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Strong anticipation and long-range cross-correlation: Application of detrended cross-correlation analysis to human behavioral data

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HIGHLIGHTS

- We apply cross-correlation analysis to series accounting for coordination processes.
- In the long term, series present similar long-range correlation properties.
- The matching of long-term fluctuations could result from short-term coupling processes.

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ABSTRACT

In this paper, we analyze empirical data, accounting for coordination processes between complex systems (bimanual coordination, interpersonal coordination, and synchronization with a fractal metronome), by using a recently proposed method: detrended cross-correlation analysis (DCCA). This work is motivated by the strong anticipation hypothesis, which supposes that coordination between complex systems is not achieved on the basis of local adaptations (i.e., correction, predictions), but results from a more global matching of complexity properties. Indeed, recent experiments have evidenced a very close correlation between the scaling properties of the series produced by two coordinated systems, despite a quite weak local synchronization. We hypothesized that strong anticipation should result in the presence of long-range cross-correlations between the series produced by the two systems. Results allow a detailed analysis of the effects of coordination on the fluctuations of the series produced by the two systems. In the long term, series tend to present similar scaling properties, with clear evidence of long-range cross-correlation. Short-term results strongly depend on the nature of the task. Simulation studies allow disentangling the respective effects of noise and short-term coupling processes on DCCA results, and suggest that the matching of long-term fluctuations could be the result of short-term coupling processes.

1. Introduction

Synchronization with the environment has often been described in terms of anticipation. For example, when participants have to synchronize finger taps with the beats emitted by a metronome, a mean negative asynchrony is consistently reported, suggesting that participants do not react to auditory stimuli, but rather anticipate their occurrence. Such anticipatory behavior can be underlain by the formation of an internal model that allows short-term predictions about the time of occurrence of the next metronome signal. A number of representational models, based on phase correction [1] and/or period correction [2], have been proposed for explaining synchronization in tapping tasks [3]. This kind of local short-term anticipation, based on internal models and corrective processes, is referred to by Dubois [4] as *weak anticipation*.

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Dubois [4] evoked a second kind of anticipative behavior, which he called *strong anticipation*, which is supposed to occur without reference to any internal model [5,6]. Strong anticipation is based on the embedding of the organism within its environment, creating a new organism–environment system, which possesses lawful regularities that allow the emergence of anticipation.

Stephen and Dixon [7] noted that two divergent approaches to strong anticipation have to be distinguished. The first one suggests that strong anticipation results from an appropriate local coupling between the organism and its environment. For example, the synchronization of the rhythmic oscillations of a limb with a periodic metronome has been successfully accounted for by a model of coupled oscillators, including a parametric driving function [8,9]. More sophisticated models in physics have shown that, during the synchronization between a slave and a master system, the presence of time delays in the master system yields the slave system to synchronize with future states of the master [10]. These models of coupled oscillators suggest that anticipation could emerge from the macroscopic properties of the organism–environment system. This conception supposes that anticipation is based on local time scales [6].

A second approach considers that strong anticipation could be based on a more global coordination between the organism and its environment. Stephen, Stepp, Dixon, and Turvey [5] analyzed synchronization with a chaotic metronome: In that case, local predictions are difficultly conceivable, because of the intrinsically unpredictable nature of the pacing signal. Indeed, the authors showed that tapping behavior in this situation exhibited a mix of reaction, proaction, and synchrony to metronome signals. Importantly, they observed a close matching between the fractal exponents of the chaotic signals and those of the corresponding inter-tap interval series. In this kind of strong anticipation, the organism is not adapted to the states of the environment but to their statistical structure. The presence of $1/f$ scaling in the environment is essential in this coordination process: the organism exploits the complexity of the environment, and especially the long-range correlated structure of its evolution over time, as a resource for a more adaptive and efficient behavior [5,7].

Note that the concept of strong anticipation was primarily introduced to account for the adaptation of (complex) organisms with their (complex) environment. Anticipation suggests a directional relationship, with a slave system attempting to anticipate the future states of a master system. The principles that underlie strong anticipation, however, can be extended more generally to coordination processes between equivalent systems [11]. In that case, systems mutually adapt, with a kind of bidirectional anticipation. Strong anticipation, in this context, suggests that the complexity of both systems is an essential resource for their effective coordination. For example, Marmelat and Delignières [11] analyzed interpersonal coordination in a task where participants had to move pendulums in synchrony. Results revealed a poor local correlation between the series of oscillation periods produced by the two participants of each dyad. The authors analyzed the scaling properties of the series of periods produced by participants, separating short-term and long-term scaling behaviors. They evidenced a close correlation between long-term fractal exponents, but, in the short term, series behaved more independently.

The hypothesis that coordination could occur not only on local and short-term scales but following multiple and interpenetrated scales suggests that strong anticipation should be revealed by the presence of long-range cross-correlations between the series [12]. Long-range cross-correlations can occur between two series that both present long-range correlations. In that case, each series has long memory of its previous values, and additionally each series has also a long memory of the previous values of the other.

Podobnik and Stanley [13] introduced detrended cross-correlation analysis (DCCA) for analyzing long-range cross-correlations between two simultaneously recorded non-stationary time series. This method is an extension of the well-known detrended fluctuation analysis (DFA), which was initially proposed by Peng et al. [14–16], as a method for quantifying serial correlations in non-stationary time series. To date, DCCA has essentially been applied to artificial series, and to some real-data sets related to stock markets [17–19], road traffic [20–22], climate [23], or encephalography [24]. In this paper, we analyze some data sets collected in experiments about synchronization processes in human behavior, with the aim of seeking for statistical signatures of strong anticipation.

We first present the algorithms of DFA and DCCA, and we briefly discuss some formal properties of their expected results. Then we examine the results obtained with experimental series collected in situations that could be considered as emblematic of strong anticipation processes in human behavior: inter-limb coordination, interpersonal synchronization, and synchronization with fractal metronomes. Then we analyze some results obtained with simulated data sets, especially for evidencing the effects of short-term autoregressive processes.

2. Methods

2.1. Detrended fluctuation analysis (DFA)

DFA has been successfully applied to various processes, including physiological processes [25], psychological [26], sensorimotor [27–29], geophysical [30], climate [31] or financial [32,33]. DFA exploits the diffusion property of fractional Brownian motions, stating that in such processes the variance is a power function of the time interval over which it is computed [34]:

$$\operatorname{Var} x(t) \propto \Delta t^{2H}, \tag{1}$$

where H is the Hurst exponent.

Consider a series $x(t)$ of length N. The series is first integrated, by computing for each t the accumulated departure from the mean of the whole series:

$$X(t)=\sum_{i=1}^{t}\left[x(i)-\bar{x}\right]. \tag{2}$$

Integrating the series is an essential step. Generally, experimental time series are too stationary to be properly modeled as fractional Brownian motions, and the diffusion property expressed in Eq. (1) does not hold for raw data. Integration provides the series with a diffusion property and allows a proper estimation of the scaling exponent (for details, see Ref. [35]). Omitting integration can yield erroneous results, for example the spurious detection of crossover in the diffusion plot [36].

This integrated series is divided into k non-overlapping intervals of length n. The last $N-(kn)$ data points are excluded from analysis. Within each interval, a least-squares line is fit to the data (representing the trend in the interval). The series $X(t)$ is then locally detrended by subtracting the theoretical values $X_n(t)$ given by the regression. For a given interval length n, the characteristic size of fluctuation for this integrated and detrended series is calculated by

$$F(n)=\sqrt{\frac{1}{N-kn}\sum_{t=1}^{N-kn}\left[X(t)-X_n(t)\right]^2}. \tag{3}$$

This computation is repeated over all possible interval lengths. Typically, F increases with interval length n. A power law is expected:

$$F(n)\propto n^{\alpha}. \tag{4}$$

α is expressed as the slope of the double logarithmic plot of $F(n)$ as a function of n (i.e., the *diffusion plot*). The value $\alpha=0.5$ indicates the absence of correlations (white noise), $\alpha>0.5$ indicates persistent long-range correlations, meaning that large (small) values are more likely to be followed by large (small) values, and $\alpha<0.5$ indicates anti-persistent correlations, meaning that large values are more likely to be followed by small values and vice versa. The values $\alpha=1$ and $\alpha=1.5$ correspond to $1/f$ noise and to Brownian noise (integration of white noise), respectively [16,37]. The α exponent is linked to H through simple relationships: for fGn, $\alpha=H$, and for fBm, $\alpha=H+1$.

