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Distinct ways of timing movements in bimanual coordination tasks: Contribution of serial correlation analysis and implications for modeling

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ABSTRACT

Bimanual coordination dynamics have been conceived as the outcome of a global coordinative system, and coordination stability properties and theories of underlying processes have often been generalized over various bimanual tasks. In unimanual timing tasks it has been shown that different timing processes are involved according to tasks, yielding distinctive correlation properties in the within-hand temporal patterns. In this study we compare unimanual with bimanual, tapping with oscillation, and self-paced with externally paced tasks, and we analyze the correlation properties of temporal patterns at both the component level and the coordinative level. Results show that the distinctive signatures of event-based *versus* emergent, and self-paced *versus* synchronization timing control known from unimanual tasks persist in the corresponding bimanual coordination tasks. Accordingly, we argue that these different timing processes, and related temporal patterns at the component level, constitute a task-dependent background on which coordination builds. One direct implication of these results is that the bimanual coordination paradigm should be considered multifaceted and not governed by some unitary generic principle. We discuss the need to assess the relationship between temporal patterns at the component level and the collective level, and to integrate serial (long-range) correlation properties into bimanual coordination models. Finally, we test whether the architectures of current bimanual coordination models can account for the experimentally observed serial correlations.

1. Introduction

In the bimanual coordination paradigm participants are generally asked to produce regular rhythmic movements with the two hands, fingers, or forearms by maintaining a constant phase relationship between the two movements. Different theories of bimanual coordination have been proposed, based on different (sometimes emblematic) ways of doing experiments, analyzing data, and modeling. For instance, commonly used task modalities include continuous (*e.g.*, oscillatory) or discontinuous (*e.g.*, tapping) movements, and the presence or absence of an external pacing signal for prescribing the rhythm of movements. While the different accounts of coordination would ideally come together to form a coherent and comprehensive picture, they have often been neither directly opposable nor easily comparable because of methodological differences.

Bimanual coordination tasks basically have two interrelated goals: an absolute timing goal defined by the maintenance of a regular rhythm by the two limbs and a relative timing goal defined by the maintenance of a stable phase relationship between the limbs. Despite that, the dynamics at the relative timing (coordinative) level have mostly been studied separately from the within-limb (component) dynamics, and some authors have stressed the need to establish links between these two levels (Peper, Ridderikhoff, Daffertshofer, & Beek, 2004; Riley, Santana, & Turvey, 2001; Schöner, 2002).

Absolute timing governs the production of movements with stable and reproducible temporal patterns, without interaction with other timed movements and without an external prescription of time intervals. Absolute timing has typically been studied by analyzing time intervals produced in unimanual self-paced movement tasks. Comparative studies based on variability analysis (Robertson et al., 1999; Zelaznik, Spencer, & Doffin, 2000; Zelaznik, Spencer, & Ivry, 2002) and neurophysiological investigation (Ivry, Spencer, Zelaznik, & Diedrichsen, 2002; Spencer & Ivry, 2005; Spencer, Zelaznik, Diedrichsen, & Ivry, 2003) have shown that two distinct forms of timing control, namely, *event-based* timing and *emergent* timing, are engaged according to the discontinuous/continuous character of movements. Event-based timing (also referred to as *explicit timing*, Robertson et al., 1999; Zelaznik et al., 2002) implies an explicit representation of the temporal pattern by an internal timekeeper. This central representation determines cognitive events that trigger

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motor responses. Event-based timing was nicely captured by the well-known Wing and Kristofferson's (1973) model. This kind of timing mode is involved in discontinuous rhythmic movements such as finger tapping. In emergent timing (also referred to as *implicit timing*, Robertson et al., 1999; Zelaznik et al., 2002), the temporal regularity is assumed to come from a continuous modulation of the dynamical (and not explicitly temporal) properties of the effector system, so that no explicit representation of time is needed. Timing emerges from the dynamical, limit-cycle properties of effector's motion, and especially stiffness plays a major role for determining movement frequency (Delignières, Lemoine, & Torre, 2004). Emergent timing is supposed to be involved in continuous movements, like forearm oscillations or circle drawing.

Serial correlation analyses based on the autocorrelation function and the bi-logarithmic power spectra of series of produced movement periods have furthermore provided statistical signatures that distinguish between the two modes of timing control (Delignières, Torre, & Lemoine, 2008; Delignières et al., 2004). Event-based timing is characterized by the presence of differenced white noise in the successive periods, yielding a negative lag 1 autocorrelation and a positive slope in the high-frequency region of power spectra. Emergent timing is characterized by simple white noise affecting the successive periods, yielding a non-negative (slightly positive or zero) lag 1 autocorrelation, and a non-positive (slightly negative or zero) slope in the high-frequency region of power spectra. A deeper analysis of these signatures will be proposed later. These methods allowed evidencing the exploitation of event-based timing in discontinuous tasks and emergent timing in continuous tasks (Delignières, Torre, & Lemoine, 2008; Delignières et al., 2004).

Despite these statistical differences, the series of periods in both self-paced tapping and oscillations have been shown to exhibit persistent long-range correlation or $1/f^{\beta}$ noise, revealed by a very slow power-law decay of the auto-correlation function over lags, and a negative slope of between -0.5 and -1.5 in the low-frequency region of log-log power spectra. These results suggest that both event-based and emergent timing generate $1/f^{\beta}$ noise (Delignières et al., 2004; Delignières et al., 2008; Gilden, Thornton, & Mallon, 1995; Gilden, 2001).

Relative timing governs the production of stable and reproducible coordination patterns between multiple component movements, or between a movement and external events (sensorimotor synchronization). Unimanual rhythmic movements have been widely studied in synchronization tasks, where participants have to produce movements in synchrony with the signals of a metronome dictating the rhythm. Synchronization has been shown to modify the statistical properties of unimanual tapping (Chen, Ding, & Kelso, 1997; Torre, Lemoine, & Delignières, 2006; Torre & Wagenmakers, 2008) and of unimanual oscillations, compared to self-paced movements (Torre et al., 2006). Notably, the series of periods show anti-persistent correlation (a short period is likely to be followed by a long period, and vice-versa), revealed by a positive slope in the low-frequency region of power spectra, instead of $1/f^{\beta}$ noise. At the same time, the series of asynchronies (i.e., the time intervals between the movement goal and the signal of the metronome) have been shown to present $1/f^{\beta}$-like correlation. Thus, the serial correlation properties of the series of periods in unimanual tasks provide distinctive signatures of the involvement of event-based timing (tapping) *versus* emergent timing (oscillations), and of absolute (self-paced) *versus* synchronization (externally paced) timing.

Studies of bimanual coordination have focused on relative timing properties and their dependence on factors such as movement frequency (Kelso, 1995), behavioral information (*e.g.* Schöner & Kelso, 1988; Zanone & Kelso, 1992), attention (Monno, Temprado, Zanone, & Laurent, 2002; Temprado, Zanone, Monno, & Laurent, 1999), and perceptual cues Bingham (2004). Bimanual coordination theories generally consider coordination dynamics as the outcome of general coordinative principles that regulate the relative timing between components. Very few studies adopting this perspective, to our knowledge, have addressed the relation between the relative timing pattern between limbs and the timing processes and resulting temporal patterns at the component level. Nevertheless, in a task where participants have to perform bimanual coordination paced by a metronome for instance, the levels of timing that are likely to contribute to the coordinated movement patterns include (i) the absolute timing of the movements of each limb, (ii) the synchronization between the movements of the limbs and the metronome, and (iii) the relative timing between the two limbs. Considering a self-paced coordination task for instance, the absolute timing patterns of the limb movements can be highly variable, while the relative timing between limbs remains stable (Schöner, 2002), provided the two absolute timing patterns have very similar structures of variability. Bimanual coordination does not presuppose any particular temporal pattern in the component movements. Thus, coordination between limbs could not be considered responsible for the finding of any reproducible temporal pattern in the limb movements in bimanual coordination compared with unimanual tasks.

A few recent articles have proposed to extend the distinction between event-based and emergent timing, established in unimanual tasks, to the control of bimanual coordination. Summers, Maeder, and Hiraga (2005) and Summers, Maeder, Hiraga, and Alexander (2008) compared the variability of periods of the hands, and of the relative timing between hands, in bimanual coordination of intermittent *versus* continuous movements. Simultaneously, they assessed the attentional cost associated with the two conditions. They showed that the coefficients of variation of periods were not correlated between the intermittent and continuous conditions, suggesting the engagement of different timing processes (Robertson et al., 1999). Moreover, the attentional demand was higher for intermittent than for continuous coordination. Finally, the coefficients of variation of the relative timing series were not correlated between the intermittent and continuous conditions. The authors thus concluded that two different timing modes were operating, event-based in the former case, and emergent in the latter. However, although this conclusion is certainly consistent with the literature, in principle the differences in the variability of periods and relative timing could have been due to distinct coordination processes rather than to distinct timing modes.

