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Dynamic Encounters: Long Memory During Functional Stabilization

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We explored the problem of actively stabilizing an inherently unstable system. A method for analyzing scale-invariant time series was used to examine hand displacement and rod angle of an inverted pendulum actively balanced by normal individuals. Estimation of the Hurst exponent revealed long-term fractal correlations for more than 3 min into the past. Two regimes, a short-term time scale of positive correlation (persistence) and a long-term time scale of negative correlation (antipersistence), were revealed, and their transition points were modulated by the rod's natural frequency. Such nonlocal temporal structure constitutes a physical characteristic known as *long memory* and may be considered inherent to the coordination dynamics itself. The implications of long-memory processes are discussed in terms of the dynamical mechanisms underlying ecological encounters and how affordances require a persisting environment for their definition.

Evidence and theory suggest that the coordination of human perception and action may be understood as a self-organizing complex system that exhibits great flexibility by operating nearby critical points of instability. Although stability has emerged as the central theoretical concept for the dynamical understanding of coordination in perception–action tasks (e.g., Kelso, 1995; Turvey, 1990), the implications of a more basic state—instability—and its associated variability have only recently been fully recognized within the motor control literature (Newell & Corcos, 1993). Be-

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cause of the uncertainty and idiosyncracies that an overarching context of instability affords, a behavioral system must rely on dynamical mechanisms that not only accept fluctuations as inherent to the process of control but also be able to exploit such instabilities for the system's own requirements. Further, such a dynamical mechanism must be sufficiently generic to exhibit the property of generating compatible control strategies across many different spatial and temporal scales. Indeed, a significant characteristic of a complex system is that it manifests similar phenomena across multiple spatio-temporal scales. That is, a complex system exhibits properties of scale invariance and self-similarity (Mandelbrot, 1982; Voss, 1989) in virtue of operating nearby critical points in which fluctuations occur at all space and time scales (Bak & Chen, 1991).

The problem of achieving functional stability within a context of instability appears in many domains including brain dynamics (McKenna, McMullen, & Shlesinger, 1994), postural stability, and engineering problems such as the control of locomotion in legged robots (Jordan & Jacobs, 1990; Raibert, 1986; Werbos, 1994; White & Sofge, 1992). Furthermore, learning, adaptation, and long-term development can now be conceptualized in terms of stabilizing previously unstable patterns of behavior (Thelen & Smith, 1994; Zanone & Kelso, 1992). However, current models typically exhibit dynamics that are restricted to stable states such as limit cycles or point attractors. Mode-locking, if present, means fixed phase- and frequency-locked states, although the aperiodicity of chaotic dynamics has been used to capture fluctuations such as those in sleep and postural control (Freeman & Skarda, 1985; Yamada, 1995).

Behind dynamical accounts of human perceptual–motor performance is the assumption that the experimental data reflect trajectories that, given infinite time, would have asymptotically evolved onto a stable, stationary attractor (Kugler & Turvey, 1987; Treffner & Turvey, 1995, 1996). In contrast, recent biological experiments have shown that stationarity is an exceptional and rare state of affairs. More often than not, biological systems (including the human brain) tend to avoid stable attractor dynamics (Fuchs, Kelso, & Haken, 1992; Kelso & Ding, 1993; Kelso & Fuchs, 1995). Thus, although the cooperative behavior of hypothesized neural ensembles exhibits tendencies for attraction toward fixed phase- and frequency-locked states (e.g., Peper, Beek, & van Wieringen, 1995; Treffner & Turvey, 1993), a more precise analysis reveals that such ensembles exhibit only relative coordination (DeGuzman & Kelso, 1991).

Recent studies of the neural correlates of perception–action phenomena have revealed that near behavioral instabilities or critical points low-dimensional dynamics govern human cortical activity as measured by highly sensitive bihemispheric superconducting quantum interference devices (Fuchs et al., 1992; Kelso et al., 1992; Kelso & Fuchs, 1995) and electroencephalogram arrays (McKenna et al., 1994; Wallenstein, Nash, & Kelso, 1995). At these critical points, cortical activity may be characterized by only a few spatial modes (i.e., degrees of freedom) and their corresponding time-dependent amplitudes. Importantly, the relative phase between the neural modes is specific to the corresponding behavioral transitions observed during the coordination task. Theoretical considerations together with neurophysiological data indicate that the underlying process in such situations is not that of settling onto a stable attractor but rather that the system tends to dwell in coherent metastable states, often inhabiting a region near instability. Hence, by introducing a small degree of stochastic fluctuations to the model equations (assumed to reflect real biological noise), the stability of patterns may be probed and new regimes discovered appropriate to the external conditions. These examples illustrate a fundamental point: Generic mechanisms (inherent to the dynamics) exist for entering and exiting neural and behavioral states. The transitions found in brain dynamics provide a mechanism for rapidly switching between metastable states and, hence, confer the necessary flexibility and adaptability to satisfy task-specific exigencies.

The preceding summary of recent discoveries in the dynamical and neurodynamical bases of behavior does not imply that the microscopic, neural determinants of behavior have been found or take precedence over other levels of description. Indeed, within the ecological approach to psychology, it has been emphasized that to gain insight into behavioral principles, one should carefully determine the appropriate grain size and units of analysis commensurate with the phenomenon to be explained (Shaw & Turvey, 1981). Consequently, it has been suggested that the appropriate unit and level of analysis for ecological psychology is the *encounter*, that is, an event at the macroscopic, ecological scale that involves the organism interacting with its environment (or another organism) via the detection of invariant quantities within the surrounding ambient energy distribution (i.e., information; Reed, 1996; Warren & Shaw, 1985).

To investigate the ability of an actor to harness a context of instability at the ecological scale of encounters, an experimental window is required that reduces the problem to its bare essentials but that retains the richness and complexity of the basic phenomenon. To this end, we investigated the dynamics underlying the ability to balance an inherently unstable inverted pendulum in a relatively stable, upright orientation. Stabilizing an inverted pendulum provides a paradigmatic instance of "intelligent control" (Makarovic, 1991; Miller, Sutton, & Werbos, 1990; Werbos, 1994). Within a biological context, problems include those of how an actor (and a brain) learns to stabilize and adapt over time within an intrinsically unstable and potentially unfamiliar context and how the functional topology of an action system is revealed in spatio-temporal (not instantaneous) patterns of movement variability (Riccio, 1993; Riccio, Martin, & Stoffregen, 1992; Stoffregen & Riccio, 1988). A classic problem in control engineering, pole balancing by human individuals exhibits behavior quite distinct from analogous engineering models (e.g., Barto, Sutton, & Anderson, 1982; Sutton, Barto, & Williams, 1992; Suykens, DeMoor, & Vandewalle, 1994). The aperiodic trajectories observed depart from the highly uniform, periodic oscillations obtained through conventional techniques such as neural nets. The problem of how to stabilize an unstable fixed point may bear some resemblance to the problem of stabilizing a chaotic system. However, whereas control of a chaotic system involves continually perturbing the behavioral trajectory onto one of an infinite number of preexisting unstable periodic orbits (Garfinkel, Spano, Ditto, & Weiss, 1992; Kelso & Ding, 1993; Schiff et al., 1994), functionally stabilizing an unstable system requires continual perturbation and results in behavior that is functionally stable, but aperiodic. We hypothesized that the aperiodicity observed in many human tasks requires continual active control—it does not exist a priori—and that it requires a special kind of contact between actor and environment; that is, it requires information-based coordination (Gibson, 1979/1986; Kelso, 1994; Reed, 1996; Turvey, 1990). In pole balancing, if control stops, the pole drops; the unstable fixed-point repeller in the dynamics of a vertically balanced rod implies a falling rod.

Complementing the analysis of information-based coordination underlying particular phase transitions in behavior (e.g., Kelso, 1994), one can inquire whether a more global analysis focusing on the statistical properties of the ensemble average of trials can yield signatures characteristic of a dynamical self-organized system. That is, are the two levels of analyzing experimental trials (individual vs. ensemble) compatible, and can a global analysis provide insight into how the dynamical mechanism underlying functional stability is designed? Such a statistical dynamics strategy has proved particularly successful in the physical sciences like thermodynamics and statistical mechanics in which the Gibssian ensemble average plays a prominent role (West & Deering, 1996).

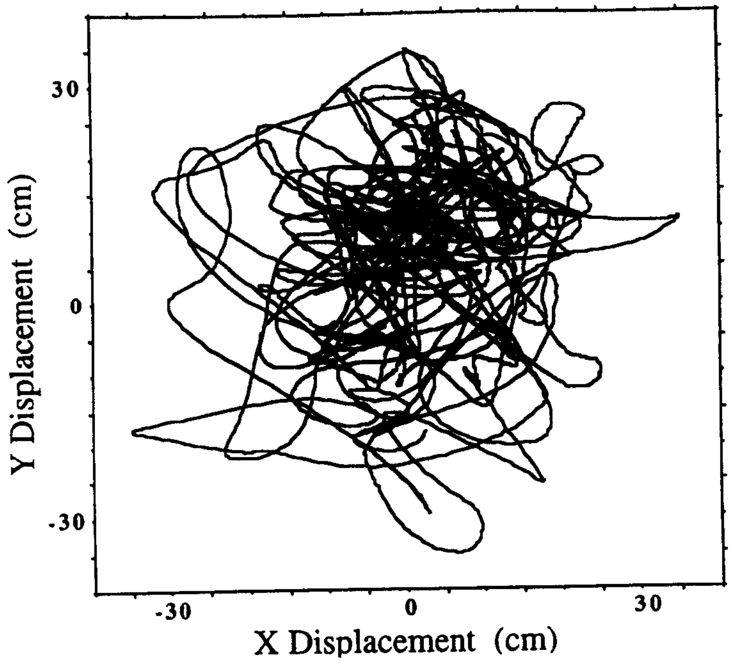

FIGURE 1 Two-dimensional projection onto the ground plane of a three-dimensional pole-balancing trial.

Figure 1 shows the trajectory of a finger obtained from a participant freely balancing a pole in three-dimensional space. Such trajectories are quite typical of the pole-balancing task, and when projected onto the horizontal plane (e.g., the floor), such trajectories seem to contain little order or pattern. Indeed, they resemble a *random walk,* defined as a trajectory that possesses no correlation from one step to the next. Thus, any direction is equally likely from one moment to the next—it is random. Given this resemblance, we investigated whether the kinematic trajectories of the putative variables specific to action (hand position) and those specific to perception (rod angle from vertical) conform with stochastic dynamics. A stochastic time series analysis technique involved calculation of the Hurst exponent to determine whether some degree of order was embedded within the apparently disordered perturbations produced by the hand during balancing.

