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ARTICLE

# Interpersonal Synchronization Processes in Discrete and Continuous Tasks

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**ABSTRACT.** Three frameworks have been proposed to account for interpersonal synchronization: The information processing approach argues that synchronization is achieved by mutual adaptation, the coordination dynamics perspective supposes a continuous coupling between systems, and complexity matching suggests a global, multi-scale interaction. We hypothesized that the relevancy of these models was related to the nature of the performed tasks. 10 dyads performed synchronized tapping and synchronized forearm oscillations, in two conditions: *full* (participants had full information about their partner), and *digital* (information was limited to discrete auditory signals). Results shows that whatever the task and the available information, synchronization was dominated by a discrete mutual adaptation. These results question the relevancy of the coordination dynamics perspective in interpersonal coordination.

**Keywords:** synchronization, timing, mutual adaptation, complexity matching

## Introduction

Three main frameworks have been proposed for accounting for interpersonal coordination processes: the mutual adaptation (Konvalinka et al., 2010), the coupled oscillators model (Schmidt et al., 1990) and the complexity matching effect (Almurad et al., 2017). These frameworks have emerged from more global paradigms, the information-processing approach to sensorimotor synchronization (Repp, 2005), the synergetic approach to coordination (Haken et al., 1985), and the theory of information transfer between complex networks (West et al., 2008), respectively. Each of these frameworks has received convincing empirical support, and the question remains whether they represent alternative (and competing) accounts for similar realities, or specific models for different situations. We first present in details these three theoretical approaches.

## Mutual Adaptation

The information-processing approach supposes that interpersonal synchronization is essentially based on representational processes of anticipation. This approach takes its origin in studies about sensorimotor synchronization, focusing on the synchronization of simple movements such as finger tapping with a periodic metronome (for reviews see Repp, 2005; Repp & Su, 2013). Experimental evidences showed that in such situations

synchronization is achieved by a correction of the current inter-tap interval on the basis of the last asynchrony. Vorberg and Wing (1996) and Pressing and Jolley-Rogers (1997) propose to account for this process by the following model:

$$I(n) = I^*(n) - \alpha A(n-1) + \gamma [B(n) - B(n-1)] \quad (1)$$

where  $I(n)$  represents the series of inter-tap intervals produced by the participant,  $I^*(n)$  the time intervals provided by an internal timekeeper, and  $A(n)$  the asynchrony between the  $n^{\text{th}}$  tap and the  $n^{\text{th}}$  metronome signal.  $B(n)$  is a white noise process corresponding to the motor error produced at the  $n^{\text{th}}$  tap. As in tapping tasks  $I(n)$  is bounded by two successive taps, the influence of motor noise is modeled by the differenced term  $[B(n) - B(n-1)]$  (Wing & Kristofferson, 1973). In the first formulations of this model,  $I^*(n)$  was considered an uncorrelated white noise source (Vorberg & Wing, 1996; Wing & Kristofferson, 1973). However the analysis of prolonged series showed that the timekeeper should rather be modeled as a  $1/f$  source (Delignières et al., 2004; Gilden et al., 1995).

Then research was extended to the study of synchronization with variable metronomes, especially presenting fractal fluctuations, which are supposed to represent the kind of fluctuations encountered in natural situations (Delignières & Marmelat, 2014; Hunt et al., 2014; Kaipust et al., 2013; Marmelat et al., 2014; Rankin & Limb, 2014; Torre et al., 2013). These experiments showed that synchronization, in those situations, was similarly achieved by a discrete correction of the last asynchrony (Delignières & Marmelat, 2014; Thaut et al., 1998; Torre et al., 2013).