Kennerley, Diedrichsen, Hazeltine, Semjen, and Ivry (2002) analyzed bimanual coordination of discontinuous *versus* continuous movements in split-brain patients and showed a strong temporal coupling in the first case and temporal uncoupling in the second case. Regarding these results, Ivry, Diedrichsen, Spencer, Hazeltine, and Semjen (2004) argued that the representational basis for continuous and discontinuous movement coordination was different: Continuous movement coordination was assumed to need no representation of an event-structure by a timekeeping entity and was considered an emergent coordination with analogy to emergent timing, in contrast to the event-based coordination of discontinuous movements. It seems straightforward, indeed, to assume that coordination of discontinuous movements would be achieved on the basis of a congruence between events rather than by a coupling of parameters that determine movements, given that the within-hand timing of unimanual discontinuous movements is known to be

event-based rather than emergent.[1] However, without analyzing the collective level and the component level simultaneously, one cannot determine whether the temporal patterns are the result of coupling processes or whether the within-hand timing plays a significant role in coordination.

Regarding the difference between self-paced and synchronization tasks, unimanual studies have shown that external pacing of oscillations causes an *anchoring* effect, i.e., a reduction of the variability of oscillators in the vicinity of metronome beats (Byblow, Carson, & Goodman, 1994; Carson, 1995). Focusing on the influence of external pacing on bimanual coordination, Fink, Foo, and Jirsa (2000) and Jirsa, Fink, Foo, and Kelso (2000) examined simultaneously the limit-cycle dynamics of the two oscillating limbs and the stability properties of coordination in bimanual oscillations with a metronome. In addition to the reduction of spatial variability at the oscillator level, they observed a global stabilization of coordination. The authors assumed that the local anchoring of oscillators could *serve* the global stabilization of coordination (Fink et al., 2000). They accounted for this effect by extending the HKB model (Haken, Kelso, & Bunz, 1985) *ad hoc*, by adding a parametric driving term that couples the position of each oscillator to the auditory signal. Fink et al. (2000) and Jirsa et al. (2000) addressed the collective level and the component level simultaneously. However, while they focused on the changes in the within-cycle dynamics of oscillators, our present study proposes to focus on the qualitative changes in the cycle-to-cycle dynamics due to the synchronization process. This could provide a complementary perspective for assessing the effect of external pacing on the global stability of coordination and, more generally, the relationship between the statistical properties at the component level and the collective level.

In this study we address the question of whether coordination patterns are the outcome of a coordinative system that regulates the relative timing between limbs, or whether distinct forms of timing control at the component level contribute to coordination. We hypothesize that the distinct timing processes and related temporal patterns at the component level constitute the background on which coordination bases. In others words, we suppose that according to the nature of the task, effectors are engaged in different timing control modes, and that coordination builds on this intrinsic componential dynamics. To pursue this hypothesis, we analyze simultaneously the relative timing series at the coordinative level in bimanual coordination tasks, and the temporal patterns at the within-limb level in bimanual and unimanual tasks. We compare tapping with oscillation, and self-paced with externally paced tasks, which have commonly been implemented in bimanual coordination studies and have been shown to involve different forms of timing control in unimanual movement tasks. We rely on serial correlation analysis of the within-limb temporal patterns for detecting and discriminating between the involved timing processes.

The investigation proceeded in three stages. The first stage aimed at revealing the statistical signatures of event-based *versus* emergent timing and of absolute *versus* synchronization timing that are known from previous unimanual movement studies. These distinctive statistical properties served as qualitative references for comparison with the statistical properties obtained in bimanual coordination tasks.

The second stage aimed at characterizing the within-hand temporal patterns in bimanual coordination. Our hypothesis predicts that the distinctive signatures of timing modes in the unimanual tasks persist in the corresponding bimanual coordination tasks. If coordination was not based on distinct timing processes and related temporal patterns at the component level, we should obtain similar and non-specific temporal patterns at the within-hand level, whatever the movement and pacing conditions. Beyond the theoretical issue, one consequence of verifying our hypothesis would be that bimanual coordination paradigm should be considered multifaceted, and that the methodological diversity of coordination studies should be taken into account when advancing or challenging alternative theories.

In the last stage, we characterize the correlations of relative timing series in the bimanual coordination tasks. Knowing the temporal patterns at the component level, we ask whether they can fully predict the observed relative timing pattern. In this way, we tested whether formalizations of current bimanual coordination models can account for serial correlations in relative phase when the correlation properties at the component level are taken into account.

2. Method

2.1. Participants and apparatus

Twelve participants (8 male and 4 female, mean age 29 ± 7 yrs) took part in the experiment. Ten participants declared themselves right-handed, and two left-handed. They were non-musicians and declared no particular competence involving specific coordination between the upper limbs, and no neurological injury or recent upper limb injury. They gave written informed consent and were not paid for their participation. The local ethics committee approved the experiment.

Participants were seated comfortably, with the elbows slightly flexed and the forearms supported in a horizontal position. The continuous movement tasks consisted in performing smooth and regular forearm oscillations holding one or two wooden joysticks, 15 cm in length, with a single degree of freedom in the frontal plane. The angular displacement of the joysticks was captured by two potentiometers. The discontinuous movement tasks consisted in performing sequences of discrete taps with the index finger(s) on one or two flat pressure sensors. The positions of the joysticks and the pressure sensors were adjusted to the participants'comfort. Data were recorded via a LabJack U12 device, with a sampling frequency of 300 Hz.

2.2. Experimental conditions

The experiment was composed of two sessions during which the participants performed eight tasks, four per session. The experimental conditions crossed three factors: continuous (oscillatory) *versus* discontinuous (tapping) movements, self-paced *versus* synchronized movements, and unimanual *versus* bimanual coordination tasks. The eight tasks were randomly assigned to the participants over the two sessions. Each task consisted of performing a series of 600 taps or oscillation cycles (trial duration about

[1] At this point, it might be mentioned that arguing for the involvement of emergent timing in bimanual oscillations and event-based timing in bimanual tapping does not exclude the involvement of any cognitive representation of an event structure in coordination of continuous movements. For instance, Spencer and colleagues (Spencer & Ivry, 2007) recently proposed an event-based account of the stability of bimanual coordination, using a concomitant repeated vocalization task. Actually, some salient, discrete events can easily be defined even in continuous and smooth movements (e.g., the reversal points in oscillation, or a spatial reference point in circling). Thus, certain experimental conditions such as discrete vocalizations during coordination (Spencer & Ivry, 2007; Spencer, Semjen, Yang, & Ivry, 2006), attentional focus (Hiraga, Summers, & Temprado, 2005), or haptic information (Kelso, Fink, DeLaplain, & Carson, 2001) might indeed reinforce these discrete events and favor the exploitation of an event structure in continuous movements. Accordingly, finding an event basis of coordination in such experimental conditions does not contradict the hypothesis of emergent processes as the preferential and 'normal' way for coordinating continuous movements; it rather shows the ability to exploit complementary resources for the temporal control of coordination according to the given task constraints.

5 min), with a required frequency of 2 Hz (500-ms periods). For the oscillation tasks, participants were instructed to perform the oscillations as smoothly and regularly as possible, with an amplitude of approximately 45° on either side of the vertical axis. No physical stop or other systematic feedback was given in order to maintain this amplitude. For the tapping tasks, participants were instructed to produce taps that were as brief as possible by minimizing the contact duration on the pressure sensor. For the self-paced tasks, the movement was presented by a 30-s video showing in close-up one (or two) hand(s) performing the task at the required frequency. Participants did not move while watching the video. Then they immediately began the task, following the required frequency as accurately as possible. Note that we did not use the classical synchronization-continuation paradigm in order to avoid possible influences of timing modes favored in the synchronization phase on those engaged in the continuation phase (Jantzen et al., 2004; Jantzen et al., 2005; Kolers & Brewster, 1985); such influences could notably occur in the case where oscillations are continued after being first paced by discrete auditory events, favoring an event-based control of timing. For the synchronization tasks, a PC-driven metronome delivered an auditory signal at the required frequency during the whole duration of the trial. The participants were instructed to keep the taps, or the pronation reversals of oscillations, on the beep. For the unimanual tasks, participants performed the movements with their dominant hand. The bimanual coordination tasks were identical to the corresponding unimanual tasks, except that the primary goal was defined in terms of relative phasing between the hands, with a required relative phase of 0° (in-phase). By definition in this mode of coordination the two hands move in mirror symmetry. In self-paced conditions participants were instructed to maintain the frequency initially imposed by the video display. In synchronization conditions they were asked to focus their attention on the between-hand synchronization as a priority, and to keep synchronized with the metronome.

