Disentangling Stability, Variability and Adaptability in Human Performance: Focus on the Interplay Between Local Variance and Serial Correlation

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We address the complex relationship between the stability, variability, and adaptability of psychological systems by decomposing the global variance of serial performance into two independent parts: the local variance (LV) and the serial correlation structure. For two time series with equal LV, the presence of persistent long-range correlations (or $1/f^\beta$ noise) increases the global variance. We hypothesized that a coadjustment between these two determinants of variability constitutes a resource for adaptive systems whose appropriate functioning under critical conditions requires the outcome variance to be limited. To test this hypothesis, we looked at the bimanual coordination dynamics at comfortable (stable) and critical (close to phase transition) frequencies. Results showed that a negative correlation appeared gradually as the theoretical stability of coordination modes decreased and reached significance only in the critical condition. We propose that the emergence of a mutual adjustment between LV and serial correlations might be an indicator of effective adaptation to stabilize behavior.

Keywords: local variance, persistent long-range correlations, adaptability, stability, variability

Stability, variability, and adaptability are three highly entangled notions bringing interaction between the statistical and functional levels of assessment of the dynamics of a given system and its behavior over time. Understanding the relationship between these concepts constitutes a key issue in research on complex biological systems in fields like human motor control and performance. In the present study, we propose to address this issue by decomposing the notion of variability into two essentially independent ingredients: the local variance (i.e., the variance of increments between the successive states of the variable) and the structure of serial correlations (i.e. the way these increments are arranged over time). We use the framework of bimanual coordination dynamics to provide the experimental basis to test the relationship between local variance and serial correlations.

Stability can be specified either by the property of a system to resist changes, that is, to exhibit minimal variation while facing changing conditions, or by its ability to recover a state of equilibrium after perturbation. We refer to the invariant performance of a system in the wake of varying conditions as static stability. This may be contrasted with a dynamic form of stability, which refers to reproducible and predictable *patterns of changes* in the system's functioning under varying internal or external constraints. While static stability implies that the variables determining the system's

state are maintained within a limited range, the dynamic definition allows the stability of some global behavior to be maintained by changing states of the system (Ahn, Tewari, Poon, & Phillips, 2006).

A general assumption is that enhanced variability of a given behavior reflects its reduced stability. Therefore, behavioral stability has often been appropriately inferred from the observation of small variance. However, even though stability and variability (as assessed by basic Gaussian statistics) are obviously two related aspects, the invariant nature of this relationship is arguable. One may intuitively wonder, for instance, which of the following two behaviors should be termed "more stable": the behavior that exhibits the smallest fluctuations or the behavior that is perpetuated *in spite of* maximal variability (e.g., Riley & Turvey, 2002).

Whenever we study a system that is governed by any external constraints, the issue of behavioral stability raises the notion of adaptability, i.e. the capacity of a system to react and comply with the constraints without breaking down or exhibiting any significant decline in behavior given the requirements of the situation/task. But restoring congruence between the system's organization or functioning and the environmental constraints in order to recover a stable state is only possible when the system has sufficient resources of variability to draw from. While this appears obvious when considering the dynamic form of stability, it is also true for static stability. Observing invariants in performance under changing environmental constraints does not always mean that the underlying organization of the system has not (been) varied to achieve a stable performance. Thus, when dealing with (self-controlling/organizing) open systems, the notion of adaptability might be considered a generalization of the notion of stability.

At this point, the relationship between variability and stability becomes even trickier since, due to adaptability, the behavior that is functionally the most stable is clearly not necessarily the less

variable. Good examples have indeed been provided by a body of studies on heart rate variability with aging and disease (e.g., Goldberger et al., 2002; Iyengar, Peng, Morin, Goldberger, & Lipsitz, 1996; Saeed, 2005). Displaying several examples of heart rate time series, Goldberger et al. (2002) notably showed that the series that exhibited the smallest variability were associated with patients with severe heart failures while the most variable and weakly stationary series were recorded from healthy individuals. At the same time, those studies showed the structure of serial correlations in the heart rate time series were a better indicator for health or dysfunction than just the magnitude of the fluctuations. Actually, healthy heartbeat fluctuations exhibited persistent long-range correlations ($1/f^\beta$ noise). This specific correlation structure was altered either towards uncorrelated white noise or excessive periodicity in patient populations.

A Short Review of $1/f^\beta$ Noise and Variability in Biological Systems

Most natural time series exhibit some form of serial correlations, especially fractal temporal structures (Bassingthwaighte, Liebovitch, & West, 1994; Newell & Slifkin, 1998; West, 2006). The continuum of fractal processes can typically be defined by spectral indexes β ranging from -1 to 3 (see Eke et al., 2000, for details). More specifically, $1/f^\beta$ noise denotes a particular form of serial correlations, situated at the frontier between fractional Gaussian noises (fGn, i.e. stationary series) for $-1 < \beta < 1$, and fractional Brownian motions (fBm, i.e. nonstationary series) for $1 < \beta < 3$. Within the fGn family, in particular, one can moreover distinguish between antipersistent (negatively correlated) and persistent (positively correlated) processes for $-1 < \beta < 0$ and $0 < \beta < 1$, respectively (white noise corresponding to $\beta = 0$). Persistent fGns are long-range correlated, which basically means that the series auto-correlation function exhibits a slow asymptotic decay following a power function $C(k) = |k|^{-\gamma}$ (where $0 < \gamma < 1$ at lags k, and γ and β are related through the Wiener-Khintchine theorem), instead of the typical exponential decay of short-range correlations (e.g., ARMA processes). Of particular importance to our present concerns is that $1/f^\beta$-series are characterized by persistent long-range correlations, the strength of which increases as β tends towards 1.

Clinical approaches, such as those mentioned above, and research on human motor behavior (e.g., Chen, Ding, & Kelso, 1997; Delignières, Torre, & Lemoine, 2008; Jordan, Challis, Cusumano, & Newell, 2009; Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009) and cognition (e.g, Gilden, 2001; Gilden, Thornton, & Mallon, 1995; Holden, Van Orden, & Turvey, 2009; Kello, Beltz, Holden, & Van Orden, 2007; Van Orden, Holden, & Turvey, 2003) have contributed to ground the postulate that $1/f^\beta$ noise is the typical statistical outcome of complex systems under normal functioning conditions. This structure might break down with aging, disease, or any extrinsic constraint perturbing the system (Gilden & Hancock, 2007; Hausdorff et al., 1997; Lipstiz & Goldberger, 1992; Peng et al., 2002; Van Orden, 2007). $1/f^\beta$ noise has commonly been considered as reflecting the adaptive capacity of systems under various constraints, by warranting an optimal compromise between stability and variability.

It, therefore, seems reasonable to consider that the relation between stability and variability may be mediated by the temporal structure of fluctuations (Jordan et al., 2009). A comprehensive view of both aspects of variability (local and serial) to address behavioral stability is both timely and warranted.

