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CHAPTER

5

Principles of Dynamic Pattern Formation and Change for a Science of Human Behavior

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INTRODUCTION

In person-oriented research (Magnusson, 1995) the goal is to understand individual function and development as a complex, dynamic, holistic, interacting system. This chapter seeks to affirm, and perhaps supplement, the person approach both conceptually and methodologically. Because pattern analysis figures prominently in person-oriented research, and because my charge here is to discuss some key concepts in the study of complex systems, I begin with a brief review of how patterns form and change in nature. Before proceeding, a caveat is in order: the intent here is not to broker physics or to try to "physicalize" human behavior. Instead, it is to elaborate pattern-formation principles as a foundation for understanding the patterns of behavior produced by brains and people, and how these patterns may be modified both by internal factors (intentions, values, memories, emotions, etc.) and interactions with the environment (Kelso, 1995). Clearly this builds upon, but also goes beyond, theories of self-organized pattern formation in physical and chemical systems (e.g., Haken, 1983; Nicolis & Prigogine, 1989).

I also address the question of how to identify relevant pattern variables—or "regularities" as Murray Gel-Mann (1994) might say—and their time-dependent dynamics (equations of motion) in complex living systems. This is an empirical issue that has to be guided by theoretically motivated strategies. I advance one particular strategy—seeking qualitative change—as a means of identifying relevant pattern variables and the pattern-forming dynamics (stability, change, etc.) at both behavioral and brain levels. I show how qualitative change complements, and is complemented by, more standard correlational approaches. Then, I address a number of implications that arise from this "complex systems" view using the example of an elementary law of coordinated behavior that describes how different, individual components of a complex system are coupled together. These implications include how we are to understand the whole–part relation, the connection between levels, and perhaps even dichotomies in general. Like Magnusson (1995; chap. 3, this volume), I view such dichotomies and either-or propositions in science as shackles impeding progress and insight. In my view, a synthesis is needed that embraces contradictions.

In addition, I briefly describe how two essential aspects of individual functioning–intention and learning–may be incorporated into the present law-based approach to understanding human behavior. Such an approach attempts to reconcile individual diversity with features of behavior (albeit limited) that are common to us all. Finally, I sketch several main themes or core principles that stem from the laws of human coordinated behavior–so-called coordination dynamics–that have been identified through empirical and theoretical research over the last two decades or so. These principles represent a first attempt to explore the meaning of coordination dynamics in the broader context of human experience and activity.

One overall goal I have is to put clothes (in the sense of spelling out the theory–experiment relation) on sometimes vague, even mystical new ideas from so-called "complexity theory," such as self-organization, emergence, and symmetry-breaking. This, and related terminology, is frequently invoked in a metaphorical fashion. But science demands that we go beyond metaphor by checking the validity of concepts, usually by observation and experiment. As we reach the end of a century in which remarkable achievements have been made by reductionist science, I believe it is time to eliminate the tension between reductionistic and holistic thinking. Understanding ourselves depends on it.

SOME ELEMENTARY CONCEPTS OF PATTERN FORMATION IN NATURE

Self-Organization. In a wide variety of systems that exchange matter, energy, and information with their surroundings, spatiotemporal patterns arise spontaneously as a result of a large number of nonlinearly interacting components. Although the word "self-organization" is used (abused, possibly) in a wide variety of scientific contexts, it is restricted here to the spontaneous formation of pattern and pattern change in so-called open systems that are far from equilibrium. How far from equilibrium, no one really knows. Self-organization means there is no "self" inside the system responsible for emergent pattern. Rather, under certain conditions, the system organizes itself. There is no ghost in the machine, instructing the parts how to behave.

That the organism is an open system is one of the two essential criteria for life postulated by Francis Crick in *Of Molecules and Men* (1966), yet it has received much less attention in biology than Crick's other criterion, the need for organisms to reproduce and pass on "copies" of themselves to their descendants. Here we see a dichotomy between a complex system's natural ordering tendencies and the need (certainly in living systems) to guide that order in specific ways. The computer–an organized system constructed by human beings–and the computer metaphor with its attendant constructs (programmed instructions, encoding, decoding, central processing unit, etc.), have amplified this dichotomy in fields ranging from psychology to molecular genetics. To some, the dichotomy doesn't exist because self-organization is irrelevant. The molecule is the message. The organism is an information-processing device. I will say more about this later on.

Collective Variables. Emerging patterns are characterized by collective variables or what physicists call an order parameter (e.g., Haken, 1983). Collective variables are relational quantities that are created by the cooperation among the individual parts of a system. Yet they, in turn, govern the behavior of the individual parts. This is sometimes referred to as *circular causality*, the consequences of which have yet to be fully appreciated in a number of scientific fields (e.g., materialist views of mind). In self-organizing systems the stranglehold of linear causality is broken. At best, simple cause–effect relations are the exception, not the rule. One can intuit why the concept of collective variable is central to a science of complex living systems. The reason is that interactions in such systems are so complicated that understanding may be possible only in terms of system-specific collective variables. I hesitate to call these "macroscopic quantities" because the identification of collective variables depends on the level of description. What is "macro" at one level (or for a given scientific discipline) may be "meso" or "micro" at another.