A number of improvements have been proposed to the initial DFA algorithm, for example by using polynomial detrending [38,39]. Another proposed improvement was to use a sliding window in place of non-overlapping intervals [40]. However, this latter option appears to be time consuming, and does not seem to afford substantial benefits. In this study, we used the original algorithm.

2.2. Detrended cross-correlation analysis (DCCA)

DCCA works on two time series $x(t)$ and $y(t)$ of equal length N. The first steps are similar to those of DFA. The two series are integrated, by computing for each t the accumulated departure from the mean of the whole series:

$$X(t)=\sum_{i=1}^{t}\left[x(i)-\bar{x}\right]\quad\text{and}\quad Y(t)=\sum_{i=1}^{t}\left[y(i)-\bar{y}\right]. \tag{5}$$

These integrated series are divided into k non-overlapping intervals of length n. Note that Podobnik and Stanley [13] proposed using overlapping intervals. However, considering that DCCA results have to be compared to those of DFA, we think it preferable to use the same procedure in both methods, and we used non-overlapping intervals in this study [41].

The series $X(t)$ and $Y(t)$ are then locally detrended, and the covariance of these two detrended series is calculated as

$$F_{\mathrm{DCCA}}^2(n)=\frac{1}{N-kn}\sum_{t=1}^{N-kn}\left[X(t)-X_n(t)\right]\left[Y(t)-Y_n(t)\right]. \tag{6}$$

This computation is repeated over all possible interval lengths. Typically, $F_{\mathrm{DCCA}}(n)$ increases with interval length n. A power law is expected:

$$F_{\mathrm{DCCA}}(n)\propto n^{\lambda}. \tag{7}$$

λ is expressed as the slope of a double logarithmic plot of $F_{\mathrm{DCCA}}(n)$ as a function of n, and the interpretation of λ is similar to that of the DFA exponent α.

In both cases (DFA and DCCA), we considered interval lengths ranging from $n=10$ to $n=N/2$. In order to avoid any bias due to the logarithmic distributions of the points in the diffusion plots, we divided the abscissa into intervals of $0.1(\log_{10}\Delta t)$, computed the average points within each interval, and determined the regression slopes over these average points. The resulting diffusion plots included 13 points for an initial series length of 512 data points. The estimation of the regression slopes in the short term and long term was performed on the first five points and the last five points, respectively.

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2.3. DCCA cross-correlation coefficient

Zebende [42] noted that λ did not allow one to measure the strength of cross-correlation, and introduced the DCCA cross-correlation coefficient $\rho_{DCCA}(n)$, defined as

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA}(n)}{F_{DFAx}(n)F_{DFAy}(n)}. \tag{8}$$

$\rho_{DCCA}(n)$ is a set of coefficients, which can vary between −1 and 1, and it represents the evolution of cross-correlation with n (see also Ref. [43]). One could question, however, the true meaning of these coefficients, as $\rho_{DCCA}(n)$ does not represent cross-correlations among raw data, but among integrated and detrended series. As previously explained, integration is an essential step in the DFA algorithm. However, integration tends to inflate correlations in the series, and clearly yields an overestimation of cross-correlations. On the other hand, detrending allows avoiding spurious correlations related to the presence of trends in the series. Then $\rho_{DCCA}(n)$ seems affected by two opposite influences, and its interpretation remains tricky. In this study, we computed in complement the *windowed detrended cross-correlation coefficients* [$WDCC(n)$]. In this method, cross-correlation coefficients are computed in non-overlapping intervals of length n, ranging from 10 to $N/2$, after data detrending within each interval. Then cross-correlation coefficients are averaged for each n. In this method, detrending allows to control for the influence of trends in the series, but correlations are computed on raw data, and then follow a more familiar metrics.

These measures of cross-correlation provide dimensionless indexes that allow for comparison between conditions or between experimental and simulated series. Three aspects are particularly relevant in the results: cross-correlations in the shortest intervals, the growing rate of cross-correlation with increasing n, and the asymptotic value reached in long intervals.

2.4. General properties of DCCA

By construction, DCCA results possess some general properties that are useful as a reference for analyzing experimental results. First, the application of DCCA to identical series yields results identical to those of DFA. Considering $x(t) = y(t)$, $F_{DFAx}(n) = F_{DFAy}(n) = F_{DCCA}(n)$, and $\alpha_x = \alpha_y = \lambda$.

If one series is an affine transformation of the other, $y(t) = ax(t) + b$, one can easily show that $F_{DFAy}(n) = aF_{DFAx}(n)$, and $F_{DCCA}(n) = \sqrt{F_{DFAx}(n)F_{DFAy}(n)}$. In the log–log plot, the curves are vertically offset from one another, DCCA being midway from the two DFAs, but the slopes remains identical ($\alpha_x = \alpha_y = \lambda$).

In the present algorithm, $F_{DFAx}(n)$, $F_{DFAy}(n)$, and $F_{DCCA}(n)$ are computed on the same sets of non-overlapping intervals. Then, considering that both time series are measured on identical units, perfect synchronization implies that $F_{DFAx}(n) = F_{DFAy}(n) = F_{DCCA}(n)$. Any local difference between $x(t)$ and $y(t)$ entails a decrease of $F_{DCCA}(n)$, with respect to $F_{DFAx}(n)$ and $F_{DFAy}(n)$. $F_{DCCA}(n)$ is bounded by an upper limit, $F_{DCCA}(n) \leq \sqrt{F_{DFAx}(n)F_{DFAy}(n)}$, and it tends to decrease as the synchronization between the two series decreases. Within each considered interval, detrending allows controlling for spurious covariance due to local trends. When the synchronization is close between the two series, two simultaneous data points are likely to be both located either above, or below, the average trend. In that case, the contribution of each pair of points to the computation of covariance is positive (residuals $X(t) - X_n(t)$ and $Y(t) - Y_n(t)$ being both positive, or both negative), and $F_{DCCA}(n)$ cannot be lower than the lowest $F_{DFA}(n)$. When the synchronization is weaker, one of the two integrated values can be above the current trend, and the other below. In that case, the residuals are of opposite signs, and the contribution of the pair to the covariance is negative. The accumulation of discrepant pairs yields a decrease of $F_{DCCA}(n)$, which can in that case be lower than the lowest $F_{DFA}(n)$.

These discrepancies in signs, however, are not absolute, and they depend on the interval length (n) considered. A given difference between $x(t)$ and $y(t)$ could result in residuals of opposite signs in short intervals, but not in large intervals. Linear detrending allows one to control for the effects of trends at the time scale defined by the length of the interval considered. So $F_{DCCA}(n)$ is sensitive to punctual discrepancies for very short intervals, and to trend discrepancies for long intervals. One could suppose that the use of polynomial detrending could partially reduce this effect. But generally, for a given level of synchronization between the two series, the difference between $F_{DCCA}(n)$ and the value expected in the case of perfect synchronization is expected to be larger for short interval lengths, and to decrease as the interval length increases. The direct consequence is that λ should be systematically higher than α_x and α_y, especially when computed on short intervals.