Finally this approach has been extended to interpersonal synchronization, especially in the study of synchronized finger tapping (Konvalinka et al., 2010; Nowicki et al., 2013; Pecenka & Keller, 2011). Here also, results suggested that interpersonal synchronization was achieved by a process of mutual adaptation, based on the correction of the last asynchrony. The initial model can be extended for synchronized tapping:

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$$\begin{cases} I_1(n) = I_1^*(n) - \alpha_1 A_1(n-1) + \gamma_1 [B_1(n) - B_1(n-1)] \\ I_2(n) = I_2^*(n) - \alpha_2 A_2(n-1) + \gamma_2 [B_2(n) - B_2(n-1)] \end{cases} \quad (2)$$

where the index notation refers to participants 1 and 2, respectively. Asynchronies ( $A_1(n)$  and  $A_2(n)$ ) correspond to the time interval between the  $n^{\text{th}}$  taps produced by both participants (then  $A_1(n) = -A_2(n)$ ). In the domain of interpersonal synchronization, this kind of process is referred to as *mutual adaptation* (Gebauer et al., 2016; Heggli et al., 2019; Koban et al., 2019; Konvalinka et al., 2010, 2014).

### The Coupled Oscillators Model

The coupled oscillator model, while initially introduced by Yamanishi et al. (1980) for bimanual tapping, was then essentially developed for accounting for continuous rhythmic tasks such as finger or forearm oscillations. This model supposes a continuous coupling between the two effectors, considered as self-sustained oscillators, and could be expressed as follows:

$$\begin{cases} \ddot{x}_1 + \delta \dot{x}_1 + \lambda \dot{x}_1^3 + \gamma x_1^2 \dot{x}_1 + \omega^2 x_1 = \\ (\dot{x}_1 - \dot{x}_2) [a + b(x_1 - x_2)^2] + q_1 \varepsilon_1 \\ \ddot{x}_2 + \delta \dot{x}_2 + \lambda \dot{x}_2^3 + \gamma x_2^2 \dot{x}_2 + \omega^2 x_2 = \\ (\dot{x}_2 - \dot{x}_1) [a + b(x_2 - x_1)^2] + q_2 \varepsilon_2 \end{cases} \quad (3)$$

In this model  $x_i$  represents the position of oscillator  $i$ , and the dot notation refers to derivation with respect to time. The left side of the equations represents the limit cycle dynamics of each oscillator, and includes a linear stiffness parameter ( $\omega$ ) and damping parameters ( $\delta$ ,  $\lambda$ , and  $\gamma$ ). The right side represents the coupling function, characterized by parameters  $a$  and  $b$ . Finally  $\varepsilon_{1,2}$  account for continuous white noise perturbations. This model has been shown to account for the typical empirical features observed in bimanual coordination, such as the differential stability of the in-phase and anti-phase coordination modes, and the transition from anti-phase to in-phase when pacing frequency is progressively increased (Haken et al., 1985; Schöner et al., 1986).

Schmidt et al. (1990) evidenced similar features in an interpersonal synchronization task: In an experiment in which two seated participants were asked to visually coordinate their lower legs, they showed that anti-phase and in-phase coordination patterns emerged as intrinsically stable behaviors, anti-phase being less stable than in-phase coordination, and they also evidenced a spontaneous transition from anti-phase to in-phase when oscillation frequency was progressively increased. Similar results were obtained in other interpersonal tasks involving different effectors (Richardson et al., 2007; Schmidt et al., 1998), suggesting that the coupled oscillator model could be extended to interpersonal coordination, for continuous movements.

In contrast with the previous approach, this model supposes a continuous coupling between the two

systems, and excludes any form of discrete, cycle-to-cycle correction of asynchronies.

In the initial model, which was conceived for accounting for the coordination of limbs belonging to the same organism, the two oscillators were supposed to be driven by the same stiffness parameter ( $\omega$ ), stable over successive oscillations (Haken et al., 1985; Kay et al., 1987; Schöner et al., 1986). Torre and Delignières (2008), however, showed that a more realistic model should consider  $\omega$  as presenting fractal fluctuations over time.