Control Parameters. These are analogous to what a social or behavioral scientist might call an independent variable. But the concept is entirely different, and the implications for experimental design in the social, behavioral, and cognitive sciences far reaching (Kelso, 1990). In physical systems, control parameters refer to naturally occurring environmental variations or specific experimental manipulations that move the system through patterned states and cause them to change. In fact, you only know for certain you have identified a control parameter if, when varied, it causes the system's behavior to change qualitatively or discontinuously. Qualitative change does not mean that quantification is impossible. To the contrary, qualitative change is at the heart of self-organized pattern formation and, provided care is taken to evaluate system timescales (e.g., how quickly a control parameter changes relative to the typical time of the system to react to perturbations; see Kelso & Schöner, 1987), quantitative predictions ensue that may be, and have been, tested experimentally. I discuss some of these later in the chapter.

(Nonequilibrium) Phase Transitions. When a continuous change in a control parameter crosses a critical value, the system's behavior may change qualitatively or discontinously. Such qualitative changes always arise due to *instability.* Instability is the dynamical mechanism underlying spontaneous, self-organized formation of patterns and pattern change in nature's open systems. In such systems that are open to material and communicational exchanges with their environment, these are called *nonequilibrium* phase transitions (the term preferred by physicists) or bifurcations (the mathematical term used in dynamical systems theory). Because all living systems are dissipative, and dissipative systems always contain fluctuations (Einstein's famous fluctuation–dissipation theorem) I have followed the physicists' terminology (Haken, 1983; Kelso, 1984; Kelso & Haken, 1995). Moreover, this way of trying to understand the functional behavior of living things goes beyond mere metaphor or mathematical curiosity. In biological self-organization, fluctuations are always present, constantly probing the stability of existing states and allowing the system—through the mechanism of fluctuation enhancement—to discover new collective states whether of behavior (Kelso, 1984; Kelso, Scholz, & Schöner, 1986; Schöner, Haken, & Kelso., 1986) or the brain (Fuchs, Kelso, & Haken, 1992; Kelso et al., 1991, 1992; Wallenstein, Kelso, & Bressler, 1995).

Collective Variable Dynamics. The patterns that emerge at such nonequilibrium phase transitions are defined as attractors (stable fixed points) of the collective variable dynamics. That is, the collective variable may converge in time to a certain limit set or attractor solution, a so-called nonequilibrium steady state. Stable fixed point, limit cycle, and chaotic solutions—as well as a variety of other transient and irregular behaviors (see following comments) are thus possible in the same system, depending on the values of control parameters (and their dynamics).

Comments on Complexity

Definitions of Complexity. According to a May 6, 1997, article in *The New York Times* by George Johnson (see also Horgan, 1996) researchers on complexity are still trying to struggle with the definition of complexity, as if defining it were a precondition for studying it. Science still cannot define life, but that has not prevented major discoveries in the biological sciences. The same, I expect, will be true of "consciousness" and other tantalizing subjects of interest to contemporary science. Definition is not a necessary precondition for discovery. Johnson and others wonder how the essence of complexity can be captured and quantified in a precise and objective way. Yet one of the most fascinating results from complex systems research in the last 20 years is that the key quantities that characterize the behavior of complex living systems (collective variables or order parameters) are *function* or *context-dependent.* This does not mean that every possible context a system finds itself in requires a new collective variable or order parameter. Rather, the same order parameter and the same order parameter dynamics have been shown to apply over a range of contexts. For example, many studies have shown that a phase-like quantity captures the complex, time-varying coupling between different kinds of things (e.g., fireflies, heart cells, neurons, limb movements, brains, lovers, etc.; see Kelso, 1995). One of the most profound impacts of the "new sciences of complexity" (to some of us in the trenches they are not so new) is that the key to understanding ourselves lies in the complementary nature of objective physical description and the no-less-fundamental, apparently subjective context-dependence of living systems. The sciences of life and mind rest on this complementarity (Kelso, 1997).

Types of Complexity. These elementary concepts of pattern formation represent one of nature's main themes for handling complexity and are at the core of what some call "emergent properties." One can intuit that enormous *material complexity* (very many microscopic subsystems) is compressed near instabilities giving rise to lower dimensional behavior that is described by the dynamics of collective variables. The collective variable dynamics are essentially nonlinear, a consequence of which is rich *behavioral complexity,* including phase transitions, chaos, and stochastic features (Kelso,1988). Complicated transient phenomena typical of "messy systems" are also possible, though a great deal of care needs to be taken to distinguish them as real (not artifactual) phenomena.