Looking at the Interplay Between the Magnitude and the Correlation Structure of Variability

Two time series, which are similar with regard to their Gaussian statistics, can actually contain very different correlation structures and are, therefore, likely to be generated by different organizations of the underlying processes. This assertion is a common argument to emphasize the importance of a time series approach to complex systems (Hausdorff et al., 1997; Newell & Slifkin, 1998; Riley & Turvey, 2002; Slifkin & Newell, 1998). However, the possibility of series with different forms of correlation but same variance does not necessarily imply that the serial correlation properties may not have any effect on variance. It is important to take into account that the serial (long-range) correlation properties are likely to affect the series global variance (Gilden, 2001; Madison, 2001). Consequently, one can argue that variance is not an appropriate statistic for separately assessing the correlation structure and the magnitude of variability.

A solution for a separate assessment of the magnitude of variability and serial correlations is to consider the local variance (LV) of the series. We determined LV as the variance of the series of increments I_i (i.e., the differenced series) composing the original series X_i. Note that an alternative estimate can be obtained by computing the sum of the squared differences between adjacent values, divided by the number of differences (minus one):

$$LV = \frac{\sum_{i=2}^{N}(X_i - X_{i-1})^2}{(N-1)-1} \tag{1}$$

This equation gives a measure of variance based on local differences between data points (Madison, Forsman, Blom, Karabanov, & Ullén, 2009), which converges toward the variance of increments for sufficiently long series. Similar measures of local variability, based on the analysis of differences between adjacent values, have been proposed in the literature (Collier & Ogden, 2004; Delignières, Fortes, & Ninot, 2004; Madison et al., 2009; Ogden & Collier, 2002). Despite some algorithmic divergences, these estimates all provide equivalent measures of the local variability of the series, in terms of variance or standard deviation. The advantage of LV is to provide an index of the magnitude of local fluctuations in the series, independently of the fluctuations generated by serial correlations. While the variance of a series is codetermined by LV and serial correlations, the latter two are independent by nature. Thus, a given pattern of serial correlation can demonstrate different magnitudes of LV and, conversely, similar LVs can underlie very different correlations structures.

As the relationship between LV and the serial correlation structure will be a key issue in this study, we elaborate on their independence further. Consider two series of increments I_1 and I_2 equal in mean and variance. Integration of the two series of increments gives the series of successive values of the correspond-

ing variables X_1 and X_2. If X_1 contains antipersistent fractional Gaussian noise (negative correlations between successive values, meaning that a positive increment is most likely to be followed by a negative increment) and X_2 contains persistent fractional Gaussian noise (positive long-range correlations between the successive values, meaning that a positive increment is most likely to be followed by another positive increment), then the global variance of X_2 will be higher than the variance of X_1, and the probability for the variables to attain or exceed a given limit value is higher for X_2 than for X_1. Figure 1 illustrates this relationship between the increments composing a series, the nature of correlations between the increments, and the global variance of the series.

Note that one could argue on a formal basis that there is a relationship between the series LV and the correlation structure. In fact, the LV (Equation 1) corresponds to half the value of the series lag-1 variogram (V(1)), which is defined for all lags $k > 0$ by:

$$V(k) = \frac{E(X_i - X_{i+k})^2}{2}. \qquad (2)$$

It can be demonstrated that for all k, V(k) equals the variance of the series minus the lag-k auto-covariance (Beran, 1994):

$$V(k) = VAR(X) - \gamma(k); \qquad (3)$$

Then, for k = 1:

$$LV = \frac{VAR(X) - \gamma(1)}{2}. \qquad (4)$$

Thus, this equation suggests that the LV is dependent on the correlation structure of the time series. Indeed, a strong negative correlation exists between the LV and the lag-one auto-covariance in a set of simulated series with fixed variance. It is important to note, however, that the variance cannot be assumed to be fixed across a set of experimental series, and equation 4 simply shows that the global variance of series can be expressed as the linear combination of the LV and the lag-one auto-covariance, which both can vary independently:
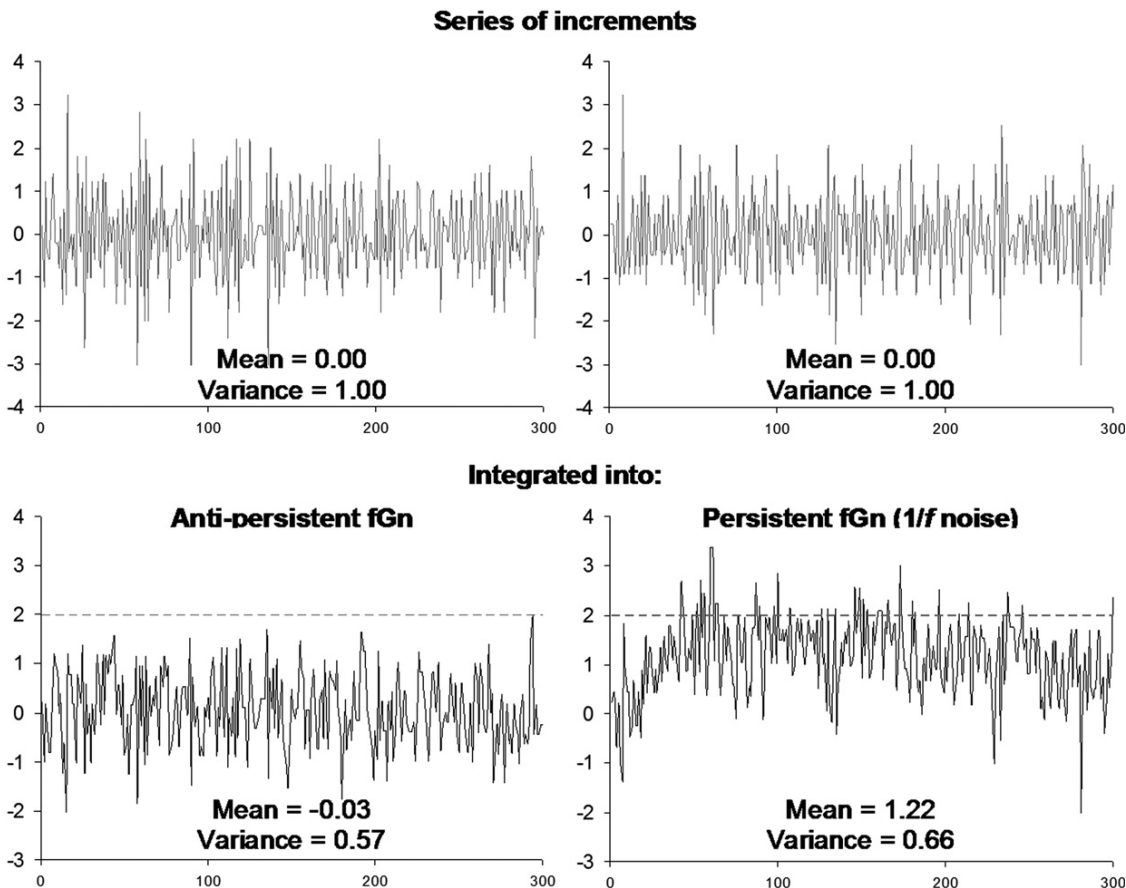
$$VAR(X) = 2LV + \gamma(1). \qquad (5)$$

Figure 1. Top graphs: series of increments obtained after differentiation of series of anti-persistent fGn (left) and persistent fGn, or $1/f^{\beta}$ noise (right). The series were subsequently normalized to obtain increments with equal variance. Bottom graphs: new series of anti-persistent fGn and $1/f^{\beta}$ noise obtained after re-integration of the series of increments; the new series are rescaled with respect to the original series. Despite the series of increments being equal in mean and variance, their different arrangement over time, i.e. the different structures of serial correlations in the outcome (integrated) series cause different global variances: persistent long-range correlations yield a higher global variance in series.