METHOD

Apparatus

A one-dimensional pole-balancing apparatus was constructed, consisting of an aluminum rod constrained to pivot about a precision bearing inserted into the base of the rod. The pivot was attached to a linear bearing and, hence, restricted the pivot-housing assembly to slide along a one-dimensional steel track 180 cm in length. Toppling motion of the rod was constrained to the two-dimensional, frontal plane (Figure 2). The complete assembly was positioned on a table adjusted to waist height.

Six different aluminum rods were tested (30, 45, 60, 75, 90, and 105 cm) with corresponding natural frequencies of 0.91, 0.74, 0.64, 0.57, 0.53, and 0.49 Hz, respectively, and natural periods of 1.10, 1.35, 1.56, 1.74, 1.90, and 2.06 sec, respectively. The whole apparatus was positioned on a table such that the pivot of the rod was 1 m above the floor, which approximately corresponded to the waist height of a participant.

Participants

Four normal, right-handed graduate students (two men and two women) from Florida Atlantic University participated in the experiment. None of the participants had prior experience of the pole-balancing task.

Procedure

Each participant was asked to balance the rod for as long as possible or until the experimenter indicated the trial was complete. Displacement time series were re-

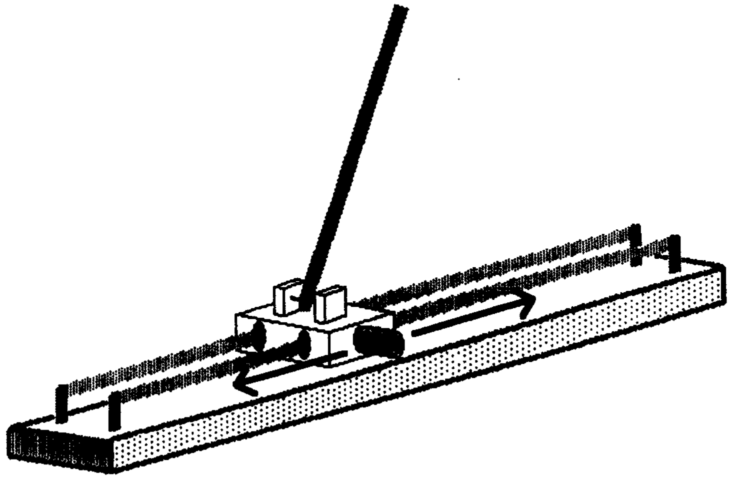

FIGURE 2 Pole-balancing apparatus showing one-dimensional track along which the bottom of the rod plus hand can laterally move.

corded at a sampling frequency of 100 Hz using an Optotrak camera (Northern Digital, Waterloo, Ontario, Canada) with infrared light-emitting diodes placed at the bottom, the middle (center of gravity), and the top of the rod. The displacement and the angular deviation from vertical was detected in the frontal plane, providing the two time series from which further measures were computed. The participant was free to stand and move laterally in front of the balancing apparatus set on the table. Thus, the participant actively controlled the inverted pendulum by using his or her forefinger and thumb to grip the pivot housing and, hence, sliding the bottom of the rod from side to side. To facilitate acquisition of the balancing skill, individuals attempted to balance the longer (and easier) rods before attempting the shorter (and more difficult) rods. For reasons of subsequent data analysis requirements, we asked participants to attempt to balance for as long as possible up to a possible limit of 5 min. Three consecutive 5-min trials were required before the participant proceeded to the next shorter rod. At the sampling frequency used, each 5-min trial resulted in a time series consisting of 30,000 data points.

Analysis

The relation between noise and temporal random processes was emphasized by Mandelbrot (1982) in his development of fractional Brownian motion. This concept permits the quantification of the type of noise or randomness underlying a stochastic process. In pure Brownian motion, no correlation exists between the direction or size of the steps in a time series; it is purely random. In a fractional Brownian

process, some degree of "constrained randomness" may exist, and when it does, the correlations simultaneously exist across multiple time scales. Fractional Brownian motion is, therefore, related to the geometry of self-similar structures and its quantification through the fractal dimension (Feder, 1988; Mandelbrot, 1982; Voss, 1989). Such fractal temporal structure is not only of mathematical interest but may be due to underlying generative dynamical mechanisms (Liebovitch & Yang, 1997; Mannella, Grigolini, & West, 1994).

Consider as an example the process that generated the spatial, two-dimensional, $x(t)$, $y(t)$, trajectory or *trail* shown in Figure 1 (trails do not possess a temporal dimension). If we then, as is typical, plot the time series of this trail for a single dimension—for example, $x(t)$ versus t—we obtain the *trace* of the variable $x(t)$ that is implicit within the spatial trail. Typical traces of simulated data are shown in Figure 3. Note that the trace is a time series of the integral or sum of the *increments*, $\Delta x(\Delta t) = x(t_2) - x(t_1)$. For pure Brownian motion, the increments, Δx, have a Gaussian distribution (i.e., fractional Gaussian noise or white noise) and have mean square displacement or variance:

$$\langle \Delta x^2 \rangle \propto \Delta t \qquad (1)$$

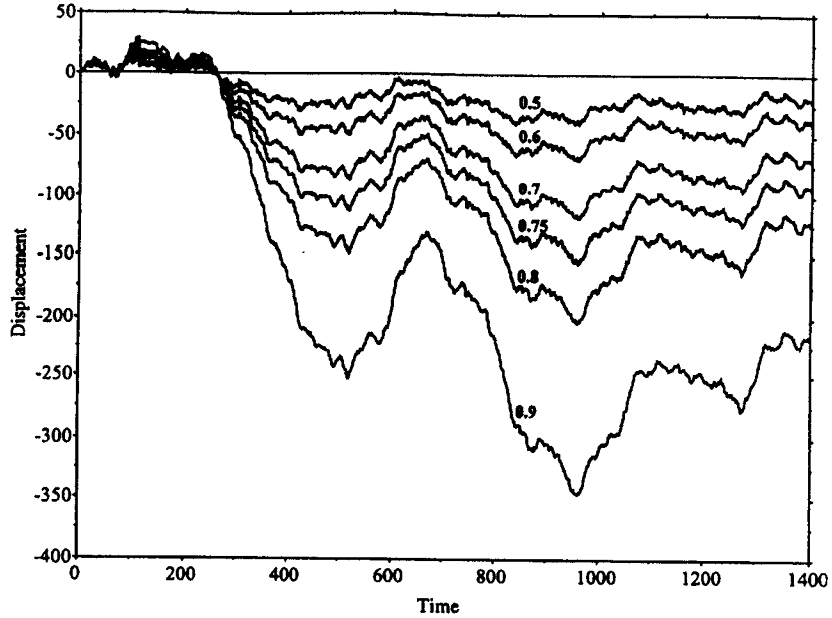

FIGURE 3 Traces of six mathematically generated time series of known Hurst exponents, $Hs = .5$, .6, .7, .75, .8, and .9, where $H = .5$ corresponds to pure Brownian motion.

where the angled brackets denote an ensemble average calculated over many samples. Hence, the step size, Δx, increases as $\sqrt{t}$, which is the defining characteristic of a random walk. In pure Brownian motion, the mean square increments only depend on the time difference, Δt, where all ts are statistically equivalent. Hence, Brownian motion possesses the property of independent increments, and future changes in $x(t)$ are completely independent of previous increments (Voss, 1992).

The relation in Equation 1 can be generalized to include motion that is not strictly Brownian, that is, fractional Brownian motion (Mandelbrot, 1982):

$$\left\langle \Delta x^2 \right\rangle \propto \Delta t^H \tag{2}$$

where the parameter, H, has a value $0 < H < 1$. Known as the *Hurst exponent*, H is a measure of the dispersion or spread generated by a fractional Brownian process. It describes the type of correlation that exists between some point in the time series of the process and all other points in the past. For pure Brownian motion, $H = .5$, and Equation 1 is reproduced describing the situation of independent increments in which no correlation exists between some point in the present and all points in the past. Such behavior is completely random (Figure 3, $H = .5$). However, if $H \neq .5$, global correlation exists at many and arbitrarily long time scales. If $H > .5$, there is positive correlation of the increments, and the direction of change in past increments is preserved; this is called *persistence*. The positive correlation coefficient will increase from 0 to 1 as H increases from .5 to 1. For example, increases (or decreases) in the past will tend to be followed by increases (or decreases) in the future. Conversely, with $H < .5$, there is negative correlation of the increments, and the direction of past increments is reversed; this is called *antipersistence*. The negative correlation coefficient will decrease from 0 to –.5 as H decreases from .5 to 0. That is, increases (or decreases) in the past will tend to be followed by decreases (or increases) in the future. Processes with $H \neq .5$ and, hence, correlations between the increments, are said to exhibit long-run or long-range correlations between the increments, are said to exhibit long-run or long-range correlations (Beran, 1994; Mandelbrot & Wallis, 1969). Figure 3 shows the time series of six data sets of known H mathematically generated using the midpoint displacement algorithm (Peters, 1991; Voss, 1989). It is clear that, as H changes from $H = .5$ (random walk) through $H = .9$ (high positive correlation; persistence), the profile becomes increasingly smoother with less change in direction from moment to moment.

Note that each time series in Figure 3 displays a trace of the increments, that is, the integral or running sum of the increments.

Scaling relations such as that in Equation 2 imply that a single, predominant scale of measurement does not exist and that the patterns exhibited will be fractal or self-similar at multiple spatial scales, temporal scales, or both. Thus, the same kind of correlation results as the times series of increments is viewed at increasingly greater magnification levels. However, the scaling in so-called "random fractals" is not exactly equivalent to the self-similarity of spatial fractals (Mandelbrot, 1982; Voss, 1989). Given the composition ofEquation 2, to magnify both temporal and displacement axes by similar amounts, different scaling factors are required. Precisely, when $H \neq .5$ the time series is self-affine rather than self-similar, meaning that, if the temporal scale is increased by a factor N, the spatial scale need only be increased by the smaller factor, N^H. Thus, under magnification, the spatial dimension enlarges faster than the temporal dimension. Thus, although a trace (in time) may be self-affine, the trail (in space) will be self-similar. Because self-similarity and self-affinity have the property of dilation invariance, the fractal analysis of temporal perception becomes an essential addition to the psychophysics toolbox (e.g., Gilden, Thornton, & Mallon, 1995).

