Dynamical Systems: It's about Time!

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What is a dynamical system? In simple terms, it is a means to describe the temporal unfolding of a system. It is concerned with two fundamental concepts, change and time. For example, a psychological process, such as memory or cognitive development, unfolds by progressing through a series of discrete states that occurs over time. Every dynamical model has time as a variable, although it is often represented implicitly (Ward, 2002). In more formal terms, a simple dynamical model is a differential equation, such as the following simple linear one $dx/dt=at$. A somewhat more complex model involves feedback, $dx/dt=ax-bx^2$, which provides a mechanism by which the system can *self organize*. (In this latter example, $-bx^2$ is a negative term and will decrease the rate of change of x at an accelerating rate as x gets larger.) Mathematics is the language of dynamical systems, which is both a strength and a weakness for the psychological sciences.

Although the study of dynamical systems has had a long and venerable history in the physical sciences (Abraham, Abraham, & Shaw, 1992), it has yet to have a major impact in the psychological sciences. This seems somewhat paradoxical given that psychologists are interested in a wide range of phenomena that change over time, including learning, memory, thinking and development. How can we explain this failure to explicitly incorporate dynamical systems in the study of these phenomena? The crux of the problem is that dynamical systems theory is couched in mathematical terms. This is true for both the conceptual foundations as well as for the analytic techniques. Accordingly, many of the key concepts are inaccessible to the average psychological scientist, and the same is true for quantitative techniques that have been proposed specifically for addressing psychological questions. One of the principle goals of this book is to familiarize readers with these techniques, and hopefully present them in a manner that will make them accessible to a much larger contingent of psychological researchers.

Given the theme of this book, you may be wondering why I was given the assignment of writing this introductory chapter. I am not an expert in dynamical modeling, nor do I have a great deal of experience with modeling in general. I am not a quantitative psychologist, and I have a limited background with differential and difference equations, which are the staples of dynamical systems. Nevertheless, my interests in the development of behavior have instilled in me an appreciation for the importance of studying the emergence of new behaviors over time and the myriad of factors that contribute to these changes. These changes over time, which involve the formation of new patterns, represent one of the central themes in dynamical systems. I have also been fortunate to work with a number of graduate and postdoctoral students who helped me navigate through the jargon and the mathematics to learn about the basic concepts and analytic tools. This knowledge has led me to a much more sophisticated appreciation of the dynamics of behavior, and has provisioned me with new tools for studying behavior and development. In this chapter, I provide a very selective review of some key concepts in dynamical systems that help to broaden our understanding of human behavior. This review is organized into four sections: Statical vs dynamical models, Time scales of human behavior, Nonlinear analyses, and Behavioral variability.

Statical vs Dynamical Models

By definition, motion perception involves a dynamical system in which the state of the stimulus display is continuously changing. Paradoxically, it was commonly believed for much of the 20th century that that motion or event perception was processed as a series of static images. Once these images were sequentially encoded, an inferential process was applied to decide whether these images represented the same object moving in space and time or whether these images corresponded to different objects in different locations. The problem with this interpretation is that it began with a statical model of visual perception, which was unable to explain how the perception of structure-from-motion was not present in any static image, but emerged only from structural changes that were perceived over time.

A compelling example of this effect was first demonstrated by Johansson (1973) who showed moving point-light displays of people walking to observers. These displays consisted of 13 point-lights corresponding to the head, shoulders, elbows, arms, hips, knees and ankles of a person walking. When these displays are shown as a static image they are typically not recognized or recognized very slowly as a person walking. By contrast, moving versions of these displays are recognized quickly and unequivocably as a person walking. Figure 1 simulates this effect by showing a series of six sequential frames from a moving point-light display of a person walking. The point to emphasize is that the structure of this stimulus display is not present in any single image, but rather is an *emergent* property of the transforming optical array. If the structure is indeed an emergent property of the motion information, then it would seem that the static images are insufficient for explaining the percept.

This conclusion was anticipated by J. Gibson (1966), who rejected the view that visual perception is based on a statical model and argued persuasively for the primacy of motion in visual perception. In essence, his position was that visual information in the optic array is changing continuously through both self and object motion, and thus it seemed reasonable to assume that we had evolved to perceive motion information directly. This theoretical perspective led eventually to a significant reinterpretation regarding how we perceive the visual world, and it is much more common today to study the perception of the changing optic array as opposed to perception of a static image.

Aside from the field of motion perception, the vast majority of psychological research is still primarily oriented toward statical models of behavior. In general, a statical model assumes that the relevant state of the modeled system remains constant, and thus focuses exclusively on the current relations between the state variables (Ward, 2002). For example, human memory has been modeled over the past 150 years as a static system consisting initially of two general systems of memory, short-term and long-term, and later expanded to include episodic and semantic memory systems. In spite of each of these systems differing in terms of their temporal dynamics, little attention is given to how these memories develop over time. The majority of the research focuses on the output or the product of the system. For example, research reveals that we remember more items in working memory when we rehearse them or store them categorically. Ironically, most of these models emphasize their relationships between variables independent of time, even though memory is inherently a temporal process. Likewise, learning is a time-critical process, as new knowledge and skills are organized over time, but we tend to focus on the

products or outcomes of this process. What is lacking in these and other domains is a way of modeling how the behavior changes over time.

