Goldfield

Let us, then, return to Bernstein's degrees-of-freedom problem with the tutorial on energy transactions at microscopic and macroscopic scales in mind.

Assembly as a reduction of dimensionality. Kay (1988) offers a framework for addressing the df problem which is based upon the process by which energy loss at the level of microscopic components in a nonconservative system results in reduction of degrees of freedom at the level of observed behavior. Consider the example of a damped mass-spring system (see Fig. 2.4), a block attached to a vertical support via a spring, riding on a rough surface. This system may be characterized by two degrees of freedom, since its equation of motion ($mx = -k(x - x_0) - bx$) requires two coordinates, position and velocity, to describe the evolution of the system at any time. Because of friction, the block always comes to rest, and when position and velocity are plotted against each other by means of a phase-plane diagram, the system's final behavior is a point with a mathematically zero dimension. Thus, the friction makes the damped mass-spring a nonconservative process: it generates overall energy loss in the system.

Kay considers human action systems as abstractly similar to physical devices such as the mass-spring system, in the sense that the behavior of an actor may be described in terms of the same equation of motion as the behavior of the mass-spring. He proposes two-constraint processes by which energy flow in action systems results in a reduction of dimensionality (see Fig. 2.5).

Resource dynamics. Bingham (1988) proposes that the degrees of freedom of action systems are dependent upon the energy flows in the nonconservative dynamics (resource dynamics) of the microcomponents of the body: bones, tendons, ligaments, nerves, blood, and blood vessels. For Bingham, understanding the process of assembly of these components into functional macroscopic systems (what he calls task-specific devices, TSDs) involves working backward from the dynamics of the TSD in specific contexts to infer the particular resource dynamics used. As he acknowledges, this is a very difficult problem, since the resource dynamics are nonlinear.

Consider a specific example of this approach. Bingham begins by distinguishing four systems which comprise the dynamic resources (see Fig. 2.6): the link-segment, musculotendon, circulatory, and nervous systems, respectively. Each of these has distinctive nonlinearities. One might not ordinarily suppose that constraints imposed at the ankles would influence performance at the wrists, but such influences might be mediated by the circulatory system. Bingham, Schmidt, Turvey, and Rosenblum (1991) specifically examined the influence of tonic activity at the ankles on coordination at the wrists as a way of inferring the participation of nonlinearities in circulatory and nervous system resource dynamics on

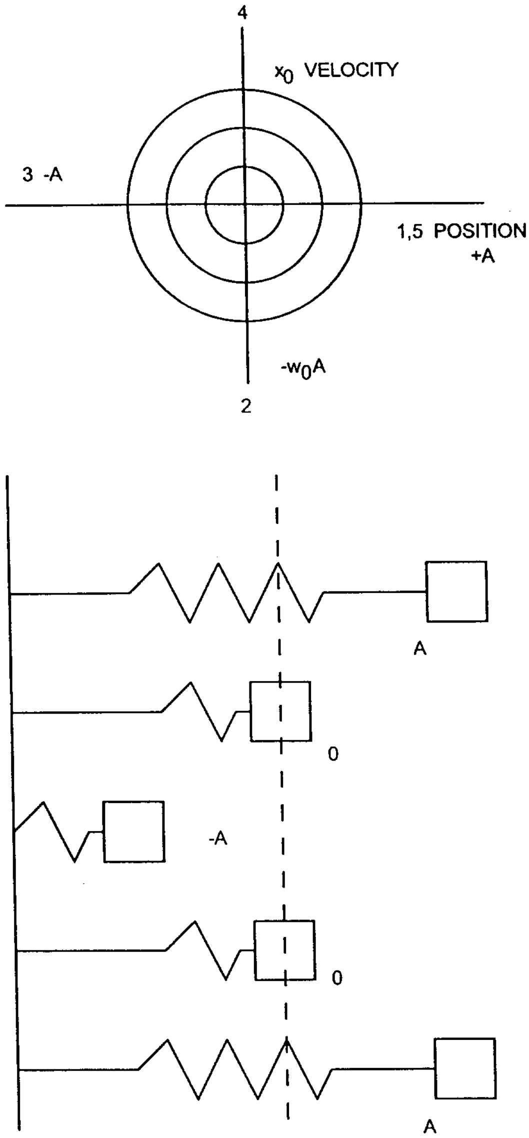

Figure 2.4. Phase portrait of the family of orbits (all possible trajectories) of an *mk* system. This is plotted on the phase-plane (position versus velocity). The family of orbits depends upon initial conditions (the energy put into the system, e.g., different masses). For fixed parameters, the size of the trajectory, but not the shape, changes.