The Hurst exponent for a time series can be estimated using the technique of variance analysis as given in Equation 2. Experimentally, this involves recording the kinematic time series (the trace) of some variable, x, and then, in correspondence with Equation 2, retrieving the exponent by calculating the slope of the linear region in a log–log graph of Δx^2 versus Δt (e.g. Collins & De Luca, 1993, 1994, 1995a, 1995b; Mitchell, Collins, De Luca, Burrows, & Lipsitz, 1995; Newell, Slobounov, Slobounov, & Molenaar, 1997; Riley, Mitra, Stoffregen, & Turvey, 1997; Riley, Balasubramaniam, Mitra, & Turvey, 1998; Treffner & Kelso, 1995b). However, problems exist with the estimation of H using this technique because periodicities in the underlying process may emerge as prominent "small-amplitude, low frequency oscillations" (Collins & De Luca, 1995b, p. 61) in the log–log graph, thus eliminating the possibility of a valid linear fit (see also Newell et al., 1997; Riley et al., 1998; Treffner & Kelso, 1995b). One method of alleviating the problems due to inherent periodicities is to average over trials and over participants to smooth out the variability (Collins & De Luca, 1993). Further problems remain when attempting to determine the extent of the linear region, especially if the two moderately linear regions are connected by a small smoothly curved "elbow." This problem is addressed either by estimating the linear region by eye or including points until some threshold for the linear fit is passed (e.g., $r^2 = .985$; Riley et al., 1997). Finally, it has been shown that the above variance analysis method tends to underestimate the time of transition from persistence to antipersistence by as much as an order of magnitude when compared to alternative methods (discussed next; Liebovitch & Yang, 1997).

An alternative approach to the variance analysis method of estimating H is rescaled-range (*R/S*) analysis. This method was discovered and employed for hydrodynamical analysis by Hurst (1951) in an analysis of the pattern of annual discharge for the Nile River and its long-term storage by the Aswan Dam. The ratio of the range relative to the standard deviation, *R/S*, describes how the dispersion (range) of a measured variable within some temporal window, Δt, increases (or decreases) as Δt increases (Bassingthwaighte, Liebovitch, & West, 1994; Feder, 1988; Liebovitch, 1998; Liebovitch & Todorov, 1996; Schepers, van Beek, & Bassingthwaighte, 1992). *R/S* analysis involves calculating the range, R, for the original data in a time series for multiple nonoverlapping windows, Δt, where Δt is chosen to be a power of 2 (to allow equal logarithmic binning), and the maximum Δt is no greater than half the maximum length of the time series (to ensure at least two samples at the largest window size; Bassingthwaighte et al., 1994). The present algorithm was tested for accuracy by applying it to a set of time series that were mathematically generated to have a known Hurst exponent (Peters, 1991). Because this experiment involved trials of 300 sec in duration, the values of Δt chosen were 0.02, 0.04, 0.08, 0.16, 0.32, 0.64, 1.28, 2.56, 5.12, 10.24, 20.48, 40.96, and 81.92 sec. For a given Δt, the range, R, was normalized by the standard deviation, S. Note that in accordance with standard procedures (e.g., Bassingthwaighte et al., 1994; Churilla et al., 1996), S is computed using the increments, Δx, rather than the raw recorded values of the time series— for example, hand displacement, $x(t)$, or rod angle, $\theta(t)$. A mean value of R/S was then computed from the various estimates of R/S for given Δt.

From an analysis of approximately 900 natural time series (e.g., lake levels, tree rings, sunspots, mud varves), Hurst developed an empirical power-law relation between R/S and Δt (Feder, 1988):

$$\frac{R}{S} \approx \Delta t^{H} \tag{3}$$

From Equation 3 it is possible to estimate the value of H from the gradient of the graph of $\log(R/S)$ versus $\log(\Delta t)$, using least squares linear regression to yield both an estimate of H and an accuracy of the linear fit. If a linear region is found across several orders of magnitude of Δt, then scaling is said to exist, and the Hurst exponent is an estimate of the global correlational structure across multiple time scales.

Although scaling may exist within a time series, inspection of the log–log graph of R/S versus Δt may indicate that a single linear fit is impossible, possibly implying that more than a single scaling region exists. In such cases, two linear regions can sometimes be found with a transition point in which one regime switches to the other. For example, persistence ($H > .5$) may exist over a short-term time scale, and antipersistence ($H < .5$) may occur over a long-term time scale. Such a bilinear region implies that the underlying dynamic may involve a unitary process that exhibits both short-term and long-term behavior (e.g., Newell et al., 1997; Treffner & Kelso, 1995b, 1997). Alternatively, separate open-loop and closed-loop control processes have been proposed to establish the persistence and antipersistence regions found in postural balance data (Collins & DeLuca, 1993), although the interpretation of persistence as a signature of an open-loop postural control process has been questioned (Newell et al., 1997; Riley et al., 1997; Riley et al., 1998).

RESULTS AND DISCUSSION

Strategies of Control

Inspection of the displacement time series revealed that the top of the pole was usually displaced the least in comparison to the middle and the bottom of the pole (Figure 4A). Hence, the resultant behavior of the actively stabilized rod appeared to

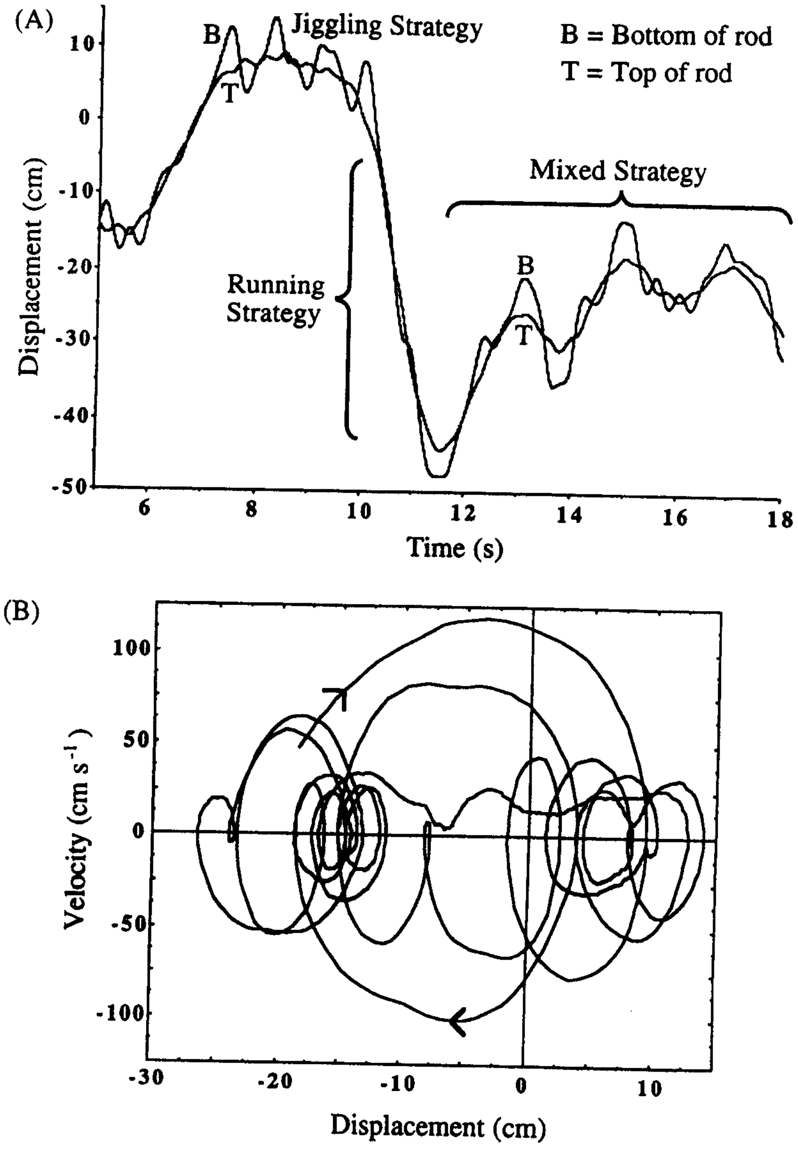

FIGURE 4 (A) Time series of a representative trial showing the three strategies that participants typically invoked while balancing a rod using the one-dimensional pole-balancing apparatus. (B) Phase plane representation of the same data depicted in (A). Cycles within cycles were apparent, indicative of the lack of simple limit-cycle behavior.

pivot around the top of the pole (as in a normal gravity pendulum) rather than the bottom (as in an inverted pendulum).

The position–velocity phase plane suggested that the dynamics were not simply that of a periodic limit cycle typical of a simple gravity pendulum and were not that of the asymptotic convergence onto minimal or near-zero error as seen in the "bang-bang" control strategies used in engineering and neural network solutions to the pole-balancing problem (e.g. Miller et al., 1990). Instead, the phase plane contained regions indicative of differential stability. Tight cycles corresponded to relatively periodic motion due to a "jiggling" strategy of stabilization. This corresponds to a strategy whereby alternating forces of comparable magnitude are applied in order to maintain zero net displacement of the pole. This was the closest analogy to bang-bang control that we observed.

In contrast to the jiggling strategy, larger circuitous cycles in the phase plane of Figure 4B (or the linear regions in Figure 4A) indicated a "running" strategy whereby the hand and the top of the pole were both displaced in the same direction until an overcompensatory motion was necessary to avoid the impending end-of-track constraint. Typically, once the danger of this constraint had been avoided, another bout of jiggling began. A third, mixed strategy was also observed and appeared to be a composite of the jiggling and running strategies (Figure 4A). Hence, the resultant motion did not appear to be due to a dynamics based on a stable, fixed point.

When viewing the phase portraits and time series together, similarities were noted between the phase portraits of chaotic and intermittent dynamics. For example, inspection of the phase portrait in Figure 4B revealed tight cycles that intermittently change into larger circuitous excursions reminiscent of the archetypal manifold of chaotic phenomena, namely, a homoclinic tangle in phase space. The short-term cyclicities and periodicities that accompany jiggling were interspersed with epochs of large-scale escape motion, which suggests a possible correspondence with the homoclinic tangle nearby an unstable fixed point in nonlinear dynamical systems (Kelso & Ding, 1993; Strogatz, 1994). Indeed, in a perception–action coordination experiment related to this task, the most general nonlinear equation exhibiting chaotic trajectories (the Shilnikov attractor) was recently shown to underlie the human brain's global activity (Kelso & Fuchs, 1995).