In order to avoid any confusion, let me emphasize that my intent is not to dismiss or minimize the importance of what I have referred to as statical models. Analysis of any fundamental process first requires identification and categorization in order to establish the meaning and reliability of the observed phenomena (Rapoport, 1972). For example, the study of cognitive development has involved repeated efforts to understand what children know and don't know about concepts at different ages. This knowledge is a prerequisite to trying to understand how these concepts develop (Flavell, 1971; Siegler & Alibali, 2005). Without statical models of behavior, it is doubtful that scientists could agree on the variables that should be studied (cf. Ward, 2002). Still, studying the changes in these variables and how they evolve over time is necessary for obtaining a more complete understanding of behavior. It would thus be misleading to suggest that either model is sufficient for understanding human behavior, because these models are complementary and not contradictory.

The challenge for the investigator is to know the strengths and limitations of both models. As a case in point, Bob Freedland and I were interested in studying the transition in human infants from belly crawling to hands-and-knees crawling (Freedland and Bertenthal, 1994). At the time of this study, it was commonly reported in the literature that hands-and-knees crawling involved moving only one limb at a time akin to the interlimb pattern produced by a horse when walking. Interestingly, the majority of evidence for this report was not based on empirical data, but rather was based on applying a static model for explaining how the infant remained balanced while supporting the trunk off the ground. In essence, this model stipulates that a minimum of three limbs are required to keep the center of mass of the body over the polygon of support formed by the limbs in order to maintain a balanced system and avoid tipping (Raibert, 1986). The problem with this logic is that it was based on the wrong model. Animals sometimes use three legs to balance when they move slowly, but they usually move faster and more flexibly by employing a dynamically balanced system (Alexander, 1992). During dynamic balance, quadrupeds support themselves with only two limbs during portions of the gait cycle. The same is true for human infants who tend to not move one limb at a time while crawling, but instead move diagonally opposed limbs simultaneously and 180^{o} out of phase with the other pair of limbs. Freedland and I confirmed this prediction with motion analyses of the infant's crawling pattern, but it is debatable whether we would have collected the requisite data if we had assumed that crawling conformed to a statical as opposed to a dynamical model.

Time Scales of Human Behavior

Why is so little attention devoted to the dynamics of behavior? My sense is that the temporal dimension is often obscured by the time scale at which a behavior is studied. For example, we think of social behaviors as learned over an extended period of time, but once acquired these behaviors function automatically in a seemingly fixed way. Of course, these behaviors are all dynamically assembled each time they're executed, but the assembly often takes place at a faster time scale than our sampling rate. It is thus essential to consider in our modeling that human behaviors operate at multiple time scales, and that these time scales are hierarchically related.

An excellent framework for thinking about the relation between these time scales was proposed by Alan Newell (1990). In this framework, intelligent systems are built up

from multiple levels of systems in hierarchical fashion (see Table 1). Each system is a collection of elements or components that are linked together and interact, thus producing behavior. As one moves up the hierarchy of system levels, size increases and speed decreases. Expansion occurs in time as well. It was estimated that each new level would be about a factor of ten bigger than the next lower level.

Let's examine these levels in a little more detail. In the biological band, we are dealing with neuronal processes in the brain. Information is coded by neural activity which lasts approximately 1ms for individual neurons, and 10ms for neural circuits. From this timing information, it is possible to establish real-time constraints on cognition as a function of neural activity. For example, there are available approximately 100 neural operations per second of cognitive activity. A simple sentence, such as "Please pass the salt," or your reaction to it will take approximately 1sec. By contrast, rapid transit chess (10s per move) requires multiple cognitive operations (encode opponent's move, understand consequences, decide upon a move and make it), and thus it takes longer than a single cognitive operation. This task would be impossible for humans if it took more than a few seconds to engage in each of the necessary cognitive operations. For similar reasons we would predict that humans could not play 1 sec chess in an intelligent fashion.

As can be seen in Table 1, it is possible for humans to cognitively process information at rates faster than 1sec, and these rates are often assessed in reaction time experiments. It is possible to identify a stimulus or retrieve some item from memory or choose one operation over another in approximately 10 to 100ms, but multiple operations are usually necessary to complete a task. For example, deciding whether two letters on the screen (e.g., 'a' and 'A') are the same or different requires that both are identified, compared and followed by a response indicating 'same' or 'different.' Typically, each of these operations will take place serially, which explains why reaction time studies require more than 100ms. In some cases, it is possible to perform operations simultaneously (e.g., visual search for a target stimulus (e.g., blue circle) that differs from multiple distractor stimuli (e.g., red circles) by a single dimension). Thus, some cognitive operations are automatic and do not require conscious attention, while other cognitive operations are more controlled and do require conscious attention to perform each operation. This difference will influence the time course for assembling these behaviors, and suggest somewhat different dynamics. Perhaps, this is more information than you needed to get the point, but let me reiterate it anyway. Each level of processing is hierarchically related to the previous level in terms of simpler operations combining and producing a more complex operation at a slower time scale than that occurring at the previous level.

What happens beyond 10sec at the next band? The rational band operates in a time frame spanning minutes to hours. Reasoning, problem solving, decision-making and other operations that depend on prior knowledge and logical reasoning are processed at this time scale. At higher bands, social, historical, and evolutionary factors will come into play. These bands are distinguished from earlier bands because now actions are no longer a function of a single individual, but instead are a function of multiple individuals or agents distributed over time and space.

This framework is useful for highlighting an important principle of dynamical systems – causality is multilevel and multi-determined (e.g., Abraham, Abraham, & Shaw, 1992; Kelso, 1995). Human behaviors that are assembled at relatively slow time scales, such as social behavior or learning academic skills, are a product of multiple processes that

proceed at faster time scales but cooperate in the formation of these more complex behaviors. Although it is sometimes cumbersome or even impossible to explain behaviors in terms of lower-level constituents, it serves as a valuable reminder that all behaviors (from neural to social to cultural) are part of a continuum and are dynamically assembled over multiple time scales. In the same way that this framework challenges the logic for a mind-body dualism, it undergirds the notion that human behavior is unified across time scales. The same dynamic principles apply at all time scales, and thus it is possible to apply the same analytic tools at every level of the hierarchy. In essence, the goal is to identify the pattern or structure created by the evolution of the system. This structure is a function of multiple factors, and various techniques have been developed to decompose a control system into its key dimensions or factors (Abarbanel, Brown, Sidorowich, & Tsimring, 1993).