Considering that the stiffness parameter, in Equation (3), represents the main determinant of the frequency of oscillations, Roume et al. (2018) proposed to translate the previous model at the cycle level as follows, using the preceding notation:

$$\begin{cases} I_1(n) = I^*(n) + \gamma_1 B_1(n) \\ I_2(n) = I^*(n) + \gamma_2 B_2(n) \end{cases} \quad (4)$$

where  $I^*(n)$  represents a common “timekeeper”, corresponding to the series of stiffness in Eq. (3), and the noise terms summarizing perturbations at the cycle level. Obviously, the term “timekeeper” does not refer in this model to the seminal concept of cognitive timekeeper introduced by Wing and Kristofferson (1973), but to an emergent property of systems (Schöner, 2002). In contrast with the model of Eq. (2), synchronization is not obtained by means of a cycle-to-cycle correction of asynchronies, but simply by the presence of a common “timekeeper”.

### The Complexity Matching Effect

The concept of complexity matching states that the transfer of information between complex networks is maximized when they present similar levels of complexity (West et al., 2008). The main argument supporting this theory is that the response of a complex network to the stimulation of another network increases with the matching of their complexities. This phenomenon has been qualified as a kind of “ $1/f$  resonance” between systems (Aquino et al., 2011). Recently Mahmoodi et al. (2018) showed that the maximization of information transfer was directly related to the matching of the fractal properties of the series of crucial events characterizing the two systems in interaction.

Marmelat and Delignières (2012) proposed to apply the complexity matching framework to interpersonal coordination, surmising that interacting systems tend to match their complexities, in order to optimize information exchange and to enhance their synchronization. Such an attunement of complexities has indeed been observed in several experiments (Abney et al., 2014; Almurad et al., 2017; Coey et al., 2016; Delignières & Marmelat, 2014; Marmelat & Delignières, 2012; Stephen et al., 2008). In contrast with the previous model, which is essentially based on a local and continuous coupling

between the two oscillators, the complexity matching effect refers to a global, multiscale coordination between systems (Stephen et al., 2008; Stephen & Dixon, 2011).

Roume et al. (2018) proposed a very general model for accounting for the complexity matching effect between two interacting systems. This model is quite similar to that advocated for the continuous coupling model, except that the two systems are not driven by a common “timekeeper”, but just tend to attune their complexities:

$$\begin{cases} I_1(n) = I_1^*(n) + \gamma_1 B_1(n) \\ I_2(n) = I_2^*(n) + \gamma_2 B_2(n) \end{cases} \quad (5)$$

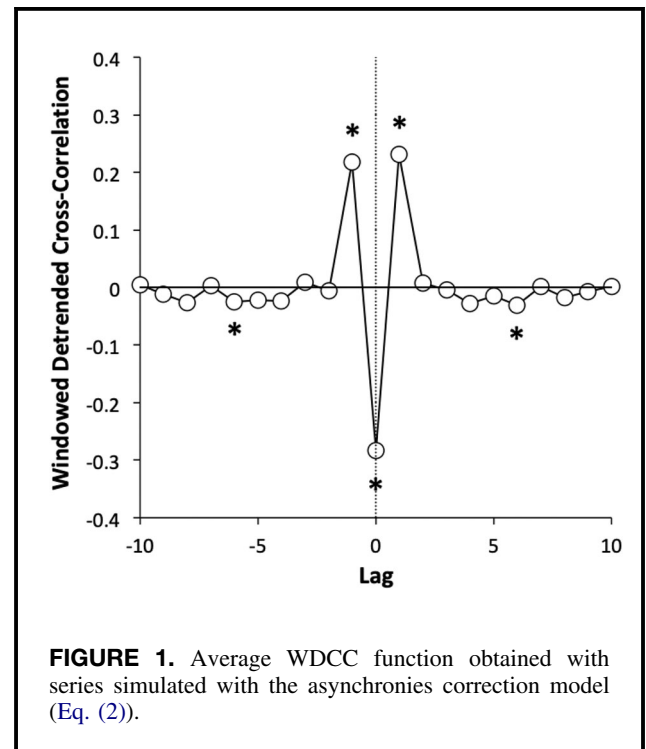
where  $I_1^*(n)$  and  $I_2^*(n)$  are considered as long-range cross-correlated fractal series. As the previous model, the complexity matching hypothesis supposes that synchronization is achieved without any process of asynchronies correction.