To provide additional support for the independence between the series LV and correlation structure and to illustrate the respective influences of these two properties of variability on the global variance of the time series, we generated 200 synthetic series varying the LV and the structure of correlations. The simulation results presented in Table 1 show that both factors affect the series global variability while being mutually independent.

Now consider that the variables X_1 and X_2 describe the behavior of a system that must stay within given limits to not break down and continue functioning successfully. It becomes evident that some forms of serial correlation, as for example antipersistent fGn, allow the system to "tolerate" a higher variability between the successive states of behavior than persistent fGn does. Generally speaking, the stronger the persistence of correlations, the smaller the tolerable variability between successive behavioral states (and vice versa).

From a mathematical point of view, LV and serial correlations are independent dimensions of a series. Then, what would it mean to observe a correlation between these two dimensions? A positive correlation between the degree of persistence of serial correlation and LV would straightforwardly augment the series variance and push the variable near extreme values. A negative correlation, in contrast, would have a "conservative" effect, containing the series variance and maintaining the variable within its initial boundaries. Then, the interplay between the LV and serial correlations provides the system with a potential degree of freedom to adapt to nonoptimal functioning conditions where the outcome variance needs to be contained. Taking it a step further, no correlation between the LV and serial correlations should be found under unconstrained functioning conditions that enable the system to maintain the target behavior without the need to contain the outcome variability. In contrast, under conditions requiring the system to contain the outcome variability and avoid the required behavior to break down, the emergence of a negative correlation between the LV and the persistence of serial correlations may indicate the presence of adaptive processes.

The Framework of Bimanual Coordination Dynamics

To test our present hypothesis, the rhythmic bimanual coordination paradigm (Kelso, 1995) provides a very useful experimental framework in four ways: a) it is attached to strongly established theoretical models for the intrinsic stabilities of coordination dynamics provided by the dynamical systems approach (Haken, Kelso, & Bunz, 1985); b) fluctuations have been shown to play a significant role in coordination dynamics, contributing to the qualitative change in the coordinative behavior (Collins, Park, & Turvey, 1998; Kelso, 1984; Kelso, Schöner, Scholz, & Haken, 1987; Schöner, Haken, & Kelso, 1986); c) fluctuations in produced relative phase series have been shown to contain $1/f^{\beta}$ correlations (Torre & Delignières, 2008; Torre, Delignières, & Lemoine, 2007); and d) it offers a straightforward way to assess behavior in different stable or critical conditions of performance, determined individually.

When performing bimanual coordinated oscillations, participants are spontaneously able to produce two stable spatio-temporal relationships between the limbs: in-phase and anti-phase coordination. These stability regimes are the attractors of bimanual coordination dynamics, defined by the collective variable relative

Table 1
Basic Independence Between the Local Variance and the Structure of Long-Range Correlations, and Their Respective Influences on the Global Variance of Time Series

Series of increments		Integrated into:									
		Anti-persistent fGn			White noise			Persistent fGn			
Mean 0.00 and Local variance 1.00	Theoretical H	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
	Estimated H	0.00 (±0.15)	0.11 (±0.21)	0.30 (±0.23)	0.39 (±0.14)	0.51 (±0.15)	0.56 (±0.22)	0.71 (±0.16)	0.83 (±0.19)	1.02 (±0.14)	1.16 (±0.14)
	Mean	0.00 (±0.00)	0.00 (±0.01)	0.00 (±0.01)	−0.01 (±0.01)	0.01 (±0.04)	−0.03 (±0.06)	0.07 (±0.20)	−0.04 (±0.34)	−0.34 (±0.73)	0.91 (±3.89)
	Variance	0.35 (±0.03)	0.37 (±0.03)	0.41 (±0.03)	0.45 (±0.03)	0.50 (±0.02)	0.60 (±0.04)	0.70 (±0.06)	0.95 (±0.08)	1.47 (±0.16)	2.24 (±0.53)
Mean 0.00 and Local variance 2.00	Theoretical H	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
	Estimated H	0.00 (±0.15)	0.11 (±0.21)	0.30 (±0.23)	0.39 (±0.14)	0.51 (±0.15)	0.56 (±0.22)	0.71 (±0.16)	0.83 (±0.19)	1.02 (±0.14)	1.16 (±0.14)
	Mean	0.00 (±0.00)	0.00 (±0.01)	0.00 (±0.01)	−0.01 (±0.02)	0.01 (±0.06)	−0.05 (±0.08)	0.10 (±0.28)	−0.06 (±0.49)	−0.48 (±1.04)	1.28 (±5.51)
	Variance	0.70 (±0.06)	0.74 (±0.05)	0.81 (±0.06)	0.89 (±0.07)	1.01 (±0.04)	1.19 (±0.09)	1.42 (±0.12)	1.89 (±0.15)	2.96 (±0.32)	4.50 (±1.06)

Note. The data presented in this table were obtained as follows. 1) We used the algorithm proposed by Davies and Harte (1987) to generate 10 sets of 10 series with theoretical Hurst exponents ranging between 0.1 (antipersistent fractional Gaussian noise) and 0.99 (persistent fractional Gaussian noise, or $1/f^{\beta}$ noise). 2) The series were differenced to obtain the corresponding series of increments. 3) The series of increments were normalized to a) zero mean and unit variance (top half of the table) and to b) zero mean and a variance of 2 (bottom). 4) Finally, the series of increments were integrated to obtain the original time series, modulo their local variances. The series' Hurst exponents were then estimated using the $^{\text{Low}}\text{PSD}_{\text{We}}$. The table shows that both the persistence of the long-range correlations (from left to right) and the local variance (top and bottom) affect the series' global variance. Comparison of the estimated Hurst exponents for series with local variances of 1 and 2 shows that the local variance and the long-range correlation properties are independent.

phase (φ) centered on 0° and 180°, respectively. While the coordinative system is intrinsically bistable at low movement frequencies, it is monostable beyond a critical oscillation frequency, as the relative stability of the anti-phase coordination decreases with increasing frequency until complete disappearance of the attractor. These essential properties of bimanual coordination dynamics have been formalized by the HKB- (Haken et al., 1985) potential function (*V*), which represents the stability of coordination as a function of the target relative phase and the movement frequency:

$$V(\varphi) = -a\cos(\varphi) - b\cos(2\varphi), \qquad (6)$$

where an increase in the ratio k = b/a is related to an increase in the required oscillations frequency. The minima in $V(\varphi)$ represent the attractive patterns. Because of the differential stabilities of in-phase and anti-phase, bimanual coordination dynamics typically shows a nonlinear phase transition: incremental protocols driving participants through gradually increasing oscillation frequencies provided empirical evidence for the breaking down of anti-phase coordination and the abrupt spontaneous switch to in-phase at individual critical frequencies. This transition is announced by a critical increase in the fluctuations of relative phase (Kelso, Scholz, & Schöner, 1986).