Let me emphasize, however, that the availability of these analytic techniques for helping to identify causal factors contributing to the assembly of a specific behavior is no substitute for a well-developed conceptual framework. This framework is necessary for interpreting the results from these analyses in a meaningful way. The best strategy for approaching this problem is to begin with a theoretical model for the behavior. Thelen, Schoner, Scheier, and Smith (2001) present an excellent example of such a model for explaining the development of the AnotB error by infants between 7 and 12 months of age.

This error was first reported by Piaget (1954) in studying the development of the object concept. In numerous replications of the original task, infants are presented with two similar opaque containers with lids, and are initially trained to search reliably for an object hidden in container A. When the object is then hidden in container B in full view of the infant and a short delay imposed before allowing the infant to search, a majority of infants try to retrieve the object from container A rather than container B. Eventually, infants avoid this error and search correctly in container B. Most explanations for this accomplishment focus on the development of a specific skill, such as knowledge of existence constancy, increasing strength of object representations, or inhibition of perseverative reaching (e.g., Diamond, 1991; Munakata, 1998; Spelke, 1998). By contrast, Smith, Thelen, Titzer, and McLin (1999) proposed that success on this task involved perceptual, motor, and historical components that could be integrated in real time in order to serve the demands of the task.

This model was developed more formally as a dynamic field model (Thelen et al., 2001) in which a one-dimensional field gives the probability of reaching in a given direction (see Figure 2). This ‘movement planning field’ receives two inputs describing the ‘task input’ with peaks at A and B representing the two containers, and a ‘specific input’ with a transient peak at A or B representing attention to the hiding of the object. In addition, the movement planning field receives input from a second one-dimensional memory field that maintains a record of the location of recent reaches.

The resting level of the movement planning field determines whether an action is self-sustaining or completely input driven. When the activation level is low, the peak corresponding to attention to the hiding event decays rapidly, and search reverts to the A location, which is still activated by the memory field. When the resting level activation is high, the field is able to generate self-sustaining peaks and the model correctly chooses the B location. In this model, the resting activation level acts as a control parameter for the field and determines in cooperation with all the other intrinsic and extrinsic variables

whether location A or B will be chosen. Although this model has its limitations, it is nevertheless an exemplary example for showing that behavior is the outcome of multiple variables that unfold over time at different rates. Finally, it is worth repeating that the success of this model is in part a function of selecting a dynamical model, but it is also a function of conceptualizing the relevant variables and not limiting them to either content knowledge or perceptual and motor skills, but rather the real-time integration of all these variables.

Nonlinear Analyses

In the language of dynamical systems, self-organized behaviors of complex systems are dynamically stable, which means they settle into a specific attractor state or temporal pattern from a number of initial states. Dynamical systems theory describes three main types of temporal organization or attractors: fixed, cyclic and chaotic (locally stochastic but globally stable). Psychological science has tended to emphasize the first, which is fixed or homeostatic. As previously discussed, the focus is on the end point or the product of the process with little regard as to how that result emerged. The study of biological clocks and rhythmic oscillations (e.g., walking) in the motor system has advanced the science to include cyclic attractors. Now we are discovering that the unexplained variance or error term associated with random Gaussian or Poisson distributions may have more temporal and spatial structure than heretofore recognized. The standard statistical toolbox of the psychological scientist is limited to linear analyses, and thus misses this additional structure which is nonlinear. The application of nonlinear dynamical analyses to chaotic attractors provides us with an approach for recovering important sources of information about the structure of the data.

Let me try to illustrate this point with an example discussed by Ward (2002). What do a Bach concerto, alpha waves, heartbeats, earthquakes, thunderstorms, and reaction times in cognitive experiments all have in common? The answer is that the time series fluctuations of all these phenomena exhibit a 1/f power spectrum. This distribution is also referred to as pink noise, which is different from the more familiar white noise. Strictly speaking, white noise is a time series of fluctuations having roughly equal spectral density at all frequencies in a given range. A prototypical example of white noise is a time series of samples from a Gaussian or normal distribution. The power spectrum of such a time series is essentially flat, i.e., zero slope in log-log coordinates. This means there are no correlations whatsoever between any samples taken at different points in the time series; samples are independent and identically distributed. If a periodicity were present in the time series, then the power spectrum would show a peak at that frequency. For example, a pure tone of 300Hz would display a single peak in the spectrum at 300Hz indicating that there were correlations in the time series corresponding to a 300Hz frequency. In pink noise, the correlations in the time series of fluctuations occur at several frequencies, ranging from very long to very short with no one preferred frequency. The power spectrum of this time series shows a slope of -1 plotted in log-log coordinates. This means that the power spectrum is inversely proportional to the frequency (i.e., power~1/f). Noise with this spectral pattern is referred to as pink noise, because its spectrum is similar to colored light that is perceived as pink. (This light is dominated by low frequency (long wavelength) photons, but has some higher frequency (short wavelength) photons as well.)