From such a rich phenomenology, a simple taxonomy of stabilization control strategies is suggested (a) to go with the intrinsic tendencies of the system (persistence), (b) to go against the system (antipersistence), (c) to jiggle the system, or (d) all of these. Although useful for an initial understanding of the global strategies at work, this taxonomy does not necessarily imply that independent control strategies exist and that switching between them is required. Rather, the taxonomy impels further development in terms of searching for a single dynamical mechanism that contains implicit within it these various control strategies.

Global Temporal Structure

R/S analysis was conducted on the time series of both the hand displacement and the rod's angle from vertical for each 300-sec trial. Figures 5A and 5B show the Hurst plot for hand displacement and rod angle for a single representative participant. A prominent discontinuity between two linear scaling regions was apparent. There was low between-rod variability, as indexed by the standard error bars. The Hurst plots averaged across all participants for a single long rod (105 cm; Figure 5C) and a single short rod (45 cm; Figure 5D) are also shown. It was again apparent that between-subjects variability was low as indexed by the standard error of *R/S*.

In Figure 6, the Hurst plot of hand displacement for the *R/S* data averaged across all four participants and all six rod lengths is shown. A linear region was found over a short-term time scale from $\Delta t = 0.02$ to 2.56 sec ($y = 0.95x + 1.58$, $r^2 = .999$; Figure 6B). This was obtained by performing the linear regression over the first eight points in Figure 6A. The inclusion of the ninth point at $\Delta t = 5.12$ sec yielded a marginally altered regression ($y = 0.926x + 1.556$, $r^2 = .998$). Because the slope of the linear region represents the Hurst exponent, and considering only the slope of the first regression equation, persistence ($H > .5$) exists over the short-term scale ($H = .95$). Random surrogate data was created by randomly reordering (shuffling) the raw data to remove any possible correlation. In contrast to the previous results, analysis of the reshuffled data yielded $H \approx .5$ as expected for a completely random time series.

A linear region was also found over the long-term time scale from $\Delta t = 10.24$ to 81.92 sec ($y = 0.291x + 2.014$, $r^2 = .992$; Figure 6C). This was obtained by including the last four points in Figure 6A in the linear regression. The exclusion of the point at $\Delta t = 10.24$ sec (to yield the last three points) produced a perfect linear fit ($y = 0.259x + 2.07$, $r^2 = 1$). Considering only the slope of the first regression equation, antipersistence ($H < .5$) exists for the long-term scale ($H = .29$). Reshuffling the data yielded $H \approx .5$.

As $\Delta t = 2.56$ sec can be considered the upper bound on the short-term region of persistence and $\Delta t = 10.24$ sec can be considered the lower bound on the long-term region of antipersistence, the transition time, T_{trans}, between persistence and antipersistence can be inferred to occur in the vicinity of the log-scaled point midway corresponding to $T_{trans} = 5.12$ sec.

R/S analysis was also conducted on the time series of rod angle. In Figure 7, the Hurst plot for rod angle whereby averages were taken across all participants and all rod lengths is shown.

As in the case of hand displacement, it can be seen that, for rod angle, there is a linear region over a short-term time scale from $\Delta t = 0.02$ to 1.28 sec ($y = 0.936x + 1.556$, $r^2 = .998$; Figure 7B). This was obtained by performing the linear regression over the first seven points in Figure 7A. Inclusion of the eighth point at $\Delta t = 2.56$ sec yielded a marginally altered regression ($y = 0.9x + 1.556$, $r^2 = .998$). Con-

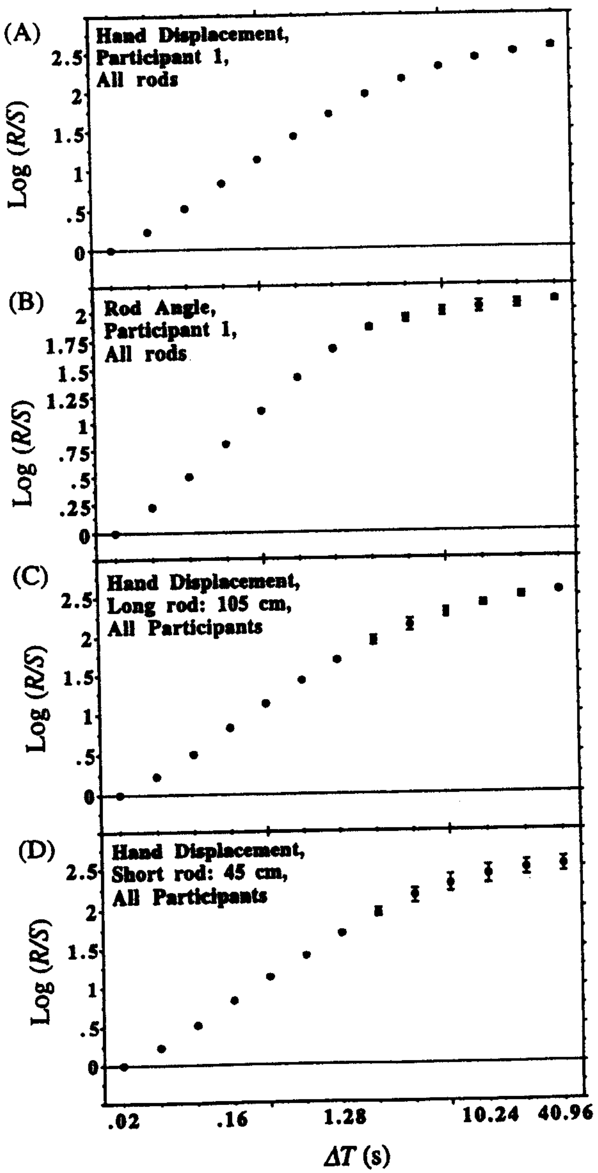

FIGURE 5 Hurst plots exhibiting a crossover between two linear regions, together with the variability around averaged data points. (A) Hurst plot for the hand displacement variable. Data are shown for one participant and have been averaged across all six rod lengths. (B) As in (A) but plotted for rod angle. (C) Hurst plot for hand displacement of a single long rod averaged across all participants. (D) Hurst plot for hand displacement of a single short rod averaged across all participants.

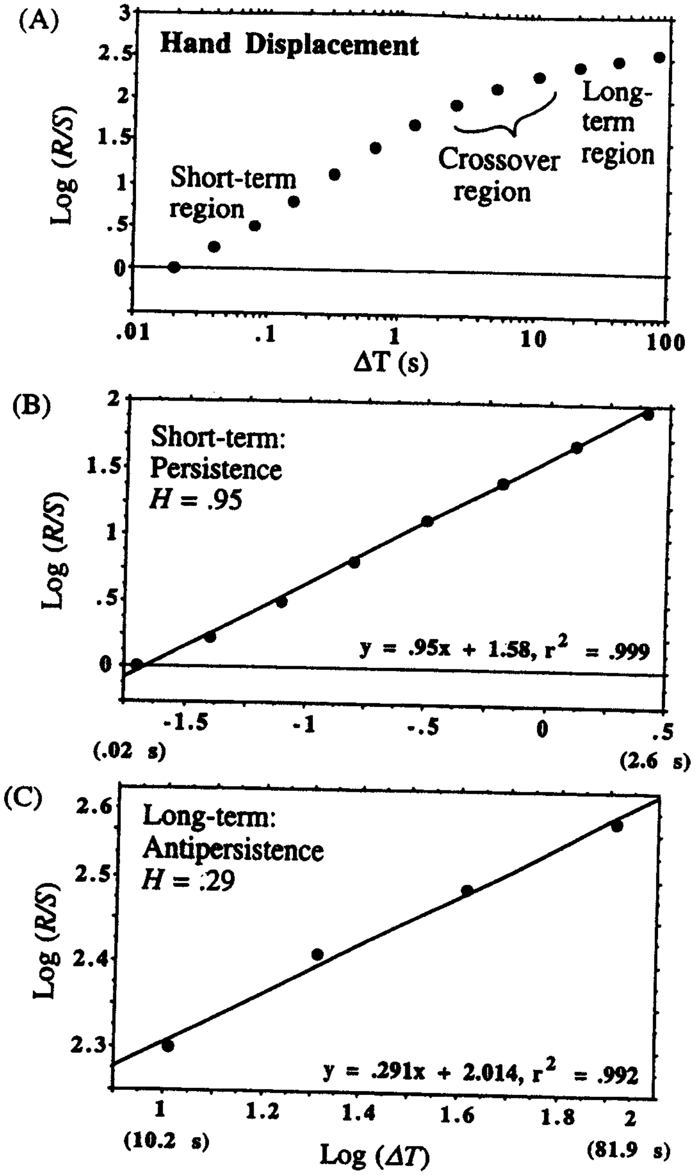

FIGURE 6 Hurst plots for hand displacement averaged across all participants and all rod lengths. The values of *H* obtained are indicated. (A) Both short-term and long-term regions and their crossover region. (B) Short-term persistence region. (C) Long-term antipersistence region.