### Windowed Detrended Cross-Correlation Analysis

These three frameworks are based on very distinct hypotheses that are not so easily distinguishable in experimental data. For example, complexity matching was initially thought to be revealed by a close matching of the scaling properties of the series produced by the two interacting partners. However Marmelat and Delignières (2012) showed that the matching of scaling properties could just represent the consequence of local corrections of asynchronies. As well, Fine et al. (2015), in an experiment where dyads coordinated swinging pendulums, showed that global complexity matching could be linked to local continuous coupling.

Roume et al. (2018) proposed a method for unambiguously disentangling between these three hypotheses: the Windowed Detrended Cross-Correlation analysis (WDCC). This method computes the average cross-correlation function between the series produced by the two partners, within short intervals (e.g., 15 successive data points). Data are detrended in each interval in order to avoid spurious inflations of correlation due to local non-stationarities. The authors proposed a formal analysis of WDCC properties, and showed that mutual adaptation should yield positive peaks in the cross-correlation function, at lags 1 and  $-1$  (in the simple case where participants correct their current performance on the basis of the just preceding asynchrony). They also showed that the attunement of complexities produces a positive correlation at lag 0, depending on the level of cross-correlation between the ‘timekeepers’ of each participant in the dyad.

They first submitted to WDCC series produced by the asynchronies correction model (Eq. (2), see Figure 1). In this simulation, they used the same correction parameter for both participants ( $\alpha_1 = \alpha_2$ ), supposing a perfect case of symmetric correction of asynchronies. A leader/



**FIGURE 1.** Average WDCC function obtained with series simulated with the asynchronies correction model (Eq. (2)).

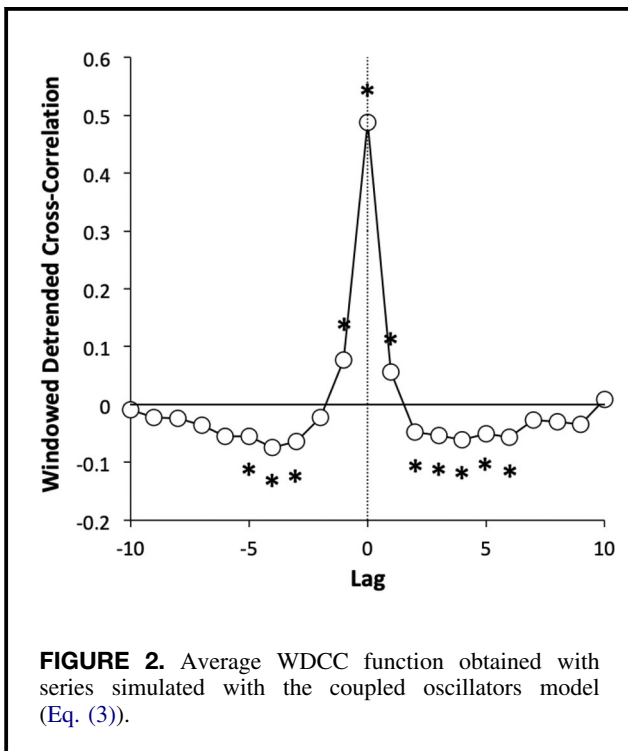
follower relationship could also be modeled by assigning different parameters to participants (e.g.,  $\alpha_1 > \alpha_2$ ). In that case the lag  $-1$  WDCC is higher than the lag 1 WDCC, suggesting that participant 1 tends to follow participant 2, which in turn tends to lead synchronization.

Roume et al. (2018) performed a similar analysis with series simulated with the coupled oscillator model (Eq. (3)). The results are reported in Figure 2. The main feature is a strong positive peak at lag 0, which is not surprising considering that the two oscillators share the same stiffness series.