Finally, the distinction between short-term and long-term slopes has frequently been evoked in fractal analysis. A number of authors have shown that, when applied to biological series, DFA results cannot be considered as homogeneous over the whole series, and that they should be analyzed separately over the short term and the long term [37,44]. Biological series cannot be considered as pure fractal processes, and they are often contaminated by noise, and by short-term correlated processes that mainly act on local scales [45,46]. Generally one assumes that relevant information about long-range correlation in the series (and especially the accurate estimation of the fractal exponent) is obtained from the long-term region of the diffusion plot [35]. DCCA is likely to be affected by similar phenomena, as synchronization between series could correspond to a mix between short-term coupling and long-term coordination. So separate short-term and long-term analyses seem necessary in both DFA and DCCA.

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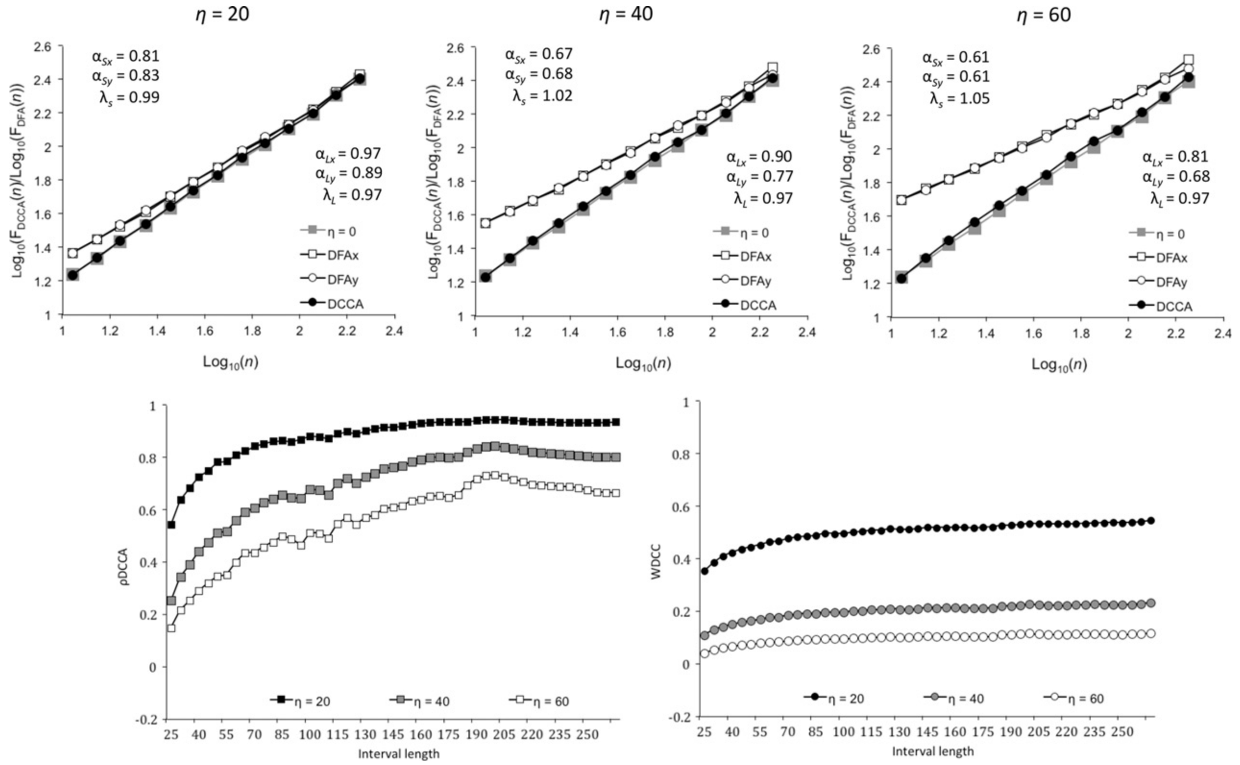

Fig. 1. Effect of noise on perfect synchronization. Top row: average DFA and DCCA diffusion plots ($N = 10$), for low (left), normal (middle), and strong (right) coupling conditions. Bottom row: $\rho_{\mathrm{DCCA}}(n)$ and $WDCC(n)$.

2.5. Effect of noise on perfect synchronization

The last part of this section aims at analyzing the effect of noise on synchronization. Noise is omnipresent in experimental series, and a correct identification of its influence on statistical and graphical results is essential for proper interpretations. We performed a simulation study in which we generated ten series of fractional Gaussian noise ($N = 512$), with a mean α exponent of 0.9, using the method proposed by Davies and Harte [47]. We added a constant of 1000 and adjusted the standard deviation of the fractional Gaussian noise in order to obtain a coefficient of variation of about 2% for each resulting series.

DFA and DCCA were first applied on each series, considering the limit case of perfect synchronization ($x(t) = y(t)$). As expected, we obtained identical results for α_x, α_y, and λ, with identical values in the short term and the long term, and the correlation between α exponents was maximal ($r = 1.0$) in both the short term and the long term. The cross-correlation coefficients $\rho_{\mathrm{DCCA}}(n)$ and $WDCC(n)$ were maximal (1.0), whatever the considered interval length.

In a second step, we added to each series $x(t)$ and $y(t)$ independent uncorrelated noises. We constructed three new sets of series, according to the standard deviation of the added noise: $\eta = 20$, $\eta = 40$, or $\eta = 60$. The DFA and DCCA results are illustrated in Fig. 1 (note that in all figures the graphs represent point-by-point averages of single results). As reported in earlier experiments, noise induced a flattening of DFA slopes, especially in the short-term region [48], and this effect increased with noise strength.

An important observation is that noise had no observable effect on the DCCA slopes: whatever the level of added noise, the DCCA curves remained superimposed to that obtained with the original series. This does not mean, however, that noise had no effect on synchronization: correlations between α exponents were dramatically reduced by noise, in the long term ($\eta = 20$: $r = 0.963$; $\eta = 40$: $r = 0.768$; $\eta = 60$: $r = 0.442$), as well as in the short term ($\eta = 20$: $r = 0.523$; $\eta = 40$; $r = 0.040$; $\eta = 60$: $r = -0.067$). Finally, noise induced lower $\rho_{\mathrm{DCCA}}(n)$ in short intervals, a lower asymptotic limit in long intervals, and a slower increase with interval length.

3. Experimental series

In this section, we analyze a set of experimental series representative of synchronization and coordination processes in human movement. In all cases, strong anticipation represents a sustainable hypothesis for explaining the relationships between the two interacting systems. In a first step, our aim was to establish the statistical signatures of each experimental situation, and their shared features, but also their differences. In light of the previous considerations about DFA and DCCA, we expected to obtain initial insights about the nature of the coordinative processes at work in each situation.

3.1. Synchronization between effectors during bimanual timing tasks

The first example is emblematic of an important domain of research in human movement, which focuses on inter-limb coordination. The dynamical systems approach to coordination has massively exploited bimanual coordination tasks, in order to evidence the emergent properties that underlie the macroscopic behavior of complex systems [49].

In these experiments, participants have to perform cyclical bimanual movements, maintaining a stable phase relationship between effectors. The two limbs are considered as a system of coupled oscillators, exhibiting macroscopic properties [50,51]. Bimanual coordination represents a nice example of close coordination between complex (sub)systems, embedded to form a global functional system for performing a particular goal. As such, one could hypothesize that bimanual coordination could be achieved by processes of complexity matching similar to those evoked in strong anticipation.

The present series were collected in an experiment in which 12 participants performed bimanual oscillations and bimanual tapping [52,53]. In the bimanual oscillation task, participants performed smooth and regular forearm oscillations holding two joysticks. The bimanual tapping task consisted in performing sequences of discrete taps with the index fingers on two flat pressure sensors. Participants were instructed to synchronize the reversal points of the motion of the joysticks in the oscillation task (in-phase coordination), and to synchronize taps in the tapping task. This experiment used the synchronization–continuation paradigm: for 30 s, participants synchronized their movements with a video model, inducing an initial frequency of 1.5 Hz. Then the model was removed and participants had to continue following the initial tempo for 600 cycles. Participants were able to perform the task adequately, and we observed a mean relative phase of -6.33° (± 3.76) for bimanual oscillations, and -2.21° (± 4.58) for bimanual tapping.