The magnitude of fluctuations has been considered tightly related to the occurrence of phase transition. As the anti-phase attractor basin disappears gradually, fluctuations are likely to contribute towards phase transition by pushing the coordinative behavior beyond the limits of the stability zone. The variance of produced series of relative phase has generally been taken as an appropriate indicator of the stability of the coordinative system under various extrinsic or intrinsic constraints. (For an alternative approach to coordination stability using Recurrence Quantification Analysis for a separate estimation of the strength of attraction of the coordination pattern and the noise inherent in the system, see for example Kudo, Park, Key, & Turvey, 2006; Pellecchia, Shockley, & Turvey, 2005; Richardson, Schmidt, & Kay, 2007; Shockley & Turvey, 2006).

Other work focusing on the structure of serial correlation rather than the magnitude of fluctuations has shown that the series of relative phase in bimanual coordination contain persistent long-range correlations, or $1/f^{\beta}$ noise (Torre, 2010; Torre & Delignières, 2008; Torre et al., 2007), instead of varying randomly over time. In particular, Torre (2010) found a negative correlation between the movement frequency at which the participants switched from anti-phase to in-phase coordination and the strength of the long-range correlations in the relative phase series produced. This result highlights that there may indeed be a relationship between the stability of bimanual coordination and the long-range correlation properties observed. However, the respective roles and functional interrelations between serial correlation properties and the magnitude of fluctuations remain to be uncovered. By examining how these two properties of variability may work hand in hand in a system in the conditions of stable and intrinsically unstable performance, the present paper will contribute to conceptual advances on the relationship between stability, variability, and adaptability in behavior.

In sum, the bimanual coordination paradigm serves as an appropriate experimental vehicle to address the issues under consideration. Specifying our above hypotheses with regard to the bimanual coordination framework yields the following predictions:

we expect to find no correlation between the LV and the persistence of long-range correlations in the series of relative phase produced in the intrinsically stable coordination regimes, as in in-phase and anti-phase at sub-critical oscillation frequency. In contrast, a negative correlation between the series LV and the persistence of correlations should be observed in anti-phase coordination at a critical frequency, where the variability of relative phase needs to be contained for avoiding phase transition and maintaining the required coordination pattern.

Methods

Participants and Device

Fourteen young adults (4 female, 10 male) took part in the experiment. Twelve participants declared themselves righthanded, and two left-handed. None of them declared any neurological or recent upper-limb injury. They had no extensive practice in music and declared no particular competence involving specific upper-limb coordination. Participants signed a written consent and were not paid for their participation; the experimental procedures were approved by the local institutional review board (Montpellier 1 University). Please note that a part of the dataset collected from the experiment has been used in a recent publication (Torre, 2010).

Participants were comfortably seated with their elbows supported on each side of the body. They performed bimanual forearm (pronation/supination) oscillations holding two 15-cm joysticks with a single degree of freedom in the frontal plane. The positions of the joysticks were adjusted to each participant so that his/her forearms rested in a horizontal position while performing the task. Potentiometers located at the axes of the joysticks allowed measuring their angular displacement, and data were collected using a *Nanologger* (Digimétrie, Perpignan, France) analog interface with a sampling frequency of 500 Hz. A PC-driven auditory metronome was used to pace the oscillations.

Task and Procedure

The task consisted in performing bimanual coordinated oscillations following the tempo imposed by the metronome. Participants had to perform one complete oscillation cycle within the metronome period, starting with maximal pronation on the beep. The amplitude of oscillations was of approximately 45° on each side of the vertical axis. The bimanual oscillations were performed either in in-phase or anti-phase coordination.

There were two parts to the experiment. The first part was designed to determine the individual transition frequencies (f_T) for each participant. Therefore, participants performed 10 trials following a classical incremental protocol driven by the metronome: the starting frequency was of 1 Hz and successively incremented by 0.2 Hz, with plateaus of 10 s. Participants started each trial in anti-phase coordination and maintained this pattern until the occurrence of the spontaneous transition to the in-phase coordination. They were instructed to make no effort to maintain anti-phase coordination when they felt themselves about to switch to inphase. For each participant, the individual f_T was determined as the median of the 10 observed transition frequencies.

In the second part of the experiment, participants performed bimanual oscillations in four conditions: a) in-phase coordination

at individual comfortable oscillation frequency (IP-COMF), b) in-phase at individual critical frequency (IP-CRIT), c) anti-phase at comfortable frequency (AP-COMF), and d) anti-phase at critical frequency (AP-CRIT). The comfortable oscillation frequencies were defined as 64% of the individual f_T. This percentage was chosen so that none of the individual comfortable frequencies was inferior to the limit of 1 Hz, which can be considered as a minimal frequency of comfort (see the study by Temprado, Zanone, Monno, & Laurent, 2001, on comparable forearm pronation-supination movements using two joysticks). The critical oscillation frequencies corresponded to the frequency levels that preceded the individual f_T in the incremental protocol. With regard to the main hypothesis of this study, the three first conditions do not exert any critical constraint on the coordinative system as there is no risk for the occurrence of phase transition; only for the AP-CRIT condition the task constraints are such that, without containing the variability of relative phase, there is an actual risk for participants to experience a phase transition.

Results from the first part of the data collection have already been reported in Torre (2010). Torre (2010) presented an analysis of the data from phase 1 and from a single condition (anti-phase coordination at critical frequency) of phase 2. The study showed that the noise distributions surrounding the phase transition in bimanual coordination were indeed 1/f distributed and correlated with the individual transition frequencies.

The time series of 512 oscillations produced by each participant in the four experimental conditions were subjected to analysis. The series length was determined so as to find an optimal compromise between two main methodological requirements. First, the performance of fractal analysis in terms of accuracy and variability of estimations has been shown to decrease markedly with the series length (see Delignières et al., 2006). Secondly, the protocol should allow the observation of the coordinative system under steady states and, therefore, prevent from within-trial changes due to learning, notably in the AP-CRIT condition.