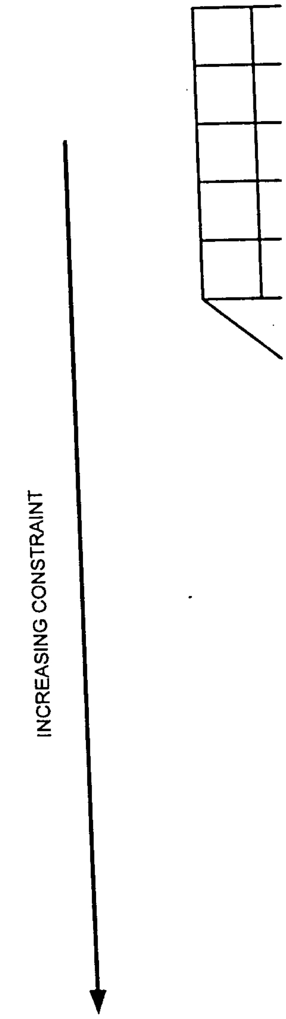

Figure 2.5. How coordin
(Adapted from Kay, 1988.
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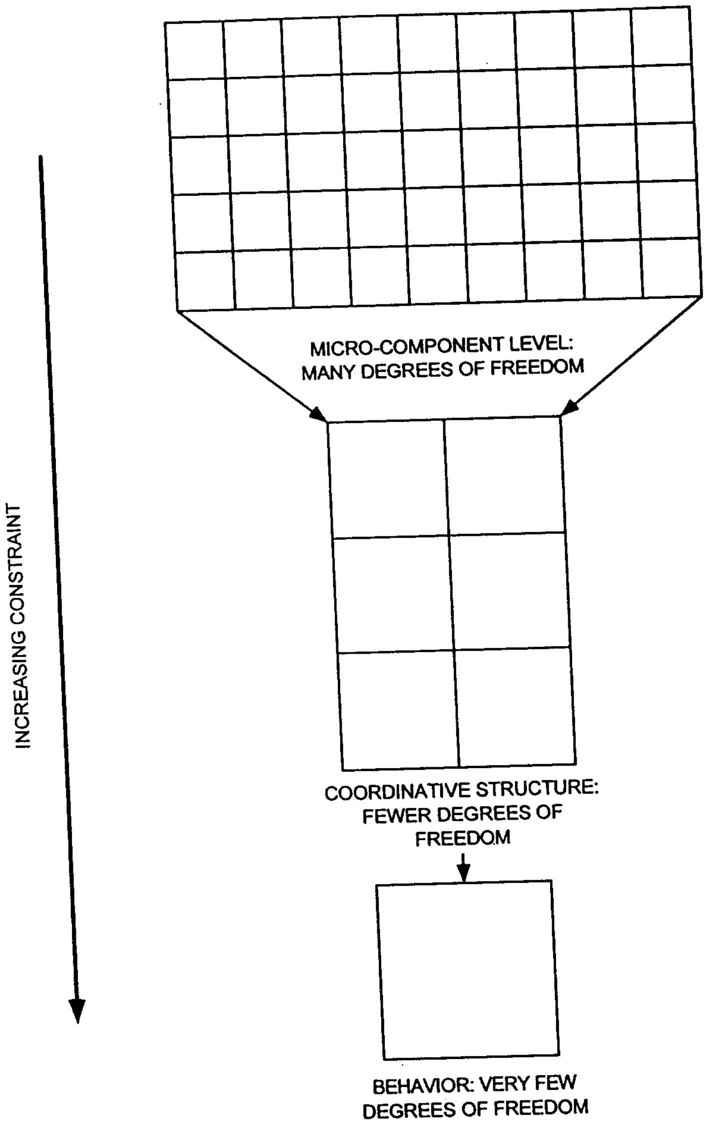

Figure 2.5. How coordinative structures reduce the dimensionality of a dynamic system. (Adapted from Kay, 1988. Copyright © 1988 by Elsevier Science Publishers, Inc. Reprinted by permission.)