We analyzed the series of periods simultaneously produced by the right and the left effectors. The results of DFA and DCCA analyses are reported in Fig. 2. The long-term α exponents were higher in oscillation than in tapping, a result that was already described in the unimanual performance of these tasks [52]. In both tasks, the three curves appeared closely superimposed in the long term, and they were characterized by very similar mean exponents. Additionally, the long-term individual exponents were strongly correlated (oscillations: $r = 0.999$; tapping: $r = 0.999$).

The short-term α exponents were lower than their long-term counterparts, reflecting the presence of a noisy component in the analyzed series (see above, and [48]). Over the shortest intervals, $F_{\mathrm{DFA}}(n)$ values remained close between the two series, suggesting a similar evolution of variability in the short term. Correlations between short-term α exponents remained very high, though a little bit lower than those observed in the long term (oscillations: $r = 0.929$; tapping: $r = 0.985$). The short-term λ exponents were also lower than their long-term counterparts, but they remained close to the corresponding α exponents.

Finally, $\rho_{\mathrm{DCCA}}(n)$ revealed high levels of cross-correlation in the shortest intervals, and a final asymptotic level close to 1.0. $WDCC(n)$, however, showed lower (and maybe more realistic) correlation levels, just reaching in the long term 0.65 for bimanual tapping, and 0.6 for bimanual coordination.

These results can be considered as representing a nice example of strong coordination in human behavior. The two effectors produce long-range correlated and long-range cross-correlated series, suggesting that they behave as a single embedded complex system. The DFA slopes are slightly lower in the short term, denoting the presence of noise in the system that locally perturbs synchronization. This results in rather moderate $WDCC(n)$ values, which however can be considered as representative of very close coordination in human behavioral data. The most important results are the close matching of mean DFA and DCCA slopes, and the close correlation between individual α exponents, especially in the long term. Note that these results are very similar to those previously obtained in the previous simulation study about the effects of noise on perfect synchronization, considering a quite low level of noise perturbation.

3.2. Interpersonal synchronization

The second set of series was collected in an experiment on interpersonal coordination [11]. In contrast with the previous example, these series represent coordination between two physically independent systems that interact for achieving a common goal. Interpersonal coordination has been shown to possess similar macroscopic properties to inter-limb coordination [54], and the present set of data has been interpreted as a typical example of strong anticipation [11].

In this experiment, 22 participants were randomly paired into 11 dyads. Participants in each dyad were instructed to perform synchronized oscillations with pendulums, following an in-phase pattern of coordination. They were instructed to oscillate at the preferred frequency of the dyad, as regularly as possible. The task was performed in three conditions, characterized by increasing levels of coupling between participants. In the weak coupling condition, audition was limited with earplugs, and participants were instructed to visually fix a target in front of them on the wall. In the normal coupling condition, visual and auditory feedbacks were fully available, and participants were invited to visually fix their partner's pendulum. In the strong coupling condition, participants were instructed to cross their free arms (arm-in-arm), in order to add haptic information to visual and auditory feedbacks. Series of 512 oscillations were collected in each condition.

Results showed that the dyads were able to perform this coordination task adequately, with a mean relative phase of -2.15° (± 8.64) in the low coupling condition, -1.67° (± 7.50) in the normal coupling condition, and -2.36° (± 7.15) in the

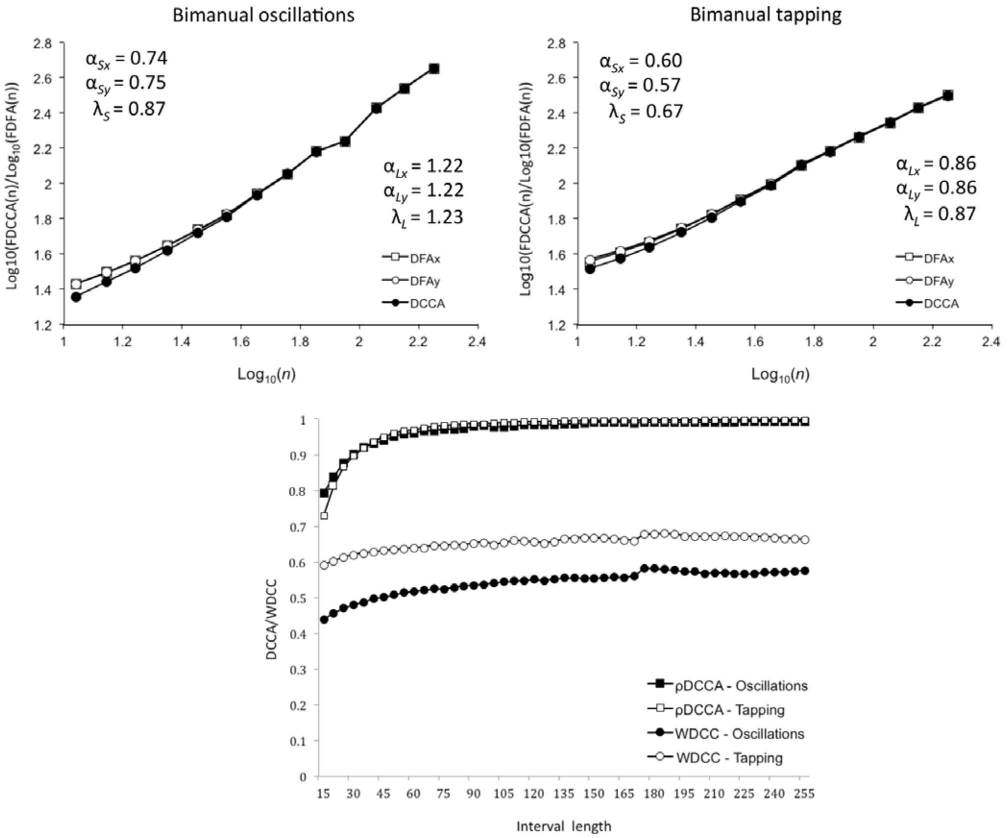

Fig. 2. Bimanual coordination tasks. Top row: average DFA and DCCA diffusion plots ($N = 12$), for bimanual oscillations (left) and bimanual tapping (right). The α and λ short-term exponents are reported on the left part of each graph, and the long-term exponents on the right. Bottom row, left: $\rho_{\mathrm{DCCA}}(n)$ for bimanual oscillations and bimanual tapping; right: windowed detrended cross-correlation $WDCC(n)$. In both cases, results are averaged over intervals of five values.

strong coupling condition. We observed that, within each dyad, one of the two participants presented higher F_{DFA} than the other for the shortest interval, whatever the coupling conditions. Participants were ordered in each dyad on this basis.

The results of DFA and DCCA are reported in Fig. 3. The F_{DFA} curves presented very similar shapes, except in short intervals where $F_{\mathrm{DFA}x}(n)$ was higher than $F_{\mathrm{DFA}y}(n)$ (due to the previously evoked ordering of participants). This difference tended to slightly increase as the coupling strength increased. In the long term, similarly to the previous example, the three curves were closely superimposed, and the correlation between individual α exponents was close to 1.0, whatever the coupling condition (low: $r = 0.999$; normal: $r = 0.998$; strong: $r = 0.999$). In contrast, correlations between individual short-term α exponents did not reach significance, except in the normal coupling condition (low: $r = -0.209$; normal: $r = 0.675$; strong: $r = 0.410$).

Finally, $F_{\mathrm{DCCA}}(n)$ decreased dramatically in short intervals, with respect to $F_{\mathrm{DFA}x}(n)$ and $F_{\mathrm{DFA}y}(n)$, and especially in the low coupling condition, denoting a quite low level of covariance in the short term. This resulted in high short-term λ exponents, with respect to the corresponding DFA slopes.