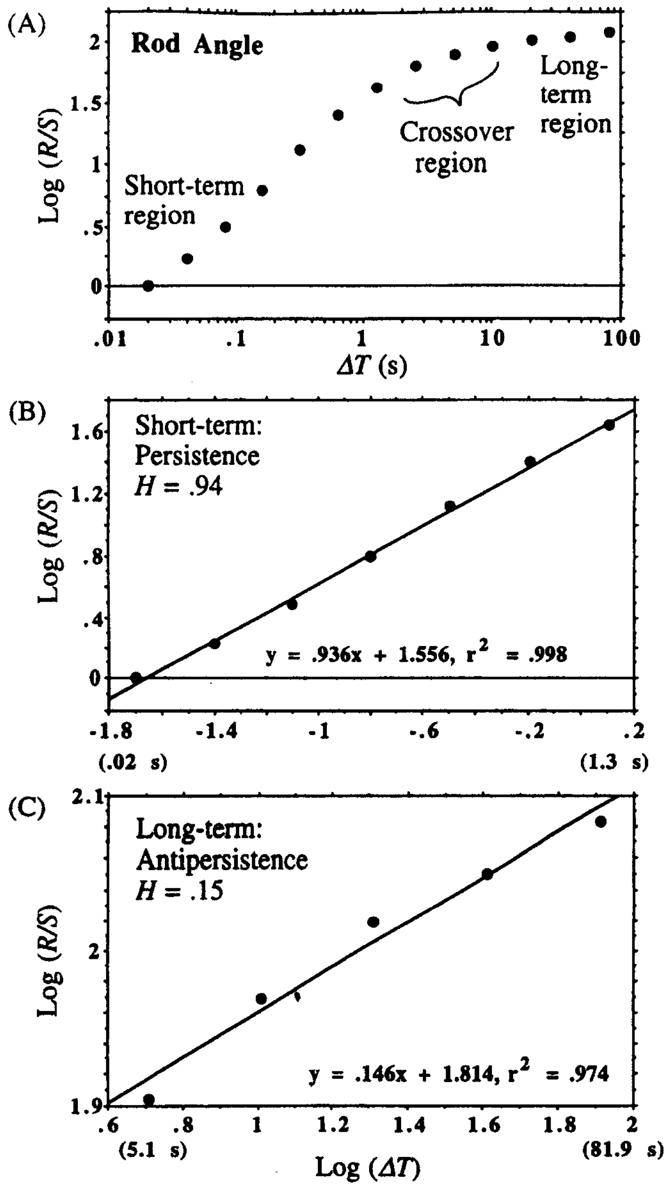

FIGURE 7 Hurst plots for rod angle averaged across all participants and all rod lengths. The values of H obtained are indicated. (A) Both short-term and long-term regions and their crossover point. (B) Short-term persistence region. (C) Long-term antipersistence region.

sidering only the slope of the first regression equation, persistence ($H > .5$) existed for the short-term scale ($H = .94$).

A linear region was also found over the long-term time scale from $\Delta t = 5.12$ sec to $\Delta t = 81.92$ sec ($y = 0.146x + 1.814$, $r^2 = .974$; Figure 7C). This was obtained by performing the linear regression over the last five points in Figure 7A. The exclusion of the eighth point at $\Delta t = 2.56$ sec (to yield the last 4 points) yielded a marginally altered regression ($y = 0.124x + 1.849$, $r^2 = .987$), and exclusion of the ninth point at $\Delta t = 5.12$ sec (to yield the last 3 points) yielded a perfect linear fit ($y = 0.107x + 1.879$, $r^2 = 1.0$). Considering only the slope of the first regression equation, antipersistence ($H < .5$) exists for the long-term scale ($H = .15$).

Because $\Delta t = 1.28$ sec is the upper bound on the persistence region for rod angle and $\Delta t = 5.12$ sec is the lower bound on the antipersistence region, the transition between persistence and antipersistence is inferred to occur in the vicinity of the log-scaled point midway corresponding to $T_{\text{trans}} = 2.56$ sec.

From the preceding, one may conclude that persistence and antipersistence occurred as prominent characteristics of active stabilization. Hence, the particular style of coordination exhibited scale independence, and the extent of this scale-independence was amplified in the long-term region such that anticorrelation existed between points separated by as much as 80 sec. Importantly, a transition occurred between persistence and antipersistence for both variables of hand displacement and rod angle. Further, the transition occurred at an earlier time for the angle ($T_{\text{trans}} = 2.56$ sec) than for the hand ($T_{\text{trans}} = 5.12$ sec).

To more accurately pinpoint the time of the transition from persistence to antipersistence, we used an alternative method of revealing the transition point between persistence and antipersistence (Treffner & Kelso, 1997; Voss, 1994). In this method, local estimates of the Hurst exponent, H_{local}, are obtained from the local gradients formed by pairs of points in the Hurst plots of log (R/S) versus log (Δt). The value of each local slope is then plotted against the values of Δt corresponding to the midpoint of the logarithmic axis from which the slope is calculated. The transition point, T_{trans}, between persistence and antipersistence is the time, Δt, at which the graph of the estimates of H_{local} intersect the line where $H = .5$. In Figure 8, the plot of H_{local} averaged over participants and rods for hand displacement and rod angle is shown. This graph corresponds to the local slopes of the pairwise segments within Figures 6A and 7A. For all participants, rods, and the purported controlled variables (hand and angle), the point in which their corresponding H_{local} graphs crossed over the horizontal line at $H = .5$ was calculated. The crossover points in units of log(t) were then entered into an analysis of variance with independent variables of rod length (short through long) and controlled variable (hand and angle). The main effect of controlled variable was significant, $F(1, 15) = 292.74$, $p < .001$. Thus, the transition from persistence to antipersistence occurred earlier for the rod angle ($T_{\text{trans}} = 2.17$ sec) than for hand displacement ($T_{\text{trans}} = 7.69$ sec). It is instructive to compare these transition times with those obtained from the linear-region method of estimating the transition point ($T_{\text{trans}} = 2.56$ and

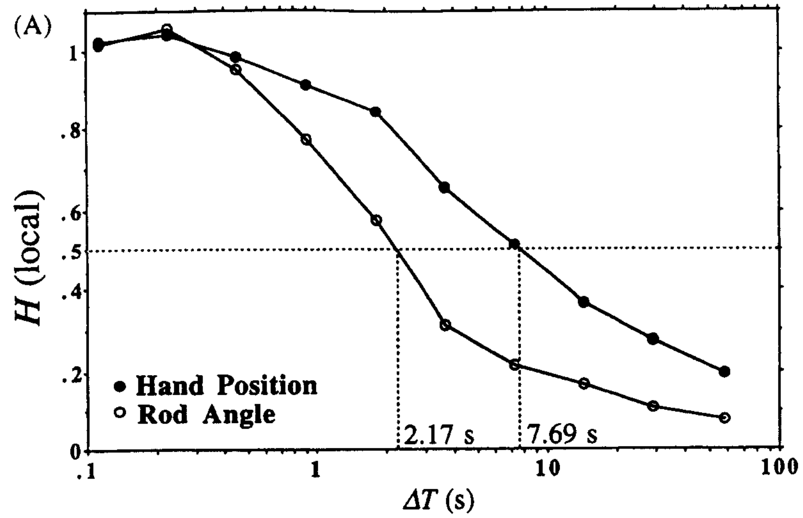

FIGURE 8 Local-slope Hurst plot for hand position and rod angle averaged across all participants and all rods. The earlier transition from persistence to antipersistence for the rod angle is apparent.

5.12 sec for rod angle and hand displacement, respectively). Averaging the results from both methods, T_{trans} = 2.37 and 6.41 sec for rod angle and hand displacement, respectively.

Although neither rod length nor its interaction with controlled variable was significant, $F(5, 15) = 1.677$ and $F < 1$, respectively, there was a linear ordering of transition point by rod length and by hand displacement (angle: T_{trans} = 1.95, 2.06, 2.15, 2.20, 2.28, and 2.39 sec; hand: T_{trans} = 6.19, 6.86, 8.13, 8.39, 8.40, and 8.61 sec, corresponding to 30-, 45-, 60-, 75-, 90-, and 105-cm rods respectively).

Very Long-Range Correlation

Previous studies of long memory in postural control (Collins & De Luca, 1994) have suggested that if a sufficiently long record of performance could be obtained then because of boundary conditions, such as the base of support during standing (or the end-of-track constraint in the present task), eventually Δx^2 would saturate to a constant value and might, for example, yield $H \approx .5$ (i.e., a loss of correlation). To evaluate whether there was such an upper limit on the long-term region beyond the maximum value of Δt calculable for the 300-sec trial (maximum Δt = 81.92 sec), a single participant who had previous experience in the task and had developed some skill at balancing the pole attempted continuous balancing of the 105-cm rod for a full 30 min, without any break in performance. That is, if the participant dropped the rod or for any reason disrupted the continuity of balancing, the trial was abandoned, and a new attempt initiated. After many attempts to produce a single contiguous bout of balancing, the participant succeeded in producing a 30-min time series (36,000 points; sampling rate = 20 Hz) from which the Hurst exponent was recovered using both the linear region and local-slope methods. Because the time series was 1,800 sec in duration, the values of Δt chosen for the R/S calculation were 0.1, 0.2, 0.4, 0.8, 1.6, 3.2, 6.4, 12.8, 25.6, 51.2, 102.4, 204.8, 409.6, and 819.2 sec.

Using the standard R/S method, two regions were apparent in the Hurst plot for hand displacement. A linear region of the short-term time scale was found from Δt = 0.10 sec to Δt = 3.20 sec ($y = 0.873x + 0.874$, $r^2 = .998$), obtained by performing the linear regression over the first six values of Δt. Inclusion of the seventh point at Δt = 6.4 sec yielded a drop in the linear fit ($y = 0.833x + 0.853$, $r^2 = .995$). Therefore, considering the slope of the first regression equation only, persistence ($H = .87$) existed over the short-term time scale.

A linear region was also found for the long-term time scale from Δt = 12.80 sec to Δt = 204.80 sec ($y = 0.254x + 1.351$, $r^2 = .990$). Inclusion into the regression of the last two points at Δt = 409.6 sec and 819.2 sec yielded a drop in the linear fit ($y = 0.208x + 1.421$, $r^2 = .969$). However, the last two points, although producing a comparable slope (slope = 0.159) were not considered sufficiently linear with the preceding points to constitute inclusion. Considering, therefore, only the first regression, antipersistence ($H = .25$) existed over the long-term time scale.

Because the upper bound on the linear persistence region was considered to be Δt = 3.20 sec, and the lower bound on the antipersistence region was considered to be Δt = 12.80 sec, the transition point between persistence and antipersistence occurred in the vicinity of the log-scaled midpoint corresponding to T_{trans} = 6.40 sec. To ascertain the reliability of the estimated transition point, an analysis was conducted using the local-slope method. In this case, a value of T_{trans} = 9.68 sec was found. This may be considered comparable to the preceding value as it is also located between the lower (3.20 sec) and upper (12.80 sec) bounds. Averaging from the two methods yields T_{trans} = 8.04 sec for the persistence–antipersistence transition in hand displacement for balancing a long rod by a skilled participant.

Of interest is the magnitude of the upper bound on the long-term antipersistence region, Δt = 204.8 sec. Thus, on average, any two points separated by more than 12.8 sec and up to 204.8 sec (i.e., 3.4 min) remained anticorrelated. That is, there was a tendency for the controlling hand to oscillate in alternating directions during all temporal intervals separated by between 12.8 sec and 3.4 min.