2.3. Data reduction and analysis

We analyzed the time series of three variables: the periods (PER) for all tasks, the asynchronies (ASYN) between the movement and the metronome for the synchronization tasks, and the relative phase (RP) for the bimanual coordination tasks. The series of periods were defined as the within-hand time intervals between the onsets of two successive taps for the tapping tasks, and as the within-hand time intervals between two successive reversal points in maximal pronation for the oscillation tasks. The series of asynchronies were defined as the time intervals between the onsets of one hand's taps and the corresponding signals of the metronome, and as the time intervals between one hand's pronation reversal points and the signals of the metronome, according to the performed movement. The RP series (in degrees) were computed using the point estimate method, and defined as the difference between the timings of the corresponding right and left tapping onsets or pronation reversal points, normalized by the completed period of the dominant hand.

For all variables we retained for analysis the last 512 points of the series, and we examined the autocorrelation functions (ACF) and the power spectra. Regarding the ACF, we focused in particular on the lag 1 autocorrelation which provides information about the very short-range dependence in the series. Regarding the power spectra, the series of 512 points have been shown to be an acceptable length for obtaining accurate results with spectral analysis (Chen et al., 1997; Delignières et al., 2006; Gilden, 2001). The power spectra were computed using ${}^{low}PSD_{we}$, an improvement of the classical spectral analysis including some preprocessing operations before the application of the Fast Fourier Transform (for details, see Eke et al., 2000). For a reliable estimate of the spectral index, Eke et al. proposed to limit the fitting of the regression line of the power distribution to the low-frequency region of the log-log spectra, determined as $f < 1/8$ of the maximal frequency in the signal. We retained the same boundary frequency in order to perform separate estimations of the regression slopes in the low-frequency and the high-frequency regions of the spectra.

2.4. Statistical analysis

For testing the statistical difference from zero of the lag 1 autocorrelation of PER series, and of the high-frequency spectral slopes of PER series, we performed single-means *t*-tests with zero reference, per variable and experimental condition.

This current study refers to previous evidence that PER series produced in self-paced tapping and self-paced oscillations possess persistent long-range correlation, or $1/f^{\beta}$ noise, arising from the underlying timing processes (Delignières et al., 2004; Delignières et al., 2008; Gilden, 2001; Gilden et al., 1995). The presence of $1/f^{\beta}$ noise in experimental series has often been affirmed on the basis of the linear log–log power spectrum with slope $-\beta$, where β is between 0.5 and 1.5. Recent studies, however, have stressed the fact that the linear shape of power spectra is likely to mimic the presence of long-range correlation in series, even if they only contain short-range correlation. These studies showed the need of a statistical test for the presence of genuine long-range correlation (Thornton & Gilden, 2005; Wagenmakers, Farrell, & Ratcliff, 2004). For attesting the presence of long-range correlation in PER series collected in the unimanual and bimanual self-paced conditions, we applied the ARFIMA/ARMA modeling method (*Autoregressive Fractionally Integrated Moving Average*, Torre, Delignières, & Lemoine, 2007a; Wagenmakers et al., 2004). Since a recent study also evidenced persistent long-range correlation in RP series in bimanual oscillation tasks (Torre, Delignières, & Lemoine, 2007b), we further performed ARFIMA/ARMA modeling on the RP series obtained in bimanual coordination tasks.

This method consists in fitting 18 models to the series, 9 ARMA models and 9 ARFIMA models, the latter differing from the former by inclusion of a fractional integration parameter. The method selects the best model on the basis of a goodness-of-fit criterion (*Bayes Information Criterion*) based on a trade-off between the accuracy of the fit and the parsimony of the model. Two complementary criteria can then be used for attesting the presence of long-range correlation: (i) the number of series that are better fit by an ARFIMA model than an ARMA model, and (ii) the mean sum of weights captured by ARFIMA models for all series (the weight of a model is derived from the value of the goodness-of-fit criterion and represents the probability that this model is the best of the 18 candidate models for a given series; for details see Torre, Delignières, & Lemoine, 2007a).

These statistics provided a complete qualitative characterization of the time series collected in the unimanual and corresponding bimanual conditions. In addition to this qualitative approach, we tested for quantitative differences between the unimanual and corresponding bimanual conditions, considering each criterion (lag 1 autocorrelation, high-frequency slope, low-frequency slope) and each experimental condition (self-paced tapping and oscillations, synchronization tapping and oscillations), and using paired *t*-tests.

Finally, for an assessment of the coordination between the two effectors, we performed a 2 (movement) × 2 (pacing condition) repeated measures ANOVA on the low-frequency slopes of RP series. Furthermore, we computed the spectral coherence between the individual power spectra of the right and left PER series in the four bimanual coordination conditions. As the spectral characteristics in high-frequency regions essentially express how uncorrelated noise contributes to the signal, the analysis focused on the coherence between the low-frequency components to assess coordination

between the effectors' timing patterns. This was done by averaging the squared coherence coefficients obtained in the above-defined low-frequency region.

3. Results

3.1. PER and ASYN series in unimanual tasks

The aim of the analysis of PER and ASYN series obtained in unimanual tasks was to provide a reference for qualitative comparison with PER and ASYN series in the corresponding bimanual coordination tasks. We summarize the results for unimanual tasks in Table 1.

The average autocorrelation functions, computed by point-by-point averaging per variable and experimental condition, are shown in Fig. 1. In self-paced conditions, the mean lag 1 autocorrelation of PER series was negative ($t_{11} = -3.20$; $p < 0.05$) in tapping, but positive ($t_{11} = 3.72$; $p < 0.05$) in oscillations (see Table 1). For the synchronization conditions, the mean lag 1 autocorrelation of PER series was negative ($t_{11} = -8.93$; $p < 0.05$) in tapping, but not significantly different from zero ($t_{11} = 1.70$; $p > 0.05$) in oscillations. The mean lag 1 autocorrelation of ASYN series was positive in both cases. The autocorrelation functions of both synchronization tapping and synchronization oscillations ASYN series showed a slow power-law like decay (Fig. 1).

The average log–log power spectra, computed by point by point averaging per experimental condition and variable, are also represented in Fig. 1. Slope values are shown and also reported in Table 1. For self-paced conditions, the mean slope in the high-frequency region of the log–log power spectra of PER series was positive and significantly greater than zero in tapping ($t_{11} = 3.57$; $p < 0.05$), and not significantly different from zero in oscillations ($t_{11} = -0.38$; $p > 0.05$). In the low frequency region, power spectra exhibited negative slopes in both conditions.

For synchronization conditions, the mean slope in the high-frequency region of log–log spectra of PER series was positive ($t_{11} = 7.62$; $p < 0.05$) in tapping, and negative ($t_{11} = -2.81$; $p < 0.05$) in oscillations. The mean slopes in the low-frequency region were positive and close to 1.00 in both conditions. Regarding ASYN series, the log–log power spectra revealed $1/f$-like shapes in both cases, with negative slopes over the entire range of frequencies.

ARFIMA/ARMA modeling detected long-range correlation in 11 of 12 PER series (92%) in self-paced tapping, with a mean weight of ARFIMA models of 0.95, and in 12 of 12 PER (100%) series in self-paced oscillations, with a mean weight of 0.92. These results confirmed the presence of $1/f^{\beta}$ noise in PER series in unimanual self-paced tapping and oscillations.

3.2. PER and ASYN series in bimanual tasks

Taking the task-specific statistical properties of PER and ASYN series obtained in the unimanual tasks as reference, we tested for the persistence of these properties in the corresponding bimanual coordination tasks. The analyses were performed separately for each hand. For comparison with the results obtained in the unimanual tasks and for greater conciseness, we only present the results obtained for the dominant hand (the same that performed the unimanual tasks) in the bimanual coordination tasks. Results for the non-dominant hand were qualitatively and quantitatively similar. Table 2 summarizes the results obtained in bimanual tasks. PER and ASYN series collected in bimanual tasks presented means and standard deviations similar to those of their unimanual counterparts.

The average autocorrelation functions are represented in Fig. 2. These functions are similar to those of their unimanual counterparts (see Table 2 for the values of lag 1 auto-correlation).

The average log–log power spectra obtained in bimanual tasks are also represented in Fig. 2. These spectra are qualitatively similar to those obtained in the unimanual tasks. Notably, in the self-paced conditions the mean slope in the high-frequency region of the spectra of PER series was positive ($t_{11} = 6.01$; $p < 0.05$) in tapping, but not significantly different from zero ($t_{11} = 0.25$; $p > 0.05$) in oscillations. The mean slope in the low-frequency region was negative in both cases. In the synchronization conditions, the mean slope in the high-frequency region for PER series was positive ($t_{11} = 11.22$; $p < 0.05$) in tapping, but not significantly different from zero ($t_{11} = -1.74$; $p > 0.05$) in oscillations. Finally, for ASYN series the power spectra showed in both cases $1/f$-like shapes, with negative slopes over the entire range of frequencies.