$\rho_{\mathrm{DCCA}}(n)$ started with quite low values, especially in the low coupling condition, but quickly reached an asymptotic value close to 1. In contrast, $WDCC(n)$ remained moderate, and never exceeded a value of about 0.2. Note that the $WDCC(n)$ slopes allowed one to clearly distinguish between coupling conditions, and they were ordered according to coupling strength.

Interpersonal coordination has been presented as very similar to inter-limb coordination [54]. The present analyses, however, reveal a completely different statistical picture between the two tasks. In both cases, we observed a very close matching between series fluctuations in the long term, suggesting that series share essential statistical properties. However, this matching occurs in interpersonal coordination despite a rather low local covariance. In contrast with the previous example, these results revealed a very different statistical behavior in the short and the long terms. DFA and DCCA were closely matched in long intervals, and the α long-term exponents were strongly correlated. In short intervals, the series presented a low covariance, suggesting a rather poor local synchronization, in contrast with bimanual coordination, where effectors appear strongly coupled on local scales. These results at least suggest that coupling, in these two situations, works following different time scales. Bimanual coordination has been modeled through the well-known HKB model [50], which supposes a continuous coupling between effectors. This kind of coupling could explain the strong matching of exponents observed even on short scales. The results obtained for interpersonal coordination suggest in contrast a discrete form of

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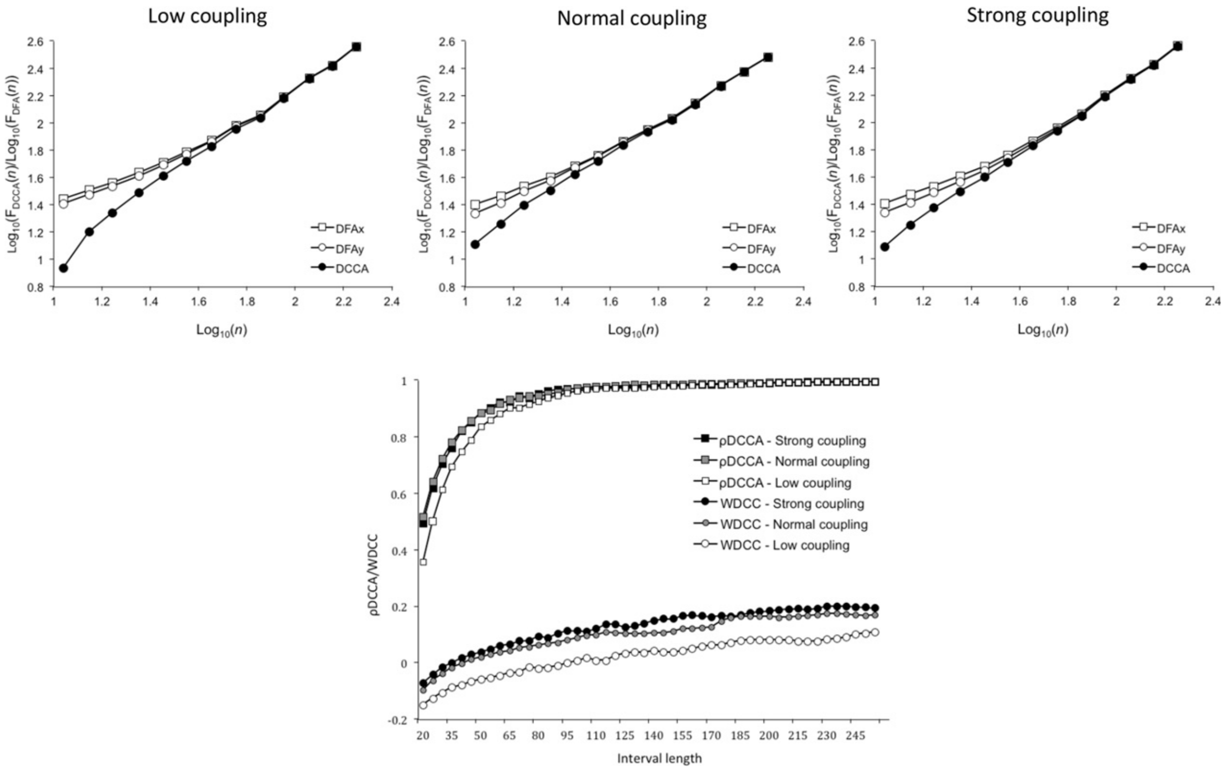

Fig. 3. Interpersonal coordination task. Top row: average DFA and DCCA diffusion plots ($N = 11$), for low (left), normal (middle), and strong (right) coupling conditions. Bottom row: $\rho_{\mathrm{DCCA}}(n)$ and $WDCC(n)$.

coupling, which could occur at the time scale of a complete oscillation. This hypothesis will be examined latter. These results raise a central question: could a complete matching in the long term originate from a rather weak coupling on local scales?

3.3. Walking in synchrony with a fractal metronome

The third example is representative of another kind of situation, in which participants have to synchronize with a fractal metronome. This situation induces a unidirectional relationship between an organism and its environment, and it was used in the first paper that evoked strong anticipation processes in human behavior [5].

The present series were collected in a pilot study, during which 11 participants walked on a treadmill, and had to synchronize the right heel strikes with metronome signals administered through an earphone. Metronome signals presented fractal fluctuations around a mean value of 1135 ms. Fractal fluctuations had mean α exponent of about 0.9, and their standard deviation was adjusted for obtaining a coefficient of variation of 2%. Series of 512 steps were collected. Results showed that participants were able to maintain synchrony with the metronome, with a mean asynchrony of about −52.8 ms (±46.9). This negative asynchrony, which is a common result during synchronization with regular metronomes [3], shows that, despite the unpredictability of the inter-onset intervals produced by the metronome, participants did not react to signals, but were able to anticipate their occurrence.

The DFA and DCCA results are reported in Fig. 4, with $x(t)$ corresponding to the series of stride intervals produced by the participant, and $y(t)$ to the series of inter-onset intervals of the metronome. As previously, the DFA and DCCA curves tended to join together in the longest intervals, and the long-term α exponents were strongly correlated ($r = 0.973$). In contrast, there was no correlation between the short-term α exponents ($r = 0.083$), and $F_{\mathrm{DFA}x}(n)$ was clearly larger than $F_{\mathrm{DFA}y}(n)$, which is consistent with the asymmetrical nature of the task. Interestingly, over short intervals, $F_{\mathrm{DCCA}}(n)$ values were closer to the lowest $F_{\mathrm{DFA}}(n)$ than in the previous example, suggesting a better local synchronization. This resulted in higher $WDCC(n)$ values, approaching 0.4 in the longest intervals.

