LIVING IN THE PINK: INTENTIONALITY, WELLBEING, AND COMPLEXITY

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A barrel racer trains many years to move in sync with her horse. To keep her seat, she rises and falls in phase with powerful centripetal lunges around each barrel. The result is a skilled coordination in which rider and horse gallop together. Consider another example. A teacher steps forward while speaking. Every step pre-engages coordinative structures, flexing and extending muscles across torso, arms, and neck to guarantee balance in a continuous anticipatory flow. The racer needs only to race, and the teacher to teach, but what happens is a vastly complicated coordination of minds and bodies with their environments. Coordination is essential to cognition and behavior, yet except in motor coordination it has not been a prominent topic of cognitive science.

In this essay, we discuss how complexity science has filled this gap. We begin with problems inherited from conventional cognitive science, for example the question of intentionality. We then discuss conceptual building blocks of complexity with respect to brains, bodies, and behavior. These include constraints, phase transitions, interdependence, and self-organized criticality – concepts that address emergent coordination among system components. From there we go on to discuss ubiquitous pink noise in human performance. Pink noise is a fundamentally complex phenomenon that reflects an optimal coordination among the components of person and task environment. Departures from this optimum occur in advanced aging and dynamical disease, including Parkinson's disease, as we will discuss. We conclude this essay with a survey of present challenges and opportunities for complexity and cognitive science.

1 INTENTIONALITY AND OTHER DILEMMAS

Intentionality is central to subjective experience and permeates all human activities. It plays an equally prominent role in cognitive experiments, with special significance for cognitive science. Before meaningful data can be collected, intentions must be invoked in the participant to perform as instructed. Data -- the foundation of what scientists know about cognition -- depend fundamentally on the will, purpose, and goals of the participant. Yet the role of intentions in data collection and laboratory experiments is usually ignored [Vollmer, 2001]. Indeed a *Science Watch* forum concluded that experiments tap involuntary, automatic, or unconscious processes exclusively [Science Watch, 1999].

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Intentionality suggests a capacity to bring behavior into existence, to cause behavior. The intention to step forward to teach, for example, might cause the right leg to move forward. Yet intentions cannot be ordinary causes and still make sense scientifically. This is because the causal viewpoint ignores the question of what causes the intention in the first place. Maybe the intention to step was caused by the intention to teach, and the intention to teach was caused by the intention to remain employed. Still what caused the intention to remain employed? Either the intention to remain employed has a magical status, as a prime mover homunculus, or we enter the logical regress of seeking the cause of the cause of the intention to behave [Juarrero, 1999].

Intentions also require that cognition stays open to outside factors to promote intended goals, while at the same time ignoring irrelevant factors that might derail them. Once instructed to pay close attention to ball handling in a basketball game, for example, the observer will fail to notice the man in the gorilla suit who stops and pounds his chest while walking through the scene [Simons and Chabris, 1999]. How does the mind stay connected to the outside world, but only selectively, in pursuit of its goals? The question is to the crux of selective attention, the capacity to turn a blind eye to aspects of the environment that are irrelevant to purposes at hand [Mack and Rock, 2000]. A conventional solution might be a decision device that could select relevant factors and purposes. Yet which homunculus decides whether things capture involuntary attention?

Of course dilemmas in conventional cognitive science are not limited to questions of intention [Hollis *et al*., 2009]. Take for example the coming into existence of a completely novel insight or novel behavior. The dilemma stems from equating cognition with information processing, either as *mentalese* by analogy to language, *computation* by analogy to computer software, or *activation* by analogy to neurons, synapses, and action potentials. For information processing, novelty becomes either a simple combination of existing structures, juxtaposed or added together in representations, or novelty must preexist in some way before the novel behavior is realized. The latter solution yields another logical regress: If the cause of novelty preexists, then what caused the preexisting cause of novelty?

Another dilemma in conventional cognitive science is presented by the protracted failure to connect mind to body. Conventional theories have failed to bridge the gap that separates mind and body. This failure to naturalize mental constructs stems from the causal gamble that functional components of cognitive activities, perception, and memory can be isolated and explained [Bechtel, 2009]. Yet the gamble has led to a hodgepodge of conflicting mechanisms, with little agreement about details such as boundaries or number of mechanisms, the ontological status of mechanisms, the relation between cognitive mechanisms and brains, or the developmental basis of cognitive mechanisms, e.g., [Dreyfus, 1992; Harley, 2004; Searle, 1980; Stanovich, 2004; Thelen and Smith, 1994; Uttal, 2001; 2007; Watkins, 1990; Weldon, 1999]. Lacking clearly worked out cause and effect relations, mind and body appear to lack common currency for interaction. And regarding the results of neuroimaging research: “How do we say something is somewhere if we do not exactly know what that something is?" [Greenberg, 2002, p. 111].

The often-voiced hope of the larger research community is the possibility that converging data and theory may themselves sort out the existing hodgepodge. Perhaps converging operations remain to be discovered, maybe through a triangulation of mutually acceptable results about brain, behavior, and conscious experience [Roepstorff and Jack, 2004]. However, this hope continues to rest on the assumed causal and methodological transparency among brain, behavior and consciousness. Transparency requires concatenated effects, meaning effects follow one from the other like dominoes tipping one into the next down a line. Consequently, interaction effects must be additive in proportion to factorial manipulations, but linearity and additivity are scarcely evident or nonexistent [Van Orden and Paap, 1997]. Each cognitive factor appears to interact multiplicatively with every other, and each interaction changes in the context of every new additional factor. Consequently, the sum of evidence across the vast empirical literature of cognitive science yields an equally vast higher-order multiplicative interaction [Van Orden *et al*., 2001]. The unsupported assumption of transparency and concatenated domino effects has resulted in a crisis for measurement, which is seldom discussed [Michell, 1999].

Complexity theory circumvents these dilemmas by emphasizing emergent coordination, temporary dynamical structure, and the creation of information in behavior. Complexity science is not concerned with cause and effect primarily, so it averts dilemmas that arose from seeking causes of behavior as information processors or homunculi. Those efforts are replaced by a search for strategic reductions to laws, principles, and mechanisms of emergent coordination. Such strategic reductions find the same principles at work across different systems and at all levels of a system. In the next section we describe ideas from complexity science that introduce these principles.

2 CONCEPTUAL BUILDING BLOCKS

The view of human behavior as emergent coordination offers a new and theory-constitutive metaphor for cognitive behavior, a complete reconstitution of method, theory, and assumptions. In this section, we define theoretical terms of complexity science that have proven useful in cognitive and behavioral science. They culminate in the ideas of self-organized criticality and soft-assembly: Living systems are attracted to optimal temporary states of flexible coordination, which best guarantees contextually appropriate behavior and the wellbeing of the actor.

2.1 Constraints and Control Parameters

Constraints arise in relations among a system's components, and they reduce the degrees of freedom for change. Consider the constraints that limit the range of motion of an arm or a leg. Relations among joints, muscles, fasciae, and the nervous system allow limbs to move some ways, but not others. They reduce the degrees of freedom for change in limb motion. An expanded example of constraints, less tangible perhaps, is the indefinite sea of constraints among living beings and their worlds [Shanon, 1993]. These include relations with artifacts and the environment, the myopic limits on attention and stream of consciousness, the constraints that arise from idiosyncratic details of each actor's previous history, and in relations to other living beings.

Even with limiting constraints, however, a body in motion retains far too many degrees of freedom to be explicitly or mindfully controlled. For example, estimating the parts to be coordinated, a human body has something like 10^2 joints, 10^3 muscles and 10^{14} cells (Turvey, 1990). For each part that must be causally controlled, a conventional model must accord one controlling structure to each degree of freedom. Given that behavior is highly variable, causal resources are quickly overwhelmed, historically well known as the degrees-of-freedom problem in on-line kinematics of behavior [Bernstein, 1967].

In contrast to causal control, complexity science emphasizes constraints as temporary structures, not unlike the temporary coordination among molecules in a convection cell. They are conceived as emerging from the temporary coupling among embodied components and among components and the environment [Van Orden *et al.*, 2003]. Like a newly formed convection cell controls the fluid molecules of which it is composed, constraints reduce degrees of freedom in coordination. Emergent constraints have the capacity to further self-organize into still higher-order emergent structures. That is to say, first-order emergent structures may combine iteratively into second-order and still higher-order temporary dynamical structures. This iterative capacity has been observed in brain data, for example [Ito *et al.*, 2005]: First-order emergent patterns of coordination, visible in coordination among signals of separate EEG leads, were themselves part of the second-order coordination across time. Iterative higher-order emergence is bounded only by material, temporal, metabolic, and informational limits of the system.

Constraints that control behavior are summarized mathematically in control parameters. To explain, consider the stepping behavior in infants: Soon after birth, and long before learning to walk, a young infant, held above the ground with feet touching the floor, will move legs and feet as though stepping. This early stepping behavior then disappears and remains absent until later in the first year, when it reappears. A conventional causal story sees two different causes behind the two instances of stepping behavior, with no connection in between: Initial stepping behavior is attributed to primitive reflexes that quickly disappear as the baby matures; and the later stepping behavior is attributed to the maturation of a motor schema for walking [McGraw, 1945].

The constraint account, in contrast, focuses on a single control parameter to capture the developmental sequence of stepping behavior. In particular, there are two main constraints that determine the availability of stepping behavior: (1) the strength of the baby's leg, and (2) the weight of the leg. The relevant control parameter is a ratio that pits leg strength against leg weight. Early in development, the baby's legs are relatively light in weight compared to how strong they are, making initial stepping possible. As the baby gains weight, however, gravity's pull on the heavy legs exceeds the strength of the legs, and stepping behavior disappears. In turn, as the baby builds more strength during the first year, stepping behavior reappears [Thelen and Smith, 1994].

The control parameter for stepping behavior captures two salient relations between the infant actor and her environment. Specifically, the numerator in the example (leg weight) summarizes *embedding* constraints in the infant's relation to the environment. This type of constraint delimits *affordances*, the dispositions of the surrounding environment directly relevant for action [Gibson, 1979]. Conversely, the denominator in the example (leg strength) concerns *embodied* constraints of the actor. This second type of constraint refers to *effectivities*, the capacities and capabilities of the actor to exploit the available affordances [Shaw *et al*., 1982].

Explaining change in behavior through changes in control parameters has several advantages compared to traditional accounts. First, control parameters give a more inclusive account of development because they can account for individual differences across participants. Imagine, for example, an infant with very strong (or very skinny) legs. Such a child is likely to retain the capacity for stepping behavior throughout the first year. The changing control parameter for this particular child can be measured precisely. Conventional accounts, on the other hand, require exceptional assumptions to account for idiosyncratic differences. The initial stepping reflex might be stronger in this child than in another, inhibition of the reflex might be delayed, or the motor schema might mature earlier than predicted – or some combination of these possibilities. Further problems arise in having to determine normative development in this case. Yet, movement and its development is hardly uniform [Adolph, 2009].

Second, control-parameters can account for ubiquitous context effects. In stepping behavior, context changes in holding a non-stepping baby upright in a shallow pool, as opposed to outside of the pool, and previously nonexistent stepping will now appear. Or the context can be changed by placing weights on the legs of a baby who can step – and existing stepping behavior will disappear [Thelen *et al*., 2002]. Conventional accounts assume that successful performance reflects the presence of an underlying cognitive structure, while unsuccessful performance reflects its absence. Such accounts are quickly overwhelmed by the sheer number of context effects, often found in the same person and after only trivial changes of context [Kloos et al., 2009; Van Orden *et al*., 1999].