A similar analysis was conducted for the time series of rod angle obtained during the 30-min trial. However, instead of two linear regions spanning the Hurst-plot as observed for hand displacement, three linear regions were apparent. The first linear region, corresponding to the usual short-term time scale, was found from Δt = 0.10 sec to Δt = 1.6 sec ($y = 0.861x + 0.862$, $r^2 = .997$). This was obtained by performing the linear regression over the first five values of Δt. Inclusion of the sixth point at Δt = 3.2 sec yielded a drop in the linear fit ($y = 0.794x + 0.822$, $r^2 = .989$).

Using the first regression only, persistence existed over the short-term time scale ($H = .86$).

The second linear region was found over a time scale from $\Delta t = 3.20$ sec to $\Delta t = 204.80$ sec ($y = 0.271x + 1.027$, $r^2 = .998$). Thus, antipersistence existed over the long-term time scale ($H = .27$). By inference, the transition occurred at the log-scaled midpoint between 1.6 sec and 3.2 sec corresponding to $T_{trans} = 2.26$ sec. The analysis was also conducted using the local-slope method. In this case, a transition value comparable to the linear region method was found as $T_{trans} = 2.11$ sec. Averaging both methods yielded $T_{trans} = 2.19$ sec for the persistence–antipersistence transition in rod angle.

However, a third linear, very long-term, time scale for rod angle was found from $\Delta t = 204.80$ sec to $\Delta t = 819.20$ sec ($y = 0.478x + 0.537$, $r^2 = .994$). Because the slope of this region corresponded to an exponent $H \approx .5$, the implication is that between $\Delta t = 204.80$ and $\Delta t = 819.20$ sec, the motion of the rod angle did not exhibit self-similar correlations characteristic of persistence and antipersistence but, instead, indicated pure random motion. Hence, the very long-term region corresponded to ordinary Brownian motion whereby no correlation existed between points.

In Figure 9, H_{local} estimated using the local-slope method for the rod angle during the 30-min trial is shown. As can be seen, there is an extended region of antipersistence that eventually returns toward $H \approx .5$ beyond approximately 3.3 min.

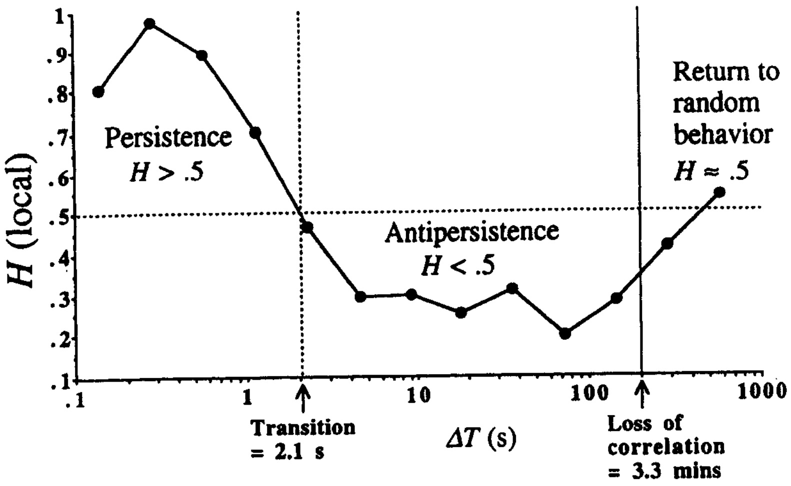

FIGURE 9 Local-slope Hurst plot for the extended duration trial of 30-min continuous balancing. The return to $H = .5$ is apparent, indicating a limit on the long-memory effect of antipersistence and the loss of all correlation beyond 3.3 min.

In sum, for the very long trial, comparable Hurst exponents were found for persistence of both the hand ($H = .87$) and the rod angle ($H = .86$) and for antipersistence of the hand ($H = .25$) and the rod angle ($H = .27$), and an additional very-long term region was revealed for the rod angle at which $H \approx .5$, and the long-memory effect was lost. Note that for persistence in the hand $H = .87$, which was less than the average value of $H = .95$ obtained with the lesser skilled participants. Because only one highly skilled individual was tested, our conclusions regarding skilled performance in this task are tentative. Given this caveat, examination of Figure 3 would imply that the highly skilled individual's hand motion was less smooth (less positive correlation) than that of the lesser skilled participants.

GENERAL DISCUSSION

In contrast to pure Brownian motion for which a Hurst value of $H = .5$ implies a lack of correlation between some point in a time series and all others, this analysis revealed that on average, $H = .95$ ($H_{hand} = .95$ and $H_{angle} = .94$) for all points temporally separated by up to approximately 3 sec (Figures 6 and 7). In correspondence with the "running" strategy of rod control shown in Figure 4A, $H = .95$ implies persistence in the changes in displacement of the hand and that increases in hand position (or rod angle) tend to be followed by further increases, and similarly, decreases tend to be followed by decreases. That is, one can consider the hand's motion continuing in the same direction or the pole pivoting and falling in the same direction for short periods of up to 3 sec. However, it should be noted that *R/S* analysis has been shown to slightly underestimate the true Hurst exponent when $H > .75$ (Bassingthwaighte et al., 1994; Liebovitch & Yang, 1997; Schepers et al., 1992). Given such possible underestimation, the analysis indicates that the true degree of persistence may be even greater than estimated and even closer to unity.

In contrast to the short-term persistence regime, for all points in the hand and angle time series separated by more than approximately 5 sec, the average Hurst exponent was $H = .22$ ($H_{hand} = .29$; $H_{angle} = .15$; Figures 6 and 7). Such antipersistence or the tendency for reversals implies that increases in the past tend to be followed by decreases in the future and vice-versa.

Averaged across all rods and participants, the transition from persistence to antipersistence occurred earlier for rod angle ($T_{trans} = 2.5$ sec) than for hand displacement ($T_{trans} = 6.5$ sec). Importantly, it was found that antipersistence extended surprisingly far into the past. The current position of the hand or angle remained correlated with events that had occurred as much as 80 sec previously. To the extent that there is a demonstrable long-range correlation with prior events, it might be said that the past continues to have an influence on the present. Alternatively, one could choose to reject such a past–present distinction and, instead, define the act called "balancing" as a macroscopic event having extended spatio-temporal dynamic structure (cf. Riccio, 1993). Indeed, as regards basic psychological theory, it is quite enticing that long-term fractal correlation is referred to as *long memory* (Beran, 1994; Chen, Ding, & Kelso, 1997; Liebovitch & Yang, 1997).

Persistence was maintained longer for the action-related variable (hand displacement) than for the perception-related variable (rod angle). However, the hand is functionally less constrained in movement than the angle, because the angle can only depart from perfect verticality up to a relatively small value of approximately 10° before which the angle must be reduced to avoid loss of balance. In contrast, the hand can continue to move in a given direction primarily determined by the actor's intentions, although the pole angle and the end-of-track constraint will together constrain the direction and extent of hand motion.

To gain some understanding of the factors that entail a persistence–antipersistence transition at T_{trans}, it has been proposed that this may be a natural consequence of physical parameters such as the effective mass and inertia of the system (Liebovitch & Yang, 1997). Thus, if the relaxation time of the system is of the order of the observation time, then inertial effects will be observed. The influence of physical properties on the coordination dynamics was investigated in this experiment by manipulating the length of the pole and, thus, altering its moment of inertia and, hence, natural frequency of oscillation (Kugler & Turvey, 1987). For the rod angle, the persistence–antipersistence transition was ordinally related to the rod length in that an earlier transition was revealed for the shortest rod (T_{trans} = 1.95 sec) than for longest rod (T_{trans} = 2.39 sec). Likewise, for the hand position, the transition occurred earlier for the shortest rod (T_{trans} = 6.19 sec) than for the longest rod (T_{trans} = 8.61 sec). It is important to emphasize that the transition times between persistence and antipersistence do not merely reflect the inherent mechanics of the rod (e.g., Pittenger, 1990), because the transition times do not exactly correspond with the natural periods of the rods (range: $T \approx$ 1–2 sec). Rather, it seems the transition times reflect temporal properties of the overall coordination dynamics considered as a unity.

Similar to the effect on persistence of physical properties such as inertia is the influence of the track-end constraint on antipersistence. Liebovitch and Yang (1997) hypothesized that the long-range anticorrelation observed in both cell membrane voltage fluctuations (Churilla et al., 1996) and in pole balancing (Treffner & Kelso, 1995b) may reflect an underlying bounded potential. They performed extensive numerical simulations of fractional Brownian motion with various boundary conditions such as hard or soft mirror reflectance forces. Their results provided support for the hypothesis that antipersistence could arise from the physical boundaries of a system. However, a bounded potential would explain that anticorrelations must exist at some time scale, but it does not account for the specific character of antipersistence, that is, fractal anticorrelated structure. Indeed, the physical source of long memory remains somewhat uncertain (Mandelbrot & Voss, 1983) but a dynamic mechanism is presumably responsible (Mannella et al., 1994). In sum, both the hand and the rod angle exhibited long-range anticorrelations due to a complex dynamical system constituted by the dual constraints of an intrinsically unstable system operating within a bounded potential and an active perceptual system attempting to maintain upright balance.

In examining previous evidence of nonlocal temporal structure in naturally unstable systems, unlike the dual-scaling regions in the current data, single-valued Hurst regimes have been found. In a study of metronome-paced finger tapping, Chen et al. (1997) compared both the time series of the temporal errors between taps and the metronome pulses and the time series of the intertap intervals. Only for the error time series did they find persistence (H = .72) after averaging over trials and participants. It was concluded that the long-memory effect in their task was due to intrinsic random noise in the nervous system compounded with delays due to a sensory–motor feedback loop. However, no crossover regime was found. Similarly, a study of the interstep period in human walking around an athletic track found that under self-paced conditions at either slow, medium, or fast speeds, walking exhibited persistence ($H > .5$) for up to 1 hr into the past (Hausdorff, Purdon, Peng, Ladin, Wei, & Goldberger, 1996). However, when the walkers synchronized their locomotion with a metronome, the long-memory effect of persistence disappeared. This result may appear at odds with the data of Chen et al. (1997) that showed persistence even under strict synchronization conditions. However, Chen and colleagues emphasized that misleading results can be obtained depending on the type of raw time series employed as input to the analysis of long-memory effects. They concluded that the error time series was, at least in this class of perception–action tasks, a candidate for a type of variable that produces a "fundamental time series." Interestingly, this notion is none other than the relative phase (and its fluctuations) that has been identified as a significant collective variable or order parameter in many other studies, starting with the well-known phase transitions in bimanual coordination found by Kelso (e.g., 1981, 1984).