One of the first reports showing the presence of 1/f noise in human cognition was presented by Gilden, Thornton, and Mallon (1995). These investigators were concerned

with the production of temporal and spatial intervals from memory. Subjects were given an example of a spatial or temporal interval and then were instructed to reproduce the interval for some period of time. The errors in replication were treated as a time series so that the power spectra for these errors could be derived. Figure 3 shows the power spectra of the errors from 6 experiments in which the time intervals varied between 0.3 and 10 sec in duration. Overall, these spectra approximate 1/f at frequencies less than about 0.2 Hz, and there is a quadratic trend that becomes progressively more pronounced with shorter target durations.

Previous psychological models of time estimation assumed that subjects' responses were produced by two interacting processes – an internal clock to time the interval and a motor program to generate the key presses at the right times; both of these processes were also sources of white noise. By analyzing some of the nonlinear structure in the data, Gilden et al. (1995) improved upon this generic model by showing that the internal clock was a source of 1/f noise, whereas the motor program remained a source of white noise. This new model was tested by simulating the time interval data using different combinations of 1/f noise and white noise for each of the different frequencies. The right panel of Figure 3 shows that this model did a very good job of simulating the empirically derived spectra. These results were replicated when subjects judged a fixed spatial interval. Although the specific generator of the noise was not determined, this study is noteworthy because it represents an innovative application of a nonlinear analysis for showing that another mechanism capable of generating 1/f noise is involved in these cognitive judgments of time estimation. Given the ubiquity of 1/f noise in physical and biological systems (Gilden et al., 1995), it seems reasonable to assume that 1/f noise is more common in psychological data than heretofore imagined.

As a final comment about nonlinear modeling, it is worth noting that there are additional forms of nonlinear structure (such as brown noise or Brownian motion), and it would behoove researchers to begin conducting nonlinear analyses of their time-ordered data in order to gain a more complete assessment of the mechanisms contributing to the time series.

Behavioral Variability

As previously discussed, dynamical modeling is focused on the unfolding of behavior across time scales, and seeks to model both the traditionally explained as well as unexplained variance in behavior. This perspective is certainly at odds with mainstream psychological science that focuses on group means and central tendencies at fixed points in time. What is missed by focusing exclusively on means instead of the variability that accompanies these means? I would like to address this question by commenting on the pervasive role of variability in behavior and its implications for the study of behavior and its development.

Let me begin, however, by clarifying what is meant by variability in this context. In a classic study by Arutyunyan, Gurfinkel, and Mirsky (1969) comparing pistol shooting performance by novices and experts, it was reported that experts as compared to novices shot more accurately with less variability. I suspect that most readers would find this result consistent with their intuitions that variability would decrease with expertise, but the direction of the effect actually depends on the measure. Thus, it was also reported that experts as compared to novices showed more *movement variability* involving their wrist and shoulder in order to compensate for local perturbations, such as respiration or ground

reaction forces. By contrast, novices showed little movement variability and held the pistol rigidly. In the former case variability referred to the outcome of the performance, but in the latter case variability referred to the behavior itself. It is this latter form of behavioral variability involving changes over real and developmental time that will be discussed below.

What do we know about developmental changes in behavioral variability? One of the most remarkable characteristics of humans is the degree to which we change over time. From cradle to grave, our thoughts and actions are continuously evolving and taking on new forms. Consider, for example, the relatively uncoordinated movements of the human infant and how quickly those movements are transformed into skilled actions that support reaching, standing, walking, etc. Likewise, the mental concepts of a preschool child are fragmented and incomplete relative to those of a grade school child or someone even older. Later in life, some of our basic processing skills may begin to falter even as we continue to acquire new knowledge about the world. Developmental psychologists have been quite successful in describing many of the outcomes that take place across the life span. Yet, the explanation for these developmental changes has proven much more elusive than one might expect.

Most traditional theories of behavioral development emphasize stable patterns of performance that are interrupted by temporary and abrupt changes in behavior (e.g., Flavell, 1971; Piaget, 1952). From this perspective, it is difficult to appreciate how and why behavior changes, and we are often left with incomplete or mysterious explanations to account for the development of new forms. Recent research is beginning to challenge this common perspective by revealing that behavior is much more variable than assumed previously, and that this variability is not merely a correlate of change but instead is often a contributor to the change itself (Bertenthal & Clifton, 1998).

By definition, human development is a complex system, and like other complex systems it reveals global or long-term stability along with local or short-term variability. Until recently, the detailed analyses necessary to reveal short-term variability were typically unavailable, but this situation is gradually changing as developmental researchers are beginning to engage in more longitudinal studies and microgenetic analyses. As a consequence, it is becoming increasingly apparent that the fine structure of behavior reveals considerable variation as a function of task, context and time. Siegler and Jenkins (1989) show, for example, that young children's addition strategies differ not only across individuals, but within individuals across testing sessions, and even from one problem to the next. Edelman (1992) reviews evidence revealing that patterns of the same nerve in genetically identical organisms or corresponding neurons in the same cortical column or on the right and left side of the same brain show considerable structural variability at a micro level of analysis. Not only does this evidence debunk the view that the brain is akin to a computer (in which all connections are fixed), but it also suggests that brain development is governed, not by a deterministic, but by a stochastic (or statistically varying) set of cellular processes, such as cell division, movement, and death.

Is this evidence of variability meaningful? Not necessarily, but it becomes meaningful if it is shown that the structure of this variability is systematically related to other factors, like experience, development, learning, etc. Let's consider the movement or sway variability associated with postural development.