At the minimum, context sensitivity requires that performance reflect some form of interaction between the cognitive structures of the actor and the context of the environment. Yet complexity goes well beyond a mere interaction. In each different context, a different mesh of available constraints reduces degrees of freedom to favor kinematics suitable for that context or task protocol, e.g. [Balasubramaniam *et al*., 2000; Flach, 1990; Riley, 2007; cf. Glenberg, 1997]. No two situations yield identical constraints, so a laboratory's situated mesh of constraints specifies a unique niche for performance [Flach *et al*., 2007]. In a similar vein, no two persons embody identical constraints because no two persons have identical histories. Consequently, behavior in the same task will differ in quality as well as quantity [Ashby et al., 1993; Balakrishnan and Ashby, 1991; Holden, 2002; Holden *et al*., 2009; Luce, 1986; Maddox *et al*., 1998; Molenaar, 2008].

2.2 Critical States

As behavior changes across development, say from the presence of early stepping behavior to its absence, the relevant control parameter passes through a critical value, a value that defines a critical state of the system. In the stepping example, the critical value (and therefore the critical state) is reached when the pull of gravity exactly equals leg strength. Now the two opposing actions, stepping and not stepping, are in precise balance, and therefore equally possible. In this critical state, even tiny changes in control parameters may tip the balance and break the symmetry of the poised alternatives. That is to say, even tiny changes in the environment-infant system can be relevant contingencies that break symmetry.

Given that relevant contingencies are necessary to enact behavior, and they suffice to enact behavior, they can be conceived as causes. For example, a hungry dieter who comes across a candy bar will likely eat it, though he might prefer to have made a healthier choice. The simple contingency of first coming across the candy bar enacts behavior consistent with the need for food. The mere sight of the candy bar therefore causes the dieter’s lapse in healthy eating. Laboratory findings sometimes discover nothing but effects of contingencies. This might explain why scientists take the prevalence of reported contingency effects to imply the lack of intentionality in laboratory behavior, e.g. [Science Watch, 1999]. Conscious will might be nothing more than the illusion of causality after all, e.g. [Wegner, 2002]. Yet these conclusions are misguided. Before a contingency can enact behavior, the body must already be in a critical state. Available constraints must first specify propensities to act. Only then do mere contingencies have the power to cause behavior.

Critical states exist until relevant contingencies occur. Importantly, critical states are not perturbed by irrelevant factors, factors that do not favor a particular action over any other. Change in a baby’s arm weight or finding a toy candy bar while hungry are not sufficiently relevant to the specified critical states. Only relevant events can favor a relevant propensity. So, in a sense, the critical state can “filter out” irrelevant contingencies, and explain selective attention. It is the critical state that allows the actor to stay open to outside events, without being derailed by irrelevant factors.

The prominent role of critical states, susceptible to relevant contingencies, may also explain why mindful, forbidding self-control is notoriously difficult to put into action. It is well known, for example, that a dieter forbidding himself to eat candy, or telling himself to "eat healthily," are ineffective diet solutions [Baumeister and Heatherton, 1996; Rachlin, 2000]. A focus on healthy or unhealthy edible things has the side effect of instantiating propensities to eat that remain susceptible to accidental candy bars. In an effective solution the dieter concentrates on the abstract end-goals of dieting, such as facilitating connectedness to others, or a change in personal wellbeing [Fujita and Han, 2009]. The more abstract goal is less likely to include propensities for kinematics to grab up the first food available. The abstract focus makes candy bars less salient as food and more salient as diet busters.

Critical states are not only relevant to understanding selective attention and the relevance of contingencies. Far beyond, they are proposed to be the center of coordination. Rather than coming into existence passively, as control parameters change, complex systems are drawn toward critical states, they self-organize critical states [Bak, 1997; Bak *et al.*, 1987]. Note the superficial paradox of self-organized criticality: Critical states are by nature unstable, given that the smallest relevant contingency can collapse the system into one action or another, so critical states must be repellers, boundaries between basins of attraction. However, critical states can also be attractors [Chialvo, 2008].

2.3 Phase Transitions

As the system passes through a critical state, a phase transition takes place. The term phase transition comes from thermodynamics and describes how phase relations among molecules change suddenly and qualitatively to more efficiently dissipate heat. As a system passes through a critical state (and a control parameter passes through the critical value), the system components suddenly and spontaneously reorganize to produce a different kind of behavior, together at almost the same time. Immediately before a phase transition, disorder will increase in the system. This increase coincides with the break up of existing structure prior to the reorganization. After the phase transition, the level of disorder drops to a lower level than the level it was originally. This drop is called negentropy, and it stands for the difference between the entropy before the start of the phase transition and the entropy immediately after the phase transition. Negentropy coincides with the emergence of new thermodynamically advantaged structure due to an increase in how quickly the system can export entropy.

Changes in entropy have been observed for phase transitions that occur during problem solving [Stephen *et al.*, 2009]. Given the turning direction of the first gear in a chain of gears, the problem to be solved was the turning direction of the last gear. Typical participants transition from tracing the direction of each gear to a parity strategy, after the insight that every other gear turns in the same direction [Dixon and Kelley, 2006; 2007; Schwartz and Black, 1996; Dixon and Bangert, 2004]. Angular velocities of finger movements were densely sampled across trials of separate gear problems. As expected, entropy in angular velocity increased just prior to the phase transition, while negentropy was observed immediately after. The pattern was replicated in densely sampled eye movements in the gear-turning task [Stephen *et al.*, 2009], and it was found in a balance-beam problem-solving task

[Cox and Hasselman, 2009]. Negentropy results are compelling. They suggest that new problem solutions are thermodynamically advantaged, a profound similarity between phase transitions in problem solving and phase transitions in nonliving physical systems.

Bifurcation theory provides a mathematical account of phase transitions in nonlinear dynamical systems. The change from the absence to the presence of a behavior, say, from absent stepping behavior to stepping behavior, is one kind of bifurcation, while a change from one type of behavior to a different type of behavior is a different kind of bifurcation. Through reliable mathematical accounts, the nature of phase transitions can be understood [Meillassoux, 2008]. Moreover, if bifurcation theory should fail to illuminate changes among coordinative structures in human behavior, we would lack any other alternative in which qualitative changes generalize across instances.

Phase transitions occur in many living and nonliving systems. A mix of chemicals forms qualitatively different patterns when the petri dish is tipped; amoebas lacking sufficient food resources transition from single-celled organisms to a multi-cell spoor-bearing slime mold [Nicolis, 1989], coordination between human behavior and a metronome-beat transitions from syncopation to synchrony as the metronome speed increases [Kelso, 1995], just to name a few. Despite differences in types of systems, these phase transitions share common diagnostic patterns, called catastrophe flags, with common theoretical underpinnings.

Examples of catastrophe flags include critical fluctuations and critical slowing, both of which were observed in phase transitions of brain and behavior [Kelso *et al*., 1992]. The behavioral task was to flip a switch repeatedly between the beats of a metronome, in syncopation with the metronome beats. This task was chosen because syncopation behavior loses stability at a critical value of metronome frequency, and then transitions to synchrony, flipping the switch on the beat [Kelso, 1995]. To test for catastrophe flags in this phase transition, metronome frequency was increased incrementally to perturb the coupling between participant and metronome. SQUID brain images, EEGs, and behavioral measures were recorded continuously. Indeed, just before the phase transition, the perturbation produced critical fluctuations and critical slowing. That is to say, in all measures there was a nonlinear increase both in the variability in the phase relation between beat and behavior (demonstrating critical fluctuations) and in the recovery time after perturbation to regain syncopation (demonstrating critical slowing). It was as though a protracted struggle occurred in brain and body to decide which propensity would be expressed, syncopation or synchrony.

The crucial finding, however, was that brain and behavior reorganize together, at the same time, too close in time to allow information processing. In particular, the lag in reorganization of brain and behavior was no more than 170 msec, not enough time for information processing, though sufficient time for the creation of information in the collapse of a critical state. The virtually simultaneous reorganization of brain and body agrees with reports of ultra-fast cognition, reliable perception after impossibly brief visual displays, for example, and reliable cognitive performance with electric speed. Perception and action occur too fast to allow for information processing to take place. Sometimes the body appears to make do with one-way activation, traveling at speed, from eye to hand [Fabre-Thorpe *et al*., 2001; Fabre-Thorpe *et al*., 1996; Greene and Olivia, 2009; Grill-Spector and Kanwisher, 2006; Thorpe, 2002; VanRullen and Thorpe, 2002].

2.4 Interdependence and Soft-Assembly

Is it surprising that finger movements reveal the same changes in entropy as eye movements during the phase transition in a problem-solving task? Neither finger movements nor eye movements have an obvious causal connection to the participant's reasoning or to the novel insight. Yet they both show characteristic signatures of a phase transition. Complexity theory anticipates such coupling. This is because components of a complex system are interdependent, one with another; they change each other's dynamics as they interact with each other. Interdependence allows soft assembly of behavior, meaning that behavior emerges and cannot be parsed further, or reduced, into component functions that would exist in a dormant state, even when their behavior is not present [Hollis *et al*., 2009; Kloos and Van Orden, 2009; Turvey and Carello, 1981].

Interaction-dominant dynamics are the basis of interdependence and emergence; interactions among components dominate the intrinsic dynamics of the components themselves [Jensen, 1998]. Interaction-dominant dynamics originate in multiplicative interactions and feedback among the interacting components. As a result, they predict non-additive, strongly nonlinear effects [Holden *et al*., 2009], and emergent properties that cannot be deduced from causal properties of components [Boogerd *et al*., 2005]. In contrast, *component-dominant dynamics* underlie the expectation of additive effects embedded in Gaussian random variability [Van Orden *et al.*, 2003]. Gaussian variability, for example, is the variability of independent perturbations that sum up as measurement noise.

A consequence of interdependence is to allow a system's phase space to be reconstructed from a well-chosen one-dimensional data series of repeated measurements. In essence, if every part affects every other part then coordinated changes can be recovered from measured values kept in the time-ordered sequence in which they were collected. The reconstructed phase space is a rearrangement of data points as neighbors, which means they are close together in the phase space and products of the dynamics in that neighborhood. Phase space reconstruction requires the right tools of course, and elegant mathematical theorems, now taught in undergraduate mathematics classes, prove that higher-dimensional neighborhood structures can be unfolded and made available for additional analysis [Mañé, 1981; Takens, 1981].

If each component's dynamics is entangled with the dynamics of every other component, it can become impossible to isolate components and study them separately. So how do we determine which components are involved in a particular cognitive activity? This concern reflects the strategy of seeking isolated components, typical of conventional information-processing accounts. It is motivated by the idea that the parts of a system have distinct functions that are preserved or encapsulated through component-dominant dynamics. Component-dominant dynamics underlie the expectation that behavioral effects result from interaction among components that do not change their intrinsic properties [Van Orden *et al.*, 2003]. An arch is an example of a component-dominant system. While blocks interact to form an arch, they are not interdependent in their function. Supportive properties of a particular arch can be deduced from the material composition and arrangement of the component blocks.