Finally they analyzed series produced by the complexity matching model (Eq. (5)). In that case  $I_1^*(n)$  and  $I_2^*(n)$  were modeled with long-range cross-correlated series, obtained with the method described by Zebende (2011) and Balocchi et al. (2013). Results are reported in Figure 3, and are quite similar to those obtained with the coupled oscillator model with, however, a typically lower level of cross-correlation at lag 0.

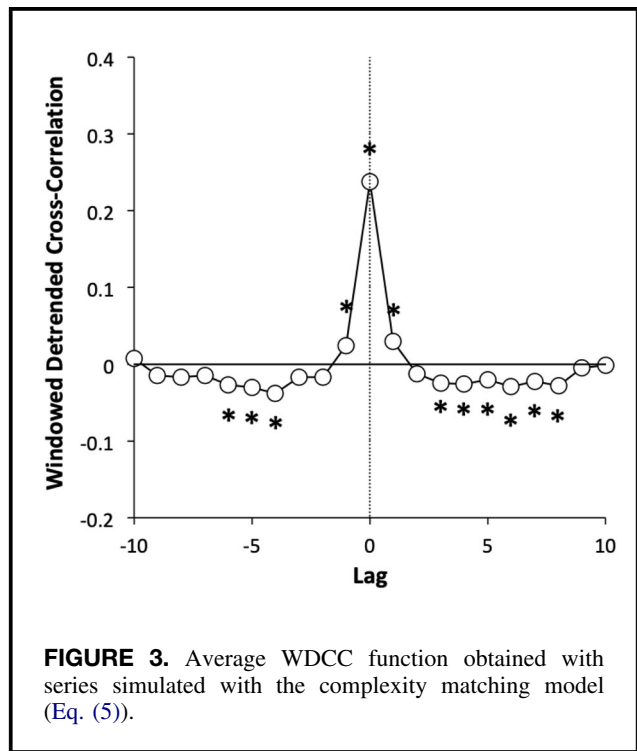
### Synchronization and Timing Processes

The theoretical frameworks we previously presented have been introduced on the basis of very specific experimental paradigms. The computational approach has mainly exploited discrete rhythmical tasks such as finger tapping (Repp, 2005). In contrast, the coupled oscillator model was essentially developed for accounting for continuous rhythmic tasks such as forearm oscillations (Haken et al., 1985; Kelso, 1995; Schönér et al., 1986). This observation is important, as it has been showed that



discrete and continuous tasks elicit very different timing processes (Delignières et al., 2004; Robertson et al., 1999; Zelaznik et al., 1998), referred to as event-based timing in the first case, and emergent timing in the second (Delignières & Torre, 2011; Ivry et al., 2002).

The seminal approach to event-based timing was introduced by Wing and Kristofferson (1973a, 1973b), who suggested that in discrete tasks such as finger tapping, the rhythmic behavior was governed by an internal, cognitive timekeeper, generating periodic cognitive events that trigger discrete motor responses. In contrast, Schöner (2002) developed a dynamical theory of timing, suggesting that in continuous tasks such as forearm oscillations, the rhythmic behavior emerges from the properties of the effector, conceived as a self-sustained oscillator, and especially its stiffness properties. These two models opposed a cognitive, top-down conception, and a bottom-up, emergent approach to motor control. A number of experimental contributions showed that these two kinds of timing processes were specifically exploited, in discrete and continuous rhythmic tasks, respectively. Robertson et al. (1999) showed that a discrete timing task such as finger tapping and a continuous rhythmic task such as circle drawing, were sustained by different timing processes. Delignières et al. (2004), analyzing the series of inter-tap intervals produced in a tapping tasks and the series of periods produced during forearm oscillations, clearly evidenced the task-dependent nature of timing. Especially, if the series of inter-tap intervals produced in self-paced tapping are characterized