Data Analysis

Relative phase series were determined by point estimate as the time lag between the dominant and the nondominant hands' oscillation peaks, normalized by the current period of the dominant hand. Mean and variance were computed for each series.

As mentioned in introduction, we additionally determined the series LV as the variance of the series obtained by differentiation of the original relative phase, i.e., the series of increments between the successive states of relative phase.

In order to reliably assess the long-range correlation properties in experimental time series, it is strongly recommended to combine different methods of fractal analysis, ideally working in the time and frequency domains (Delignières et al., 2006; Rangarajan & Ding, 2000). Note that all fractal methods yield a specific index of long-range correlations, all these indexes being related to each other through simple linear relationships. Therefore, a suitable procedure for an accurate and dependable assessment consists in performing multiple estimations of the index of long-range correlations for each series, to convert the different estimators into a same fractal exponent (e.g., the commonly used Hurst exponent H), and finally average the estimations obtained per series to

approach the "true" exponents (Delignières et al., 2006; Torre et al., 2007).

Here, we combined two complementary methods: $^{low}PSD_{we}$ (Eke et al., 2000) working in the frequency domain, and DFA (Detrended Fluctuations Analysis, Peng, Havlin, Stanley, & Goldberger, 1995) working in the time domain. We selected these methods because of their reliable performances on relatively "short" experimental series (see Delignières et al., 2006). $^{Low}PSD_{we}$ is an improvement of the classical spectral analysis as it includes a number of preprocessing steps before the Fast Fourier Transform. The spectral exponent $\beta \in [-1, 3]$ is estimated by the negative of the linear regression slope of the power spectrum in bilogarithmic coordinates and, as proposed by Eke et al. (2000), the high-frequency power estimates ($f > 1/8$ of maximal frequency) are excluded from the fitting of β. For $-1 < \beta < 1$, the series is a fractional Gaussian noise (fGn) containing either antipersistent correlations ($-1 < \beta < 0$) or persistent long-range correlations ($0 < \beta < 1$). White noise is characterized by $\beta = 0$. For $1 < \beta < 3$, the series belongs to the family of fractional Brownian motions (fBm). In particular, persistent long-range correlations, or $1/f^{\beta}$ noise, are characterized by $0.5 < \beta < 1.5$. Negative indexes reveal antipersistent correlations in the series. The spectral index β is related to the Hurst exponent by $H = (\beta + 1)/2$, in the case of an fGn, and by $H = (\beta - 1)/2$, in the case of an fBm,

DFA exploits the diffusion properties of the series, analyzing the relationship between the mean amplitude of fluctuations and the size of the observation window within which these fluctuations are measured. For fractal series, a power-relationship characterized by the scaling exponent $\alpha \in [0, 2]$ is expected. For $0 < \alpha < 1$, the series is a fractional Gaussian noise (fGn) containing either antipersistent correlations ($0 < \alpha < 0.5$) or persistent long-range correlations ($0.5 < \alpha < 1$). White noise is characterized by $\alpha = .5$. For $1 < \alpha < 2$, the series belongs to the family of fractional Brownian motions (fBm). Persistent long-range correlations are revealed by $0.75 < \alpha < 1.25$. For an fGn, $H = \alpha$, and for an fBm, $H = \alpha - 1$. At the end, the separate estimates provided by the two methods were averaged to obtain a mean H for each relative phase series.

Note that the estimation of the exponents of long-range correlations using the DFA and the $^{low}PSD_{we}$ is on the basis of fitting a regression line to the diffusion plots/power spectra obtained. However, performing linear regression on such graphs is relevant only if the series do indeed contain long-range correlations. Therefore, we complemented the two analyses with the Auto-Regressive (Fractionally Integrated) Moving Average (ARFIMA/ARMA) modeling method, which allows for the presence of "genuine" long-range correlations to be assessed through statistical inference. Basically, the method consists in fitting 18 models to the experimental series: nine ARMA (p, q) models, with p and q varying systematically from 0 to 2, and the corresponding ARFIMA (p, d, q) models, where d is the fractional integration parameter, and to select the best model using a goodness-of-fit statistic models (for more details on the method the reader is referred to Torre, Delignières, & Lemoine, 2007b, and Wagenmakers et al., 2004). Two complementary indicators can then be used to conclusively infer the presence of long-range correlations: the percentage of series for which the best fitting model is an ARFIMA model and the sum

of weights concentrated by the tested ARFIMA models compared with the ARMA.

Finally, we tested for the differential stability of coordination in the four experimental conditions, in particular for the actual criticality of AP-CRIT, by applying a two-way ANOVA 2 (Coordination) × 2 (Frequency) with repeated measures on both factors, on the variance of relative phase series. The same analysis was applied to the mean Hurst exponents and the LVs. To test the central hypothesis of this study, we determined Pearson's linear correlation coefficient (r) between the series' LVs and mean Hurst exponents for the four experimental conditions.

Results

The individual transition frequencies determined in the first part of the experiment ranged between 1.7 and 2.4 Hz. Consequently, the individual oscillation frequencies used for the subsequent experimental conditions ranged between 1 Hz and 1.5 Hz for the comfortable conditions and between 1.5 Hz and 2.2 Hz for the critical conditions.

The results for the mean relative phases, variances, and LVs obtained in the four experimental conditions are summarized in Table 2. To check the actual variability of the global variances of the relative phase series produced across participants, we computed the coefficient of variance (CV) for the four experimental conditions. The CV was of 41% in the IP-COMF condition, 41% in IP-CRIT, 37% in AP-COMF, and 43% in AP-CRIT, thereby showing that the variance of the relative phase did vary substantially across participants.

Using ARFIMA/ARMA modeling, the presence of long-range correlations in relative phase series was statistically assessed for 14 of 14 (100%) series produced in the IP-COMF condition, for 13 of 14 (93%) series in IP-CRIT, for 14 of 14 (100%) series in AP-COMF, and for 12 of 14 (86%) series in AP-CRIT. The sum of weights concentrated by ARFIMA models (i.e., the probability that an ARFIMA model is indeed the best fitting model for the series) was of 0.96, 0.95, 0.98, and 0.94, for IP-COMF, IP-CRIT, AP-COMF, and AP-CRIT, respectively. These results allow us to conclude that the series of relative phase produced in the four experimental conditions contained genuine long-range correlations (Torre, Delignières, & Lemoine, 2007b), to be estimated by the DFA and ^{low}PSD$_{we}$.

Figure 2 shows the averaged diffusion plot and power spectrum given by the DFA and the ^{low}PSD$_{we}$. The estimation of the long-range correlation properties of relative phase series using ^{low}PSD$_{we}$ yielded β indexes of 0.50 (±0.24) for IP-COMF, 0.42 (±0.15) for IP-CRIT, 0.28 (±0.24) for AP-COMF, and 0.45 (±0.32) for AP-CRIT. Estimations performed by DFA yielded α exponents of 0.83 (±0.11) for IP-COMF, 0.78 (±0.10) for

IP-CRIT, 0.78 (±0.16) for AP-COMF, and 0.82 (±0.20) for AP-CRIT. The mean Hurst exponents obtained after converting into the Hurst exponent and averaging the two estimations per series are displayed in Table 2.