How do we know if a system is driven by component-dominant or interaction-dominant dynamics? The crux is whether the system shows strongly emergent properties. Component-dominant systems have only weakly emergent properties and their behaviors can be deduced from causal properties of components and their arrangement, see also [Boogerd *et al.*, 2005]. Conversely, interaction-dominant systems have strongly emergent properties, visible in catastrophe flags discussed earlier. They are also expressed in scaling relations across repeated measurements. Such scaling relations are now so commonly observed in cognitive science that they are claimed to be *universal* [Gilden, 2001; Kello and Van Orden, 2009; Riley and Turvey, 2002]. They are even found in subjective evaluations of wellbeing, such as repeated self-esteem ratings over the course of a year [Delignières *et al.*, 2004], or changes in mood over the course of a day [Isenhower *et al.*, 2009]. They provide strong evidence that human behavior soft assembles in interaction-dominant dynamics.

2.5 Homeorhesis

At one time, medicine, biology, and the behavioral sciences embraced homeostasis as the guiding dynamic of wellbeing. Figure 1 illustrates how repeated measurements would appear in homeostatic dynamics. Homeostasis assumes mean values come from set points of a system, and random noise around the mean values comes from external perturbations. Absent external perturbations, homeostasis predicts that systems come to rest at their average values.

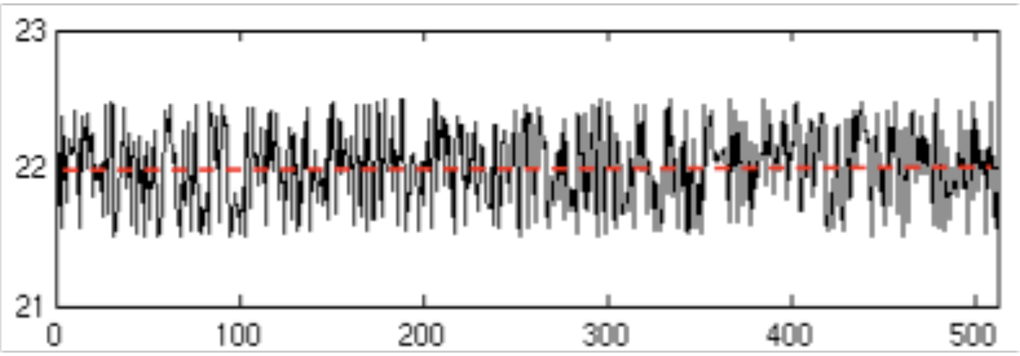

Figure 1. A random noise data series centered on a mean value indicated by the red line, to illustrate homeostatic behavior. The random variation comes from perturbations to the static mean.

In line with this hypothesis, the body was thought to sustain an average heartbeat, for example, to satisfy the average needs of cells for nutrients and oxygen. Organisms were thought to find sufficient food to maintain an average nutrient base. And medicine acquired the goal of returning systems to their capacity to sustain homeostasis, sometimes recruiting artificial devices to do the same job [West, 2006]. Although homeostasis was intuitive, it did not correctly anticipate the ubiquitous cycles in living systems. The heart does not have a reliable average time between beats and cycles of nutrient intake, energy liberation, and waste expulsion, essential for life, recur on the multiple scales of cells, organs and the body as a whole. Homeostasis was therefore challenged by the homeokinesis hypothesis, in biophysics and physiology.

Homeokinesis is the idea that a body and its relations to the environment can be broken down into distinct cycles of nonlinearly stable dynamics. Homeokinetic systems repeat their behavior in limit cycles [Iberall, 1970; Iberall and McCulloch, 1969]. Figure 2 illustrates the predicted pattern of repeated measurements governed by homeokinetic dynamics, a limit cycle plus random noise. Proponents of homeokinesis assembled most of the conceptual pieces necessary for a robust account of variability in living systems. They could, in their time, with their tools, demonstrate component limit cycles (plus random noise) in physiology and all the way out into behavior, e.g. [Kay, 1988]. However, evidence against homeokinesis existed even as it was proposed. This is because homeokinesis posited a distinction between dynamics on different timescales. For example, limit cycles of cell dynamics were thought to be independent of limit cycle dynamics of organs and organ systems, and between organisms and environments.

Homeokinesis allowed interactions between cyclic processes, in nutrient and oxygen transport for example, but not among their cyclic dynamics. Consequently, a change in an organism's circadian rhythm with the environment should not change the cycle frequencies among organs or among cells. Yet, it is now widely accepted that organism-environment cycles are linked to the cycles within organisms. For example, a feckless chicken kept in constant red light (to break the entrainment with the environment's circadian rhythm) suffers a break down of healthy coordination among heart rate, locomotor activity, and deep body temperature [Winget *et al.*, 1968]. Healthy intrinsic dynamics of the chicken's body require entrainment to the circadian rhythm to remain in order.

More slowly changing cycles were eventually recognized as supplying supportive constraints to sustain faster changing cycles [Simon, 1973; Newell, 1990]. The hypothesis predicts that more slowly changing dynamics can constrain faster changing dynamics, but not vice versa. The prediction leads to a nonsensical conclusion, however, considering current knowledge. Timescales of behavior do not overlap much with timescales of the brain. Measured changes in overt behavior happen on the time scales of years, months, days, hours, minutes, and seconds. Yet the brain's slowest delta waves index changes with a period of about 2.5 seconds [Buzsáki, 2006]. Therefore, timescales of behavior are mostly too slow to be controlled by the brain. Even conscious self-control, by some estimates, occurs more

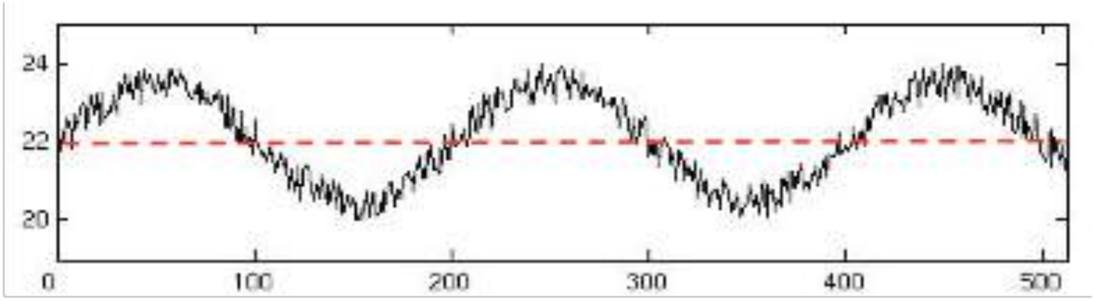

Figure 2**.** A sine-wave data series with added random noise to illustrate a homeokinetic process. The red line indicates the mean of a data series around which the limit cycle fluctuates.

slowly than cycles in the brain, e.g. [Iberall, 1992]. So how could the brain function in control of behavior? A logical conclusion might be that the brain functions to smooth out the kinematics of behavior, in a kind of dithering function, like the high-frequency dithering that makes digital music sound more like analog.

Eventually, with the development of new tools, scientists could reliably distinguish chaotic oscillators from limit cycles with random noise, e.g. [Mitra *et al.*, 1997]. As a result, limit cycles were rejected as the basis of cycles in physiology and behavior. In their place, a hypothesis of homeorhesis was proposed. Homeorhesis is the idea that the dynamics of living systems reflect flexible entrainment to changes in their environments. It predicts a kind of flow of behavior through the environment that negotiates constraints, reflecting previous as well as present relations with the environment, e.g. [Warren, 2006]. Homeorhesis hinges on the idea that the brain, body, and environment soft assemble behavior. It is therefore a direct analog to the idea of interdependence and soft-assembly discussed above.

To summarize Section 2, conceptual building blocks from complexity science enhance our understanding of cognitive behavior. Embedding and embodied constraints combine in control parameters whose critical values define critical states of phase transitions. As a system passes through a critical state, the system undergoes a phase transition, a qualitative change in its organization to soft assemble qualitatively different behavior. Phase transitions are identified using catastrophe flags like critical fluctuations and critical slowing. Phase transitions are shaped by temporary dynamical structures as constraints, which allow flexibly situated soft assembly of cognition and behavior. In the next sections, we build upon and expand these ideas to discuss nontrivial changes in how to understand cognition and behavior.

3 THE THIRD KIND OF BEHAVIOR

Before complexity science, variation in repeatedly measured values was divided into two categories: regular changes from one measured value to another, or random changes. Regular changes were thought to be the explainable variance, while random variance was equated with measurement error. In cognitive science, ex-

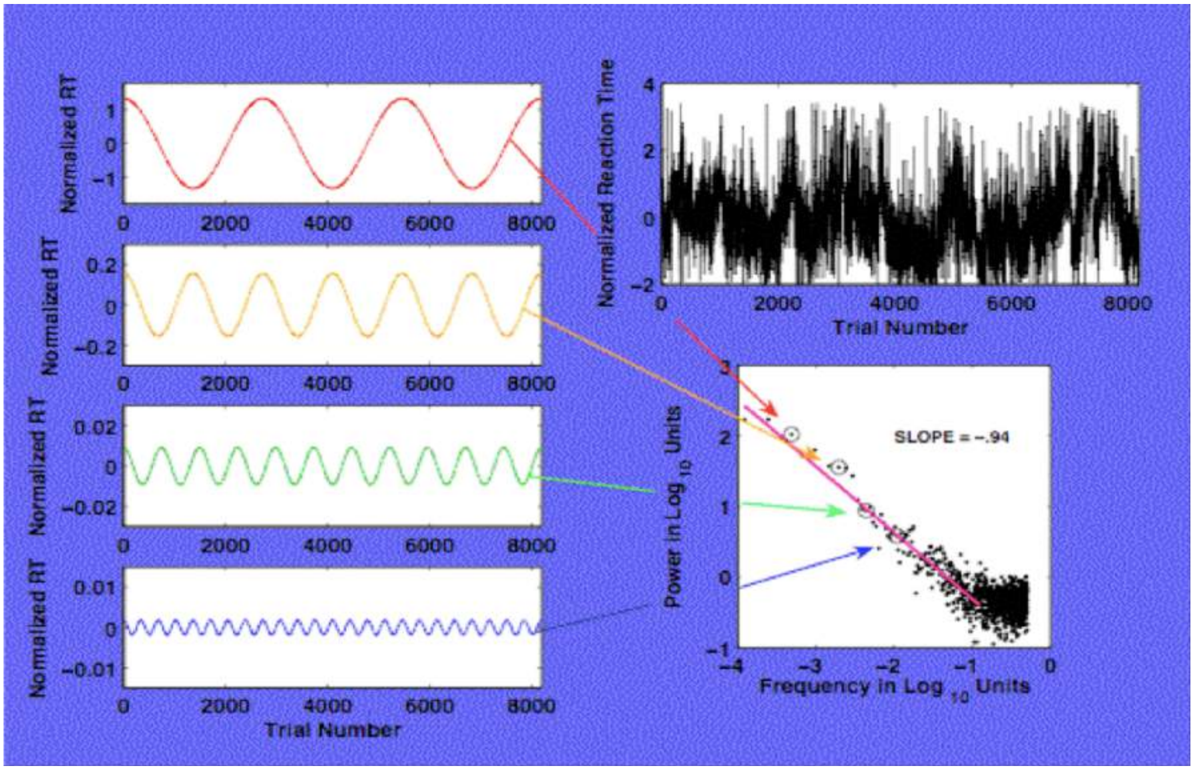

Figure 3. One person's response time data. Specific frequencies and amplitudes of change to approximate the rough graph of the data in the upper right of the figure, plus the outcome of the spectral analysis below. The spectral slope = -.94, which is approximately $\alpha \approx 1$. Note that the Y-axes in the illustrations have been adjusted to make smaller amplitude sine waves visible.

plainable variance was conscripted to reveal component mechanisms of *memory*, *reasoning*, *syntax*, *semantics*, and so on. The empirical variance we describe in this section is neither regular nor random. It constitutes a third kind of variability, one that is captured in scaling relations and that cannot be categorized by conventional approaches.