Order–Disorder/Stability–Instability/Integration–Segregation. To be both viable and flexible, complex living systems must be neither too rigid nor too plastic. Experiments, analysis, and theory suggest that they are *metastable* (Friston, 1997; Kelso, 1995). This means that biological systems tend to lie in between order and disorder, stability and instability. For the brain, this means a balance between integration (areas of the brain acting together in time) and segregation (areas of the brain acting independently). Complexity measures are highest between these regimes of dynamical behavior (Tononi, Sporns & Edelman, 1994). Of course, from the present perspective it behooves science to identify the collective or pattern variables in order to characterize the nature of functional integration, its stability, and so forth. Nevertheless, a recurring theme in complex systems expressed by the "duals" in the heading is that one should not assume living things are stable, in any asymptotic sense. As a consequence there is a need to appreciate the limitations of conventional experimental designs and statistical tools such as analysis of variance. Long-range correlations, for example, are of both practical and conceptual importance in complex systems: they arise precisely because complex systems live near critical points where competition between ordering and disordering influences is finely balanced (Bak, 1996; Iberall & Soodak, 1978; Stanley, 1971). Recent studies have demonstrated the existence of long-range correlations in human perception (Tuller, Ding, & Kelso, 1997) and timing behavior (Chen, Ding, & Kelso, 1997; Treffner & Kelso, 1997, 1999), and a case can be made that long-term correlations capture the adaptive behavior of many complex organizations, from physiologic to socioeconomic. The essential idea is that continuous adjustive changes at lower levels (such as the replacement of cells in the body or the coming and going of employees in a large company) help maintain the functional stability of the system as a whole. Long-range, power-law correlations mean that change is occurring on all scales simultaneously. It is the relation between the magnitude of change and the rate of occurrence that follows a power law (many small amplitude changes, fewer medium ones and very few large ones). The origins and mechanisms of such phenomena are as yet unknown and pose a challenge to the sciences of complexity. For living systems to "live" near critical points suggests that control parameters are tuned to just the right values. Self-organized systems may even tune themselves to stay near critical points, a notion that Bak, Tang, and Wiesenfeld (1987) call *self-organized criticality* (SOC). To me, the basic idea behind SOC is a natural extension of nonequilibrium phase transition theory in physics (cf. Haken, 1983). It suggests that in complex systems one should always be looking to identify the opposing forces or tendencies that underlie metastability. Self-organized criticality is another way of saying that complex systems have access to and thereby can change their own control parameters.

Selection and Instability. It has been suggested that many features of the development and functioning of the brain are governed by selectionist mechanisms (Edelman, 1987; Edelman & Tononi, 1996). Darwinian (natural) selection results in the differential reproduction of "fitter" individuals, that is, those whose variations better adapt to the environment or successfully compete with others. Edelman and his colleagues have emphasized like processes of selection upon variation in his theory of neuronal group selection (TNGS). Thus, instead of ignoring observed fluctuations and variance in neuroanatomy and neural dynamics, TNGS brings them on center stage, as essential to biological function. This is entirely consistent with some of the principles of self-organization described above. Selection, however, is not unique to biology. Instability and transitions in all nonequilibrium systems (alive or not) arise because of competitive forces that result in the amplification and selection of a given pattern or mode of organization (and the elimination of others). Empirical evidence for selection qua pattern forming instabilities has accumulated over the last 20 years at several levels of brain and behavioral function (see Kelso, 1995, for a review). In a number of specific cases the pattern selection equations have been identified (see Haken, 1996, for a review). Such generic mechanisms of pattern selection and change appear to complement Darwinian selection and its various extensions to the development and functioning of the brain by Edelman and colleagues. Here again, theories of selection and self-organization—merely because they arise in different disciplines, biology and physics respectively—should not be viewed as either-or propositions. In fact, Darwinian selection is assumed to act on already organized entities (e.g., genes, cells, organisms). The theory of self-organization addresses the origins of such integrated entities.

"Agent" Dynamics. A popular notion among complexologists is that every system—from economies to brains—has "agents," whose interaction on the basis of simple rules can lead to complex behavior. Anthills and bird flocking are favorite examples. Analogies to business organizations are rampant. A powerful theme emerging from such intuitions is that surface complexity arises from deep simplicity (Gel-Mann, 1994; Holland, 1995). In a sense this is no more than a restatement of physics that the diversity of the world around us is due to a small number of fundamental forces and their interactions, supplemented by historical contingency. When we deal with complex systems, however, it is a mistake (or at least a convenient fiction) to assume that our agents are simple (a typical strategy is to take a complicated entity such as a gene or a neuron, and code it as a sequence of 1's and 0's in a computer simulation). Rather, the "agents" or individual components are complex entities in their own right, whose individual dynamics have to be understood in detail. Moreover, the interactions between these agents may be complicated, web-like, and continuously modulated by many factors, both internal and external. Thus, at least one other major theme needs be struck, namely that deep (material) complexity (consider, for instance, the manifold connections among diverse neuron types in the nervous system, the large number of neurotransmitters, hormonal influences, etc.) may give rise in a self-organized fashion to surface (behavioral) simplicity and/or surface complexity (Kelso, 1988, 1995). Think of what is going on in the nervous system at multiple levels when we walk or talk, emote, think, and remember.