3.4. Cross-correlation functions

Despite obvious differences, these three examples reveal some common signatures, and especially the very close matching between the temporal structures of fluctuations in the long term. These results could suggest that similar processes could be at work in the three situations. DCCA, however, reveals the effects of synchronization considering a lag zero between

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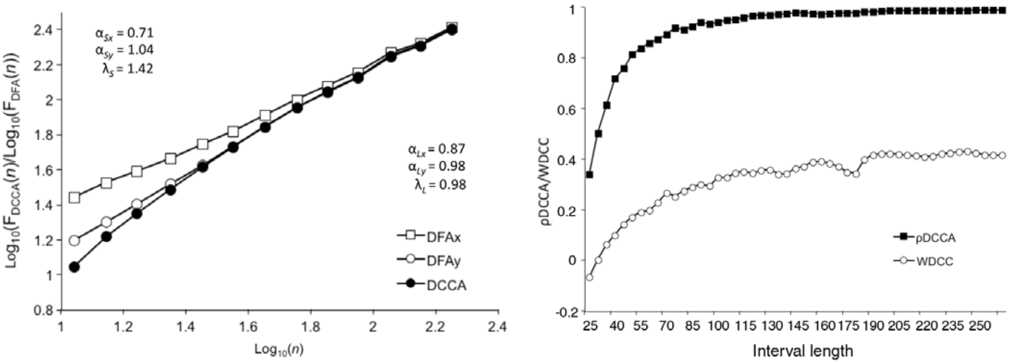

Fig. 4. Walking in synchrony with a fractal metronome. Left panel: average DFA and DCCA diffusion plots ($N = 11$). Right panel: $\rho_{\mathrm{DCCA}}(n)$ and $WDCC(n)$.

the two analyzed series, but ignores the lagged influences that could occur between systems. In order to get a more complete picture, we computed windowed cross-correlation functions (WCCFs) for all situations, from lag −10 to lag 10, between $x(t)$ and $y(t)$. In order to focus on short-range dependence, we worked on windows of short length ($n = 15$). Moreover, in order to avoid detecting spurious cross-correlation due to the presence of drifts in the considered windows, data were detrended within each window before the computation of cross-correlation.

Practically, the analysis started with a first window containing 15 points of the $x(t)$ series, beginning at the tenth point of the series. Then the cross-correlation function between this window and a sliding window of $y(t)$ was computed, from lag −10 to lag 10, after local detrending. The $x(t)$ window was then lagged by one point, and the cross-correlation function was computed again. This process was repeated over the whole series, and finally the WCCF was computed by point-by-point averaging of the obtained functions.

Another variable that could play a significant role during coordination is asynchrony, defined as the delay between the occurrence of a given event in one system and that of the corresponding event in the other. Indeed, a number of studies suggested that synchronization with regular metronomes is based on a discrete correction of asynchronies [1,55]. Asynchronies are computed as the differences between the cumulated sums of $x(t)$ and $y(t)$:

$$ASYNx(t) = -ASYNy(t) = ASYNx\,(0) + \sum_{i=0}^{t} x(i) - \sum_{i=0}^{t} y(i). \tag{9}$$

We computed the WCCF between $ASYNx(t)$ and $x(t)$, and for the two first situations between $ASYNy(t)$ and $y(t)$.

We present in the upper row of Fig. 5 the WCCF between $x(t)$ and $y(t)$. We found completely different results for the three situations. In bimanual coordination, there was a strong positive lag-zero cross-correlation, in oscillations as well as in tapping, but no correlations on other lags. In contrast, in interpersonal coordination, the lag-zero cross-correlation was low and slightly negative, and some moderate positive cross-correlations appeared at lag −2 and lag −1 on the one hand, and at lag 1 and lag 2 on the other. Finally, for the task of synchronization with the fractal metronome, there were positive cross-correlations at lag −3, lag −2, and lag −1. These results confirm that, during bimanual coordination, synchronization occurs within each cycle between the two effectors. In contrast, in the two other situations, coordination seems based on cycle-to-cycle influences.

The WCCFs between $ASYNx(t)$ and $x(t)$ are presented in the bottom row of Fig. 5. We obtained similar results for the WCCFs between $ASYNy(t)$ and $y(t)$. In all cases, there was a significant negative lag −1 cross-correlation between $ASYNx(t)$ and $x(t)$. These results should be analyzed with caution, however, because any process allowing synchronization to be maintained between $x(t)$ and $y(t)$ is likely to mechanically create a negative correlation between the interval produced and the preceding asynchrony. On the other hand, this negative correlation could reveal a direct corrective process of the current interval, on the basis of the previous asynchrony [1,55]. In other words, this negative correlation between $ASYNx(t-1)$ and $x(t)$ (and between $ASYNy(t-1)$ and $y(t)$) could be either the cause or the consequence of synchronization. We examine this issue in the following section.

4. Short-term synchronization: autoregressive unidirectional models

We present in this section a set of simulation studies dealing with simple autoregressive coupling. We especially analyzed discrete forms of coupling, occurring at the time scale of oscillation, step, or tap. In a first step, we focused on unidirectional coupling, corresponding to situations in which an organism has to synchronize its behavior with that of its environment, as for example in our third experimental situation, in which participants had to walk in synchrony with a fractal metronome.

In the following simulations, $x(t)$ represents the series produced by the organism, and $y(t)$ that of the environment. Our modeling effort is based on two main assumptions.

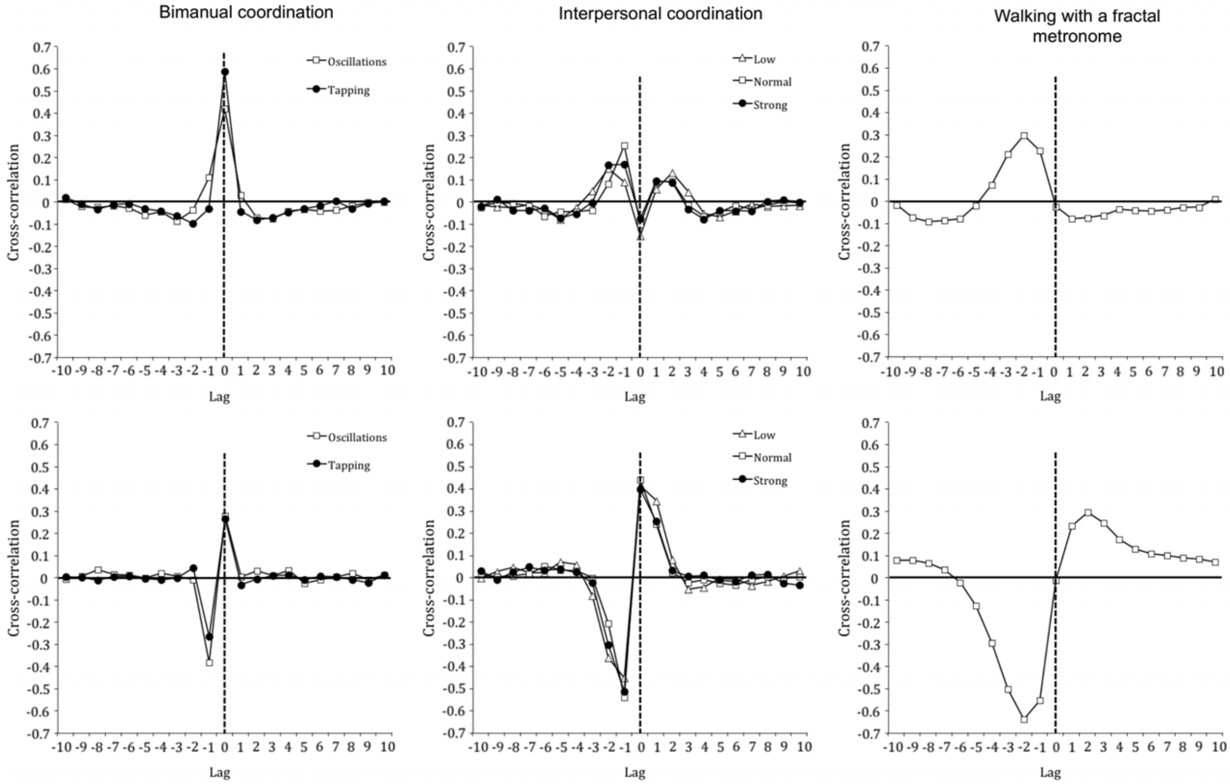

Fig. 5. Top row: windowed detrended cross-correlation functions (from lag −10 to lag 10) between $y(t)$ and $x(t)$, for bimanual coordination tasks, interpersonal coordination, and walking with a fractal metronome. Bottom row: windowed detrended cross-correlation functions (from lag −10 to lag 10) between $ASYNx(t)$ and $x(t)$.