3.1 Pink Noise

The data series on the right in Figure 3 is decomposed into sine waves of different amplitudes, shown on the left. Slow changes in the data series are captured by low frequency, high-amplitude, sine waves (top left), and fast changes in the data series are captured by high-frequency, low-amplitude waves (bottom left). Amplitude reflects the size of change S(f) between values across the data series and appears on the Y-axis of the power spectrum, plotted against the frequency (f) of changes at that size. The

Figure 4. Fractal branching of a tree.

relation between size and frequency of change is the scaling relation estimated by the slope of the line in the spectral plot.

In the scaling relation illustrated in Figure 3, the size of change S(f) is inversely proportional to its frequency (f): $S(f) = 1/f^{\alpha} = f^{-\alpha}$, with scaling exponent $\alpha \approx 1$. It is this value of the scaling exponent that reflects the third kind of behavior. It is called pink noise because visible light with the same spectral slope has a pinkish cast from power concentrated in lower, redder frequencies. We use the phrase pink noise throughout, due to its accidental association with old-fashioned phrases about wellbeing, like *in the pink* and *pink of health*. However, depending on discipline, the phenomenon may be called *flicker noise, 1/f noise, 1/f scaling, intermittency, multiplicative noise, edge of chaos, fractal time, long-range correlations, red noise, self-affinity*, or something else. Similarly, there are many ways to portray this behavior in numerical and geometric analyses, each with its own vulnerabilities and caveats [Holden, 2005]. The many different names give credence to a core thesis of complexity science that common dynamical organizations will appear in systems of different material construction, even in living and nonliving matter.

What is the meaning of pink noise? Debates about this question have taken place in every discipline that has confronted complexity, including cognitive science [Chen *et al*., 2001; Dale, 2008; Delignières *et al*., 2008; Ding *et al*., 2002; Diniz *et al*., in press; Edelman, 2008; Farrell *et al*., 2006; Gilden, 2001; Kello *et al*., 2007; 2008; Kello and Van Orden, 2009; Newell and Slifkin, 1998; Riley and Turvey, 2002; Thornton and Gilden, 2005; Torre *et al*., 2007; Torre and Wagenmakers, 2009; Wagenmakers *et al*., 2004, 2005; Ward, 2002; Van Orden, 2008; Van Orden and Holden, 2002; Van Orden *et al*., 1997; 2003; 2005]. The difficulty comes from the dual nature of pink noise, namely that it can appear as either a regular or an irregular phenomenon. The regularity is in the scaling relation, whether the basis of the scaling relations is a sine wave, square waves, V-waves, or irregularly spaced waves with different average frequencies. Yet pink noise appears irregular and unstructured in a data graph where it is an aperiodic waveform like random Gaussian noise or chaos. In truth it is neither regular nor random but a strongly nonlinear pattern that exists between their two extremes [Nicolis and Rouvas-Nicolis, 2007; Sporns, 2007; Tsonis, 2008].

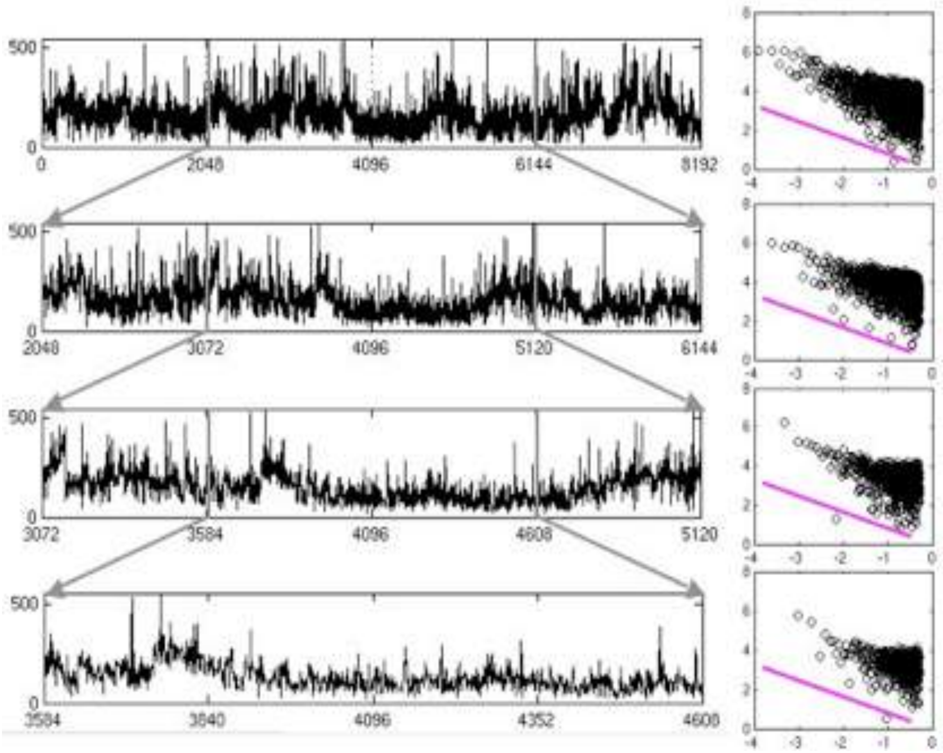

Figure 5. Trial-ordered series of reaction-time trials (left) and the resulting spectral plot (right). The top panel includes 8192 trials in the data series, while all other panels are a subset of the original data series. The first and last quarter are consecutively cut off to eventually yield a series with 1024 reaction times (bottom). The scaling relation remains very similar for each nested data series.

The crux of pink noise is self-similar structure. Mathematical pink noise expresses formal self-similarity, and empirical pink noise expresses statistical self-similarity, not unlike the branching structure of a tree. From the bottom to the top of a tree, branches become thinner in diameter as they become more numerous. The same relation holds even when a window on the tree is decreased and one considers only a part of a tree, as in Figure 4. In particular, the relation between branch diameter, S(f), is inversely proportional with how often branches of that size occur (f). The resulting scaling exponent stays within a narrow range of values. Fractal structure makes it appear that every scale of measurement is stitched together with every other scale of measurement (e.g., the decreasing scale diameters of tree branches), in a nested pattern.

Comparable statistical self-similarity in fractal patterns can be seen in repeated measures of human performance, say when a participant produces simple reaction times, trial after trial (see Figure 5). A spectral plot across the entire data series of about 8000 reaction times results in pink noise. Importantly, when the data series is cropped at both ends, such that only half of the length of the original data series is considered for the spectral plot, a similar spectral slope is obtained. Again, when the shortened data series is cropped further, the slope stays within a small range. Just as for tree branches,

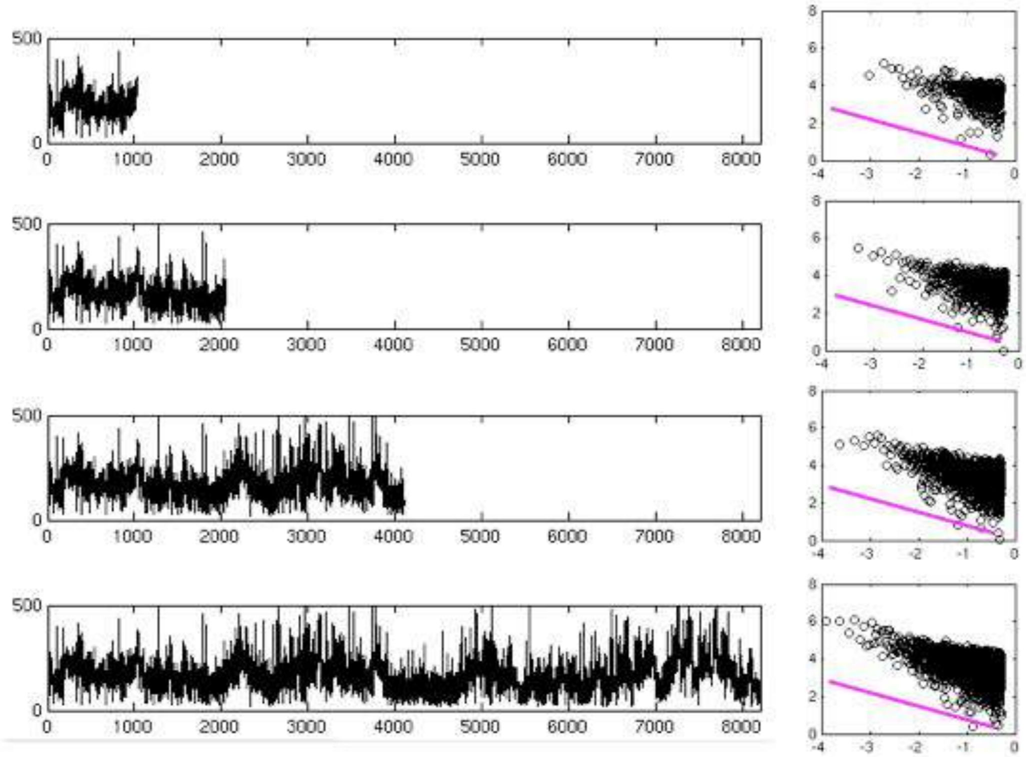

Figure 6. Trial-ordered series of reaction-time trials (left) and the resulting spectral plot (right). The top panel includes the first 1024 trials, while all other panels increase the length of the data series. The scaling relation remains virtually the same for each increasingly longer data series.

each repeatedly measured value of brain or behavior appears stitched to every other in the fractal wave.

Finally, while pink noise has statistical self-similarity, variance within a data set does not stay the same. Note in Figure 5, as the data series get shorter, values in the spectral plots shrink along the Y-axis (magnitude of changes), as well as along the X-axis (frequency of changes).

In other words, large rare oscillations disappear as the data series shrinks in length. The inverse pattern is seen as more-and-more data are collected. Figure 6 portrays changes in the magnitude of variability as a data series gets longer. Variation grows by orders-of-magnitude as we gain access to rare but much larger amplitude changes in longer data series.

Conventional theories have difficulty accounting for the fact that more data equal more extreme variability. Conventional methods assume the opposite, namely that larger data sets yield more reliably stable estimates of average performance, meaning that error variance should not increase as more data points are collected. This is a false assumption as we have tried to illustrate. Longer data series include more extreme values, which destabilize the mean value of the data. No reliable mean value exists. This fact undermines the very foundation of conventional approaches, namely that variances can be ignored because data, at heart, are equal to their mean.

How does complexity science explain the nested fractal structure of pink-noise? The self-similarity of a mature tree, for example, is produced by the iterative growth processes of the living tree. An iterative process takes its present status, or output, as input in the next time step. In the tree example, the same growth processes of branching and thickening produce all the branches at all the different scales of the tree, and so the tree grows to resemble itself on large and small scales, and in the scaling relation between size and frequency of branches. In human behavior the present status of a person is input to embodied interaction-dominant dynamics, which produce the status in the next time step, and so behavior unfolds to resemble itself across time in the scaling relation between the size of change and its frequency.

Given these considerations, the following things appear true: Pink noise is neither regular nor random. Irregular, aperiodic data points are woven as an exotic fractal pattern. At present time, each repeated measurement of brains and behaviors appears to be sewn together in this fractal pattern. Within the pattern, every measured value is long-range correlated with every other value to span the experiment. Complexity science first recognized the aperiodic, fractal pattern as a third kind of behavior.

