associative memory.* New York: Springer-Verlag.

Langs, R. (1992). Towards building psychoanalytically based mathematical models of psychotherapeutic paradigms. In R. L. Levine & H. E. Fitzgerald (Eds.), *Analysis of dynamic psychological systems* (Vol. 2, pp. 371–393). New York: Plenum Press.

Levine, R. L., & Fitzgerald, H. E. (1992). *Analysis of dynamic psychological systems* (Vols. 1, 2). New York: Plenum Press.

Maturana, H., & Varela, F. (1980). *Autopoiesis and cognition: The realization of the living.* Boston: D. Reidel

Maturana, H., & Varela, F. (1987). *The tree of knowledge.* Boston: Shambhala.

Meehl. P. (1978). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow progress of soft psychology. *Journal of Consulting and Clinical Psychology, 46,* 806–834.

Milton, J. G. Longtin, A., Beuter, A., Mackey, M. C., & Glass L. (1989). Complex dynamics and bifurcations in neurology. *Journal of Theoretical Biology, 138,* 129–147.

Minuchin, S., & Fishman, H. C. (1981). *Family therapy techniques.* Cambridge MA: Harvard University Press.
Morrison, F. (1991). *The art of modeling dynamic systems.* New York: Wiley.
Odum, H. T. (1988). Self-organization, transformity, & information. *Science, 242,* 1132-1139.
Prigogine, I., & Stengers, I. (1984). *Order out of chaos: Man's new dialogue with nature.* New York: Bantam Books.
Putnam, F. (1988). The switch process in multiple personality disorder and other state-change disorders. *Dissociation, 1,* 24-32.
Putnam, F. (1989). *Diagnosis and treatment of multiple personality disorder.* New York: Guilford Press.
Reidbord, S. P., & Redington, D. J. (1992). Psychophysiological processes during insight oriented therapy: Further investigations into nonlinear psychodynamics. *Journal of Nervous and Mental Disease, 180,* 649-657.
Roschke, J., & Aldenhoff, J. B. (1992). A nonlinear approach to brain function: Deterministic chaos and sleep EEG. *Sleep, 15,* 95-101.
Sabelli, H. C., & Carlson-Sabelli, L. (1989). Biological priority and psychological supremacy: A new integrative paradigm derived from process theory. *American Journal of Psychiatry, 146,* 1541-1551.
Sabelli, H. C., Carlson-Sabelli, L., & Javaid, J. I. (1990). The thermodynamics of bipolarity: A bifurcation model of bipolar illness and bipolar character and its psychotherapeutic applications. *Psychiatry, 53,* 346-368.
Schmid, G. B. (1991). Chaos theory and schizophrenia: Elementary aspects. *Psychopathology, 24,* 185-198.
Schore, N. E. (1981). Chemistry and human awareness: Natural and scientific connections. In R. S. Valle & R. von Eckartsburg (Eds.), *The metaphors of consciousness* (pp. 437-460). New York: Plenum Press.
Stewart, I. (1989). *Does God play dice? The mathematics of chaos.* Cambridge, MA: Basil Blackwell.
Tufillaro, N. B., Abbott, T., & Reilly, J. (1992). *An experimental approach to nonlinear dynamics and chaos.* Reading, MA: Addison Wesley.
Turvey, M. T. (1990). Coordination. *American Psychologist, 45,* 938-953.
Vandervert, L. (1991). A measurable and testable brain-based emergent interactionism: An alternative to Sperry's mentalist emergent interactionism. *The Journal of Mind and Behavior, 12,* 201-220.
Varela, F. J. (1989). Reflections on the circulation of concepts between a biology of cognition and systemic family therapy. *Family Therapy, 28,* 15-24.
Waldrop, M. (1992). *Complexity: The emerging science at the edge of order and chaos.* New York: Simon & Schuster.
Winfree, A. T. (1974, June). Rotating chemical reactions. *Scientific American, 230,* 82-95.
Winfree, A. T., & Strogatz, S. H. (1984). Organizing centers for three dimensional chemical waves. *Nature, 311,* 611-614.
Wolff, P. H. (1987). *The development of behavioral states and the expression of emotions in early infancy.* Chicago: University of Chicago Press.