It has been well established for more than a century that proprioceptive stimulation contributes to postural control (Howard, 1986). More recent research reveals that visual information also specifies self motion and contributes to the control of posture (Lee & Lishman, 1975). The coordination between visual information and posture shows marked improvements following the development of independent sitting (see Bertenthal & Clifton, 1998, for a review). In a series of experiments, my colleagues and I investigated developmental changes in the visual control of posture by infants between 5 and 13 months of age (Bertenthal, Rose, & Bai, 1997; Boker, Schreiber, Pompe, & Bertenthal, 1998; Boker, & Xu, 2000; Bertenthal, 2002). Postural control was assessed by placing infants in a 'moving room' in which the walls and ceiling oscillated back and forth at various frequencies while the floor remained stationary. Infants were seated inside the room in a specially designed seat that detected their shifting center of pressure in response to the visual stimulation of the moving walls (see Figure 4).

In one experiment (Bertenthal et al., 1997), we tested the movement variability shown by infants to a moving room oscillating at 0.3 or 0.6 Hz or remaining stationary. The results revealed that 5-month-old infants showed the greatest amount of movement variability, and that this variability declined sharply by 7 months of age (see Figure 5). Surprisingly, 9 and 13-month-old infants showed a significant increase in movement variability relative to 7-month-old infants. How can we account for this increase in movement variability? We are apt to think about posture as something static (i.e., resisting gravity and maintaining stability by minimizing movements), but, in fact, the posture of any live creature is almost always changing. We do not cease to have a posture because we walk or run or use our arms. On the contrary, postural control supports our movements by maintaining a stable frame of reference while one or more body segments are engaged in some action. In order to maintain postural equilibrium, it is not necessarily the case that movements will be minimized, but rather that the moving segments will be coordinated or structured to the continuously changing demands of the task. Consistent with this interpretation, analyses of the covariation between postural sway and visual motion from the wall movements shows that sway coherence increases linearly from 5 to 9 months of age (Bertenthal et al, 1997; Boker et al., 1998). (Note that sway coherence is a measure of the speed and accuracy by which infants compensate for the perceived postural sway induced by the moving walls.)

If we had limited our analyses to measures of sway coherence, the developmental results would have merely confirmed the standard prediction of linear improvement with age. Instead, the additional analyses of movement variability revealed a U-shaped developmental function, which offered further insight into the mechanisms responsible for the development of postural control. Our interpretation for this nonlinear developmental function was that 7-month-old infants straddle the age when learning to sit without support, and tend to reduce the problems of coordinating a new posture by stiffening some of their joints and reducing degrees of freedom. As Newell and Vereijken (199x) have shown, this stiffening of the joints is fairly common when learning new motor skills, such as skiing in adults or sitting in infants. As the skill becomes better coordinated, the performer becomes more flexible and additional movement is observed. In the case of postural control, this is exactly what we observed. Thus, the difference between movement variability prior to and following independent sitting was not in the magnitude, but rather in the structure of the response.

An analogue to the difference between structured and unstructured movements appears in the perception of biological motions (see Figure 6). As previously discussed, these displays are quickly interpreted as depicting the human form when the point-lights are spatially consistent with the major joints of a person walking. When these point-lights are spatially scrambled, the interpretation of this event becomes highly ambiguous even though the same absolute motions are preserved in the display. It is precisely because of the additional spatial structure in the canonical display that the moving point-lights are perceived as depicting the human form.

The lesson from this last example is that simply measuring the absolute amount of variation in a spatial array or a time series is not sufficient to ascertain whether that variation is interfering with or facilitating performance. More generally, this example is meant to illustrate how changes in behavioral variability offer additional sources of information for probing how behaviors evolve over time. For more information on this topic, readers are referred to Bertenthal (1999), Rosengren (2002), Siegler (1996), and Thelen (1995).

Conclusions

The theoretical biases and conceptual frameworks that we bring to the study of human behavior can have profound consequences on the phenomena we choose to study, the questions we ask about the phenomena, the experiments we perform, the analyses we conduct and the ways in which we interpret the results (cf. Beer, 2000). Until relatively recently, dynamical systems models and analyses were not applied directly to the study of human behavior. Consequently, many questions about the evolution of behavior in real and developmental time were left unanswered because the necessary conceptual frameworks and tools were not available. This situation is beginning to change as psychological scientists apply the principles of dynamical systems to the study of behavior.

As I've tried to convey in this chapter, dynamical models are a breed apart. They emphasize that human behavior is a complex system with many elements or subsystems that can combine with each other at multiple levels in an indeterminate number of ways (Kelso, 1995). Consider, for example, that a single action produced by a human agent involves the coordination of approximately 10^2 muscles, 10^3 joints, and 10^{14} cells (Turvey, 1990). In spite of the huge number of elements or degrees of freedom involved, a human body can self-organize into patterns of behavior that are described by just a few dimensions. This self-organization is an emergent process that involves the cooperation of multiple systems at different time scales; it is a nonlinear process that leads to irregular pattern formation; and it results in different patterns that evolve over space and time as a function of the interplay of the intrinsic and extrinsic dynamics. In essence, dynamical models complement the more traditional statical models by focusing on how behavior changes over time as a function of the interaction of organismic, task and environmental variables.

These principles emphasized by dynamical systems are undeniably relevant for understanding human behavior. Somewhat less clear is whether these principles can be empirically tested with a wide range of human behaviors. Thus far, much of the research has been limited to fairly simple behaviors and simulations. In order to advance the study of dynamical models of human behavior, new methods and models are required that are tailored to the data sets collected by psychological scientists. Some of these new methods and models are presented in subsequent chapters of this book, and collectively the analytic

techniques discussed in these chapters will help to enrich our understanding of human behavior.