3.2 Soft Assembly of Performance Devices

Complexity science suggests that we view performance as a soft-assembled coordination or coupling between task and participant. Given that every task entails a different set of constraints, a new coordination should emerge every time we change tasks. This was indeed found in a simple key-pressing experiment in which adults had to press a key in response to a signal on a computer screen [Kello *et al*., 2007]. Two measures were taken: (1) the time it took the participant to press the key upon seeing the signal (i.e., key-press response time), and (2) the time it took the participant to release the key to return to the ready position for the next trial (e.g., key-release response time). The two resulting data series (key press and key release) were subjected to spectral analyses, which revealed pink noise in each separate data series. Importantly, however, the two streams of data were uncorrelated. Although each measured key-press time was long-range correlated with every other key-press time, and each measured key-release time was correlated with every other key-release time, they were not correlated with each other.

A conventional explanation would posit two distinct and independent decision mechanisms, one for key-pressing and one for key-releasing. Of course positing new decision mechanisms for every dissociated effect quickly loses the elegance of parsimony, given that a myriad of trivial changes in task demands of very simple tasks yield similar dissociations, e.g. [Durgin and Sternberg, 2002]. A claim of separate decision mechanisms for separate effects also undermines generality, given that a key-press decision or a key-release decision has to be closely associated with the specifics of the task. Finally, it is not clear why a decision about pressing a key would require a different cognitive mechanism than deciding to release the key.

Complexity, on the other hand, explicitly predicts such dissociations, because performance is the becoming of a performance device entrained to the specific constraints of task demands. In some sense, task couplings create new ‘devices’ of the participant with even subtle changes in task demands. Pressing down a key entails different constraints than releasing the same key and, while the two movements are interleaved in time, their respective sources of constraint may very well change independently. To test these claims more directly, another key-press experiment was conducted, with one crucial manipulation: Instead of a predictable signal about which key to press, signals were alternated unsystematically which introduced uncertainty about which key to press until the signal appeared. Again, two data series were collected, one for the time it took a participant to press a key and one for the time it took to release the key. The results showed that uncertainty about which key to press affected the key-press data series, but not the key-release data series. More specifically, while the key-release data series retained their pink noise pattern, observed before, the key-press data series were de-correlated by the injected uncertainty and appeared closer to random noise [Kello *et al.*, 2007].

Task coupling gives a simple and sensible account of the key-press response data. Unpredictable signals injected uncertainty as an unsystematic perturbation of the entrainment to each trial’s signal to respond by pressing the key. The unsystematic perturbation resulted in less systematic coupling which de-correlated the otherwise long-range correlated data series. Key release durations were unaffected because the coupling of the key-release response was the same across all trials. The participant was always at a key contact point, at the bottom of a key-press, before the key-release response was initiated, irrespective of which key was pushed down. At the bottom of a key-press response no uncertainty exists about which key-press to key-release.

Taken together, these key-press results support the idea that the body coordinates itself into temporary performance devices to fit the specifics of the tasks. The apparent devices are soft-assembled coordinative structures. Even when tasks differ merely in uncertainty about which key to press or the direction of the finger’s motion in key pressing versus key releasing, the body will appear to create specialized devices to accommodate the different demands. Devices do not refer to permanent mental functions or components, but instead exist only so long as the specific task demands are present and performance continues.

3.3 Attraction to Complexity

As discussed in Section 2, the quality of task-person coupling reflects the extent to which the effectivities of the participant (embodied constraints) match the affordances of the task (embedding constraints). Pink noise might reflect such an ideal match between embodied and embedding constraints. Consistent with this prediction, pink noise is the central tendency of variability in skilled healthy behavior [Kello *et al.*, 2008]. Participants were asked to say the same word ('bucket') over and over. Each instance of the spoken word was then parsed identically into dozens of frequency bins and the amplitude of each frequency-bin was tracked across all spoken instances of the word 'bucket.' This resulted in dozens of separate data-series, and each data-series yielded a spectral exponent. Aggregating all the estimated scaling exponents in a histogram yielded normal Gaussian distribution around the scaling exponent of 1. In other words, the coupling of healthy skilled participants to a repetitive speech task reveals evidence of attraction to pink noise.

If pink noise reflects an optimal coupling for performance, then what are the less-than-optimal types of coupling that the system is moving away from? As we mentioned earlier, pink noise lies between regular and random behavior. Still, how do regular or random behavior appear in this complex system? Little would be gained by positing hard-assembled causes of regular behavior plus different causes of random behavior. Instead, a single control parameter may serve to produce regular and random behavior, as well as behavior in between. The critical value of the parameter should yield pink noise, bracketed by attraction to over-random and over-regular behaviors. So what is the ratio of this control parameter?

Clues came from failed attempts in physics to corroborate self-organized criticality. The designated model system consisted of grains of sand, dropped one at a time to build a pile in which eventually, a dropped grain of sand triggers an avalanche. Volume and time between avalanches were measured repeatedly but, contrary to expectations, sand pile avalanches never became sufficiently large to fill out a scaling relation between size S(f) and frequency (f). They appeared instead to be over-random inertia-driven avalanches, exclusively irregular avalanche behavior. (For a review see [Jensen, 1998].) Self-organized criticality was found only after grains of sand were replaced with kernels of rice [Frette *et al.*, 1996]. The rice kernels varied in their aspect ratio of kernel length to kernel width. Lower aspect-ratio kernels behaved like sand, while rice with higher aspect ratios yielded critical behavior. Higher aspect ratios imply greater surface area to create more friction between kernels, sufficient to build small piles of rice, distributed throughout the larger pile, at or near their threshold for toppling. With so much rice poised to topple, the rice pile could produce the large rare avalanches necessary to fill out an inverse scaling relation between size of avalanche S(f) and frequency (f) of avalanches of that size.

The control parameter of success and failure is the ratio of inertia to friction. The inertia-numerator is a source of over-random behavior, and the friction-denominator is a source of over-regular behavior, cf. [Kinouchi and Copelli, 2006]. Their ratio is the external control parameter of avalanche behavior. The specific ratio is anticipated in the ratio of inertia to viscosity of Reynolds numbers in fluid dynamics and heat transfer [Iberall, 1970], so both ratios are nominated as external control parameters of complexity.

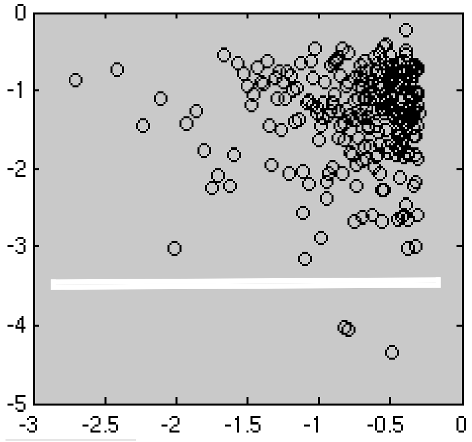

Figure 7. Spectral portrait of a random noise data series. The white line illustrates the slope of a regression line fit to the data: The slope of zero indicates the unsystematic relation between power and frequency.

Piles with 'too much' friction or 'too little' inertia are too coherent and rule-bound, like a mud pile for instance. Piles with 'too little' friction or 'too much' inertia are too random, like a sand pile. Critical behavior is found in the balance between regular and random and the same kind of control parameter can be envisioned for the coupling of task and participant. A control parameter that emphasizes over-regular tendencies yields the over-regular behavior that brackets pink noise; but if the parameter is changed to emphasize over-random tendencies, the coupling between task and person yields an unsystematic relation between size and frequency of variation across repeatedly measured behavior, the over-random bracket.

Loss of structure, due to the over-random tendencies, is indicated in data by a white noise scaling exponent. The spectral portrait of behavior dominated by unsystematic sources of variation is illustrated in Figure 7, mapping out again a relation between size of change S(f) and frequency of change (f). Size is on the Y-axis and frequency on the X-axis and their relation is the flat slope of the white line in the figure. White noise is disorderly, irregular, random noise. Changes of every size are equally likely, as though sizes and frequencies were shuffled and dealt like cards into meaningless pairs. Any particular magnitude of variation is equally likely to be paired with any particular frequency of variation. This is represented in Figure 7 by the flat white line with a slope of zero ($\alpha \approx 0$), the spectral slope of white noise.

The other bracket must be over-regular behavior. However, even the most regularly structured behavior in a living system will appear somewhat irregular, as illustrated in the data graph of Figure 8, from an over-regular heartbeat of a person with congestive heart disease. A spectral plot of the data series resembles *brown noise*, irregular behavior that is dominated by changes on slow time scales. The spectral slope of size

S(f) against frequency (f) is shown in the Figure, very close to an idealized $\alpha \approx 2$. This slope is steeper than the spectral slope of pink noise due to over-regular oscillations in behavior. The steep slope of the line in the spectral plot suggests that large over-regular changes will occur, and that still larger changes quickly become improbable. It emphasizes high-amplitude and low frequency in a relatively narrower range. All three categories of noise -- *white*, *pink*, and *brown* -- appear together in Figure 9, each with their characteristic ideal slopes.

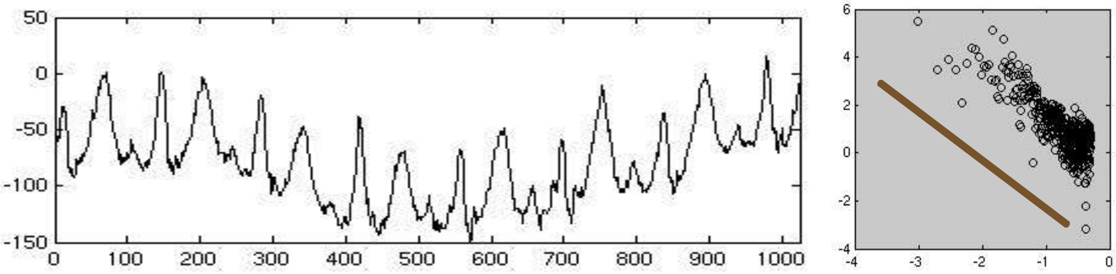

Figure 8. Heart beat data of a patient with congestive heart failure in the graph on the left and a spectral portrait of this data series on the right. The brown line illustrates the slope of a regression line fit to the data: The slope is close to -2, indicating a scaling relation close to that of brown noise with $\alpha = 2$.