The ANOVA on the variances of relative phase series showed main effects of both coordination mode, $F(1, 13) = 20.23$, $p < .05$, $\eta_p^2 = 0.61$, and oscillation frequency, $F(1, 12) = 33.28$, $p < .05$, $\eta_p^2 = 0.72$, as a significant interaction, $F(1, 13) = 21.79$, $p < .05$, $\eta_p^2 = 0.63$. LSD-Fisher's post-hoc comparison showed that only the variance in AP-CRIT was significantly higher than in the three other conditions (Figure 3, left graph). The ANOVA on the series' LV evidenced a significant main effect of oscillations frequency, $F(1, 12) = 9.15$, $p < .05$, $\eta_p^2 = 0.41$, as a significant interaction, $F(1, 12) = 7.17$, $p < .05$, $\eta_p^2 = 0.36$ (Figure 2, middle graph): the LV in AP-CRIT was significantly higher than for the three other conditions. Finally, there was a significant effect of interaction between coordination and oscillation frequency, $F(1, 13) = 6.85$, $p < .05$, $\eta_p^2 = 0.35$, on the mean Hurst exponents of relative phase series (Figure 3, right graph): post-hoc comparisons showed that the persistence of correlations was higher in IP-COMF than in AP-COMF.

Finally, the linear correlation tests between the mean Hurst exponents and LV of relative phase series showed a gradually increasing but nonsignificant negative correlation for the three noncritical experimental conditions, with $r_{12} = 0.05$ for IP-COMF, $r_{12} = -0.30$ for IP-CRIT, and $r_{12} = -0.40$ for AP-COMF. This negative correlation reached the level of significance only in the AP-CRIT condition where $r_{12} = -0.54$ ($p < .05$). Figure 4 maps these correlation coefficients onto the stability levels in the potential landscape of bimanual coordination dynamics, as defined by equation 6. Figure 5 displays the mirror-like coevolution of the LV and the mean Hurst exponents of relative phase for all participants.

Discussion

Research on human performance and health continually deals with the intimately related issues of stability, variability, and adaptability of the system in question and its time evolutionary properties. In the present study, we proposed to investigate this complex relationship by decomposing the notion of *variability* into two constitutive and essentially independent ingredients: the LV defined as the variance of increments between the successive states of the variable and the structure of serial correlations, i.e. the way these increments are arranged over time. We hypothesized that the mutual adjustment between the two dimensions of variability is a potential resource for the system to contain the outcome variance or, worded differently, *stabilize* behavior. Then, the emergence of an interdependence between the LV and the serial correlation structure may be an indicator of the system's *adaptation* to main-

Table 2

Summary of the Main Results Obtained in the Four Bimanual Coordination Conditions

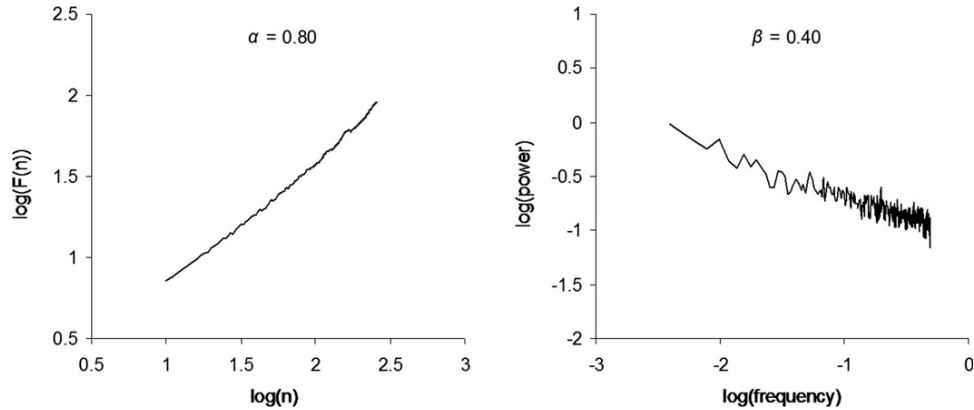|	In-phase f comfort	In-phase f critical	Anti-phase f comfort	Anti-phase f critical
Relative phase (°)	−3.03 (±3.88)	−5.47 (±8.64)	176.42 (±7.35)	172.47 (±11.49)
Local variance	112.07 (±50.90)	129.58 (±58.68)	106.58 (±48.94)	199.95 (±119.65)
Hurst exponent	0.79 (±0.10)	0.74 (±0.07)	0.71 (±0.12)	0.77 (±0.17)
Variance	64.21 (±26.37)	87.19 (±35.82)	76.00 (±28.26)	182.80 (±77.76)

Figure 2. Average diffusion plot (left) and power spectrum (right) obtained with the DFA and the $^{low}PSD_{we}$, for all experimental series of relative phase. Both graphs show consistent linear trends.

tain an appropriate behavior under constraining functioning conditions. Our present results provided empirical support for our hypothesis. Following a detailed discussion of the results, we examine the relationship of our findings to the current formalizations of the HKB model for bimanual coordination. Our results motivate a closer look at the notions of adaptability and adaptation, stability and stabilization.

The Local Variance and Serial Long-Range Correlations Coadjust in the Critical Condition

We implemented the bimanual coordination paradigm (Kelso, 1995) on the strength of the well-established knowledge about the stability properties of coordination dynamics. Of particular interest is the fact that performance of anti-phase coordination close to a critical oscillation frequency is known to be intrinsically unstable and presents a risk of occurrence of phase transition. This risk is facilitated by the stochastic fluctuations inherent to the system (Collins, Park, & Turvey, 1998; Kelso et al., 1987; Schöner et al., 1986).

Our present results were consistent with previous results as coordination produced in AP-CRIT appeared to be intrinsically less stable, with both the global variance and the LV of relative phase series being significantly higher than in the three noncritical conditions (IP-COMF, IP-CRIT, and AP-COMF).

In contrast, the results showed no difference in the persistence of long-range correlations in relative phase assessed by the mean Hurst exponents, between the critical condition AP-CRIT and the other experimental conditions. The only significant difference in the Hurst exponent appeared between IP-COMF and AP-COMF. This discrepancy between the evolutions of variance and long-range correlations as a function of experimental conditions confirms the fundamental importance of methods for long-range correlation analysis. It is apparent that variance does not affect the estimation of the long-range correlation structure in time series (Delignières et al., 2006; Eke et al., 2000).