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Table 1

TIME SCALE OF HUMAN ACTION

Scale (sec)	Time Units	System	World (theory)
10^{7}	months		
10^{6}	weeks		**SOCIAL BAND**
10^{5}	days		
10^{4}	hours	Task	
10^{3}	10 min	Task	**RATIONAL BAND**
10^{2}	minutes	Task	
10^{1}	10 sec	Unit task	
10^{0}	1 sec	Operations	**COGNITIVE BAND**
10^{-1}	100 ms	Deliberate act	
10^{-2}	10 ms	Neural circuit	
10^{-3}	1 ms	Neuron	**BIOLOGICAL BAND**
10^{-4}	100 μs	Organelle	

Figure Captions

Figure 1. Six sequentially sampled frames depicting a point-light walker at different phases of the gait cycle.

Figure 2. (A) The time evolution of activation in the planning field on the first A trial. The activation rises as the object is hidden and, owing to self-organizing properties in the field is sustained during the delay. (B) The time evolution of activation in the planning field on the first B trial. There is heightened activation of A before the hiding event, owing to memory for prior reaches. As the object is hidden at B, activation rises at B, but as this transient event ends, owing to the memory properties of the field, activation at B declines while that at A is sustained. (From Thelen and Smith, 2002).

Figure 3. (A) Power spectra of fluctuations in time estimations; (B) power spectra from a model. (From Gilden, Thornton, and Mallon, 1995).

Figure 4. Infant sitting in a 'moving room' surrounded by walls and a ceiling that move back and forth and simulate the optical flow induced from postural sway.

Figure 5. Movement variability (RMS – root mean square) of postural sway (+SE) as a function of condition and age. (From Bertenthal, Rose, and Bai, 1997).

Figure 6. (A) Array of 11 point-lights attached to the head and major joints of a person walking. The motion vectors drawn through each point-light represent the perceived relative motions within the figure, and that drawn above the walker depicts its perceived observer-relative displacement. (Lines connecting the point-lights did not appear in the stimulus displays.) (B) Spatially scrambled walker is identical to A except that the relative locations of the point-lights have been scrambled. (Correspondingly numbered point-lights have the same absolute motions.)