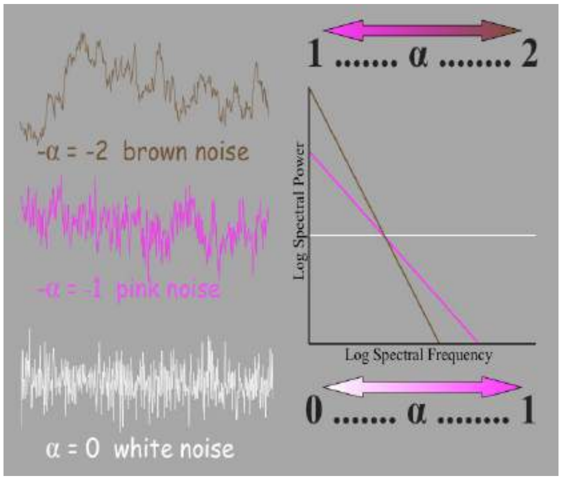

Figure 9. Summary characteristics of brown, pink and white noises. Data series appear on the left (together with their characteristic alpha values), and spectral slopes appear

Self-organized criticality predicts that performance will be drawn toward pink noise and attraction toward pink noise and away from white noise was observed as adults gained practice with a Fitt's tracing task [Wijnants *et al.*, 2009]. Adult participants produced pinker data after practice. Participants were asked to trace between two dots on an electronic tablet as the trace-time from dot-to-dot was measured. After several blocks of practice, 5500 trace-trials total, the central tendency of the spectral plot had

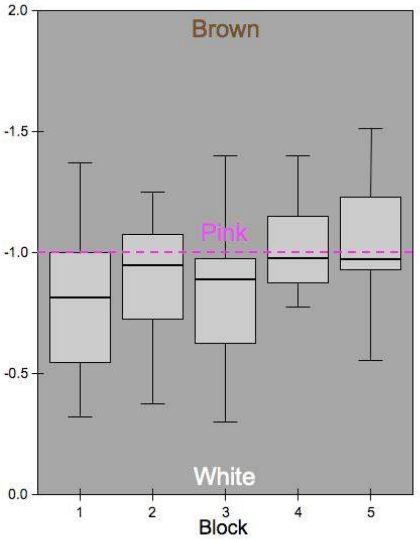

Figure 10. Change in spectral slopes of data series across five consecutive blocks of practice in a Fitt's tracing task.

moved to α ≈ 1 of pink noise. The results are portrayed in Figure 10 to illustrate the statistical character of the phenomenon in developed healthy adults.

In development, performance is drawn toward pink noise from two directions of change. One direction of change was observed in development of gait in walking and the other in cognitive performance of time estimation. In the cognitive task, preschool children and adults were asked to estimate a short time interval over-and-over, pressing a button each time it had passed. Spectral slopes of the variation in their estimates showed a developmental progression toward pink noise, and away from white noise, across age. The attraction was clearly visible in dynamics, while the average estimates only marginally distinguished the youngest children from all other children and adults [Kloos *et al*., 2009].

In the walking task children and adults walked on a treadmill while stride interval times were measured [Hausdorff *et al*., 1999]. Like in the time estimation task, spectral slopes of stride variation showed an attraction toward pink noise as age increased, but this time slopes moved away from brown noise. Spectral exponents of 4 and 5 year-olds' gaits were heavily skewed toward the α ≈ 2 of brown noise, while exponents for adults are distributed narrowly and closer to pink noise (on the white side of pink noise).

What accounts for the changes in development, and the differences between the two tasks? The plausible hypothesis for development overall is that embodied constraints and sensitivity to embedding constraints are not optimally tuned for a child (or for an unskilled adult). While both children and adults could do both tasks, the task-child system was not coordinated optimally. Components that are not well coordinated show more independent variation, which perturbs the task-system coupling of repeated measurement. Across development, children accrue sufficient constraints to better coordinate their bodies with the cognitive task. They better accommodate arbitrary and idiosyncratic task constraints, and they can better sustain constraints of intentions that follow from a scientist's instructions.

A plausible hypothesis for task differences is simply different task demands. In walking on the treadmill, the task-child system shows evidence of over-rigid control. Not unexpectedly, when learning to walk children initially lock out degrees of freedom in legs and body to avoid falling. This over-rigid control yields over-regular behavior and brown noise variation in measured gait. With practice and development the child comes to embody flexible constraints among legs and body to negotiate the varieties of terrain in the world. Fluid constraints allow less rigid control as the body flexibly adjusts degrees of freedom to negotiate the varieties of terrain with smooth gaits.

Taken together, both practice and development reveal attraction toward criticality as pink noise. These patterns provide evidence that critical states are self-organized, meaning that living systems are drawn toward states of flexible coupling in which multiple propensities for action are available. They furthermore mark the endpoint of ideal coordination between body and environment. The next issue we explore then pertains to how the pattern changes as coordination deteriorates.

3.4 Departure from Complexity

Pink noise is most prominent in simple tasks that repeat identical trials, e.g. [Gilden, 1997]. The pattern changes however as tasks get more complicated. For example, the spectral slope is whitened when trial response decisions are made more difficult [Correll, 2008; Clayton and Frey, 1997; Kello *et al.*, 2007; Ward, 2002]. Likewise, in a dual task experiment, walking on a treadmill while repeatedly estimating short time intervals whitened the spectral slope of time estimation [Kiefer *et al.*, 2009]. Fractal patterns of gait in the dual task produced pink noise, probably because walking has greater priority than time estimation. Both tasks produced pink noise as single tasks and the change away from pink noise was only found in the dual-task scenario, and only for the time-estimation task of lower priority.

In principle, one could also imagine a departure from pink noise in the direction of brown noise, as task constraints increased or participants adopted a strategy of over-rigid control. This was the case for toddlers, for example, who locked down degrees of freedom needed for flexible control of gait. Provisional evidence was found in data from a driving-simulator in which lane positions are over-constraining (Geoff Hollis, personal communication, October 6, 2008). Car position data resembled brown noise, but no condition was included that produced pinker data for comparison.

Similar departures from complexity are found in advanced aging and dynamical diseases [Glass and Mackey, 1988]. With advanced age, posture and gait show departure toward white noise in spectral plots, while heartbeat, body temperature, and neural activity (resting fMRI) show a departure toward brown noise. Figure 11 summarizes age related changes. In atrial fibrillation, a rare form of heart disease, heartbeats depart from pink noise in the direction of white noise [West, 2006]. In Huntington's disease, gait departs toward white noise [Hausdorff *et al*., 1997], and in Parkinson's disease, gait, arm movements, and speech all depart in the direction of brown noise. What's more the degree of departure from pink noise toward brown noise reliably predicts the severity of other Parkinson's symptoms [Pan, *et al*., 2007], and the degree of departure toward white noise predicts severity of other symptoms in Huntington's disease [Hausdorff *et al*., 1997].

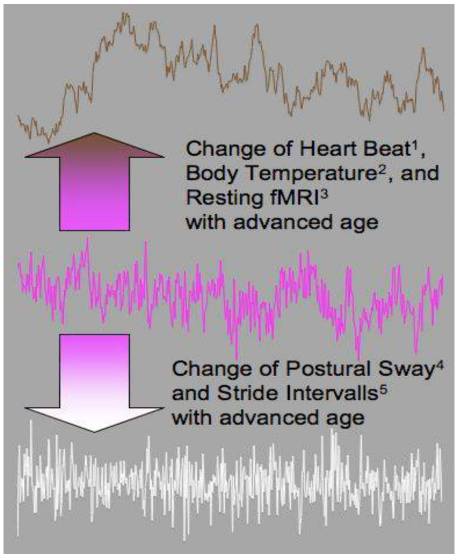

Figure 11. Departures from complexity due to advanced age. References: [1]Beckers *et al*., 2006; [2]Varela *et al*., 2003; [3]Wink *et al*., 2006; [4]Duarte and Sternad, 2008; Lin *et al*., 2008; Norris *et al*., 2005; Thurner *et al*., 2002; [5]Hausdorff *et al*. 1997.

Why does performance deviate from complexity and pink noise in much the same way for task changes, aging, and dynamical diseases? Deviations toward white noise suggest loss of structure in dynamics or sources of unsystematic perturbations to the coupling of task and person, or between organ systems. Changes from pink to brown noise as health deteriorates suggest loss of flexibility in dynamics or sources of over-rigid control. Parkinson's is typified by a loss of flexibility and over-regular movements: Patients can no longer produce smooth kinematics in response to rapid changes in the environment and they have difficulty initiating and controlling motion. Figure 12 organizes Parkinson's symptoms as they might appear in a complexity account and we discuss Parkinson's symptoms next in more detail.

Parkinson's symptoms originate in damage to areas of the brain that produce the neurotransmitter dopamine. Indeed, a conventional causal story might propose that the reduction in dopamine production disrupts a causal chain from stimulus to response, or intention to action. In line with this reasoning, dopamine has been marketed as the causal basis of the mind, the brain-within-the-brain, so to speak [Previc, 1999]. However, most prominent Parkinson's symptoms, including reduced dopamine, have not yet found their place in a causal account. How do gradual changes in dopamine availability produce qualitative changes in perception, action and cognition? Why does Parkinson's erode cognition along with mobility; and why do cognitive symptoms appear idiopathic? Why are fine-grain capacities most vulnerable early in Parkinson's? Basic neural conduction among modules is intact in Parkinson's, and the conduction rate across neurons is plenty fast to move fast-changing information through the nervous system. Why then do early Parkinson's symptoms include disruptions in fast-changing perception-action cycles? The complexity explanation is subtle, speculative, but compelling. The emphasis shifts from a faulty isolated component (such as a faulty dopamine-uptake system) to faulty coupling among components. It is the erosion of system capacities to coordinate mind, body and environment that lead to loss of flexibility in behavior [Edwards and Beuter, 1999; Goldberger *et al*., 2002a; 2002b].

Dopamine bridges synaptic gaps between neurons to perpetuate electrochemical waves of action potentials, like any neurotransmitter. Action potentials create feedback loops of neuronal activity that self-organize into larger traveling waves. Traveling waves are an observable realization of emergent constraints in motor coordination, perception, and cognition [Davia, 2005; Freeman; 2000; Hollis *et al*., 2009; Kelso, 1995]. Damage that reduces dopamine in the brain reduces the capacity for traveling waves to coordinate, which in turn affects cognitive functions, motor coordination, and the dynamics of physiology. Parkinson's is systematically progressive. The first constraints to erode are those that change on the fastest timescales -- they are necessary for detecting subtle changes in emotional tone or social alliances, for making fine-grained perceptual distinctions, and for initiating sudden or rapid movements. In other words, Parkinson's first destabilizes the capacity to rapidly organize or reorganize perception and action.

Erosion of constraints on fast timescales explains the unwelcome palsy in Parkinson's. In a sense, the palsy originates in less refined, less well-coordinated control. Palsy is a kind of overshoot phenomenon, like oscillations in room temperature around a thermostat setting. The relatively preserved capacities for constraint that change on intermediate timescales lack the finer-grain, faster-changing, automatic dithering control of constraints from faster timescales that insure smooth and precise movements. Parkinson's eventually erodes intermediate and slow timescale capacities as well, such that late-stage Parkinson's sufferers appear to express frozen postures and

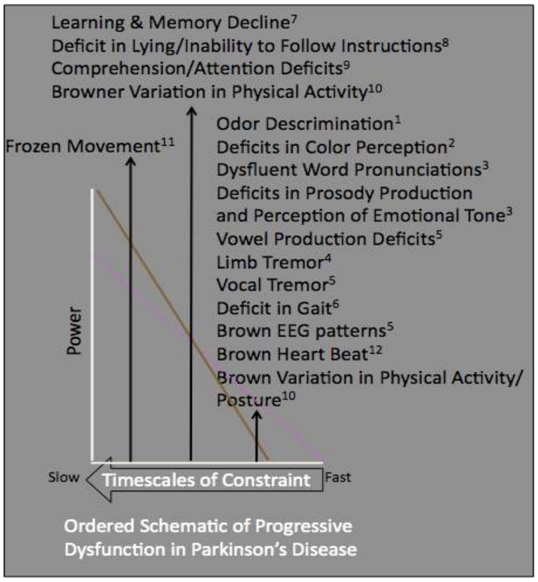

Figure 12. Approximate progression of Parkinson's disease, estimated from the cited descriptions of patients, plus pink and brown noise scaling relations as a backdrop. Parkinson's first erodes constraints changing on fastest timescales and then intermediate and slow changing constraints. Eventually sufferers appear frozen in time although they continue to move on the very slow timescales of very slowly changing constraints. References: [1]Double *et al.*, 2003; [2]Diederich *et al.*, 2002; [3]Ariatti *et al.*, 2008; Lloyed, 1999; Goberman *et al.*, 2008; [4]Aly *et al.*, 2007; Jankovic *et al.*, 1999; [5]Hertrich *et al.*, 1997; Zhang and Jiang, 2008; [6]Blin *et al.*, 1990; Frenkel-Toledo *et al.*, 2005; Hausdorff *et al.*, 1998; Hausdorff *et al.*, 1995; [7]Allain, 1995; Howard and Binks, 2000; Price and Shin, 2009; [8]Abe *et al.*, 2009; [9]Peron *et a*l., 2009; Grossman *et al.*, 2000; [1]Pan *et al.*, 2007; Schmit *et al.*, 2006; [11]Hausdorff *et al.*, 2003; [12]Haapaniemi *et al.*, 2001.

gaits, although in truth they are moving on the very slow timescales of the last remaining capacities to constrain and change behavior.