(1) First, considering the significant lag −1 cross-correlation we observed in our third experiment, we propose that the current interval produced by the organism is determined by the previous interval produced by the environment.
(2) Second, we consider that the organism produces intrinsically long-range correlated series. A number of previous studies have shown that organisms produced long-range correlated series in self-paced conditions, and that, during synchronization with a regular metronome, this source of long-range correlation was still at work and had to be considered for properly modeling the results [9,27,55–57]. We consider that this assumption also holds in the case of a fractal metronome.

Two main processes can be advocated for such discrete coupling. The first one considers that the organism uses the time interval produced by the environment during the current cycle for correcting the interval it intended to intrinsically produce for the next cycle. In its simplest formulation (one-order autoregressive processes), this *interval-based* hypothesis can be expressed as follows:

$$x(t) = (1 - \varphi_x)x_{\text{int}}(t) + \varphi_x y(t-1) + \eta\varepsilon_x(t), \tag{10}$$

where $x_{\text{int}}(t)$ represents the series of intrinsic fluctuations of the organism, φ_x is the autoregressive parameter, $\varepsilon_x(t)$ a white noise process with zero mean and unit variance, and η a constant denoting noise strength.

A second hypothesis suggests that the organism corrects the interval it intended to intrinsically produce on the basis of the previous asynchrony. This hypothesis has received some support, especially in the analysis of tapping tasks [1,55,58].

In its simplest formulation (one-order autoregressive processes), this *asynchrony-based* hypothesis can be expressed as follows:

$$x(t) = x_{\text{int}}(t) + \delta_x ASYN_x(t-1) + \eta\varepsilon_x(t), \tag{11}$$

where δ_x is the autoregressive parameter.

We modeled $x_{\text{int}}(t)$ and $y\ (t)$ by fractional Gaussian noise ($N = 512$), with a mean α exponent of 0.9, using the method proposed by Davies and Harte [47]. As in the previous simulations, these series were adjusted around a mean of about 1000, with a coefficient of variation of about 2%. In all simulations, we set $\eta = 20$. We first tested the interval-based model, for three values of φ_x (0.5, 0.4, and 0.3). This model was unable to generate the typical matching of long-term α exponents: the three parameters produced correlations of about $r = 0.062$, $r = -0.139$, and $r = -0.285$, respectively. We show, in Fig. 6

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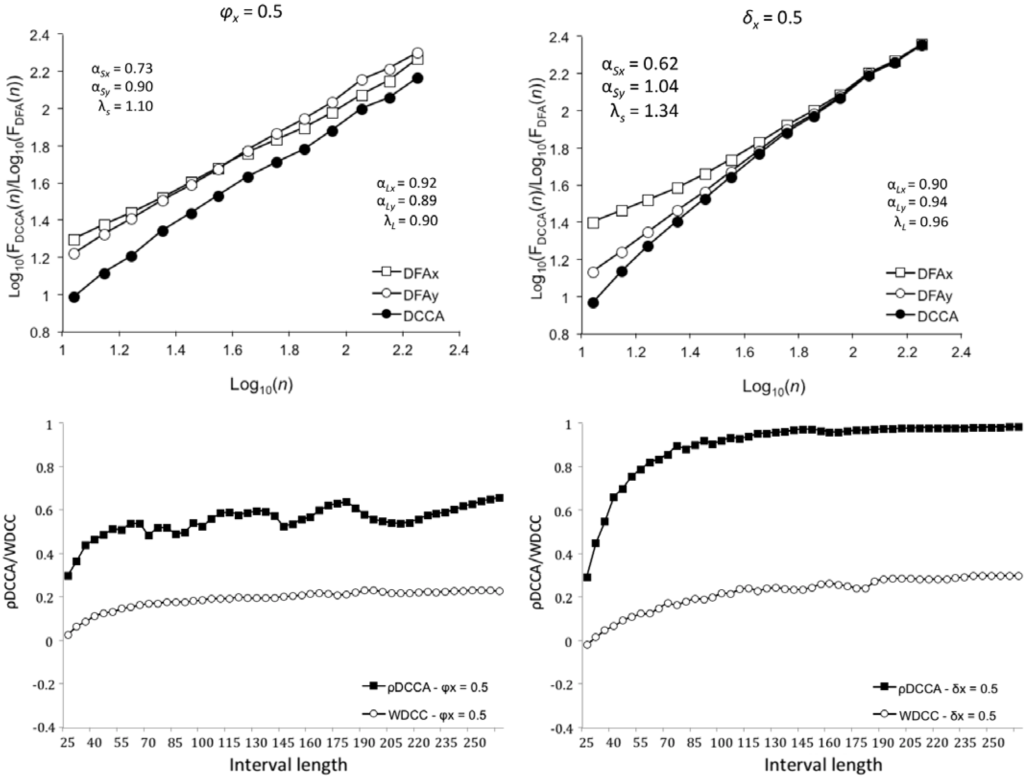

Fig. 6. Short-term autoregressive unidirectional models. Top row: average DFA and DCCA diffusion plots ($N = 10$), for the interval-based model (left), and the asynchrony-based model (right). Bottom row: $\rho_{\mathrm{DCCA}}(n)$ and $WDCC(n)$.

(left panel), the DFA and DCCA results for $\varphi_x = 0.5$. As can be seen, the graphical results are qualitatively different than those obtained from experimental data (see Fig. 4): the DFA curves appeared more or less superimposed, and $F_{\mathrm{DCCA}}(n)$ remained systematically lower than $F_{\mathrm{DFA}}(n)$, whatever the considered interval, suggesting a rather low covariance between the series on all time scales. This tendency increased with decreasing φ_x. These results are sufficient, in our mind, for rejecting the interval-based hypothesis.

Results were more convincing with the second, asynchrony-based model. We tested three values for the autoregressive parameter δ_x: 0.5, 0.4, and 0.3. We show, in Fig. 6 (right panel), the results of DFA and DCCA for $\delta_x = 0.5$. The graphical results reproduced quite satisfactorily those obtained from experimental data (see Fig. 4). The correlations between α long-term exponents were high ($r = 0.990$, $r = 0.982$, and $r = 0.963$, respectively), and in all cases the model produced non-significant correlations between short-term α exponents ($r = 0.023$, $r = -0.016$, and $r = -0.037$, respectively). One could note, however, that in all cases the model yielded lower initial $\rho_{\mathrm{DCCA}}(n)$ than experimentally observed, and lower $WDCC(n)$ in the long term.

These simulations suggest that short-term adaptive processes, based on the correction of the most recent asynchrony, could be sufficient for generating the matching of fluctuations in the long term. Note that we did not engage substantial efforts for closely fitting our experimental results. More accurate and convincing results could perhaps be obtained with more complex models, for example taking into account a set of previous asynchronies rather than only the last one [1].

This kind of autoregressive error correction model has frequently been evoked in the study of synchronization with regular metronomes [1,55,59]. Intuitively, one could conceive that, facing a regular metronome, the systematic correction of errors allows maintaining synchronization: the time of occurrence of the next onset can be anticipated on the basis of the previous asynchrony and the fixed period of the metronome. This kind of adaptation, based on an explicit model of the properties of the situation, clearly refers to what Dubois [4] called weak anticipation.

The usefulness of error correction is less clear when one has to synchronize with a fractal metronome. In that case, the exact duration of the next period remains unpredictable, and correcting the last asynchrony may have no direct and intended effect on the next.

On the other hand, error correction tends to adjust the duration of the current interval to the duration of the previous interval of the metronome. In other words, by correcting for asynchronies, the system tends to mimic, with a positive lag of one value, the fluctuations of the metronome. From this point of view, the matching of long-term scaling exponents could represent the simple consequence of the local corrections of asynchronies.