ARFIMA/ARMA modeling detected long-range correlation in 10 of 12 PER series (83%) in self-paced tapping, with a mean weight of ARFIMA models of 0.75, and in 9 of 12 PER (75%) series in self-paced oscillations, with a mean weight of 0.81. These results provided strong support for the presence of $1/f^{\beta}$ noise in PER series in bimanual self-paced tapping and oscillations, as in their unimanual counterparts.

Regarding the testing for quantitative differences between the unimanual and corresponding bimanual tasks, t-tests showed no significant differences between unimanual and bimanual lag 1 autocorrelation values in any of the experimental conditions. Likewise, there was no significant difference between unimanual and bimanual high-frequency slopes in any of the experimental conditions, and no significant difference between unimanual and bimanual low-frequency slopes, except for synchronization tapping (1.11 *versus* 1.46, respectively; $t_{11} = -2.29$; $p < 0.05$).

3.3. Coordination in bimanual tasks

Table 3 shows the results obtained with RP series. Mean RP values were close to the expected value of 0°, and variability remained moderate in all conditions.

The average autocorrelation functions are shown in Fig. 3. The mean lag 1 autocorrelation of RP series was close to zero in tapping

Table 1
Descriptive statistics and dynamical signatures for the series collected in unimanual tasks (tapping *versus* oscillation, self-paced *versus* synchronization)

	Tapping			Oscillations		
	Self-paced	Synchronization		Self-paced	Synchronization	
	PER	PER	ASYN	PER	PER	ASYN
Mean (ms)	481 (±31)	499 (±1)	−60 (±36)	493 (±48)	499 (±2)	11 (±59)
SD (ms)	33 (±12)	32 (±8)	34 (±12)	22 (±11)	17 (±5)	42 (±14)
Mean lag 1 AC	−0.11 (±0.12)	−0.33 (±0.13)	0.39 (±0.21)	0.18 (±0.17)	0.06 (±0.12)	0.75 (±0.18)
HF slope	0.41 (±0.40)	0.96 (±0.44)	–	−0.04 (±0.37)	−0.23 (±0.29)	–
LF slope	−0.49 (±0.52)	1.11 (±0.43)	−0.69 (±0.48)	−0.88 (±0.50)	1.05 (±0.69)	−0.82 (±0.28)

From top to bottom we present (1) the mean value of series, (2) the standard deviation of series, (3), the mean lag 1 auto-correlation, (4) the mean slope in the high-frequency region of the log–log power spectrum, and (5) the mean slope in the low-frequency region of the log–log power spectrum. Between-participant standard deviations in parentheses.

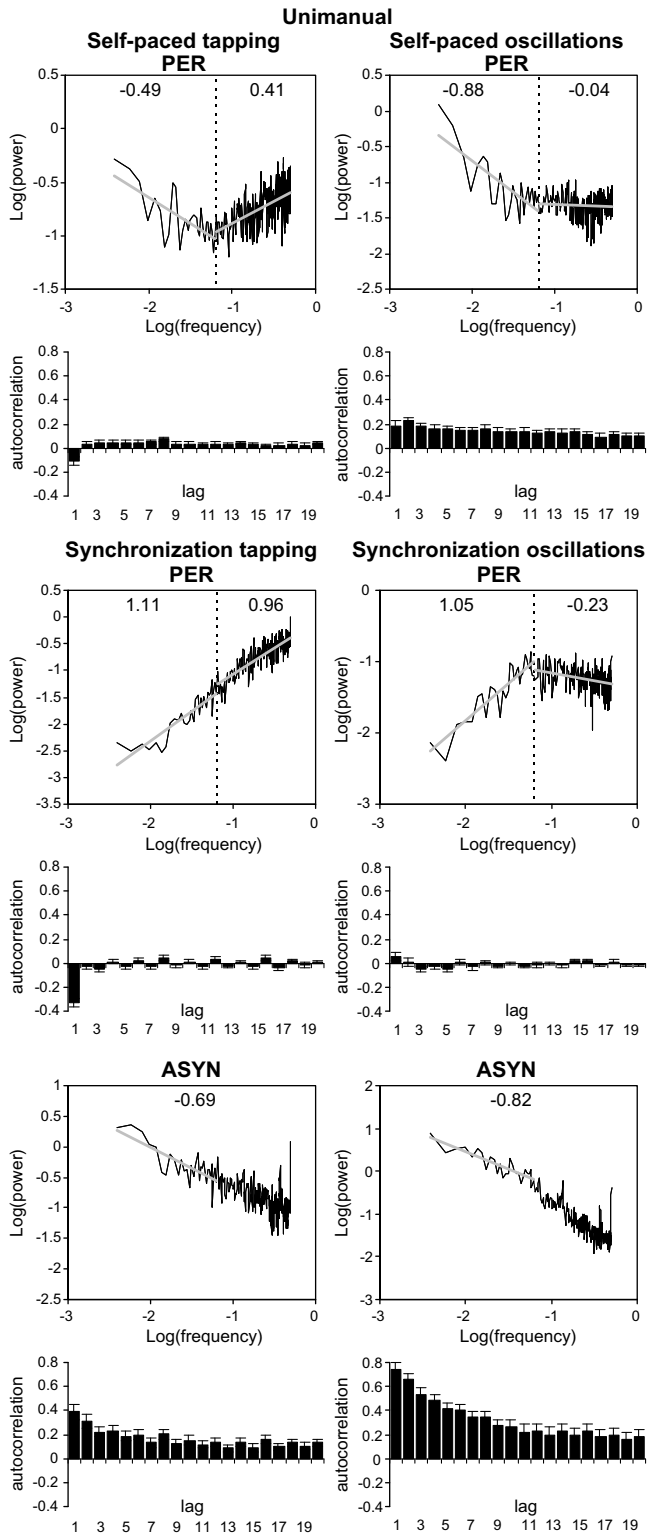

Fig. 1. Distinctive signatures of the timing processes involved in unimanual self-paced (upper panels) and synchronization (bottom panels) tasks, in tapping (left) and oscillations (right). Results are presented in the form of average log–log power spectra and average autocorrelation functions of PER series and ASYN series ($N = 12$). For the autocorrelation functions, error bars represent standard errors.

tasks, and slightly positive in oscillation tasks. For all conditions, single means *t*-tests showed that the mean autocorrelations over the successive lags ($N = 19$) remained significantly positive, although very slightly in the case of self-paced and synchronization tapping ($t_{19} = 8.77$, $t_{19} = 17.26$, $t_{19} = 5.46$, $t_{19} = 11.21$; $p < 0.05$).

The average log–log power spectra of RP series are also represented in Fig. 3. In all cases the power spectra presented negative linear slopes in the low-frequency region. The ANOVA performed on these low-frequency slopes showed only a main effect of the movement factor: the slopes were significantly steeper in bimanual oscillations than in bimanual tapping (−0.72 and −0.36, respectively; $F_{1,11} = 5.56$; $p < 0.05$).

ARFIMA/ARMA modeling detected long-range correlation in 10 of 12 RP series (83%) in bimanual self-paced tapping, with a mean weight of ARFIMA models of 0.89, in 11 of 12 RP series (92%) in bimanual self-paced oscillations, in 7 of 12 RP series (58%) in bimanual synchronization tapping, with a mean weight of ARFIMA models of 0.68, and in 12 of 12 RP series (100%) in bimanual synchronization oscillations, with a mean weight of ARFIMA models of 0.97. These results provided strong indication of the presence of long-range correlation in RP series in self-paced tapping, self-paced oscillations, and synchronization oscillations, while the presence of long-range correlation in synchronization tapping remains uncertain.

Finally, spectral coherence analysis showed high coherences between the individual power spectra of the right and left hand PER series, with mean r^2 coefficients ranging from 0.80 to 0.96 (see Table 3). Fig. 4 shows an example of the individual power spectra of the right and left PER series obtained in one trial.

4. Discussion

In this study we asked whether temporal patterns in bimanual coordination result from a coordinative system regulating the relative timing between limbs, or if distinct timing processes at the component level are engaged in a specific way in coordination. We compared tapping and oscillation, self-paced and synchronization, unimanual and bimanual task modalities, and analyzed the temporal patterns at the component level and the collective level. Our results showed that the distinctive signatures of timing evidenced in unimanual tasks persisted in the bimanual coordination tasks with the same modalities. We have organized the discussion as follows: In the first part, in order to make this article self-containing, we briefly outline the theoretical assumptions related to the distinctive signatures of timing modes evidenced in unimanual tasks. In the second part, we discuss the persistence of these distinctive signatures in bimanual coordination tasks. Then, we turn to three implications of our results: (i) the need of assessing the relationship between the temporal patterns at the component level and at the collective level for a thorough understanding of bimanual coordination, (ii) the way that current models of bimanual coordination account for the evidenced serial correlation, and (iii) the problems created by the current methodological diversity in research on bimanual coordination.