This brings us to an overarching problem in motor control and coordination and complex systems in general, which is that neither the relevant variables nor their dynamics are known a priori but have to be identified. In laboratory studies of biological coordination, the strategic focus on nonlinear qualitative change has proven enormously fruitful for both theory and experiment over the last two decades (e.g., Haken, 1996; Kelso, 1995). The reason is that if a complex multivariable system is changing smoothly and linearly, it is difficult to distinguish the variables that matter from those that do not. Observations of qualitative change (always accompanied by quantitative effects) have allowed the identification of collective variables characterizing the system's coordination states and their dynamics (equations of motion). Importantly, near critical points various theoretically motivated measures (e.g., fluctuation enhancement, critical slowing down, etc.) have enabled tests of predicted features of self-organization associated with the identified coordination dynamics (Schöner & Kelso, 1988).

This methodology of long-memory analysis offers a potentially useful complement to the transition methodology used in many laboratory tasks. Moreover, it may prove helpful outside the laboratory frame of reference to encompass more naturalistic settings (e.g., long-term epidemiological studies) and investigations of so-called "abnormal" motor performance (Treffner & Kelso, 1996). For example, well-defined transitions from persistence to antipersistence may offer a means of identifying relevant quantities in contexts in which it is not possible to directly manipulate control parameters. Moreover, the transition points themselves may be revealing of processes acting on different time scales (e.g., demarcating different kinds of memory). In this respect, variables that do not exhibit bilinearity are less interesting. Such considerations are pertinent to the overarching problem of finding the relevant variables to describe and explain motor control.

Although the macroscopic scale of analysis is crucial for the understanding of long-memory dynamics, the potential neurophysiological basis of such effects has also been investigated. In a study of the fluctuations in tidal volume during breathing in the rat, *R/S* analysis revealed persistence, either $H = .83$ when larger breaths (sighs) were included or $H = .92$ without sighs (Hoop, Kazemi, & Liebovitch, 1993). It was suggested that the persistence was due to the convergence of small-scale spatio-temporal physiochemical processes at the molecular level and large-scale spatio-temporal mechanisms acting at the neural and cellular level. Further support came from a follow-up investigation of the correlated respiratory-related neural activity in the rat's brain stem (Hoop, Burton, Kazemi, & Liebovitch, 1995). It was found that although spontaneous activity of the brain stem exhibited $H \approx .5$, when cerebrospinal fluid was introduced (containing the respiration-related neurotransmitter ACh), $H = .87$, implying persistence in the neural noise.

Other evidence of a neural correlate for long-term correlation has come from investigations into the variability of the human monosynaptic reflex (Nozaki, Nakazawa, & Yamamoto, 1995). Using the H-reflex paradigm, which permits an evaluation of the excitability of the spinal α-motorneuron pool, it was found that the variability of sequences of stimulation-induced H-wave responses exhibited long-range fractal correlation. Because such correlations were not seen for the sequences of the associated M-wave response, it was concluded that the correlations could not be due to neural conduction or to transmission at the neuromuscular junction but, instead, may be due to synaptic connections to α-motorneurons of the spinal cord.

In the cases thus far described, a single linear scaling region was found implicating a single fractal power law that can be characterized with a single value of *H*, either persistence or antipersistence. However, as with these results, recent research has revealed crossover phenomena in naturally occurring processes whereby a short-term scaling region $H > .5$ switches into a long-term region with $H < .5$. Such a crossover was found in an *R/S* analysis of the voltage fluctuations of cell membrane ion channels whereby persistence ($H = .76$) switched to antipersistence ($H = .26$) at $T_{trans} \approx 0.5$ sec with an upper limit on persistence of approximately 2 sec (Churilla et al., 1996). Similarly, a crossover was found in very long time series (24 hr) of the interbeat intervals in heartbeat for normal and pathological (congestive heart failure) individuals (Peng, Havlin, Stanley, & Goldberger, 1995). As in the study of interstep times during walking (Hausdorff et al., 1996) and the temporal errors during synchronized tapping (Chen et al., 1997), the heartbeat analysis took interevent times as the algorithm's raw data. Note that this is not a sequence of kinematic values such as instantaneous position or angle as in our pole balancing experiment. Further, note that in our experiment the raw input is a sequence of kinematic values such as instantaneous position or angle on which we calculated *R/S* based on the range (*R*) in the raw (kinematic) values and the standard deviation (*S*) of the increments, Δx. In the heartbeat (and walking) analyses, the raw data were a sequence of effectively higher order temporal values (interbeat intervals) together with the particular beat number at which that interval occurred. Given the preceding clarification, it was shown that in the pathological heartbeat data, for short time scales (less than 10–20 beats), the interbeat intervals exhibited fluctuations characteristic of white noise (i.e., the Fourier power spectrum was independent of frequency yielding white, or $1/f^0$, noise). That is, the interbeat intervals in the raw time series were uncorrelated from one beat to the next and would graphically correspond to an extremely jagged profile. Note that the integral or running sum of such incremental steps would yield Brownian or "brown noise" (e.g., see Figure 3; $1/f^2$ noise) and an uncorrelated random walk with $H = .5$ (cf. Voss, 1989). Indeed, at the long time scale the interbeat intervals were correlated and exhibited the smooth graphical profile characteristic of brown noise. The transition between the short-term white noise and long-term brown noise regions occurred at approximately 40 beats.

However, the pathological heartbeat results were in contrast to those of healthy individuals in whom, over short time scales, correlated brown noise was found in the interbeat intervals (similar to the pathological long time scale). Over long time scales, highly correlated fluctuations were found such that the Fourier power spectrum was inversely related to the frequency (i.e., a $1/f$ power-law scaling; cf. Gilden et al., 1995; Schmidt, Beek, Treffner, & Turvey, 1991). The transition between these two regimes occurred at an earlier time scale than for the pathological data, at approximately 10 beats. It was concluded that under extreme pathological conditions at short time scales, the heartbeat complex attempted to maintain a constant interbeat interval with an uncorrelated white noise strategy of interbeat intervals. In contrast, over long time scales, the heartbeat complex responded to perturbations from various factors by producing smooth variation in the interbeat intervals reminiscent of Brownian motion. Results such as these and those of Chen et al. (1997) may indicate that the control function of a complex system such as the heart operates on the basis of inherently temporal quantities or, as has been extensively investigated in perception–action tasks, the relative timing (or phase) of events (Kelso, 1995).

Crossover between scaling regions has also been found for diverse nonbiological systems including a transition at 14 days from persistent ($H \approx .92$) to random ($H \approx .52$) behavior for wave heights off the Norwegian coast (Feder, 1988) and the transition from persistent ($H \approx 1$) to independent ($H \approx .5$) behavior in the conductance fluctuations of a current carrying pore (Berge, Rakotomalala, Feder, & Jossang, 1994). Further evidence of crossover in biological systems is found in the extensive series of investigations into postural control that involved recording the center-of-pressure time series from human individuals standing on a force plate (Collins & De Luca, 1993, 1994, 1995a, 1995b; Mitchell et al., 1995). In these studies, a critical point at $T_{trans} \approx 1$ sec was typically found for the switch from persistence ($H \approx .75$) to antipersistence ($H \approx .25$). These results were summarized in a model based on two coupled springs that realized a feedback strategy whereby, during upright stance, the nervous system switches from open-loop to closed-loop control (e.g., falling forward vs. pulling back; Collins & De Luca, 1993). However, the notion that control requires information (i.e., feedback) only within the closed-loop mode of control seems less than parsimonious and incompatible with recent results on information-based perception–action. An elegant example due to Bootsma and van Wierengen (1990) showed that the previously thought of open-loop ballistic movement of a forehand smash in table tennis is in fact precisely controlled with the variability of movement of the order of 2 to 4 msec.

Further support for informational closure comes from our analysis of the putative perceptual variables detected during pole balancing (Treffner & Kelso, 1995a). Following previous studies of the perceptual support for timing the uncurling of the body near the finish of a somersault and the ability to perceive when an object pushed to its balance point will topple over (Cabe & Pittenger, 1992; Lee, Young, & Rewt, 1992), we investigated whether the onset of decelerating the hand was geared to time-to-contact information (tau or tau-dot) or instead to a less higher order variable (e.g., hand position, rod angle, or their velocities). It was found that the onset of hand deceleration ("braking") coincided with the time of the minimally varying visual variable (Wagner, 1982) and corresponded to the tau-dot function of rod angle. The onset of deceleration followed 170 msec after the time of minimal variation in this potential perceptual variable (Treffner & Kelso, 1995a). This supports a tau hypothesis that a very tightly coupled perception–action system underlies the ability to gear decelerative actions of the hand to temporally specific perceptual variables of the rod (Turvey, Carello, & Kim, 1990).

Other research on perceptual–motor coordination brings into question the conclusion that persistence is indicative of open-loop ballistic motion and is separate from antipersistence or closed-loop feedback-driven control. As shown by Engström, Kelso, and Holroyd (1996), the often separate categories of reaction and anticipation may be better understood as two related modes of a unitary underlying coordination dynamics. We believe Collins and colleagues' open- versus closed-loop distinction is analogous to the misleading distinction between reaction and anticipation. In the study of Engström et al. (1997), participants attempted to either tap in synchronization, in anticipation or in reaction to a visual metronome at various pacing rates. Depending on the parameterization of the dynamics via the control parameter of movement frequency, different modes (reaction vs. anticipation) emerged with transitions between modes exhibiting many of the familiar characteristics of

self-organized coordination dynamics. Such signatures of multifunctional systems appear analogous to the dual persistence and antipersistence regimes of this study. The major difference between the reaction–anticipation results and those of this study is that the modes of persistence and antipersistence and the transition between them reflect long-term, macroscopic, ensemble facets of the coordination event rather than the more detailed dynamical aspects within a particular trial. To this extent, the reaction–anticipation transitions and the persistence–antipersistence transitions reflect complementary grains of analysis of spatio-temporal dynamic events.