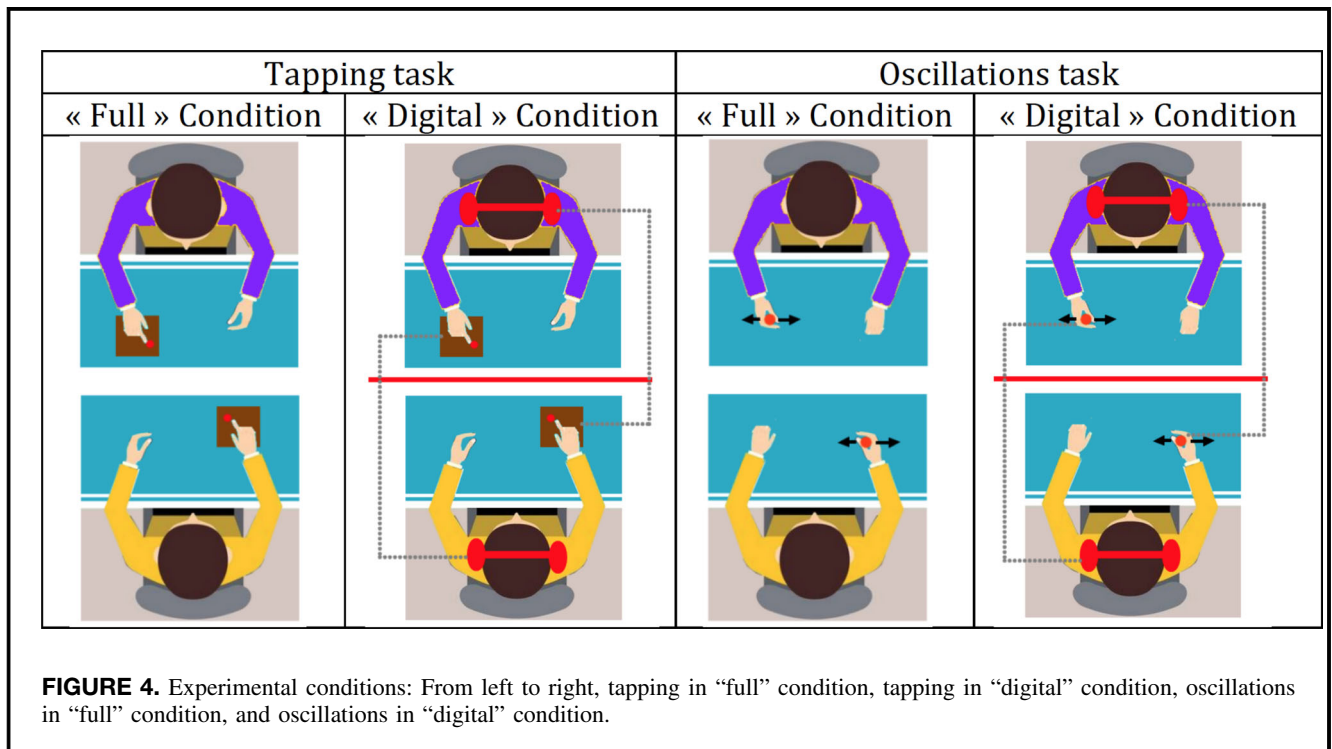


by a negative lag-one autocorrelation (as predicted by the Wing and Kristofferson's model), the series of periods produced in self-paced forearm oscillations exhibit a typical positive dependence between successive cycles (Delignières & Torre, 2011).

The aforementioned distinction is essentially based on the study of timing processes. Another line of investigation is concerned by the production of discrete vs rhythmic movements (Degallier & Ijspeert, 2010; Hogan & Sternad, 2007; van Mourik & Beek, 2004). These authors provide arguments suggesting that these two kinds of movements belong to exclusive categories, and could be considered as governed by distinct motor primitives, at the spinal level.

By extension, one could obviously hypothesize that interpersonal synchronization, in discrete tasks, is governed by discrete processes, such as the mutual correction of asynchronies described by Eq (2). In contrast, synchronization in continuous task should be based on a continuous coupling of effectors. The first aim of the present work was to test this hypothesis, in situations where participants were invited to perform interpersonal synchronized tapping, and interpersonal synchronized forearm oscillations.