Figure 1

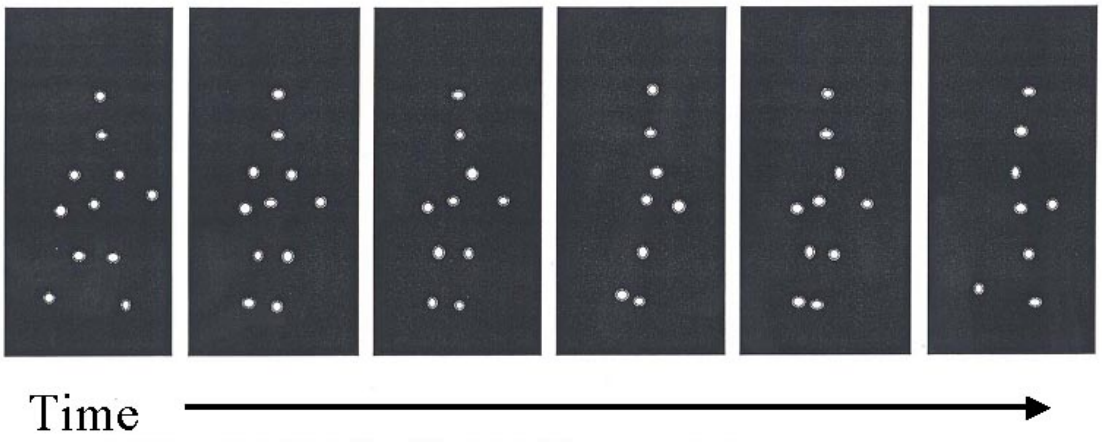


Figure 2

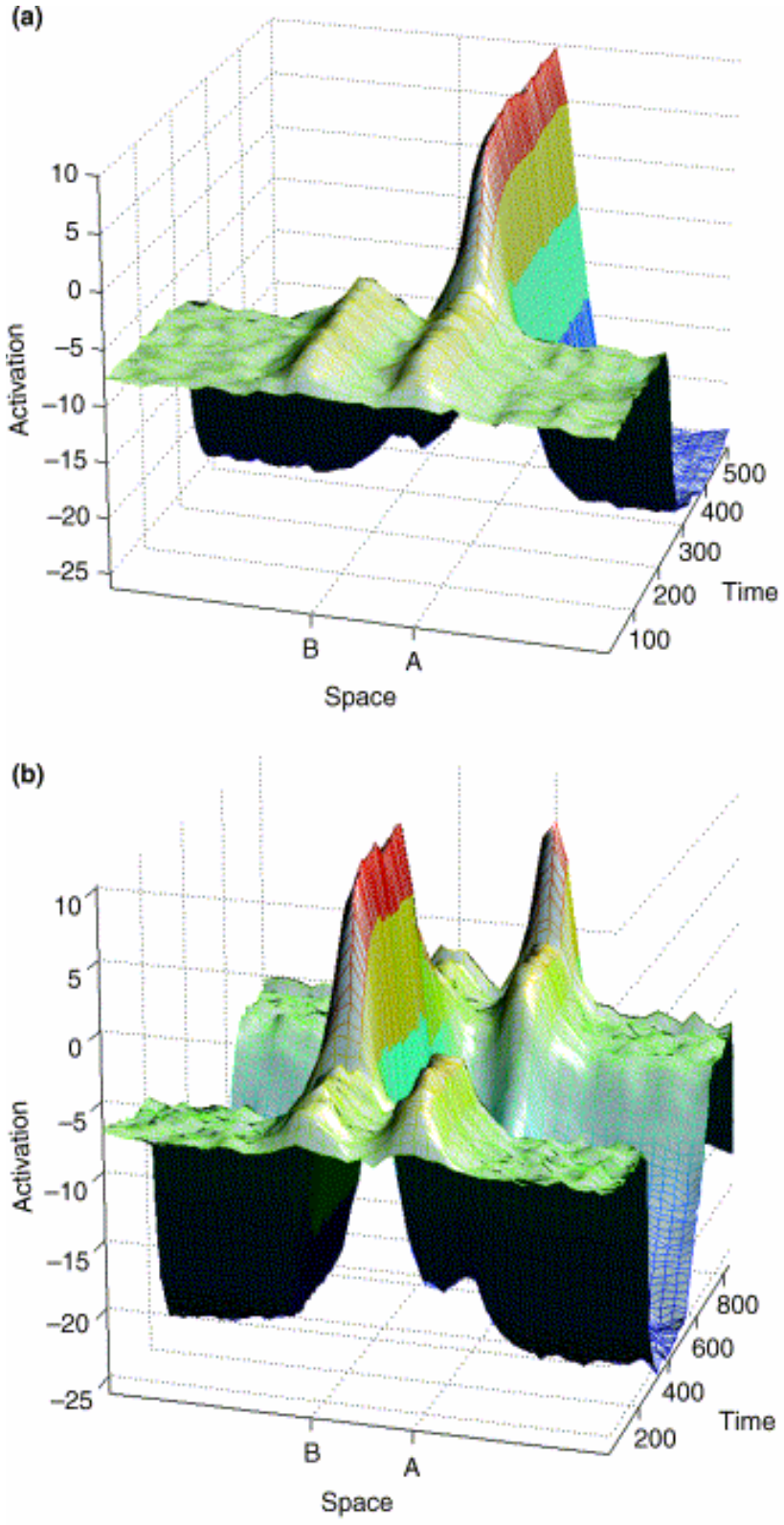

(a)
10
5
0
−5
−10
−15
−20
−25
Activation
B
A
Space
500
400
300
200
100
Time
(b)
10
5
0
−5
−10
−15
−20
−25
Activation
B
A
Space
800
600
400
200
Time