4.1. Distinctive signatures of timing modes in unimanual tasks

For conciseness, we limit the discussion of the results obtained in the unimanual tasks (Fig. 1) to the minimum account that is necessary with regard to our present concerns. We are going to distinguish between event-based and emergent timing on the basis of the characterization of short-range correlation in PER series, and between self-paced and synchronization timing on the basis of long-range correlation properties.

4.1.1. Distinction between event-based and emergent timing

Several complementary approaches to timing control have supported the distinction between two forms of timing, namely, event-based and emergent timing, involved in the performance of discontinuous and continuous rhythmic movements, respectively

Table 2
Descriptive statistics and dynamical signatures for the series collected in bimanual tasks (tapping *versus* oscillation, self-paced *versus* synchronization)

	Tapping			Oscillations		
	Self-paced	Synchronization		Self-paced	Synchronization	
	PER	PER	ASYN	PER	PER	ASYN
Mean (ms)	470 (±38)	500 (±0)	−48 (±38)	519 (±65)	499 (±2)	26 (±48)
SD (ms)	30 (±10)	28 (±6)	29 (±8)	22 (±7)	18 (±5)	41 (±13)
Mean lag 1 AC	−0.17 (±0.15)	−0.38 (±0.07)	0.35 (±0.19)	0.16 (±0.19)	0.01 (±0.15)	0.79 (±0.07)
HF slope	0.65 (±0.38)	1 (±0.31)	–	0.02 (±0.31)	−0.09 (±0.18)	–
LF slope	−0.71 (±0.35)	1.46 (±0.46)	−0.57 (±0.48)	−1.04 (±0.40)	1.07 (±0.61)	−0.83 (±0.29)

The presented results are for the dominant hand. From top to bottom we present (1) the mean value of the series, (2) the standard deviation of the series, (3) the mean lag 1 auto-correlation, (4) the mean slope in the high-frequency region of the log–log power spectrum, and (5) the mean slope in the low-frequency region of the log–log power spectrum. Between-participant standard deviations in parentheses.

(Delignières et al., 2004; Delignières et al., 2008; Ivry et al., 2002; Robertson et al., 1999; Spencer & Ivry, 2005; Spencer et al., 2003; Zelaznik et al., 2000; Zelaznik et al., 2002; see also Huys, Jirsa, Studenka, Rheaume, & Zelaznik, 2008).

Event-based timing is assumed to involve a hierarchical structure with a prescriptive entity that is responsible for the explicit representation of temporal goals, independent of the motor execution itself. Cognitive 'events' are supposed to represent the informational basis for the timing of movements, so that the event-structure contained in discrete movements shows a similar pattern. This functioning is in accordance with the formulation of the Wing and Kristofferson (1973) model for self-paced tapping:

$$\mathrm{PER}_{\mathrm{tap},n} = C_n + M_n - M_{n-1}, \quad (1)$$

where discrete cognitive events delimit the successive time intervals (C_n) given by the timekeeper, and trigger the execution of the taps at the motor level. The execution of each tap is affected by a motor delay (M_n) that is considered white noise. Thus, resulting periods of movement are affected by differenced white noise.

Emergent timing, in contrast, is assumed to need no explicit representation of temporal information. Timing emerges from the continuous regulation of the non-temporal parameters that determine the cycle duration of continuous movements such as oscillations or circle drawing. That is, there is no prescription from the cognitive level to the motor level (except a global setting of baseline stiffness), and movement implementation is an integral part of timing. Given the continuous regulation of movements during the cycle, a single error term ξ_n affects the cycle durations D_n determined by movement parameters, instead of affecting the two boundary events, so that the produced periods are given by (Delignières et al., 2004)

$$\mathrm{PER}_{\mathrm{osc},n} = D_n + \xi_n. \quad (2)$$

Accordingly, the distinctive features of event-based and emergent timing are obvious in the comparison of the short-range correlation properties of PER series, notably in the lag 1 autocorrelation and the high-frequency region of power spectra. For tapping, i.e., event-based timing, the differenced white noise that affects the successive periods (Eq. (1)) yields a negative lag 1 autocorrelation, and a positive slope in the high-frequencies of power spectra. For oscillations, i.e., emergent timing, in contrast, the presence of a single white noise term instead of differenced white noise affecting the successive periods (Eq. (2)) should yield a zero or lowered lag 1 autocorrelation, and a zero or flattened high-frequency spectral slope, depending on the correlations carried by the timing mechanism (D) itself.

Our present results reproduced these distinctive properties. In unimanual tapping, PER series presented a negative lag 1 autocorrelation and a positive high-frequency slope. Both were shown to be statistically different from zero. These distinctive properties were similar in self-paced and synchronized tapping. In unimanual oscillations, in contrast, the lag 1 autocorrelation of PER series was positive or not significantly different from zero, and the high-frequency slope was not significantly different from zero or negative, in self-paced and synchronization conditions, respectively. Thus, the characterization of serial correlation in PER series evidenced the involvement of event-based timing in unimanual tapping, and emergent timing in unimanual oscillations, whatever the pacing conditions.

4.1.2. Distinction between self-paced and externally-paced movements

In self-paced movements, the variability in periods has for a long time been assumed to reflect uncorrelated white noise inherent in the involved timing processes. Analyzing long-range correlation, Gilden et al. (1995) first evidenced the presence of $1/f^{\beta}$ noise (i.e., persistent long-range correlation) in PER series in unimanual self-paced tapping, revealed by a negative slope close to –1 in the low-frequency region in addition to the positive slope in the high-frequency region of power spectra. This result has been confirmed by a number of studies (Chen, Repp, & Patel, 2002; Delignières et al., 2004; Gilden, 2001; Madison, 2004, Yamada, 1995), and statistically attested by ARFIMA/ARMA modeling (Delignières et al., 2008; Lemoine, Torre, & Delignières, 2006). Note that this pattern of persistent correlations was sometimes attributed to the presence of drift in self-paced series (*e.g.,* Pressing & Jolley-Rogers, 1997). Obviously drift can contribute to the presence of persistent dependence in the series. However, Lemoine et al. (2006) showed that $1/f$ fluctuations were still present even when drift was removed from the series. Since the positive slope in the high frequencies was due according to the Wing and Kristofferson model to differenced white noise at the level of motor implementation, the $1/f^{\beta}$ variability was assumed to be in the timekeeping process (Delignières et al., 2004; Gilden et al., 1995; Gilden, 2001). Accordingly, the timekeeper has been modeled by the *shifting strategy model* (Wagenmakers et al., 2004), an extension of classical threshold-activation models that provides the timekeeper periods C_n (Eq. (1)) with $1/f^{\beta}$ correlations (Delignières et al., 2008).

Unimanual self-paced oscillations have classically been modeled by a hybrid limit-cycle oscillator (Kay, Saltzman, Kelso, & Schöner, 1987), assuming that the variability in successive oscillation periods was uncorrelated. Recently, Delignières et al. (2004), Delignières et al. (2008) showed that similar to self-paced tapping, PER series in self-paced oscillations present $1/f^{\beta}$ fluctuations: Power spectra of PER series presented the typical negative slope close to –1 in the low-frequency region in addition to the flattened slope in the high-frequencies that characterizes emergent timing, and ARFIMA/ARMA modeling attested the result statistically. Thus, mechanisms at the origin of emergent timing have been considered a source of $1/f^{\beta}$ noise, like event-based processes. Delignières et al. (2008) proposed to model emergent timing using the *hopping model* (West & Scafetta, 2003) for introducing a variable stiffness parameter with $1/f^{\beta}$ correlation over the successive cycles of the