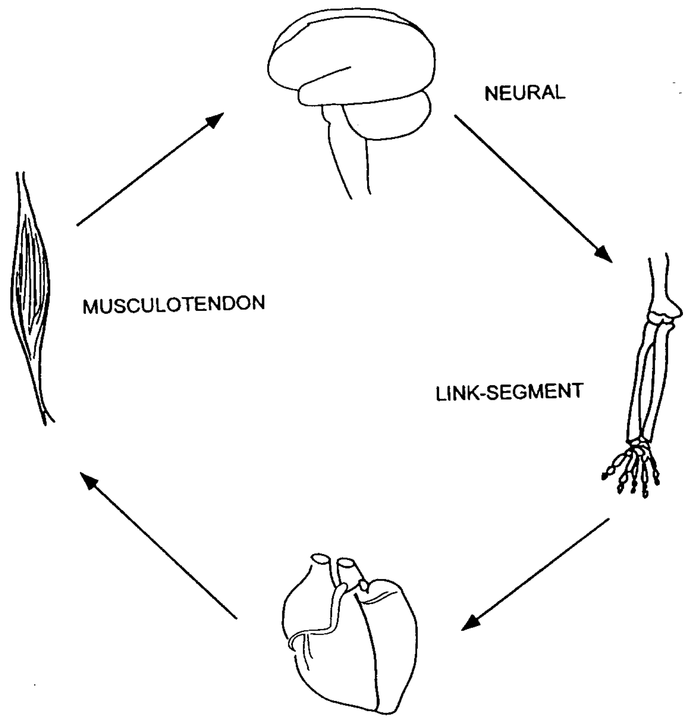

Figure 2.6. Four component subsystems comprising the action system.

behavior in a wrist-pendulum task. Of interest was whether experimental increases in tonic activity in one part of the body (the ankles) might influence wrist dynamics via circulatory resource dynamics.

The principal finding of the study was that when tonic activity at the ankle was increased, stiffness at the wrists also increased, in proportion to the wrist's inertial load. In evaluating this finding, Bingham and his colleagues worked backwards from the dynamics of the wrist to presumed circulatory dynamics. So, for example, they hypothesized that muscle activity at the ankle increased global blood pressure (this was later confirmed in a separate study), which changed the properties of the muscle so that there was increased power output in proportion to inertial load.

Modeling cooperativity. A hallmark of the second round of Bernstein-inspired research was Kugler, Kelso, and Turvey's (1980) proposal that coordinative structures were instances of dynamic regimes, systems that evolve over time and behave in a qualitatively similar way to a physical system. In this revision of the ecological approach to the study of coordination (see, e.g., Schmidt & Turvey, 1989), the microstructural resources of a single limb during locomotion were modeled by a mass-spring pendular system in a gravitational field with a linear spring attached (Turvey, et al., 1988).

Research done within the framework of task dynamics specifically begins with a rationale for selecting an equation of motion to model the dynamic system, and then conducts experiments aimed at identifying the values of parameters in the equations of motion. The rationale is based upon the abstract similarity between the body as a mechanical system and physical systems such as masses attached to springs. In the classical physical sense, dynamics is the study of how the forces in a system evolve over time to produce motions. Recently, the notion of dynamics has been expanded to include situations in which forces and motions are abstract concepts which do not require physical interpretation (e.g., Abraham & Shaw, 1987). Forces and motions then simply express relationships among variables of interest. The resulting abstract dynamics is a general science of how systems evolve over time, regardless of how the notions of force and motion are interpreted. In particular, abstract dynamics offers a theory of how low-dimensional behavior can be assembled from high-dimensional systems.