Figure 3

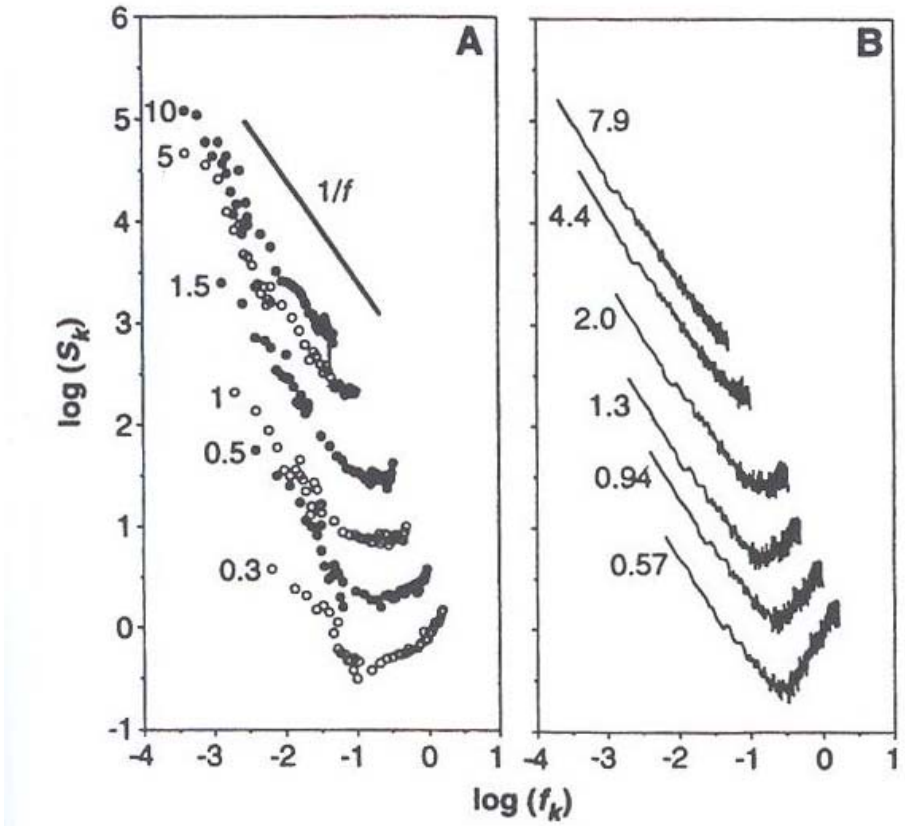


Figure 4

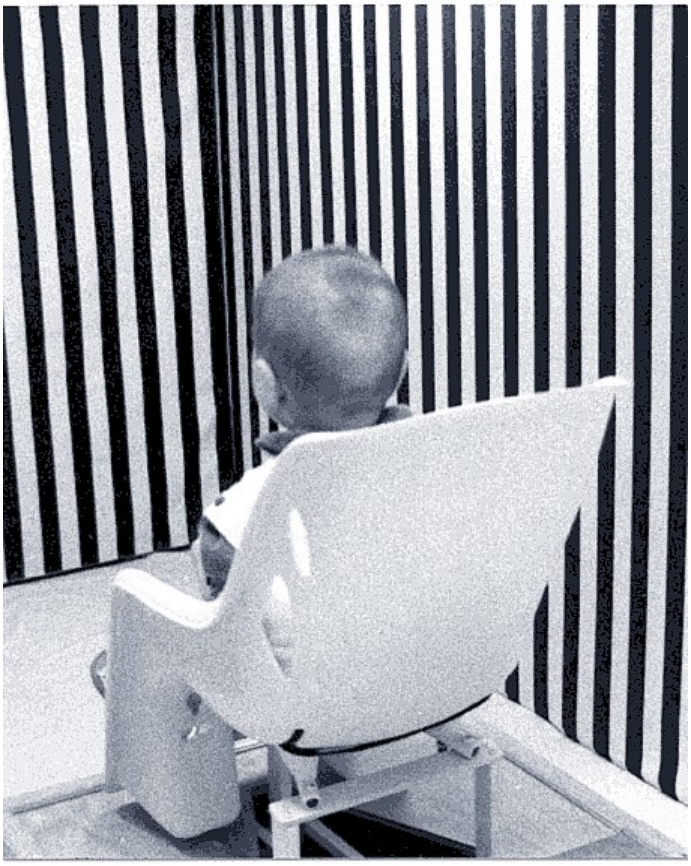
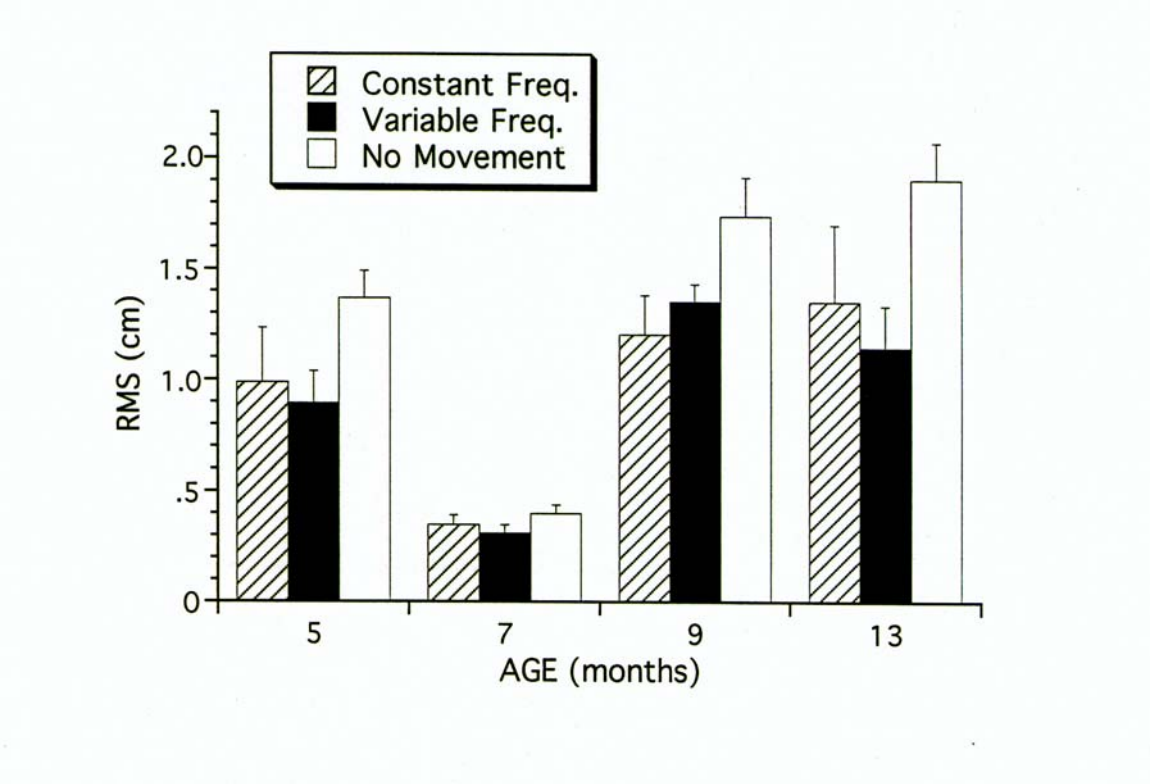


Figure 5


Constant Freq.
Variable Freq.
No Movement
RMS (cm)
2.0
1.5
1.0
.5
0
5
7
9
13
AGE (months)

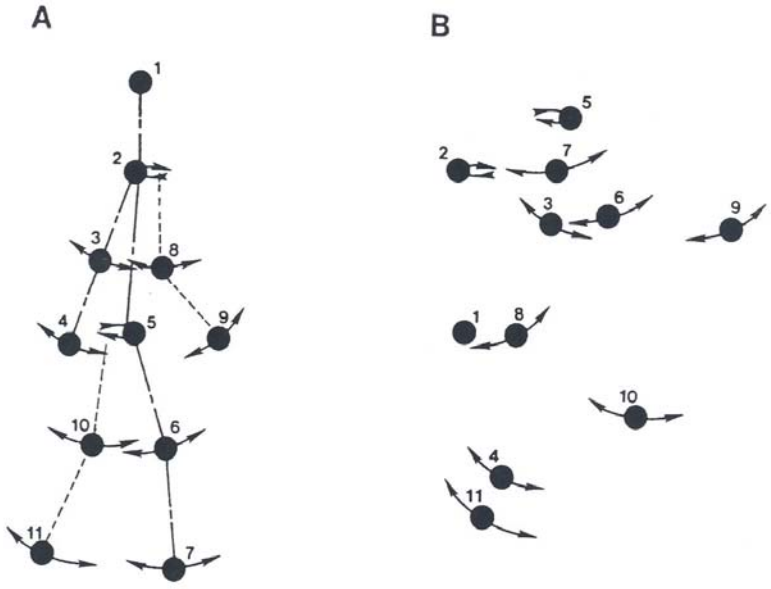



Figure 6