FINDING DYNAMICAL LAWS IN COMPLEX LIVING SYSTEMS

The Problem of Identifying Relevant Variables. A cogent remark in Magnusson (1995) is that many, if not most of the variables studied in empirical studies of development are hypothetical variables (e.g. intelligence, aggression, hyperactivity, etc) that run the risk of reification. Collinearity among variables is typical. In open, many-particle physical systems, from which the elementary concepts mentioned earlier stem, the identification of key collective variables or order parameters is less of a problem, mostly because these systems are familiar and the parts of which they are composed are homogeneous. This enhances the ability to uniquely define and objectively describe relevant quantities. Living systems, however, are hierarchically organized; the component elements and connections among them are heterogeneous; and the relevant variables are always context-, task-, or function-dependent.

How does one find relevant variables in such complex, living systems? And which can one reasonably discard as not relevant? This is precisely the problem that confronted me over 20 years ago in my efforts to understand the control and coordination of systems containing very many degrees of freedom. Put bluntly, given $\sim 10^3$ muscles, $\sim 10^2$ articulating joints, and a nervous system with $\sim 10^{14}$ neurons and neural connections, how can coordinated behavior like walking or talking emerge from a system of such complexity? The conventional approach of unraveling the material substrate component by component in such a complex system is clearly untenable. An alternative strategy was required that should specify what empirical steps need to be taken. These steps, if fully carried out at both collective and component levels, should allow different levels of description to be connected. A possible limitation here is the restriction to a laboratory frame of reference. However, some of the same steps may be adopted in other contexts such as observational or epidemiological studies. For example, qualitative change may be used to infer relevant quantities in more naturalistic settings. Where many variables may be changing collinearly, the ones that change abruptly are likely to be the most informationally meaningful, both for the phenomena of interest and our understanding of them (Kelso, 1994).

Experimental Windows. The first, perhaps hardest, step is to find or invent experimental model systems that prune away the details but retain the essence of the real-world problem. I call this the Galilean strategy. By studying balls rolling down an inclined plane and abstracting away friction Galileo was able to understand a great deal about planetary motion. To be honest, there is no formula or recipe that may be applied to this step. Moreover, the choice of a level of description is the scientist's and can only be made with informed insight. Nor, I believe, is this an issue of "top-down" versus "bottom-up". The first step at any level of description, whether one is studying biomolecular processes or social behavior, requires the identification of relevant variables and their dynamics (equations of motion).

Focus on Qualitative Change. Science always needs special entry points that enable understanding as well as appropriate abstractions. It is necessary to prune away irrelevant details while retaining the essentials. Newton did not give us the equations of motion for a leaf falling from a tree. Somewhat counterintuitively, but entirely consistent with theories of pattern formation, the focus here is on nonlinear qualitative change. Why qualitative change? The reason is that qualitative change allows us to clearly distinguish the (collective, pattern) variables that define the states of a system. If a complex system is changing smoothly and linearly it is hard to distinguish the variables that matter, so-called state variables, from those that don't. As state variables, they matter to the system itself, as well as to the scientist trying to understand or theoretically model the system. Moreover, near critical points various theoretically motivated measures are available to test predicted features of self-organization (this is discussed later). The underlying processes governing a state's stability, flexibility, and selection may thus be uncovered near critical points. Remember, in complex living systems one typically does not know the relevant (i.e., collective) state variables a priori, or the dynamical laws governing them. Within the present framework, this is one of the main scientific goals and the basis of understanding.

The Modeling Step. Finding collective state variables or order parameters is the "yin" of the complex systems strategy. The "yang" is identifying the control parameters that move the system through these collective states and cause them to change. Knowing the collective variables and control parameters enables one to obtain the lawful dynamics—the equations of motion that describe the stability and change of the system's states on a given level of description.

Next Level Down: The Individual Components. The steps alluded to here may all be repeated at the level of the individual components. Ideally, their state variables and dynamics have also to be identified empirically. In general, in complex systems it is difficult to isolate the components and study their dynamics. The reason is that the individual components seldom exist outside the context of the functioning whole, and have to be studied as such.

Derivation and Emergence. A final but nontrivial step is to derive collective states and their dynamics from the, in general, nonlinear coupling between the individual components. This is what some people call "emergence," and it allows us to see how different levels are connected. But there is no mystery here, just a lot of hard work usually involving a close collaboration between people with very different skills (e.g., in theoretical physics, applied mathematics, biology and psychology) that stresses as intimate a connection between theory and experiment as possible.

Comments on Dynamics

The Tripartite Scheme. From the preceding discussion, it should be clear that no level is any more or less "fundamental" than any other. A complete description at the collective variable level requires three adjacent tiers: The boundary conditions and control parameters that establish the context for a particular phenomenon; the collective level and its dynamics; and the component level and its dynamics. I call this the "tripartite scheme." The physicist Atlee Jackson calls it "one level down," but the basic idea is the same.