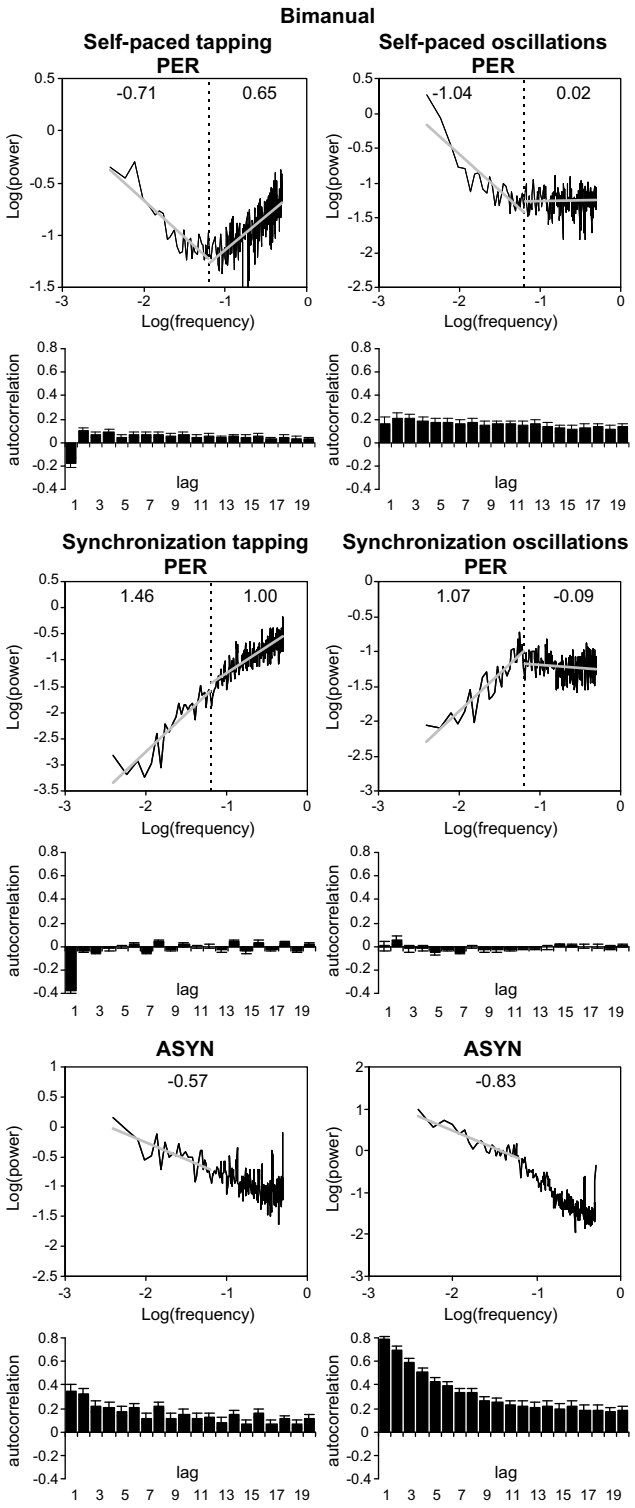

Fig. 2. Average log–log power spectra and autocorrelation functions of PER series and ASYN series ($N = 12$), obtained from the dominant hand in bimanual self-paced (upper panels) and synchronization (bottom panels) tasks, in tapping (left) and oscillations (right). For the autocorrelation functions, error bars represent standard errors. The distinctive signatures of timing processes were similar to those evidenced in the corresponding unimanual tasks (Fig. 1).

limit-cycle model, so that the resulting periods D_n (Eq. (2)) generated by the limit-cycle oscillator contained $1/f^{\beta}$ noise. A white noise term was added to account for the flat slope observed at high frequencies in the power spectrum.

Our present study reproduced previous results obtained in self-paced conditions: Spectral analysis of PER series collected in self-paced tapping and self-paced oscillations showed a negative slope characteristic of $1/f^{\beta}$ noise, and ARFIMA/ARMA modeling confirmed this result statistically.

In external pacing conditions, without the involvement of an effective synchronization process between movement and the pacing signal, the above characterized variability inherent to rhythmic movements would yield non-stationary asynchronies, since ASYN series are related to PER series by (Chen et al., 1997; Pressing & Jolley-Rogers, 1997)

$$\mathrm{ASYN}_n = \mathrm{ASYN}_1 + \sum_{i=1}^{n-1}(\mathrm{PER}_i - \tau), \tag{3}$$

where τ is the constant period of the metronome. So, if PER series contained $1/f^{\beta}$ noise as in self-paced conditions, ASYN series would exhibit persistent fractional Brownian motion, i.e., non-stationary series with positive correlations between the successive increments that correspond to the integration of $1/f^{\beta}$ noise.

Chen et al. (1997) first showed that periods in unimanual synchronization tapping contained anti-persistent noise instead of $1/f^{\beta}$ noise. Our present results are consistent with these results, showing that PER series in synchronization tapping contained anti-persistent noise, characterized by a positive slope in the low-frequency region of power spectra.

In contrast to synchronization tapping, synchronization oscillations have so far not been addressed from the point of view of serial correlation (as an exception, see a preliminary study by Torre et al. (2006)); studies have essentially focused on the stability properties of the oscillator's limit-cycle dynamics and have notably addressed the *anchoring* phenomenon, i.e., the local deformation of the phase plane trajectory in the vicinity of a landmark that is synchronized with the pacing signal (*e.g.,* Byblow et al., 1994; Carson, 1995; Roerdink, Ophoff, Peper, & Beek, 2008). Our present results revealed exactly the same effect of synchronization on serial correlation in oscillation as in tapping, PER series in synchronization oscillations containing anti-persistent noise.

Because ASYN series are the mathematical integration of PER series (Eq. (3)), it could be predicted that from the moment that the latter were anti-persistent noises, the former should present persistent, $1/f^{\beta}$-like correlations (Eke et al., 2000). This result has indeed been reported previously (Chen, Ding, & Kelso, 2001; Chen et al., 1997; Chen et al., 2002; Ding, Chen, & Kelso, 2002; Pressing & Jolley-Rogers, 1997), and the spectral analysis of ASYN series in synchronization tapping and oscillations gave consistent results in this study.

As mentioned above, despite these similar effects of synchronization on PER series in tapping and oscillations, the distinguishing features of event-based and emergent timing in the high frequency region were preserved in synchronization. In sum, the characterization of serial correlation in PER series provides statistical signatures allowing to distinguish between event-based and emergent timing, involved, respectively, in discontinuous and continuous movement tasks, and between absolute and synchronization timing processes, involved, respectively, in self-paced and externally paced conditions.

4.2. Persistence of the distinctive signatures of timing modes at the component level in bimanual coordination

Our results showed that PER series in bimanual coordination tasks presented consistent temporal patterns with specific correlation structures according to task modalities. These statistical properties were qualitatively the same as the distinctive signatures of event-based *versus* emergent, and self-paced *versus* synchroniza-

Table 3
Descriptive statistics and dynamical signatures for relative phase series (RP) in bimanual tasks (tapping *versus* oscillation, self-paced *versus* synchronization)

	Tapping		Oscillations	
	Self-paced	Synchronization	Self-paced	Synchronization
RP (deg)	−4 (±6)	−3 (±4)	−5 (±6)	−6 (±5)
SD (deg)	16 (±7)	13 (±4)	9 (±2)	9 (±2)
Mean lag1 AC	−0.08 (±0.15)	−0.03 (±0.14)	0.21 (±0.10)	0.15 (±0.12)
LF slope	−0.49 (±0.57)	−0.23 (±0.34)	-0.72 (±0.40)	-0.71 (±0.33)
Spectral coherence (r^2)	0.94 (±0.08)	0.8 (±0.20)	0.96 (±0.04)	0.95 (±0.05)

From top to bottom we present (1) the mean value of RP series, (2) the standard deviation of RP series, (3), the mean lag 1 auto-correlation, (4) the mean slope in the low-frequency region of the log–log power spectrum, and (5) the coefficient of spectral coherence between the two effectors. Between-participant standard deviations in parentheses.

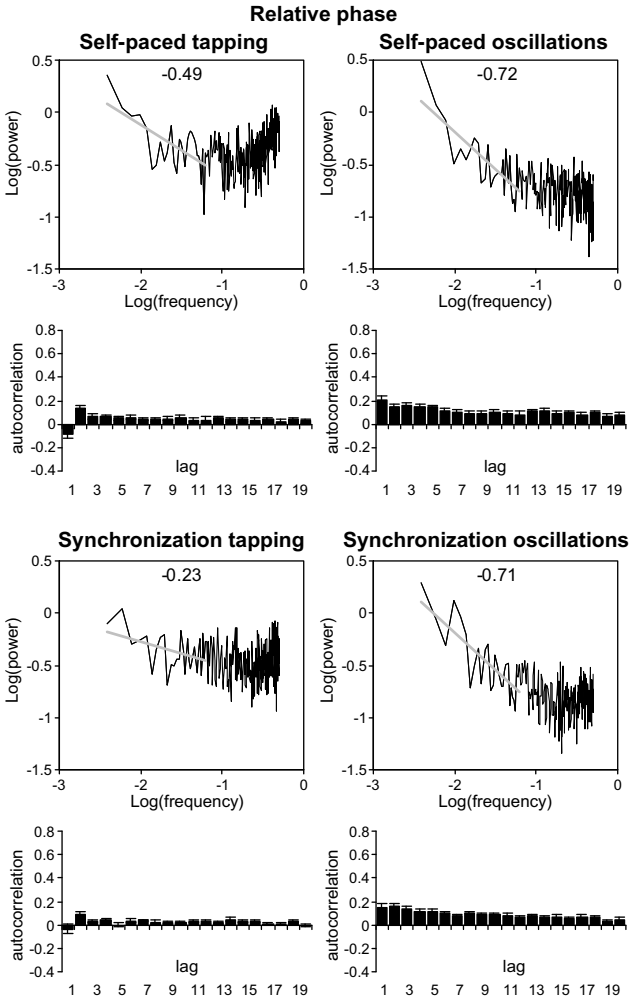

Fig. 3. Average log–log power spectra and autocorrelation functions ($N = 12$) of the relative phase series obtained in the four bimanual coordination conditions. For the autocorrelation functions, error bars represent standard errors ($N = 12$).