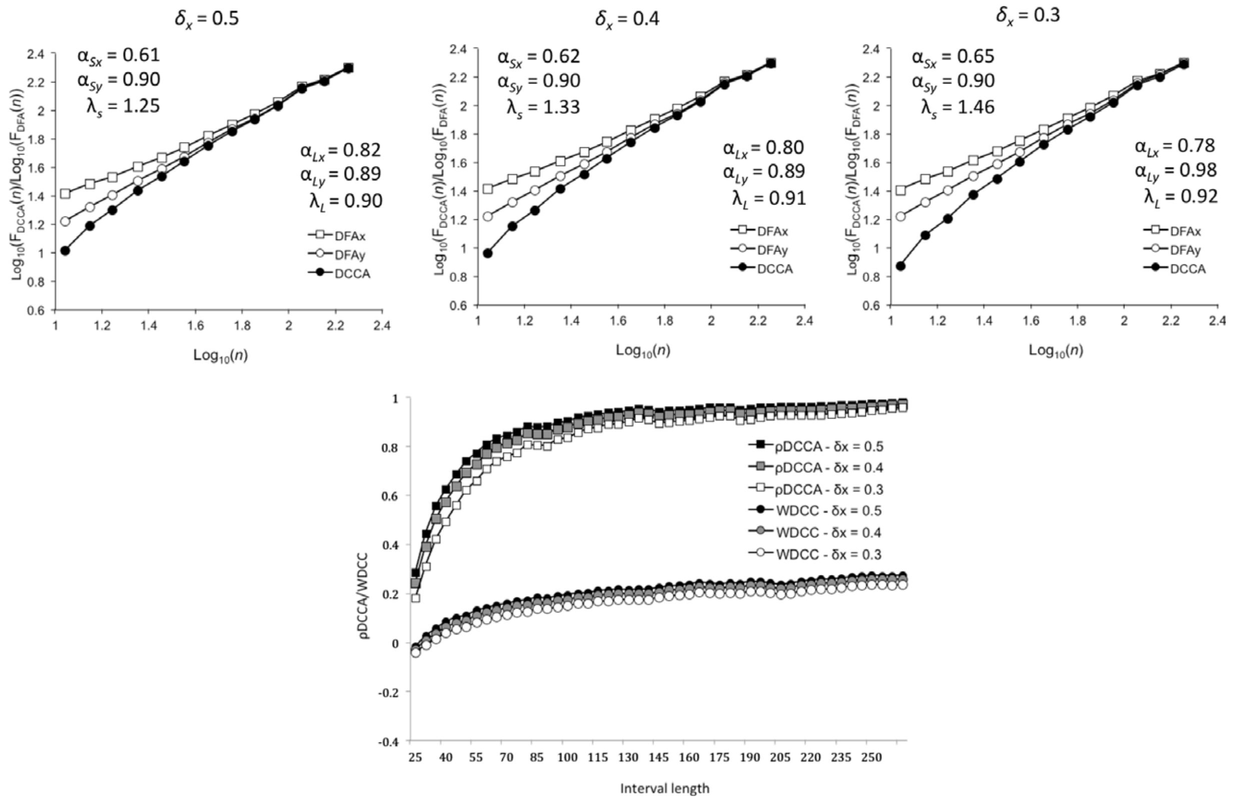

Fig. 7. Short-term autoregressive bidirectional model. Top row: average DFA and DCCA diffusion plots ($N = 10$), for three combinations of parameters (left: $\delta_x = 0.7$ and $\delta_y = 0.5$; middle: $\delta_x = 0.5$ and $\delta_y = 0.3$; right: $\delta_x = 0.4$ and $\delta_y = 0.2$). Bottom row: $\rho_{\text{DCCA}}(n)$ and $WDCC(n)$.

5. Short-term synchronization: autoregressive bidirectional models

Finally, we tried to examine the plausibility of the asynchrony-based model in the bidirectional case. The bidirectional extension of this model could be expressed as follows:

$$\begin{cases} x(t) = x_{\text{int}}(t) + \delta_x ASYN_x(t-1) + \eta\varepsilon_x(t) \\ y(t) = y_{\text{int}}(t) + \delta_y ASYN_y(t-1) + \eta\varepsilon_y(t), \end{cases} \tag{12}$$

where $x_{\text{int}}(t)$ and $y_{\text{int}}(t)$ represent the intrinsic fluctuations of each system, and δ_x and δ_y are the autoregressive parameters. We tested the following combination of values: $\delta_x = 0.7$ and $\delta_y = 0.5$, $\delta_x = 0.5$ and $\delta_y = 0.3$, and $\delta_x = 0.4$ and $\delta_y = 0.2$. All combinations corresponded to asymmetrical coupling, as suggested by the analysis of our experimental data. The results of DFA and DCCA, for the three combinations of parameters, are reported in Fig. 7. In all cases, we obtained a superimposition of DFA and DCCA slopes in the long term, and a close correlation between long-term α exponents ($r = 0.997$, $r = 0.994$, and $r = 0.989$, respectively). However, the correlations between short-term exponents were clearly higher than expected: the three above-mentioned combinations yielded correlations of about $r = 0.852$, $r = 0.653$, and $r = 0.529$, respectively. Moreover, these combinations yielded very steep DCCA short-term slopes, suggesting a very low short-term covariance between series. Finally, $WDCC(n)$ showed that all models resulted in a very weak synchronization in the long term. In contrast with the previous model, the bidirectional asynchrony-based model provides a rather poor account of empirical data.

Taken as a whole, these observations suggest that interpersonal coordination and synchronization with a fractal metronome, while sharing some essential statistical features in DFA and DCCA results, should be considered as engaging different processes.

6. Conclusion

The aim of this paper was to analyze empirical data sets, accounting for coordination processes between complex systems, by using a recently proposed method: detrended cross-correlation analysis (DCCA). In association with DFA, DCCA provides a rich set of information, combining the scaling properties of each series and that of coordination.

DCCA results, however, appeared a little bit more complex to interpret than presented in the seminal papers that introduced the method. Interpreting DCCA slopes with the theoretical background that underlies that of α exponents could

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yield inadequate conclusions. In particular, the present analyses highlight the necessity to conduct separate analyses in both the short term and the long term.

This paper shows that DFA and DCCA should be complemented by other analyses, in order to obtain a more exhaustive picture of coordination processes. The analysis of correlation between α exponents, in the short term and the long term, appeared especially important for a better understanding of coupling processes. Further improvements of the method should also be proposed for accounting for lagged coordination processes.

In our opinion, $\rho_{\mathrm{DCCA}}(n)$ does not give really useful information, considering that it tends to reach its ceiling value systematically from the moment where coordination occurs between the two systems. We consider that $WDCC(n)$ provides a more realistic measure of cross-correlation. This method allows one to clearly distinguish between experimental conditions, and offers a better test of the suitability of alternative models.

Considering the theoretical question we tried to address in this paper, the present results show that the matching of scaling exponents that has been considered as the typical signature of strong anticipation [5,11] can take its origin in very different coupling processes. Bimanual oscillations seem underlain by a continuous coupling process. As previously explained, such continuous coupling is consistent with the HKB model that has been proposed for accounting for inter-limb coordination [50]. Note that evidencing the same signature in bimanual tapping was a little bit surprising, as recent papers suggested that this task was rather governed by discrete coupling processes [52,58]. This specific point requires further investigation.

In contrast, interpersonal coordination and synchronization with a fractal metronome appeared clearly dominated by discrete cycle-to-cycle processes. However, if error correction appeared as a plausible candidate process in synchronization with a fractal metronome, it seemed unable to adequately account for interpersonal coordination processes.

Concerning this last situation, a central question remains: is there something other than short-range coupling processes in the coordination of independent complex systems? Answering this question is essential for giving a better consistence to the concept of strong anticipation. On the basis of the present results, concluding that local anticipatory processes could be sufficient for producing a global matching of fluctuations is clearly premature. Further efforts are needed in exploring these issues, especially through the proposition and the assessment of more complex models, and a more accurate determination of parameters.

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