Macro–Micro. Relatedly, the intuition is that in complex systems the best one can do is derive a given phenomenon from the level below. There are no absolute "macro" or "micro" levels. The component level may be "macro" for one scientist and "micro" for another. For example, a group of neurons in one area of the brain with a characteristic frequency response may couple with another like group under a particular set of conditions. In the present terminology, the coherent integrated activity between the groups constitutes a collective level of description. The individual activity of each group constitutes the component level. But it is easy to see that the group or ensemble may constitute a collective activity with respect to levels of description below, for example, individual neuronal properties. Dynamics is the language of understanding and transcends levels. In every case, however, dynamics must be filled with content, that is, dynamics of collective variables, control parameters, and so forth, that have to be identified one way or another in order to learn how things work.

Linkage Across Levels. Notice that the descriptors at each level are always different from each other. To use a most extreme case, the typical description of the nervous system differs greatly from the typical description of behavior. One is in the language of "internal" variables, the other is in the "external" language of overt behavior. But without commensurability of description, how is it possible to see the connection between the two? The language of dynamics serves to bridge different domains. Recent work shows that once the laws are known at the behavioral level, it is possible to derive them from the dynamics of neural populations and their excitatory and inhibitory interactions (Jirsa, Fuchs, & Kelso, 1998). Linkage across levels of description or observation is thus by virtue of shared dynamics (see Kelso, 1995).

Examples of Empirically Identified Collective Variables. I restrict discussion to a few examples that have been identified via the strategy spelled out here. By doing so, speculation is limited to a minimum. But there is reason to believe that there are many candidates for collective variables in complex, living systems. The task is to find them. Murray Gel-Mann is often quoted as saying that the "first step" in complexity research is to identify a system's regularities. But what is the research program? I have already offered a specific strategy aimed at systematically identifying the key variables characterizing behavioral patterns or regularities on a given level of description. This strategy has been found to work especially well near points of qualitative change.

For the behavior of complex, multidegree-of-freedom systems that evolve in time, the relative phase between interacting components has been identified as a key collective variable or order parameter (Kelso, 1995). The reason is that the relative phase characterizes stable functional relationships among component parts. The individual "components" may be fireflies, heart cells, neurons in vertebrate and invertebrate central pattern generators, finger and limb movements, neurons in the mammalian cortex giving rise to synchronization, even people engaged in a common task. Such coordinative coupling realized through a phase relation is ubiquitous in biology in many activities and at different levels.

In tasks that require adjustments in space such as trajectory formation, amplitude adjustments in the components are also crucial, the ratio of which may act as an order parameter (Buchanan, Kelso, & DeGuzman, 1997; DeGuzman, Kelso, & Buchanan, 1997). When events in the brain are monitored in space using a number of different recording techniques (optical dyes, high density electrode and SQuID [Superconducting Quantum Interference Device] arrays, etc.) they may be decomposed into a set of spatial patterns and time-varying amplitudes. The spatial modes then act, as order parameters (Fuchs, Kelso, & Haken, 1992; Jirsa, Friedrich, Haken, & Kelso, 1994; Kelso & Fuchs, 1995; Kelso et al., 1991, 1992, 1998). The "microscopic" basis of these order parameters and their time-dependent dynamics can be derived from basic properties of neurons and their connectivity which give rise to neural ensemble dynamics (Jirsa, Fuchs, & Kelso, 1998). In all cases but the last, the actual equations of collective variables are phenomenological, a situation not unlike where physics was 70 years ago. After it was discovered that matter consisted of atoms, it might have seemed straightforward to derive the macroscopic properties of matter directly from the individual atoms. Only much later, however, did it become possible (and then only in a few cases such as ferromagnets and lasers) to derive the equations governing macroscopic behavior from a more microscopic theory.

Developmental (Thelen, Kelso, & Fogel, 1987; Thelen & Smith, 1994), cognitive (Port & van Gelder, 1995), and social psychologists (Vallacher & Novak, 1997) have been attracted to the present approach. In the former, the developing system is viewed as a dynamic system in which patterns of behavior act as collectives—attractor states—of the component parts within different environmental and task contexts. Development has been depicted as a landscape of collective variables against time (Thelen, 1995). Thus far, this is metaphorical and the difficult task of actually identifying collective variables, the control parameters that act on them, and the collective variable dynamics (not to speak of the component level) has yet to be accomplished in the developing organism for even a single task or functional context. The same can be said for work that posits an existing "movement repertoire" on which selection acts (Sporns & Edelman, 1993). So far, only in the cases of acquiring perceptual-motor coordination (Zanone & Kelso, 1992, 1997) and learning new speech sounds (Case, Tuller, & Kelso, in press) has it been possible to identify an individual's initial "attractor landscape" (so-called intrinsic dynamics) prior to learning, and to track how it changes during the learning process. Importantly, the intrinsic dynamics turn out to be unique to each learner. How new information (the task to be learned) does or does not match (cooperates or competes) each person's preexisting dynamics determines the nature and form of the learning process (Kelso, 1995).

LAWS FOR REGULARITIES: AN ELEMENTARY EXAMPLE

In general terms some of the key level-independent attributes of living things are:

> *Synergy:* on most levels, the individual parts of a system are coupled together as functional units, thereby making it possible to coordinate a system with many heterogeneous components using only a few controls.
>
> *Multifunctionality:* in a given context, multiple forms of behavior can be generated by the same set of anatomical or functional components and for the same parameter value(s). The property of multifunctionality is seen at many scales, from pleiotropic genes and peptides to neural pattern generators.
>
> *Stability:* the ability to produce the same behavior despite perturbations from the (internal or external) environment (see comments on allostasis by Carlson and Earls, chap. 15, this volume).