The protracted unraveling of constraints from faster to slower timescales erodes capacities to coordinate brain, body and world, including the coordination of cognitive capacities. The subsequent deficit or lost cognitive capacities appear to be idiopathic symptoms because cognition expresses the idiosyncratic contingencies of a patient's mental and physical history. Idiosyncratic histories of education, language, work, hobbies, travel, and health shaped the idiosyncratic strengths and stabilities of cognitive capacities well before the Parkinson's began. They in turn shape the expressed cognitive deficits seen in an individual patient. Almost all healthy people walk and manipulate things with their hands much more – and indeed most Parkinson's patients show similar deficits in gait and hand-eye coordination. In some cases, as capacities for constraint and change erode, however, control parameters of coordination cross their critical values. Consequently patients express additional idiopathy as idiosyncratic changes to qualitatively different functioning, qualitative reorganizations of mind and body into tragically dysfunctional modes.

In sum, the accumulated evidence nominates pink noise as the signature of complexity -- its third kind of behavior -- as in variability that is neither too regular nor too random. Pink noise reflects an optimal flexible coordination that a system is drawn toward as it develops or practices. Such optimal coordination can be obtained in accrued constraints (to move performance from white toward pink noise) or by loosening up over-rigid constraints (to move performance from brown toward pink noise). Similarly, pink noise reflects an ideal from which a system departs as coordination deteriorates.

4 CHALLENGES AND OPPORTUNITIES

In this final section, we discuss challenges and opportunities that complexity presents. They include issues pertaining to the interpretation of scaling exponents, the naturalization of intentionality in principles that apply to nature generally, piecewise determinism, and emergent coordination among multiple actors. We discuss each in turn.

4.1 The Scaling Exponent Dilemma

An ideal coordination between task and person reveals itself in pink noise, a fractal pattern with a scaling exponent of about 1. A reasonable conclusion then would be that any scaling exponent reliably above or below 1 reflects a less-than-ideal coordination. More specifically, a scaling exponent closer to zero should reveal a coordination that is over-random, and a scaling exponent closer to 2 should reveal a coordination that is over-regular. Consistent with this interpretation, pink noise is characteristic of healthy adults performing a comfortable task, while white noise was found when task difficulty was increased, expertise of participants was reduced, or participants suffered dynamical diseases.

However, the simple mapping of scaling exponent to kind of coordination does not fit with all the evidence. Take for example continuation tapping, a task in which participants tap from memory after a metronome is turned off. Continuation tapping yields clear pink noise behavioral signals. However, a task in which participants tap in synch to the beat of a metronome produces whiter signals than continuation tapping [Chen *et al*., 2001]. Why so?

Intuitively entrainment in synch with a metronome should reveal over-regular coordination, because the beats of the metronome are so regular. Continuation tapping, without the metronome, should then yield less regular coordination by the same intuition. Going from tapping with a metronome to tapping without should decrease the scaling exponent (reflecting change from over-regular to less regular). Yet, this is not what was found: Variability during entrainment to a metronome yields whiter scaling exponents farther from pink noise.

Another example comes from a time-estimation task, much like continuation tapping, in which participants were either provided with accuracy feedback or not (Nikita Kuznetsov, personal communication, August 23, 2009). Accuracy feedback is another source of external control – like the entraining metronome beat -- and should therefore promote over-regular structure in performance variability. However, while time estimation without feedback yielded a pink-noise signal, trial by trial accuracy feedback whitened the signal. Despite external sources for over-regular control, the structure of variability in both examples showed over-random tendencies. How can these findings be reconciled with the idea that scaling exponents predict the type of coupling between person and task?

The dilemma stems in part from the duality of pink noise, the fact that pink noise is simultaneously regular (it obeys an orderly scaling relation) and irregular (it is aperiodic nonetheless). In every estimate of pink noise, order and disorder trade off in the repeated measurements. A scaling exponent by itself is therefore inherently ambiguous. To understand particular tradeoffs of order and disorder in performance, it is necessary to put the system in motion to examine changes in scaling exponents, rather than a static value. Nonetheless, these facts alone do not remedy the challenge to understand the whiter signals that results from entrainment and feedback.

To address the challenge, we revisit the numerator and denominator of the control parameter we have relied on until now. Recall that the numerator, on the one hand, comes from affordances delimited by embedding constraints of the environment or task. Affordances define the degrees of freedom available to the actor within the task. The denominator, on the other hand, comes from effectivities, which determine which degrees of freedom can be brought under control. In task performance, the degrees of freedom required in a successful performance must correspond as well to controllable degrees of freedom of the person's effectivities.

As for the control parameter in the example of entrainment, external sources of constraint increase when the metronome is running. This changes both the numerator and denominator of the control parameter. The numerator-source of over-random behavior is reduced as the available degrees of freedom are reduced, compared to no-metronome conditions. An environment that supplies more constraint affords fewer degrees of freedom. At the same time, however, the metronome minimizes the denominator, the source of over-regular tendencies. Entrainment to the metronome minimizes degrees of freedom that must be controlled for successful continuation tapping.

The minimum value of the denominator means minimal sources of over-regular variation. Also, the previously person-controlled degrees of freedom, for task success, become available during entrainment as uncontrolled degrees of freedom, adding sources of over-random behavior and increasing the numerator. Altogether, these changes favor over-random sources of variability. A similar argument can be made for trial feedback. Accuracy feedback supplies constraints that reduce available degrees of freedom and therefore reduce requirements for successful performance from the effectivity denominator. This releases previously person-controlled degrees of freedom. Constraints when present imply fewer degrees of freedom, so constraints when absent imply greater degrees of freedom. Whiter behavioral signals result.

However, consider another piece of evidence from the posture of elite ballet dancers [Schmit *et al*., 2005]: A dancer’s torso remains upright, while she is in motion, over her body’s center of balance. This allows the visibly unique gait in which a dancer can appear to glide across the stage. It controls for the ordinary tendency of torsos to move past the body’s tipping and falling point in each step. The over-trained posture ingrains constraints and controls degrees of freedom in posture. These constraints count among the effectivities the dancer brings to the dance. Effectivities are the sources of over-regular variation in measured performance. Nonetheless, a whiter signal is observed in dancers’ posture compared to posture of ordinary adults or different elite athletes. The control parameter that accounted for whiter scaling exponents in entrainment and feedback fails to explain the dancer's whiter posture. To address this challenge, we must address a second challenge, namely that of voluntary control and intentions.

4.2 Naturalizing Intentionality

As discussed in Section 1, intentionality has constituted a major stumbling block for conventional approaches. How then does complexity science solve the problem of intentionality? We have proposed that intentions affect behavior as constraints, not causes. Intentions as constraints are temporary dynamical structures, soft assembled from interdependent components to function in control parameters to create critical states [Riley and Turvey, 2001; Van Orden and Holden, 2002]. Constraints circumvent dilemmas that arose from viewing intentions as causes [Juarrero, 1999]. Constraints are therefor no less natural than causes. Thus the complexity account makes progress toward naturalizing intentionality.

Intentions are of the same nature as other natural constraints and should have the same consequences. In nature, constraints dampen vibration and oscillation for example. Intentions also dampen oscillations in the voluntary actions of Parkinson’s sufferers. The intention to move can eliminate palsy during movements early in the disease, and partly dampen it in later stages. In nature, oscillations happen absent constraints, but properly constrained they disappear. In Parkinson's, the palsy appears in unintentional involuntary movement, but intentional voluntary movement dampens the palsy, so long as voluntary movement exists.

The challenge from ballet dancers' posture still remains, however. We remain stuck with a control parameter that predicts pinker or browner noise in dancers' posture and elite dancers whose posture reveals whiter noise. Otherwise, this control parameter predicted the direction of change for every task and performer we have reviewed, within a plausible account of intentionality. Yet we have not successfully naturalized intentionality, due to contradictory evidence. But to meet this challenge, we look for what is common across the three exceptions here considered. What is it that is common to: (1) entrainment, (2) accuracy feedback, and (3) over-trained posture? Each example includes a prominent source of constraint, and each source of constraint functions to reduce or minimize the demands for voluntary control in task coupling.

The dancer requires less voluntary control to sustain erect posture. She has over-trained posture to stand upright, even balanced on a force plate that measures variation in posture. In contrast, a Parkinson's sufferer exhibits over-rigid control, to not fall down. Over-rigid control in Parkinson's shows up as large deviations around the center of pressure of the force plate [Schmit *et al.*, 2006]. Parkinson's patients produce a browner pattern of variation in posture, compared to healthy control participants who produce pinker variation. Thus reducing the need for voluntary control is associated with whiter signals, and exaggerated purposeful control with browner signals.

This pattern motivates a revision to the control parameter. The key evidence motivating a revised control parameter is that reduced demands for voluntary control in the coupling between task and person yield performance dynamics that depart from pink noise toward white noise. If this fact proves reliable, then reduced voluntary control is reliably distinguished in empirical contrasts by whiter noise, all other things equal.

We may combine affordances and effectivities in the numerator to define available degrees of freedom, which has been the role of the numerator all along. The numerator now equals the difference between degrees of freedom, afforded, versus degrees of freedom that can be controlled (reduced) by effectivities, as embodied constraints. Effectivities have been moved from the denominator to the numerator. What then is the denominator? We suggest that the denominator is volition, itself. Volition picks up the slack, so to speak, the remaining degrees of freedom, and reduces white noise in performance variation.

The proposal presents a historical opportunity. Since Freud, the distinction has been made between consciously controlled, strategic, voluntary behavior versus automatic, unconscious, involuntary behavior. However, no empirical evidence for reduced voluntary control has yet stood the test of time [Fearing, 1970; Goldstein, 1939; Van Orden and Holden, 2002]. Each source of evidence, in its turn, has been found to be equivocal [Bauer and Besner, 1997; Besner and Stolz, 1999a,b; Besner *et al.*, 1997; Kanne *et al.*, 1998; Pansky and Algom, 1999; 2002; Prochazka *et al.*, 2000; Tzelgov, 1997]. Presently, the distinction is supported by intuition alone but if whiter noise in task coupling (departing from pink) is a reliable consequence of reduced voluntary control, then we have naturalized intentionality.