If we accept the argument that the fluctuations that affect the coordinative behavior may play an operational role by contributing to the phase transition (Collins, Park, & Turvey, 1998; Kelso et al., 1987; Schöner, Haken, & Kelso, 1986), one can reasonably argue that containing the outcome variability may contribute to withstanding the drastic qualitative change in the coordinative behavior. In this perspective, the analysis of our empirical results beyond the mean values obtained per condition confirmed the central hypothesis of this study: we obtained a significant negative correlation between the LV and the Hurst exponents of the relative phase series produced by participants in the critical condition of performance only. Moreover, the strength of this correlation closely matched the theoretical stability regimes of bimanual co-
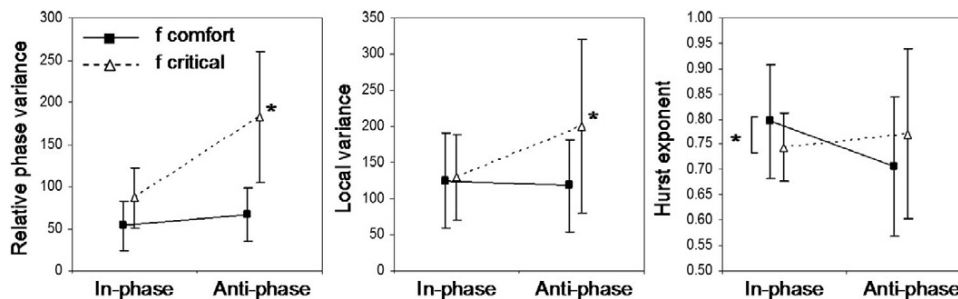

Figure 3. Relative phase variances, local variances, and mean Hurst exponents as a function of coordination mode and oscillations frequency. Error bars indicate standard deviations.
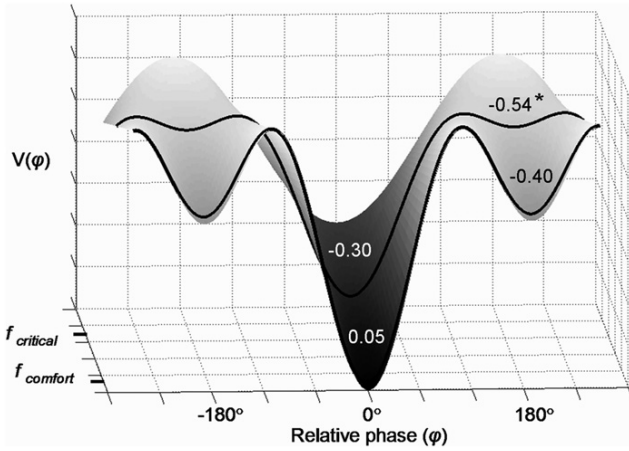
Figure 4. Coefficients of linear correlation between the local variances and mean Hurst exponents of relative phase obtained in the four experimental conditions IP-COMF, IP-CRIT, AP-COMF, and AP-CRIT. The coefficients are mapped onto the graphical representation of the potential function (Haken, Kelso, & Bunz, 1985), which formalizes the stability regimes of bimanual coordination dynamics as a function of required relative phase and oscillation frequency. The empirical correlation coefficient increases gradually as the depth of the attractors decrease, that is, as the theoretical intrinsic stability of coordination decreases. The correlation becomes statistically significant only in the critical condition of performance presenting an actual risk of phase transition.

ordination dynamics, as represented by the HKB potential function (Haken et al., 1985, Figure 3). Indeed, the correlation increased gradually with decreasing intrinsic stability of the required coordination but remained below the level of significance in the three noncritical conditions. Accordingly, we argue that when the constraints on the system are such that there is an actual risk that the required behavior breaks down or changes qualitatively, the mutual adjustment between the LV and the correlation structure of series constitutes a potential way for the system to adapt by containing the outcome variability.

The Relationship of the Present Findings to the HKB Model

The main body of studies on bimanual coordination has built on the stochastic differential equation formalism of the HKB model (Schöner et al., 1986), where the relative phase dynamics obeys the following equation:

$$\phi = -a\sin\phi - 2b\sin 2\phi + \sqrt{Q}\xi_t. \qquad (7)$$

In this equation, ξ is a Gaussian white noise process of strength Q, which represents the random fluctuations inherent in the system and affecting the coordination patterns. The deterministic part of the equation (with parameters a and b) accounts for the intrinsic stabilities, or strengths of attractiveness, of in-phase and anti-phase coordination. Specifically, this part determines the time to return to the coordination pattern following a brief perturbation (relaxation time) and, in consequence, the autocorrelational properties of the successive states of the relative phase.

Accordingly, several studies have intended to tease apart the relative contributions of the intrinsic stability (λ) of the coordination pattern performed, and the stochastic forces (Q) inherent in the system, to the variability observed in experimental data (e.g., Kudo et al., 2006; Pellecchia et al., 2005; Richardson, Lopresti-Goodman, Mancini, Kay, & Schmidt 2008; Richardson et al., 2007). One can demonstrate that the standard deviation of the relative phase produced is proportional to $\sqrt{Q/2\lambda}$ (Schöner et al., 1986). While the intrinsic stability of coordination varies as a function of control parameters, such as the required movement frequency, the magnitude of the stochastic fluctuations is assumed to be invariant across the conditions of performance.

With respect to our present work, an intuitively appealing temptation would be to connect the LV and the long-range correlation structure with the two determinants of the relative phase variability stated in the HKB formalism. In this view, one would readily draw correspondence between the structure of serial correlations with the function that determines the intrinsic stability (λ) of coordination and LV with the strength of the stochastic forces (Q). From this perspective, the results reported by Torre (2010), showing a negative correlation between the individual Hurst exponents of the relative phase produced and the frequency level at which participants switched from anti-phase to in-phase, would support the idea that the long-range correlation properties relate directly to the intrinsic stability of coordination.

However, in light of our present results, the abovementioned connections appear inconsistent. Indeed, according to the HKB dynamics, when the intrinsic stability of coordination decreases, the relative contribution of the deterministic determinant (the attractor strength) to the relative phase variability increases with respect to contribution of the stochastic random forces (assumed constant). In terms of the serial correlation properties and considering the above assumptions, this implies that we should observe a monotonic evolution (progressive strengthening or fading) of the long-range correlations with decreasing intrinsic stability. This prediction is incompatible with our present results. We observed no systematic evolution of the long-range correlation properties as a function of the experimental conditions, and no difference between the Hurst exponents obtained in the critical condition and the comfortable conditions (Figure 3). Moreover, our main result is that the emergence of an interdependence between the LV and the
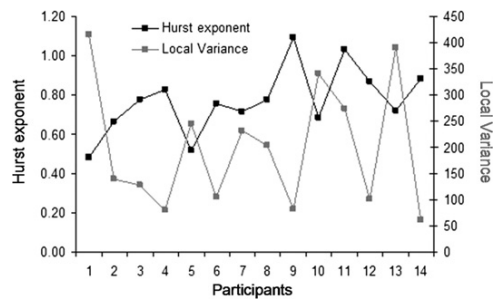

Figure 5. Illustration of the significant negative correlation between local variances and Hurst exponents of relative phase series in AP-CRIT: the graph shows a quasi-systematic opposite variation of the two measures. To highlight the correlation, participants were ordered by increasing level of local variance.

serial long-range correlations is in the critical condition *only*. This result seems inconsistent with the assumption of two formally independent determinants of the relative phase variability, as it would imply a qualitative change in the structure of the HKB model between comfortable and critical conditions of performance.