> *Invariance of function:* the ability to realize the same goal using materially different components and a multitude of pathways.
>
> *Flexibility:* the ability to switch from one mode of behavioral organization to another according to circumstances and/or the ability to recruit new components (and suppress others) to meet internal or external demands. Switching is based on stability considerations and may be viewed as a selection mechanism, that is, as a means of favoring one mode of organization over another.

These, and several other features (such as primitive memory) were identified in specific experiments and later captured in an elementary nonlinear law of coordinated behavior, the predictions of which were checked experimentally (for review, see Schöner & Kelso, 1988). This dynamical law, progressively established in a series of detailed experiments and theoretical steps, contains three essential kinds of parameters (see equation in Fig. 5.1): one that reflects whether the individual components are the same or different ($\delta\omega$); one that reflects external or internal factors (control parameters, λ_1, λ_2) that govern the strength of coupling between the components, and one that reflects the fact that all real systems contain noise or fluctuations (ζ_t) of a given strength Q. Experiments showed that the relevant collective variable describing the synergy or spatiotemporal ordering between individual components was the relative phase, φ. For high values of the coupling ratio, λ_1/λ_2 both modes of behavioral organization coexist, the essentially nonlinear property known as bistability (Fig. 5.1, left). Bistability (or, in general, multistability) confers *multifunctionality* on the system. That is, at least two forms of behavior are possible for exactly the same conditions. Notice that each is stable over a range of coupling, though the degree of stability may change. In the stable region of its dynamics, for example, near the stable fixed points (solid circles) on the left side of Fig. 5.1, the system's behavior will be restored despite any slight perturbation. As the coupling ratio is decreased, however, the system switches from one mode of behavior to another (Fig. 5.1, middle). Near the critical point, the slightest fluctuation will kick the system into a new form of stable organization.

We may refer to this spontaneous transition as a form of pattern selection or decision making that underlies the flexibility of the system's behavior (the acronyms CEVA, SVI, and ASA will be discussed later). Switching is due to instability: under certain conditions (i.e., for certain values of control parameters) one mode of behavioral organization is less stable than another. The less stable mode dies out, only to be replaced with another more stable behavioral organization that is able to persist under the new conditions. Notice in Fig. 5.1, that if the direction of control parameter values changes after this transition, the system stays in this more stable mode. Thus the system exhibits *hysteresis*, a primitive form of memory.

$$\boxed{\dot{\phi} = \delta\omega - \lambda_1 \sin\phi - \lambda_2 \sin 2\phi + \sqrt{Q}\xi_t}$$

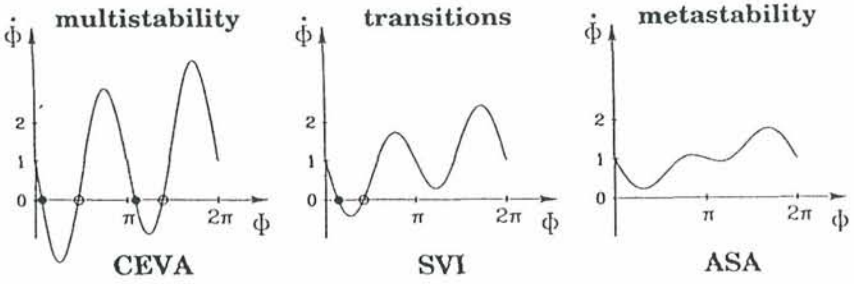

FIG. 5.1. An empirically validated elementary law of behavioral coordination.

Comments on Dynamical Laws

Predictors of Change. The stability of a given behavioral organization is portrayed in Fig. 5.1 by the slope of the function where it crosses the *x*-axis. The negative slopes near $\varphi = 0$ and $\varphi = \pi$ indicate these are stable and attracting states (solid circles). Points at which the slope is positive through the *x*-axis are unstable, repelling states (open circles). Thus, the left part of the figure shows that two different behavioral organizations are stable under the same set of conditions, one near $\varphi = 0$ and one near $\varphi = \pi$. Notice the following predicted features of change: In the middle part of the figure the stable behavioral organization near $\varphi = 0$ has shifted to a higher value. Change occurs, but the shifted behavioral organization is still stable. The slope around this shifted state, however, is less than before, meaning that the shifted state is less stable than before. Quantities like the mean and variance of the collective variable, φ have allowed this prediction to be quantitatively checked (Schöner & Kelso, 1988). In Fig. 5.1 the stable behavioral organization near $\varphi = \pi$ has totally disappeared. Mathematically, the function has lifted off the *x*-axis–called a saddle-node or tangent bifurcation–meaning that there is no longer any stable state near $\varphi = \pi$. The flattening of the function and the disappearance of the antiphase state is due to loss of stability. Predicted features of loss of stability are critical slowing down and critical fluctuations. These predictions are easy to intuit. As the slope flattens, the system will take increasingly longer to recover from a small perturbation. Thus the local relaxation time is predicted to take longer and longer as the instability is approached (critical slowing down). Similarly, the variability is expected to increase owing to the flattening of the function near the transition point (critical fluctuations). All of these predicted effects have been confirmed in a wide variety of different experiments and are open to investigation in many other systems. The take-home message is: Whether you see smooth change or abrupt, nonlinear change depends on where the system lives in the space of its parameters. Thus, on the left part of Fig. 5.1, for a large range of control parameter values, the behavior of the system changes very little. But then, as shown in the middle part of the figure, even a small change in the control parameter causes a bifurcation or phase transition which produces a large qualitative change in behavioral organization.