Beyond the discrete/continuous nature of tasks, one could also question the effect of the information available for supporting synchronization. In discrete tasks, the essential information seems concentrated around local events, especially the asynchrony between taps. As a consequence, focusing information on these events should not affect synchronization processes. In contrast in continuous tasks an unrestricted access to the behavior of the partner seems



necessary for achieving synchronization. Especially, visual information is considered essential for ensuring coupling between the two partners (Richardson et al., 2007; Schmidt et al., 1990; Schmidt & Richardson, 2008; Schmidt & Turvey, 1994). The importance of a continuous visual information has been reconsidered, however, by the discovery of the anchoring phenomenon, defined as a local stabilization around specific spatiotemporal points within movement cycles). These local anchor points play an essential role in the occurrence and the stabilization of global synchronization (Miyata et al., 2018). Especially, the reversal points of oscillatory movements are privileged and provide information that ensures stable coordination (Hajnal et al., 2009; Varlet et al., 2014).

Then the second aim of the present work was to contrast, in both tasks, a situation where information was fully available, and a situation where information about the rhythmic behavior of the partner was reduced to a series of discrete auditory events. More particularly, we hypothesize that in such condition, synchronized oscillations should be governed by a discrete process of mutual corrections of asynchronies, similar to that used in tapping tasks.

## Methods

### Participants

20 participants (mean age: 22.5 years  $\pm$  4.3), 9 females and 11 males were involved in the experiment. All were right-handed, and none of them had particular

expertise or extensive practice in music. They were randomly divided into 10 dyads.

### Tasks and Apparatus

Each dyad performed two tasks: synchronized finger tapping and synchronized forearm oscillations (Figure 4). The two participants sat face-to-face on both sides of a table. In the first task each participant tapped with his/her right index finger on a pushbutton fixed on the table. They were invited to perform discrete taps (the index finger remaining in extension between two successive taps), and both participants were instructed to synchronize their taps with those of his/her partner. In the second task they performed oscillations with a 15-cm joystick, with a single degree of freedom in the frontal plane. Participants were asked to perform regular oscillations, with amplitude of about 60 degrees on each side of the vertical position, and to synchronize their oscillations in time and direction with those of their partner. As such, the maximal pronation for participant A corresponded to maximal supination of participant B, and vice-versa.

Each task was performed following the synchronization-continuation paradigm: at the beginning of each trial the tempo was paced by a regular metronome that provided a series of 10 auditory signals, following a 1 Hz frequency. Participants were instructed to synchronize their taps in the first task, and in the second the maximal pronation of participant A and the maximal supination of participant B, following the tempo imposed by the metronome. Then the metronome was removed and

dyads were instructed to continue the task for 10 minutes, following the initial tempo (about 600 successive taps or complete oscillations were then expected during the continuation phase).

These two tasks were performed in two conditions. In the “full” condition, participants had a full access (visual, auditory) to the behavior of their partner. In the “digital” condition, participants were separated by an opaque curtain to avoid visual information, they worked on separate tables to avoid proprioceptive information, and wore noise-canceling helmets to avoid auditory information. They just received information via headphones, in the form of discrete beeps, corresponding the taps of their partner in the first task, and to the reversals in pronation in the second. Note that participant A heard a beep when participant B was at his/her reversal in supination, and participant B heard a beep when participant A was at his/her reversal in pronation.

The four experimental conditions were performed in random order for each dyad, and within each dyad, participants were randomly assigned to the A or B positions in oscillation tasks.

### Data Acquisition

In the tapping task, each participant tapped on a microswitch (Technologie Service), and data were recorded via a National Instrument acquisition card (NI USB-6002) with a sampling frequency of 200 Hz. Inter-tap intervals were then computed as the time difference between successive taps. In the oscillation task, the angular movements were recorded with a potentiometer (BOURNS 6639S-1-103, 10k resistance and  $\pm 2\%$  linearity) located at the axis of the joystick, and data were also recorded with a sampling frequency of 200 Hz. In this task the output was a sine wave, and a peak finding algorithm was used for determining the date of positive (pronation) and negative (supination) peaks. Periods were then computed as the time differences between successive positive peaks, for participant A and between negative peaks for participant B.