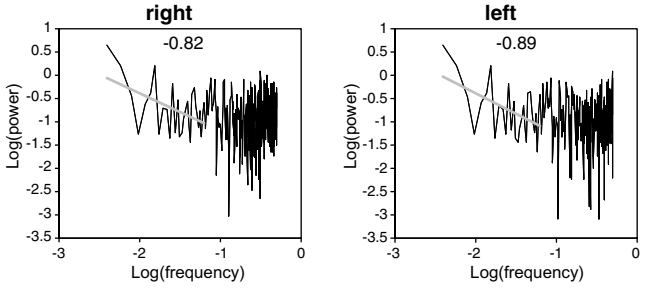

Fig. 4. Representative example of the individual power spectra obtained for the right and left hand PER series of one participant, in bimanual self-paced oscillation.

tion timing evidenced in the corresponding unimanual tasks (see Figs. 1 and 2).

In addition to the finding that the statistical properties were qualitatively the same in unimanual and bimanual series, we found no significant quantitative difference between the lag 1 autocorrelations, the high-frequency spectral slopes, and the low-frequency spectral slopes of unimanual and bimanual PER series, except for the low-frequency slopes in synchronization tapping (see Tables 1 and 2). These results showed that distinct event-based or emergent, absolute or synchronization timing processes were involved when participants performed bimanual coordination in tapping or oscillations, and in self-paced or externally paced conditions, respectively.

As mentioned in the introduction, obtaining a stable relative timing pattern given a particular structure of variability in the within-hand temporal patterns implies that this structure is highly similar or coherent across the two hands. The results of the spectral coherence analysis performed on PER series showed very high coherence coefficients ranging from 0.80 to 0.96 for the four conditions. As a comparison, we computed the spectral coherence in 20 randomly chosen pairs among simulated $1/f^{\beta}$ noise series[2] (with similar low-frequency spectral slopes about −0.9). The mean coherence coefficient computed over the low-frequency region of the spectra was only 0.29. Since the distinctive within-hand temporal patterns were similar in unimanual and bimanual tasks, the coordination or coupling process that yielded the strong coherence and the stable relative timing between the hands neither caused these correlations nor substantially modified them. In this view, we assume that the different forms of timing control yielding specific within-hand temporal patterns constitute a basis for coordination control. Saying that we do not mean that the timing of components entirely determines, or 'pilots' coordination, but that assessing coordination without a close connection to timing processes might conceal the specific ways in which timing processes contribute to build the dynamics of rhythmic coordination.

4.3. Relationships between the temporal patterns at the component level and the coordinative level

A recent study of bimanual oscillations clearly demonstrated the presence of $1/f^{\beta}$ noise in RP series, in in-phase as well as in anti-phase coordination (Torre et al., 2007b). One prevailing account of the finding of $1/f^{\beta}$ noise across diverse domains of research including human cognition and movement science considers it as a

[2] The simulations were performed using the algorithm proposed by Davies and Harte (1987), which generates 'exact' fractional Gaussian noise series with a known Hurst exponent (H). We set $H = 0.9$ for the present simulation.

typical property of the dynamics emerging from (nonlinear) interactions between components in a self-organized system. $1/f^{\beta}$ noise has been assumed to sign metastable patterns, i.e., the relative coordination that arises from the compromise between the preservation of the independence of components, and their tendency to merge into a collective behavior (*e.g.* Beltz & Kello, 2006; Kello, Beltz, Holden, & Van Orden, 2007). In this sense, the finding of $1/f^{\beta}$ noise in RP series matches very well with the dynamical systems theory of bimanual coordination, and it might be tempting to conclude in general terms that $1/f^{\beta}$ noise is a signature of coordination dynamics.

However, these results of the ANOVA performed on the low-frequency spectral slopes of RP series, and ARFIMA/ARMA modeling, consistently characterized RP series as $1/f^{\beta}$ noise in oscillations, but not in tapping. At a first glance, this seems actually consistent with the idea that coordination in tapping and oscillations involves distinct event-based and emergent forms of control. Beyond this consideration, however, it is necessary to analyze the relationship between the relative timing pattern at the collective level and the temporal patterns at the component level, to assess the respective contributions of timing and coordination.

Indeed, RP series contained $1/f^{\beta}$ noise in bimanual oscillations but not in tapping even though our results showed that PER series contained $1/f^{\beta}$ noise both in self-paced tapping and in self-paced oscillations. In a similar way, the ANOVA showed no difference in the correlation structure of RP series between self-paced and externally paced coordination even though our results showed that PER series were qualitatively completely different as they contained $1/f^{\beta}$ noise in the self-paced conditions and anti-persistent noise in the synchronization conditions. With regard to these discrepancies, one may ask what relationship, or what kind of coupling between components would account for the correlation structures in RP series, given the specific temporal patterns at the component level across task modalities. Could an identical coupling process actually be at work in each particular case mentioned above?

For instance, let us consider the case of self-paced *versus* externally paced coordination and proceed by simulation. We simulated 40 series of $1/f^{\beta}$ noise (characterized by similar low-frequency spectral slopes of about −0.9), representing PER series in bimanual self-paced conditions, and 40 series of anti-persistent noise (characterized by similar low-frequency spectral slopes of about 1.1), representing PER series in bimanual synchronization conditions.[3]

Then we computed the RP series for 20 randomly chosen pairs among the simulated series for the two conditions. Results showed that the relative phase between two uncoupled series of $1/f^{\beta}$ noise was non-stationary ($^{low}PSD_{we}$ characterized the series as fractional Brownian motions, with β exponents higher than 1.0, see Eke et al., 2000), whereas, the relative phase between two uncoupled series of anti-persistent noise was stationary (the series were characterized as fractional Gaussian noises, with β exponents of less than 1.0). Obviously, such discrepancies tend to question the idea that the same coupling applies without quantitative or even qualitative changes, whatever the conditions of performance of coordination and the corresponding structure in the temporal patterns of components.

4.4. Can current models of bimanual coordination account for empirical serial correlations?

Current bimanual coordination models have not been designed to account for serial correlation, as their aim is generally to account for stability properties at the collective or the component levels. Torre et al. (2007b) showed that, in their original formulations, neither the *multiple timer model* (Helmuth & Ivry, 1996; Ivry & Richardson, 2002; Ivry, Richardson, & Helmuth, 2002) for bimanual tapping nor the HKB model (Haken et al., 1985) for bimanual oscillations accounts for the experimentally observed serial correlations in relative phase.

The immediately following step would be to test whether the architectures of these models, notably the formalization of their respective coupling functions, could account for the observed correlations in RP series once the variability at the component level is provided with the appropriate task-specific correlation properties. Therefore, we incorporated the shifting strategy model at the timekeeper level of the multiple timer model, and the hopping model at the oscillator level of the HKB model. Both the shifting strategy model and the hopping model were shown to account for the $1/f^{\beta}$ correlations observed in unimanual self-paced tapping and oscillations (for details, see Delignières et al., 2008).

The multiple timer model for self-paced bimanual tapping is an extension of the Wing and Kristofferson model for unimanual tapping. The model assumes two (or more) co-acting timing processes, each associated with an effector. A *gating* process is responsible for the temporal coupling of these timers, by integrating the timing processes into a sequence of common cognitive 'events' that trigger the two limbs simultaneously, in the case of in-phase coordination. At the effector level, the execution of taps is affected by motor delays that have commonly been considered to contain uncorrelated white noise. Thus, the presence of correlation in RP series is necessarily related to the central timekeeper level. Obviously, because of the simultaneous triggering of the two effectors, the multiple timer model cannot account for any form of correlation in RP series between the two hands, yielding white noise whatever the structure of variability generated by the two timing processes. Thus, experimentally observed correlations in relative phase suggest a 'weaker' form of coupling between timers, rather than their integration into a single common signal as assumed by the multiple timer model.

Recently, Torre and Wagenmakers (2008) proposed to model bimanual self-paced tapping by incorporating the shifting strategy model at the level of the two timers. The functioning of the shifting strategy model is similar to classical activation-threshold mechanisms, where an activation process grows linearly in time, until reaching a threshold level. The reaching of the threshold determines a particular event in time that triggers the tap and resets the activation process. The shifting strategy model simply assumes a threshold with plateau-like variations over time and an activation process whose speed varies between successive iterations, following an auto-regressive process. The authors proposed a continuous coupling of the thresholds of the two timers, and an alignment of the onsets of the two activation processes, and showed that this coupling solution accounts for the serial correlations of RP series in bimanual self-paced tapping (Torre & Wagenmakers, 2008).