On the right side of Fig. 5.1, there are no longer any stable states in the system, where the term "stable" is used in the usual mathematical sense of asymptotic stability. Due to changes in control parameters or coupling ratio, the entire function has lifted off the *x*-axis. Note, however, that the function retains its curvature; there is still attraction to, or remnants of, previously stable states (so-called *metastability*). This effect is entirely due to broken symmetry in the dynamics, which is a result of the fact that the individual parts of the system or their properties are not the same (given by the $\delta\omega$ parameter in the equation). Due to broken symmetry, the system produces a far more flexible form of behavioral organization in which the individual components are free to express themselves yet still work together in a looser kind of harmony.

SOME SPECIAL FEATURES OF REGULARITIES IN LIVING SYSTEMS

Informational Coupling. Although collective variables may characterize the behavioral organization among physical entities in complex living systems, they themselves are not usually physical quantities defined in physical dimensions such as mass, length, and time. Collective variables reflect the coupling relation between different kinds of things. The medium through which the parts are coupled does not have to be the same for the same regularity to arise or, significantly, for the same dynamical law to govern the system's behavior. Crucial experiments show that the same collective variables and the same collective variable dynamics describe and predict the coordination activity of a system (and lack of it) whether it be the central nervous system, an organism interacting with its environment, or even shared actions between organisms (Kelso, 1994; Turvey, 1994 for reviews). Such meaningful informational coupling (what could be more meaningful to a system than information that communicates the relation between its parts), constitutes an essential difference between self-organization in the living and the nonliving.

Special Boundary Conditions. In physical experiments, physicists set the initial and boundary conditions and study how behavior evolves in space and time. Then they check their observations against known laws. The boundary conditions on living things are quite special: they nearly always include the system's intentions or goals. One of the remarkable consequences of discovering that the regularities in living systems are informational in nature is that in order to modify or change the system's behavior, its boundary conditions must be expressed in terms of system-relevant (read, informationally meaningful) variables. Thus, if a system is to learn, any new information (say a task to be learned, an intention to change) must be expressed in terms of the system's existing/current dynamics. Remember, these dynamics are at least metastable and possess memory. They correspond to the system's set of predispositions or preexisting responses prior to learning. The positive benefit of identifying relevant collective variables is that one now knows which variable is modifiable and therefore what to modify. Information is not lying out there as mere data. Rather, information is meaningful only in terms of the individual's existing capabilities. The foregoing statements are not mere intuitions. They are grounded in empirical studies and theoretical modeling of learning and intentional change (for review, see Kelso, 1995, chaps. 5 & 6).

Implications. A number of interesting implications for learning and development follow from this research. One is that change may take the form of highly abrupt transitions depending on how new information cooperates or competes with the existing (so-called intrinsic) dynamics of the learner. Another is that the learner's existing capabilities and predispositions place real constraints both on what can be learned and how it is learned. Conversely, the best learning environment is one that is structured in terms of those constraints (which, as stressed here, must be identified). The teacher must tune in to the child's preexisting capabilities and modify them. The implications for education policy (and learning theory) are apparent: the individual learner is the primary unit, not the group (although in line with the notion of level-independent dynamics, if the group is collectively organized around exactly the same information, then it may constitute a significant unit, but now at the group level of analysis).

For so-called "learning organizations," the notion of intrinsic dynamics says that you had better know the metrics of the "fitness landscape" if you want to climb up it. For foreign policy, you had better know the variables that matter and the internal dynamics of the system you are trying to change before you intervene. Said internal dynamics are a product of historical and cultural factors. They are ignored at the policymaker's peril.

GENERAL THEMES FROM THE LAW-BASED APPROACH

What lasting and durable themes, if any, emerge from these tentative efforts to identify laws of behavioral pattern formation and change in complex living systems? Laws, of course, do not have to possess any meaning at all for either the individual or society. The fundamental laws of physics presumably do not, although the philosophical foundations of quantum mechanics may be an exception. In contrast, the laws that characterize regularities in human behavior seem full of meaning. Whereas classical physics defines its variables in terms of a mechanical system, that is, n mass points possessing position and momentum in a space of $3n$ dimensions, the coordination law shown in Fig. 5.1 is defined in the space of meaningful, function-specific collective variables.