The starting point for the assembly of low-dimensional behavior is energy flow through a system (Kugler & Turvey, 1988; Morowitz, 1978). Systems through which there is energy flow are termed nonconservative, while those in which there is no energy flow are called conservative. There are three reasons why nonconservative models are being adopted in the study of biology and behavior: (1) they are more biologically realistic than conservative systems, since biological systems are open systems in which there are energy exchanges between the system and the environment, (2) energy flow induces stability, a hallmark of biological systems, and, most relevant to the present discussion (3) energy flow in nonconservative systems induces low-dimensional behavior from higher-dimensional components, i.e., during the time-evolution of a nonconservative system, degrees of freedom are being "dissipated out" (Kugler & Turvey, 1987).

We can illustrate these last two points with respect to two models of rhythmic, or oscillatory, behavior. The first, a simple conservative oscillator is the ideal undamped mass-spring:

$$m\dot{x} + k\ddot{x} = 0$$

where m = mass, k = spring stiffness, and $\dot{x}$ and $\ddot{x}$ are the position and acceleration, respectively, of the mass. This is a second-order system, meaning that it has two fundamental coordinates or components (position and velocity). The only energy exchanges that occur in this system occur within the system itself, between the mass and the spring. When the mass is perturbed away from its rest position ($x = 0$), the spring delivers a restoring force to bring the mass back to the rest position. However, since there are no losses in the system (that is, no flow of energy to the environment), the mass does not stop at the rest position, but goes through it and then oscillates around it.

Relevant to the second point above, this system exhibits one and only one stability: its frequency of oscillation is constant for constant m and k. However, the oscillation amplitude is unstable; if the mass is perturbed again, a new amplitude almost always results. Moreover (and see the third point above), the time-evolution of the system induces no reduction of degrees of freedom from the number of components to the observed behavior: the system starts out as a second-order system, i.e., having two dynamically relevant states (position and velocity), and the system's behavior is two-dimensional. Position and velocity must be known in order to know what its amplitude will be, because of the amplitude instability. On the phase-plane, which plots position versus velocity, the possible behaviors of the system fill up the entire two-dimensional plot.

An example of a nonconservative oscillator is the van der Pol oscillator (van der Pol, 1926; see Jordan & Smith, 1977). In its most abstract form, it may be described by a second order equation:

$$m\ddot{x} - a\dot{x} + bx^2\dot{x} + kx = 0$$

where m, k, $\dot{x}$, and $\ddot{x}$ are the same as for the ideal mass-spring, but where x is the velocity of the mass and a and b are coefficients on two nonconservative terms. These two terms introduce energy flow to the system: the first term (with coefficient a) always delivers energy to the mass, and the second term (with coefficient b) always takes energy away from the mass. A physical instantiation of the van der Pol oscillator is a simple mass-spring system: a mass attached at one end to a support (e.g., the ceiling) and at the other end to a freely moving mass.

The energy flow that thus occurs during the evolution of the oscillation of the van der Pol induces our above two phenomena. First, the amplitude of the oscillation is now stable in the face of perturbations. The van der Pol oscillator also exhibits other kinds of stability, including a stable relationship between two of its observables (frequency and amplitude) and a type of temporal stability (phase resetting) (see Kay, Saltzman, & Kelso, 1991). These are all due to the presence of energy flow. Second, the degrees of freedom are reduced during system evolution from the two original ones (again, position and velocity) to one. After an initial startup (transient) period, if one knows the position or velocity alone, one can predict the system behavior for all time. On the phase plane, the steady-state (post-transient) behavior occupies a very limited portion of the plot: a single cyclic trajectory, or limit cycle. Mathematically, this limit cycle is a one-dimensional object. Thus, two degrees of freedom have been reduced to one during the transient evolution of the system from an arbitrary starting point not on the limit cycle.

Abstract dynamics is, thus, a framework for describing systems that evolve over time. Dynamic models of nonconservative systems in particular allow us to investigate how high-dimensional, multicomponent systems evolve to produce low-dimensional behavior, and can be used to investigate behaviors more complex than simple rhythms.

Building a dynamic model: Methodology. How does one go about generating a dynamic model of some interesting behavior? The first step is to decide how complex a model is needed, by characterizing the complexity of the observed behavior. For nonconservative systems, the number of degrees of freedom at the component level must exceed the degrees of freedom at the behavioral level, because the degrees of freedom are reduced by the energy flow through the system. So, a first step is to characterize the complexity of the behavior of interest (Kay, 1988). This sets a lower limit on the complexity of the model.