Further studies should test whether this model could be extended to bimanual synchronization tapping. Unimanual synchronization tapping has commonly been modeled by an auto-regressive error correction process (Vorberg & Wing, 1996). Recently, Torre and Wagenmakers (2008) showed that when considering the timekeeper as a source of $1/f^{\beta}$ noise, this error correction model accounts for the anti-persistent noise in PER series in synchronization tapping. Combining the Torre–Wagenmakers model with an auto-regressive error correction process might well account for the experimental correlation properties in bimanual synchronization tapping.

For bimanual self-paced oscillations, we tested in the present study the HKB model of coupled oscillators (Haken et al., 1985;

[3] Simulations were performed using the algorithm proposed by Davies and Harte (1987). For the first set of series, we set $H = 0.9$. For the second, we used the same H value and differentiated the obtained series in order to simulate anti-persistent noise series similar to those experimentally observed in synchronization period series.

Schöner & Kelso, 1988) which accounts for coordination by a nonlinear coupling between two hybrid limit-cycle oscillators, based on the two oscillators' state variables (position and velocity):

$$\begin{aligned}\ddot{x}_1 + \delta\dot{x}_1 + \lambda\dot{x}_1^3 + \gamma x_1^2\dot{x}_1 + \omega^2 x_1 &= (\dot{x}_1 - \dot{x}_2)[a + b(x_1 - x_2)^2],\\ \ddot{x}_2 + \delta\dot{x}_2 + \lambda\dot{x}_2^3 + \gamma x_2^2\dot{x}_2 + \omega^2 x_2 &= (\dot{x}_2 - \dot{x}_1)[a + b(x_2 - x_1)^2],\end{aligned} \tag{4}$$

where x_i is the position of oscillator i, and the dot notation represents derivation with respect to time. The left side of the equations represents the limit cycle dynamics of each oscillator determined by a linear stiffness parameter (ω) and damping parameters (δ, λ, and γ), and the right side represents the coupling function determined by parameters a and b.

We combined the HKB model and the hopping model, providing the stiffness parameter ω of each oscillator with $1/f^{\beta}$ correlation over the successive cycles. The parameters of the hopping model were chosen in order to provide effectors period series with the experimentally observed correlations (for details, see Delignières et al., 2008). Parameters of the limit-cycle oscillator were set as $\delta = 0.5$, $\lambda = 0.02$, $\gamma = 1.0$, and $\omega = 4\pi$. Finally, for obtaining a variability of RP series similar to that experimentally observed, we set the coupling parameters $a = 4$ and $b = 4$. We simulated 100 series of 512 data points.[4]

This 'hopping-HKB' model provided a satisfactory account of our experimental results. Simulated PER series also contained $1/f^{\beta}$ noise, with a mean low-frequency spectral slope of −0.73 (−1.04 for experimental series), and ARFIMA/ARMA modeling detected long-range correlation in 89% of simulated series. The mean standard deviation of simulated PER series was 20 ms (22 ms for experimental series). Simulated RP series also contained $1/f^{\beta}$ noise, with a mean low-frequency spectral slope of −0.72 (−0.72 for experimental series), and long-range correlation detected in 99% of series. The mean standard deviation of simulated RP was 10° (9° for experimental series).

For bimanual synchronization oscillations, we tested the *parametric driving model* (Fink et al., 2000; Jirsa et al., 2000), an extension of the HKB model including a parametric coupling to the metronome:

$$\begin{aligned}\ddot{x}_1 + \delta\dot{x}_1 + \lambda\dot{x}_1^3 + \gamma x_1^2\dot{x}_1 + \omega^2 x_1 &= (\dot{x}_1 - \dot{x}_2)[a + b(x_1 - x_2)^2]\\ &\quad + e_1\cos\Omega t + e_2 x_1\cos\Omega t,\\ \ddot{x}_2 + \delta\dot{x}_2 + \lambda\dot{x}_2^3 + \gamma x_2^2\dot{x}_2 + \omega^2 x_2 &= (\dot{x}_2 - \dot{x}_1)[a + b(x_2 - x_1)^2]\\ &\quad + e_1\cos\Omega t + e_2 x_2\cos\Omega t,\end{aligned} \tag{5}$$

where Ω represents the frequency of external pacing. The first cosine term represents linear driving and the second a parametric driving, depending on effector position.

As for the HKB model of self-paced coordination, we introduced the hopping model at the oscillator level in the parametric driving model. Parameters of the hopping model, the limit-cycle oscillators, and the coupling function were identical to those used in the previous simulation. The driving parameters e_1 and e_2 were set to 10, and we simulated 100 series.

The 'hopping-parametric driving' model provided satisfactory account for our experimental results. In contrast to self-paced coordination, simulated PER series were anti-persistent noise, with a mean low-frequency spectral slope of 1.10 (1.00 for experimental series). The mean standard deviation of simulated PER series was 17 ms (18 ms for experimental series). Simulated RP series were $1/f^{\beta}$ noise, with a mean low-frequency spectral slope of −0.77 (−0.71 for experimental series), and ARFIMA/ARMA modeling detected long-range correlation 99% of series. The mean standard deviation of simulated RP series was 9° (9° for experimental series).

These results suggest that the coupling principles that underlie the HKB model and the parametric driving model can generate the correlation properties of RP series obtained in self-paced and in synchronization coordination, respectively. However, to cope with the variability generated at the oscillator level and to stabilize relative phase, we had to apply coupling parameters that were much stronger than those commonly reported in the literature (Assisi, Jirsa, & Kelso, 2005; Fink et al., 2000; Leise & Cohen, 2007). Further study should clarify whether these models conserve their basic stability properties (differential stability of in-phase and anti-phase, phase transition) under such parameter settings.

4.5. Bimanual coordination: a multifaceted paradigm

In sum, we have shown that the distinctive serial correlation properties of event-based *versus* emergent and self-paced *versus* synchronization timing found in unimanual tasks persist in the corresponding bimanual coordination tasks. This finding led us to distinguish the forms of timing control yielding the specific within-hand timing patterns from the control of coordination yielding a stable relative timing between the hands, considering the former as the background on which the latter builds.

Some authors have recently emphasized the need for detailed accounts of component dynamics in addition to collective dynamics for the understanding of bimanual coordination (Peper et al., 2004; Ridderikhoff, Peper, & Beek, 2005). Especially, Riley et al. (2001) suggested that correlated forms of noise at the component level might contribute to variability observed at the collective level. Our present results underline the need of analyzing the component and the collective levels simultaneously, for decomposing the respective contributions of timing control and coordinative processes in coordination. Integrating the two levels, our preliminary amended models seemed able to generate serial correlations similar to those observed experimentally.

Following from these considerations, the 'bimanual coordination paradigm' appears multifaceted, and it might be inappropriate for the studies to generalize theories and models of bimanual coordination over various instantiations of the bimanual coordination paradigm. Regarding the pacing conditions, research on the stability properties of coordination has often used a metronome to prescribe either a globally steady or a progressively increasing tempo on the rhythmic movements. In these cases, the use of the metronome has generally been considered *non-specific* (Fink et al., 2000), in the sense that it was assumed to have no effect on the dynamics of the effectors involved in coordination. One may wonder what confirms the actual non-specificity of metronome use in many studies, since Fink et al. (2000) and Jirsa et al. (2000) showed an effect on the within-cycle dynamics, and our present results showed moreover a qualitative change in the serial correlation properties of periods.

Regarding the discontinuous/continuous character of movements, one may wonder to what extent it is actually legitimate to generalize an event-based timekeeper model for bimanual tapping like the multiple timer model, to bimanual oscillations, considering it as an alternative to the coupled oscillator model (see, for example, Ivry & Richardson, 2002). Typically, the multiple timer model and the coupled oscillator model are in line with different theoretical perspectives on coordination, the information processing perspective and the dynamics systems perspective, respectively. The former has essentially conceptualized coordination dynamics in terms of congruent event-structure representing timing goals that order the movement of limbs over time, and the temporal relationship between them. The latter has considered

[4] Simulations were performed using a four-stage Runge–Kutta algorithm, following the scheme described by Burrage, Lenane, and Lythe (2007, pp. 11–12), for second-order stochastic differential equations with additive noise. We used a fixed step size of 0.001 s.

coordination dynamics as the behavior that emerges from multiple interactions in a self-organized system, without specific regard to any timing function. But at the same time, the former has essentially been based on bimanual tapping tasks, while the latter has essentially studied bimanual oscillation tasks. These theories have often been considered as contrasting - perhaps irreconcilable – accounts of the same phenomenon, bimanual coordination. Following the present concerns, one might assume that the methodological diversity that characterizes research on bimanual coordination, and the distinct ways for regulating temporal patterns that this diversity implies, have contributed to a certain extent to the parallel development of these theories. These results suggest that each approach possesses its own relevance, regarding a specific class of tasks, and that both should co-exist in a global account for timing and coordination control.

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