Obviously, if one is trying to understand something as complicated as the coordinated behavior of human beings, or the lack of it, one must be prepared to make a fool of oneself. I believe several core themes arise from the law-based approach that may provoke new (or different) patterns of thought. The first, which might be called the *principle of Coexisting Equally Valid Alternatives (CEVA)* stems from the multistability property of the elementary dynamical law shown in Fig. 5.1. Notice again on the left side of the figure that there are two stable fixed points (solid circles) for exactly the same conditions, a simple form of multistability which, as already noted, is called bistability. If we accept that bistability is a fundamental and essentially nonlinear feature of the behavioral dynamics, what might it mean? Surely it means what it says: For any specific situation or context, several alternative solutions coexist. This, I suspect is actually the general case in living systems, and may be one of the hallmarks of their complexity. One-to-one relations between cause and effect may thus be the exception, not the rule. The CEVA principle embraces simple dualisms and dichotomies. Indeed, a failure to appreciate this essentially nonlinear principle may be a potential source of human conflict, as, for instance, in the inability to recognize ideological alternatives. Though the essence of wisdom and tolerance, the CEVA principle is not taught in our schools. Marriages fail because of it. Typical either-or, hypothesis testing approaches in science are the very antithesis of the CEVA principle, which seems to embody Bohr's complementarity interpretation of quantum mechanics (but now, notice, at the "macroscopic" scale of living things). Whether you see a wave or a particle depends on what you choose to measure. Both views are equally valid, complementary representations of reality.

A second principle stems from the (apparently universal) fact that the (essentially nonlinear) dynamics contain both attractive (stable) and repelling (unstable) fixed points (open and closed circles in Fig. 5.1) which mutually coexist. I call this the *principle of Coexisting Opponent Tendencies (COT)*. For a system to be maximally flexible, adaptive, and creative, processes normally in competition with each other must coexist. The stable must coexist with the unstable. Life, as the poets have always told us, is suspended between contradictions. Depending on circumstances, opposing tendencies can sometimes collide and give rise to new ways of thinking and acting. Notice in the empirically validated law shown in Fig. 5.1, the disappearance of the stable organization near $\varphi = \pi$ is because a stable fixed point (an attractor) and an unstable fixed point (a repeller) collide, causing a so-called saddle-node bifurcation. It is the tension between opposites, stability and instability, that produces a new behavioral organization. More generally, it is this tension that, when pushed to the extreme, may lead to a new outlook.

To survive and prosper, living systems must be neither too rigid nor too plastic. I call this the *Attraction Sans Attractors principle (ASA)*. A better name might be the Principle of the In-Between (PIB). In the metastable regime of the behavioral dynamics (right side of Fig. 5.1) there are no longer any attractors (stable fixed points), though there is still attraction to where the attractors used to be. The reason is that the functioning parts of the system now have a tendency to do their own thing while still retaining a tendency to cooperate. This is likely the way large organizations work best: By allowing a certain degree of individual expression and autonomy they are able to function as a looser, more effective form of global organization. This tendency for the parts to do their own thing (individual variation) must coexist with the tendency for the system to harmonize as a whole. Likewise, in the world of politics, any trends toward global integration and homogenization must acknowledge, and live with, the parochialism of individual states. Metastable dynamics (and more generally the ASA or PIB principle) provides insight into a longstanding either-or conflict in brain theory, namely, how global integration, in which parts of the brain are locked together, is reconciled with localized, independent action of individual brain areas. Metastable dynamics says that the brain, like other complex living systems, uses a subtle blend of both. Otherwise it would be trapped in a stable collective state from which it is difficult to escape. Or, it would be too disordered, with the parts acting independently of each other. The ASA principle asserts that the greatest complexity lies between regular and irregular behavior. Interestingly, theoretical measures of brain complexity (Tononi, Sporns, & Edelman, 1994) bear this idea out. ASA arises as a natural consequence of empirically observed metastable dynamics. It is, literally, a principle of the "in between."

A fourth principle deals with the essential nature of "stability–change" in living things. I tentatively call it the *principle of Selection Via Instability (SVI)*. The SVI principle is manifest in the form of bifurcations in the observed dynamics (Fig. 5.1, middle). In SVI, variability plays a central role and pattern selection is a self-organized process, occurring without homunculus-like agents. Although instability is a universal mechanism for self-organized pattern formation and change in complex systems in nature, it has yet to be incorporated in evolutionary theory, even by advocates of punctuated equilibrium (Eldredge & Gould, 1972); and it is ignored as a mechanism by currently popular selectionist theories of brain function (Edelman, 1987). Selectionist theories often use the term self-organization but do not exploit instability for selection purposes, even though much evidence suggests that organisms do. Such theories have been criticized precisely because they lack a physical/mathematical foundation (Eigen, 1994). Many believe that selection is the *sine qua non* of biology. Still others wonder whether there is a new principle of order formation in life beyond Darwin (Kauffman, 1995). I offer SVI in the interest of resolving such conflicting visions and because it is a unifying principle of selection that applies to all self-organized systems whether living or not. And it may lie at the heart of human behavior.

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