One example of this kind of methodology is a study with adults by Kay, Kelso, Saltzman, and Schoner (1987). Their subjects performed wrist motions at various required frequencies, and the amplitude of motion was observed over several steady-state cycles, in which the subjects did not overtly change what they were doing. The resultant frequency–amplitude function had a particular form that was closely approximated by a particular nonconservative limit-cycle oscillator. Thus, a pattern of coordination was characterized by low-dimensional collective variables (an equation of motion).

A second example of the modeling methodology is the work by Haken, Kelso, and Bunz (1985) on relative phase of the rhythmic movement of the left and right finger. In earlier work, Kelso (1981, 1984) had subjects rhythmically move their index fingers or hands so that homologous muscle activation was either in phase or alternating. At a certain critical frequency, switching occurs spontaneously from the anti-phase to in-phase mode, but not in the reverse direction. Thus, while there are two stable patterns for low-frequency oscillation, only one pattern remains as frequency is scaled beyond a certain region. Here, relative phase is an order parameter or collective variable because it characterizes all observed coordinative patterns, has simple dynamics, and changes abruptly at the transition.

Haken et al. (1985) were able to model four properties of this system: the stationary states of 0 and 180 degrees, the bistability of the patterns, 2 pi periodicity, and the symmetry of the left and right hands. Their model is a potential, V, that combines two cosine functions:

$$V = -a \cos\phi - b \cos 2\phi$$

where a and b are control parameters. The behavior generated by this model is depicted in Fig. 2.7. As b/a decreases from 1.00, the ball illustrates the systems's transition from out-of-phase to in-phase ($b/a = 0$).

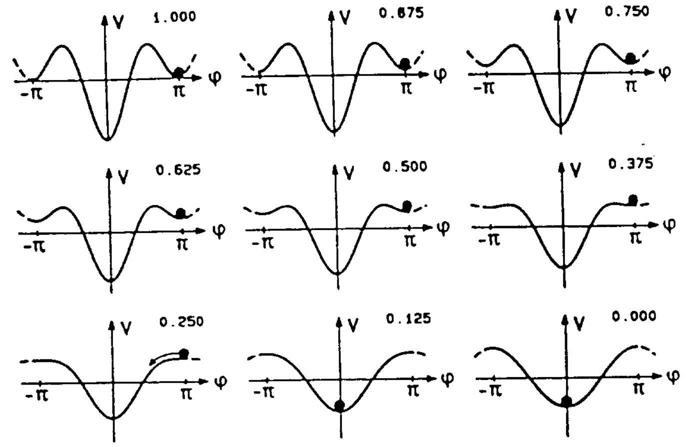

Figure 2.7. The consequence of a changing potential landscape. The potential *V/a* changes as values of *b/a* are varied. The numbers refer to the ratio *b/a*. (From Haken, Kelso, & Bunz, 1985. Copyright © 1985 by Springer-Verlag Publishers. Reprinted by permission.)

The model also makes certain predictions about the stability of the system close to transition points. As the system approaches a critical point, there may be an accompanying increase in fluctuations around the mean state of the collective variable (phase). The switch to a new pattern is accompanied by a marked decrease in fluctuations. The loss of stability is believed to be the chief mechanism that effects a change of pattern: fluctuations drive the system away from its present state. This is precisely what Kelso and Scholz (1985) and Kelso, Scholz, and Schoner (1986) found when they observed actual behavior. A second prediction is critical slowing down: when a system is close to a transition point, it reacts more slowly to external perturbation than when it is far away from the critical point. For both enhancement of fluctuations and critical slowing down, new states evolve without specific influences from the outside.

Relevance of the modeling approach for understanding development of action systems. In Chapter 1, I introduced the idea that the transformation of spontaneous activity into a task-specific action pattern involves the processes of assembly and tuning. The various equations of motion presented above may constitute a veritable bestiary of dynamic systems with characteristic attractors, on which global musculoskeletal functions may be modeled. How are such functions assembled?

I suggest here that spontaneous activity in the context of task constraints results in the formation of stable action patterns, akin to morphogenesis in biological systems or pattern formation in physical systems (Haken, 1983;

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