Related to the postural control studies of Collins and colleagues, a long-memory analysis of postural sway during upright stance versus leaning and with eyes open or closed has underscored the informational underpinnings of the persistence–antipersistence transition (Riley et al., 1997). Averaged across all conditions, a persistent region ($H = .73$) and an antipersistent region ($H = .27$) were found. However, it was shown that leaning not only reduced the degree of persistence but also the point of the persistence–antipersistence transition (leaning: $T_{trans} = 0.25$ sec vs. upright stance: $T_{trans} = 0.37$ sec). It was concluded that forward lean entailed less persistence because there was less need to actively explore the available propriospecific information specific to the limit of stability and, hence, its affording potential danger (Riccio, 1993; Riccio & Stoffregen, 1988, 1991). Because leaning made the limits of stability more proximal, the postural control system was considered to be more attuned or sensitive to the information specific to such boundaries. If propriospecific information is available in the short time scale and is utilized as proposed, this would provide further evidence against the hypothesized mechanism of Collins et al. (1993) that the nervous system effectively ignores any available information during the persistent ("open-loop") regime. Further reasons for doubting the two-process model of Collins and De Luca (1993) include the random-walk analysis of postural control by Newell et al. (1997). Although corroborating the finding of short- and long-term regions of correlation, they considered their data to be more efficiently captured by a simpler linear stochastic model that avoided an explicitly two-process mechanism. We agree with their conclusion that various forms of feedback must be available and operate continuously, although we are not committed to any particular instantiation of the dynamics.

Riley et al. (1997) also suggested that suprapostural goals and various goal-directed tasks, as well as environmental constraints (e.g., body dimensions, asymmetric tools), may play a hitherto much underappreciated role in the organization of dynamically stable tasks. We concur and offer these results as suggestive that dynamic encounters such as generic balancing tasks and postural control depend on the relation of environmental properties (e.g., rod natural frequency) to action capability (e.g., skill), thus resulting in differing performance (e.g., persistence–antipersistence transition).

Of significance in the long 30-min continuous balancing trial was the finding that all correlation was lost beyond a finite temporal limit. Thus, the long-term anticorrelation (antipersistence) exhibited in the rod angle did not extend indefinitely but only as far as 3.4 min into the past, after which $H \approx .5$. Such extended long-memory effects are surprising given the assumption that human movement cannot be correlated with motions that occurred more than a few moments prior to the current state and certainly not those that occurred several minutes previously. If a relation with the effects of past experience is deemed to exist, it is typically handled under the aegis of "memory," either short or long term. In contrast, these results indicate that long-memory effects are an implicit part of the stochastic dynamics and looking for a particular storage mechanism with which to construct all the psychological complexity of conceptual and memory structure, either functional or neurophysiological, may be somewhat misguided (Treffner, in press). In effect, perception–action systems may not only be self-organized on the basis of spatial pattern formation principles but also on the basis of the generic, fractal, temporally nonlocal structure of natural processes and events (e.g., Ding, Tuller, & Kelso, 1995; Gilden, Thornton, & Mallon, 1995; Schmidt et al., 1991; Treffner, 1997; Treffner & Turvey, 1993; West & Deering, 1996). Because such a perspective focuses on event structure, it might help clarify the nature of the memory involved in recognizing or playing an intrinsically long-term event such as a piece of music (Jones & Boltz, 1989; Levitin & Cook, 1996). Indeed, it has been shown that much music from diverse cultures exhibits the precise blend of randomness and predictability characteristic of the self-similarity and long-term correlation of 1/*f* noise (Voss, 1989). That is, the rises and falls (increments) of a melody are neither as fluctuating and random as white noise ($H = .5$) nor as predictable and uninspiring as brown noise ($H = 1.0$) but are intermediary, that is, 1/*f* noise (cf. Figure 3).

Perceptual psychologists from the ecological persuasion have long argued that there are well-defined, measurable invariant quantities embedded within changing structured energy distributions (such as light or sound) and these invariants constitute the basic, fundatmental informational quantities that nervous systems detect and on which the perception of meaningful events is based (e.g., Gibson, 1979/1986; Kelso, 1994; Reed, 1996). For example, the optical information that specifies the very long-term event of facial aging (Kim, Effken, & Shaw, 1995; Warren & Shaw, 1985) or the optical information that specifies the time remaining until contact with an approaching surface (Lee, Young, & Rewt, 1992) may both involve invariant quantities that lawfully specify a temporal event either extending from the past to the present (as in aging) or, conversely, from the present to the future (as in approaching a surface). Accepting the reciprocity of organism and environment and of perception and action (e.g., Reed, 1996; Turvey et al., 1990), and if perceptual information can directly specify change and styles of change within temporal events (Kim et al., 1995), then we should expect concomitant actions such as maintaining an upright posture to possess significant temporal structure. The persistent and antipersistent character of functional stabilization would appear to satisfy the preceding reciprocity-based requirements.

Ultimately, the commensurability of perception and action may be considered the ecological basis (anchored in persistence and antipersistence) on which a species can evolve the capacity for epistemic contact with the environment at multiple scales of informational specificity. The basis for such contact has been cogently argued to be the lawful spatio-temporal regularities in the ecological context of the organism, not internal mental representations (Gibson, 1979/1986; Mace, 1977; Reed, 1996). If so, then the individuals of a species could exploit their capacity for the direct apprehension of both long- and short-term temporal events. This would provide the basis for selection and adaptation and, ultimately, for mechanisms of development and skill acquisition (Thelen & Smith, 1994).

In a related context, Gibson (1979/1986) developed the concept of an affordance to capture the real, tangible, persisting opportunities for action that exist in the environment. An affordance constitutes an environmental resource for the members of a species (Reed, 1996). Because ecological information exists for resource specification and detection by an appropriately attuned perceptual system and because resources are defined with respect to a species and not a particular individual, it is the availability of such resources in the environment that creates selection pressure on the members of a species (Reed, 1996). It is in this respect that the temporal structure of persisting events may help explain how newly born members of a species arrive well prepared for the immediate and direct perception of potentially critical events in their environments (Thelen & Smith, 1994). The basis for such temporal continuity may be no less "genetic" in origin than it is dynamical in the sense described previously.

As argued by Reed (1996) with respect to the species-level definition of affordances, a complete description of the dynamics of encounters may require an analysis of more than the individual. That is, it requires the introduction of individuals from the individual's historic past. Again, this does not imply the adoption of genetic determinism, notwithstanding the existence of very long-range correlations and persistence in DNA sequences (Voss, 1992, 1994). Rather, it impels consideration of new ways to account for behavioral continuity and relatedness across generations (Goodwin, 1994). For example, Hurst analysis of the physical environment reveals that "the span of statistical interdependence of geophysical data is infinite ... that such span is longer than the longest records so far examined" (Mandelbrot & Wallis, 1969, p. 335). Investigation into the dynamical basis for long-range correlations at the evolutionary time scale may usefully jolt the debate on the nature of evolutionary persistence. In a recent dialogue in this journal (Coss, 1993) on how animals retain perceptual biases from former historic periods of natural selection, it was argued that:

> The evolutionary persistence of brain states restraining information as process can be viewed as an *inherent property* of the animal-environment system at *multiple levels* of organization embedded within phylogenetic, ontogenetic, and proximate time scales of change. ... What is critical in this dialogue is the need for further discussion about how perception and action are constrained by particular *biases arising from historic events*. (pp. 190–191, italics added)

From the current perspective of fractal time and long-memory effects, an individual's temporally extended encounter with its environment constitutes the relevant historical bias, but this encounter is not necessarily encoded in the memory circuits of the brain, even if the nervous system is the requisite material substrate. Rather, the influence of prior events on the present is best approached with the recognition that long memory is an inherent, irreducible, macroscopic property of the spatio-temporal dynamics of organism–environment encounters.

Furthermore, affordances have differing consequences for an organism depending on the affordance's degree of persistence or antipersistence and, hence, its relevance for commensurate activities. These differing time scales and styles of change lead to a crucial constraint on the kinds of skills an animal will develop and can learn (Thelen & Smith, 1994). For example, in this task, learning to balance a short rod of higher natural frequency took longer and consequently seemed more difficult than learning to balance a long rod of lower natural frequency. Ease of performance was revealed in the earlier transition from persistence to antipersistence for the short rod.

The foregoing conclusions on long-term, fractal, perception–action events may be less than surprising when viewed from the perspective of the theory of information-based event perception:

> Events of all types, as I said above, have a component of change and a component of persistence. ... Assuming that shorter events are nested within longer events, that nothing is instantaneous, and that sequences are apprehended, the usual distinction between perception and memory comes into question. For where is the borderline between perceiving and remembering? Does perceiving go backward in time? For seconds? For minutes? For hours? ... The optic array itself is neither frozen nor chaotic; only so could an observer detect what is changing and what is persisting in the world at the same time. The coexistence of variance with invariance in a changing pattern is perfectly easy to define mathematically. (Gibson, 1975, pp. 298–299)

The finding that fractal long-term correlations exist within the dynamics of perception–action suggests that revealing the persistence or antipersistence within continual change provides some understanding of the temporal integrity underlying dynamic encounters. Employing a metaphor, we might call the dynamical mechanisms underlying perception–action the *syntax of behavior*, whereas consideration of the affordances reveals the *semantics of experience*. However, these two perspectives may not be as polarized as the metaphor or recent critiques of ecological psychology have suggested (e.g., Michaels & Beek, 1995). Rather, information-based mechanisms of coordination dynamics (Kelso, 1994) and informational-based specification of affordances (Gibson, 1979/1986) both share the objective of defining the higher order invariants on which various perception–action behaviors are based. The only significant difference between these approaches is the degree of abstraction in the higher order invariant (and consequently the nature of the "information") assumed to organize the perception–action system. Ecological optics seeks to reveal the higher order invariant within optical change that is detected and onto which action is geared, whereas coordination dynamics attempts to identify the potentially more abstract invariant (order parameter) on which coordinated perception and action is self-organized (cf. perceptual information vs. information-based dynamics). As we have attempted to illustrate, these are best viewed as complementary endeavors working at different scales of abstraction. Thus, a challenge for future ecological investigation is to reveal the commensurate spatio-temporal structure common to both the dynamical interaction with an affordance and its informational (e.g., optical) specification. It is anticipated that further investigation of dynamical mechanisms will further our appreciation of the meaningful relation that couples the invariants of action and those of perception.

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