In order to bring the results of the present study within the broader HKB model framework, we must carefully distinguish between the empirical properties of coordination dynamics and the formalism and analytical tools used to assess these properties. One might consider that the combination of the intrinsic stability of a given coordination pattern and the stochastic fluctuations surrounding it determine the amount of supplemental or "active" stabilization needed to maintain coordination under critical performance conditions. Of special consideration is the influence of some individual factors and adaptive processes upon the intrinsic stability level of coordination. The finding of negative correlations between the individual long-range correlation properties and transition frequencies (Torre, 2010) would support the idea that the long-range correlations capture (among others) some individual determinants of the resultant stability of performance. We hope this work would encourage more systematic investigations of the individual-specific factors of performance (e.g., the role of perceptual systems, attention/arousal, corrective processes, and cognitive strategies) and their contributing roles to LV and global variability.

Adaptability and Adaptation, Stability and Stabilization in Serial Performance

Literature on $1/f^\beta$ noise in human performance and health has commonly acknowledged a kind of idealized view on the $1/f^\beta$ phenomenon as a warranty for systems' adaptability and functional responsiveness (e.g., Iyengar et al., 1996; Jordan, Challis, & Newell, 2006; Marks-Tarlow, 1999; Peng et al., 1993; Schmidt, Beek, Treffner, & Turvey, 1991). Both the specific statistical properties of $1/f^\beta$ noise (behaving at the frontier between stationary, fGn, and nonstationary, fBm processes) and the generic organization principles proposed to account for the widespread occurrence of $1/f^\beta$ noise attest to this view. Such accounts include the basic idea that systems that generate $1/f^\beta$ fluctuations are typically constituted of multiple weakly-coupled components operating at different time scales, so that an alteration of one component's functioning does not necessarily alter the macroscopic behavior of the whole system (e.g., Peng et al., 1993; Schmidt et al., 1991). Another generic explanation for the occurrence of $1/f^\beta$ noise is the assumed metastable dynamics of complex system. Metastability is characterized by the coexistence of latent patterns favoring rapid organization and reorganization between transient behaviors as shown in brain activity (Bressler & Kelso, 2001) or cognitive performance (Kello, Anderson, Holden, & Van Orden, 2008; Kello et al., 2007). Finally, $1/f^\beta$ noise has been shown to be present at all levels of observation of a system so that multiple $1/f^\beta$-networks are nested within a larger $1/f^\beta$-network and so forth, "from molecules to mindfulness" (Anderson, 2000, p. 193). It has been argued that such scaling organization may facilitate the communication and information transmission within and between $1/f^\beta$-networks (e.g., Marks-Tarlow, 1999; Soma, Nozaki, Kwak, & Yamamoto, 2003; West, Geneston, & Grigolini, 2008; Yu, Romero, & Lee, 2005)

and as such help systems' adaptability. So, although further investigations are needed to uncover the specific reasons and mechanisms underlying this generic principle, several interdisciplinary approaches in literature tend to converge towards the idea that $1/f^\beta$ noise and adaptability go together.

Now, if $1/f^\beta$ noise is an indicator of the capability of a system to adapt, then the directly ensuing question is how $1/f^\beta$ noise and its variations relate with the system's *effective* adaptation. Our present finding provides a possible explanation. In fact, the idea that the presence of $1/f^\beta$ noise signs an optimal state of adaptive functioning is apparently consistent with numerous empirical evidences showing its alteration towards either white noise or Brownian motion in the case of systems' dysfunction. In both cases, such alterations have been interpreted as reflecting a loss of complexity in the system (Goldberger et al., 2002). However, one may wonder whether these two forms of alteration of $1/f^\beta$ noise do indeed reflect comparable phenomena.

On the one hand, the change in serial correlations towards fractional Brownian motion, i.e. an increasing nonstationarity of performance over time, seems intuitively consistent with the observation of a system that quits its steady state functioning under severe constraints or pathology (see, for example Gilden & Hancock, 2007; Peng et al. 1995). This form of alteration of $1/f^\beta$ noise has been thought to reveal a simplification of the system in that a reduced set of its components exert dominant influence on the outcome behavior (Goldberger et al., 2002; Peng et al., 1993). On the other hand, the change of $1/f^\beta$ fluctuations into white noise has been interpreted in terms of a decreasing complexity of the system associated with the decline in regulation processes: a loss of coordination between the system's components leads to unpredictable behavior (e.g., Goldberger, Peng, & Lipsitz, 2002; Kyriasis, 2003; Lipsitz & Goldberger, 1992; Vaillancourt & Newell, 2002). Our present finding provides an alternative perspective on this second eventuality: it suggests that in certain conditions the whitening of $1/f^\beta$ noise may not signify the system's dysfunction and loss of regulation but, in contrast, the implementation of effective adaptive processes to stabilize the outcome behavior, which is characteristic of healthy and appropriately functioning systems. Note that our present experiment did not yield a global decrease in the persistence of long-range correlations in the critical condition of performance, as the mean Hurst exponent of relative phase series was not statistically different from any of the noncritical conditions. This might be due to the rather moderate level of constraints exerted on the system: one may suppose that as the task demands are higher and the constraints exerted on the system become more severe the individual within-series adjustment between the persistence of long-range correlations and the LV revealed by our results would systematically result in an average whitening of estimated $1/f^\beta$ noise across all participants. This account appears consistent with the idea supported by Correll (2008), that the intensity of $1/f^\beta$ noise is negatively related to the effort made by participants to answer the task requirements.

Conclusion

In sum, we propose that the presence of $1/f^\beta$ fluctuations in performance might indeed characterize the adaptive capability of a system. Effective adaptation, in contrast, may be indicated by the emergence of a negative correlation between the persistence of

long-range correlations and the LV, yielding a global stabilization of performance over time, under given constraints. Therefore, we argue that investigations into the issue of stability and adaptability of behavior as a function of different functioning conditions would be furthered by analyzing data beyond the average evolution of the statistical properties of time series. In the present study, for example, focusing on the variance of time series would have indicated a global destabilization of coordination while the evolution of long-range correlations would have indicated no effect of the critical condition of performance, thereby concealing the actual occurrence of adaptive processes. Decomposing variability into its two independent ingredients, i.e. the LV and the serial correlation properties, might contribute to disambiguate the complex relationship between variability, stability, and adaptability in behavior of complex systems and tackle some still open questions as the definition of functional stability: Is the most stable behavior the one that shows the minimal variability whatever its correlation structure or the one that has the correlation structure which tolerates a maximal variability without breaking down? The present study suggests that stabilization of performance is supported by a coadjustment of the LV and the structure of serial correlations.

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