Other challenges remain, however. Intentions satisfy needs and goals of the actor, and in this service, shape critical states that include propensities for serviceable actions. If purposeful behaviors originate in critical states, then it should be possible to connect more dots in analogies with thermodynamic systems, at least that is the challenge. Enacted behavior creates information and reduces the entropy of the critical state. In comparison, physical critical states and phase transitions concern energy and entropy. Thermodynamics creates structure and constrains molecules to better transport energy to more efficiently produce entropy. How does creation of information in behavior coincide, or does it? So far, the answer to this question has not been forthcoming [Nicolis and Nicolis, 2007]. Perhaps soft assembly of action also more effectively dissipates energy, compared to relatively hard-wired behaviors. If so then less probable, creative, and rare actions may most effectively dissipate energy -- or maybe we have it exactly backwards. Or perhaps the debt to entropy is only fully paid by social systems or ecosystems and not by individuals alone, cf. [Ulanowicz, 2000].

Another challenge also stems from critical states of propensities to act. Propensities, in some fashion, anticipate the behavior that will be enacted. Critical states concern the future because they contain anticipated propensities-to-act. However we have not yet discussed a mechanism to acquire information about anticipated activities. To meet this challenge is important as, arguably, anticipation is the quintessential cognitive activity [Changizi *et al*., 2008; Jacob, 1982; Jordan, 2008; Jordan and Hunsinger, 2008].

The opportunity to meet this challenge comes from a recent simulation of anticipation [Stepp and Turvey, 2009]. The simulation used time-delayed coupling. Imagine an environment *leader* and an organism *follower*. The organism is coupled by a time-delay to the environment. Present states of the environment are coupled to past states of the organism. The coupling term is the difference between the *current* state of the environment minus the *previous* time-delayed state of the organism. In the model, the time-delayed organism comes to minimize the difference between its current state and possible future states of the environment. In minimizing the difference, the organism successfully entrains to future environments, see also [Dubois, 2003].

The simulation also shows Pavlovian learning, perhaps the most well known example of anticipation. Imagine now the food served to Pavlov's dog, the current state of the *leader* environment, which co-occurs in delay-coupling with a past state, a sounded bell. The sounded bell's relation to the food is captured as a regularity by which to anticipate the future. The drooling dog's unconditioned-response thus becomes a means to better contend with uncertainty, to anticipate the arrival of food [Stepp and Turvey, 2009]. Indeed, the delay-coupling model shares formal parallels with a contemporary model of conditioned regulation [Dworkin, 1993].

The model predicts, necessarily, that anticipation is based on statistical regularities between past and future. Pavlov's sounded bell preceding dog food might have been 100% reliable, but most future events are much less certain and can only be known in their statistical broad strokes. Low-frequency large-magnitude oscillations in pink or brown noise are examples of broad statistical regularities. Similar regularities occur in chaos which was used to corroborate the prediction. Anticipatory tapping of college student participants successfully distinguished long-range statistical structures of different chaotic signals in metronome beats [Stephen *et al.,* 2008]. The simulated model plus its empirical support suggest a near term opportunity to integrate anticipation of the future with anticipatory propensities

to act.

4.3 Piecewise Determinism

We have relied throughout on a control parameter of task coupling that takes on different values based on task and participant. If this parameter changes its values midstream, so to speak, during performance of the task, it may also explain piecewise determinism. Piecewise determinism is behavior that changes abruptly and discontinuously [Riley and Turvey, 2002]. For example, a task coupling may change with lapsed attention or vigilance, a change in strategy, or some other reorganizing change. Task performance may even change contingent on where the previous trial's performance leaves the performer, regarding the next trial's task demands.

Piecewise determinism illustrates a challenge for measurement that stems from blind spots inherent in spectral analyses and other linear methods to estimate scaling exponents. Spectral analyses assume that data series express idealized dynamics, smoothly continuous over time. The assumptions are called Lipschitz conditions of equations that are everywhere differentiable [Strogatz, 1994; Zak, 1993]. Analyses that assume Lipschitz conditions are blind to piecewise determinism. Nevertheless, these violations of Lipschitz conditions have empirical consequences, which are realized in both quantum mechanics and are also mundane features of behavior [Zbilut, 2004]. In a key-press experiment, for example, the finger approaches a singular solution, the contact point, in finite time (response time). ‘Singular solutions in finite time’ are a predicted ‘pathology’ of systems that violate Lipschitz conditions [Strogatz, 1994]. Across trials, successive ‘intersecting singular solutions’ occur when the finger presses the same key repeatedly, another pathology confirmed.

Violations of Lipschitz conditions are found in system behaviors that start and stop and repeat themselves in piecewise determinism. The fact that piecewise behaviors have explanations in quantum mechanics presents an opportunity to broach piecewise determinism in human behavior, cf. [Giuliani *et al*., 1996]. Formal analogies can bootstrap studies of piecewise human behavior, an opportunity also recommended by a growing menagerie of recognizably quantum-like phenomena in cognitive science [Atmanspacher *et al*., 2008; Atmanspacher *et al*., 2006; Bruza and Cole, 2005; Bruza *et al*., 2009; Kelso and Tognoli, 2007; Nelson and McEvoy, 2007; Turvey and Moreno, 2006; Van Orden *et al*., 2010].

Piecewise determinism has also been discovered in task coupling data. Reanalyses of data series from Wagenmakers *et al*. [2004] and Van Orden *et al*. [2003] found piecewise determinism, where none had been reported previously [Ihlen and Vereijken, in press]. In these data, the evidence for piecewise-determinism is like abrupt changes in spectral slopes and scaling exponents during data collection. The abrupt changes are also equivalent to abrupt changes in fractal dimension. Thus piecewise data series divide into pieces with different fractal dimensions. Data with multiple fractal dimensions are called multifractals and it was advances in multifractal analysis that made possible the detection of piecewise-determinism. Previous multifractal methods required much more data than these series contained [Van Orden *et al*., 2003].

Contemporary wavelet methods are multifractal analyses to analyze shorter data series. Wavelet methods detect abrupt local changes in fractal dimension using a moving cone of wavelets; the tip of the cone hits each data point in its turn to examine local task coupling. Wavelet analysis yields a second measured aspect or dimension of data series along with a scaling exponent. Task coupling varies along two outcome measures: a center value and a spectrum of values around the center. The center value is approximately equal to the value got from a monofractal analysis, so center values can be expected to corroborate changes toward pink noise or departing from pink noise. In addition however the width of the spectrum, around the center value, varies from wide, to narrow, to virtually no dispersion at all, and the width varies independently of the center value and gives independent information about task coupling (Espen Ihlen & Beatrix Vereijken, personal communication, August 12, 2009).

The extra outcome measure allows that different task-person couplings may be more-or-less multifractal along with being more-or-less pink, a kind of more-or-less *piecewise homeorhesis*. It remains to be discovered whether optimal coupling will turn out to be multifractal pink, so to speak, or monofractal pink, or sometimes one, sometimes the other. By comparison, a protracted debate about heart dynamics concludes that cardiovascular wellness is associated with healthy multifractal dynamics [Baillie *et al*., 2009] versus unhealthy monofractal brown noise in congestive heart disease [Ivanov *et al*., 1999].

4.4 Joint Action

We began this essay with two examples, a barrel racer racing and a teacher teaching, to introduce the central ideas of coupling and coordination. The focus throughout, though, has been the task performance of individuals, and not the coupling between multiple actors as in the joint action of horse and barrel racer. The rider's skill, to move jointly with her horse, and the horse’s skill, to move jointly with the rider, are the basis for their expert coupling to the race course. With skill, coordinative structures emerge in joint action between these members of different species. Joint actions include many opportunities for complexity science, and we remedy the omission in this last section.

Recent efforts on joint action promise a synthesis or rapprochement between conventional science and complexity science. The opportunity came into being with the recognition of language as joint action [Clark, 1996] and an emphasis on the role of language to facilitate coordination [Brennan and Hanna, 2009]. Notice the implicit feedback loop from action-to-language and language-to-action. This feedback loop allows joint attention to reduce demands on language communication in a joint task, for example [Clark and Krych, 2004]. Coordination cannot be encapsulated in a task-person coupling; it emerges across actors.

The capacity for joint action is present within the first year of life [Carpenter, 2009] and constraints that emerge in joint interaction affect the architecture of cognition [Sebanz *et al*., 2006]. Notice another feedback loop, joint action supports cognitive development that makes more and new joint actions possible. Similar but much slower feedback processes have been posited in the prehistory of human evolution, and the posited feedback loops are tested in experimental semiotics to see whether similar joint actions among contemporary participants bootstrap modes of communication [Galantucci, 2009].

Joint action studies discovered coordinative structures that emerge across individuals. In the classic demonstration, human participants swung their legs together as paired volunteers [Schmidt, 1989]. One of two coordinated patterns emerged: in-phase or anti-phase leg movements between the pairs. Phase dynamics of paired leg swinging revealed phase transitions from one pattern to the other, with concomitant catastrophe flags [Schmidt *et al*., 1990]; see also [Richardson *et al*., 2007].

Again, the central tenet of complexity science is that common principles of emergence operate at multiple levels of organization in complex systems -- individuals, dyads, groups, society -- though each level may also bring into existence new possibilities for action [Marsh *et al*., 2009]. For example, both conventional and complexity studies of joint action suggest that coordination is the basis of social affiliation, and social affiliation is crucial for individual health and emotional wellbeing, another feedback loop.

Conventional studies discovered a predictive relation between social affiliation and non-conscious mimicry [Lakin and Chartrand, 2003]. The details of coordination dynamics greatly expanded this finding. A variety of manipulations affect the capacity of two individuals to entrain and the same manipulations determine how positive, friendly, and harmonious volunteers rate the experience, and each other as possible teammates [Marsh *et al*., 2006; 2007]. The degree of entrainment determines whether volunteers like each other [Ouillier *et al*., 2008].

The strength of entrainment falls off depending on whether individuals can fully focus attention on each other [Richardson *et al*., 2007]. The basis for entrainment need not be visual however [Richardson *et al*., 2005]. Two people can perform as one, although they receive only indirect auditory feedback about each other’s actions in their separate roles within a shared eye-hand coordination task [Knoblich and Jordan, 2003]. Subtle cues organize dynamics across the two people to perform together as well as a single person with all the information. Does this imply emergent joint intentionality?

Joint action has also become a focal area to introduce new nonlinear methods. Cross-Recurrence analysis, a nonlinear counterpart to correlation, was developed specifically to study shared movements, as in conversations [Shockley, 2005] and was anticipated in Recurrence Quantification Analysis, a nonlinear analog of autocorrelation [Weber and Zbilut, 2005]. These methods were built upon the mathematical theorems of phase space reconstruction, mentioned much earlier. Cross-Recurrence analysis was used first in cognitive science to quantify emergent, coordinative structures between persons in conversation. Joint gaze and joint body posture show spontaneous coordination that predicts mutual understanding. (For a review see [Shockley *et al*., 2009].)

Nonlinear methods have become more common and existing nonlinear tools, plus new tools in development, promise a truly fresh understanding of behavioral data, e.g. [Marwan, 2009; Riley and Van Orden, 2005; Zbilut and Marwan, 2008]. In retrospect, earlier accomplishments in cognitive science, though inspired by new theoretical ideas from complexity science, were also restricted by caveats on data tools from linear analysis. Future discoveries will benefit from new nonlinear tools that minimize or dispense with such caveats. We stand now, surrounded by opportunities, at a cusp linking theory with new rigorous methods for this science of complexity.

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