In each series (series of inter-tap intervals in tapping tasks, and series of periods in oscillation tasks), we deleted the first 10 data points corresponding to the initial phase of synchronization with the metronome, and we kept the following  $N=512$  data points for further analyses.

In the “digital” conditions we used a microcontroller Arduino Uno to generate the beeps. In the tapping task, the microcontroller emitted a beep when a tap was detected. For oscillation tasks, the controller was programmed so that it generated a beep at each positive to negative zero-crossing of the derivative of the signal provided that the potentiometer for participant A, and each negative to positive zero-crossing for participant B.

### Statistical Analysis

We first characterized the series of time intervals produced by each participant, in terms of means and variability (inter-tap intervals in tapping tasks or periods in oscillations tasks). Considering that standard deviation, in such prolonged tasks, could be strongly affected by drifts (Collier & Ogden, 2001), we assessed variability through *Local Variance*, defined as the variance of increments in the series (Marmelat et al., 2012).

$$LV(I) = \text{Var}(I(n) - I(n-1)) \quad (6)$$

with  $n=2, 3, \dots, N$ .

In order to assess the scaling properties of the series of time intervals produced by participants, we applied the Detrended Fluctuation Analysis (Peng et al., 1993). We used the *evenly spaced DFA* algorithm proposed by Almurad and Delignières (2016). Finally, in each condition we computed the correlation coefficient between the samples of  $\alpha$  DFA exponents characterizing the series produced by participants A and B.

Then we characterized synchronization within dyads by computing the series of asynchronies. Note that the A and B positions being interchangeable in dyads, and randomly assigned, we discarded the signs by considering the absolute values of asynchronies. In order to get a valid comparison between conditions, we computed the series of relative asynchronies (*RelAsyn*), defined as the absolute value of the time difference between the two events  $t_A$  and  $t_B$  produced by participants A and B, respectively, divided by the preceding interval produced by participant A, and converted into percentage:

$$RelAsyn(n) = 100 * ABS(t_A(n) - t_B(n))/I_A(n) \quad (7)$$

In this equation  $t_A(n)$  represents, for participant A, the time of the  $n^{\text{th}}$  tap in tapping tasks or the time of  $n^{\text{th}}$  reversal point in oscillation tasks, and  $I_A(n) = t_A(n) - t_A(n-1)$ . We then computed the mean and the standard deviation of the series of relative asynchronies. All these variables were analyzed using a two-way ANOVA (2 Tasks (Tapping/Oscillations) X 2 Conditions (Full/Digital)).

Finally we applied the WDCC algorithm (Roume et al., 2018), in order to reveal the nature of interpersonal synchronization. We computed cross-correlation functions, from lag  $-10$  to lag  $10$ , considering windows of 15 data point. We used the sliding version of WDCC: The cross-correlation function was computed over the first available interval (from point 11 to point 26), then the interval was lagged by one point, and the process was repeated up to the last available interval. Before the computation of each cross-correlation functions, the data within each window in both series were linearly detrended. Then the cross-correlation functions were point-by-point averaged. Note that before averaging, the cross-correlation coefficients were transformed in  $z$ -

**TABLE 1. Descriptive statistics of series and asynchronies (standard deviation in brackets): Time intervals, local variance,  $\alpha$ DFA, correlation between  $\alpha$ DFA samples, relative asynchronies and asynchronies variability.**

	Tapping		Oscillations	
	Full	Digital	Full	Digital
Intervals (sec)	0.767 (0.095)	0.748 (0.079)	0.960 (0.099)	1.330 (0.222)
Local variance (sec <sup>2</sup> )	0.007 (0.004)	0.010 (0.004)	0.006 (0.003)	0.022 (0.013)
$\alpha$ DFA	0.892 (0.132)	0.906 (0.122)	0.881 (0.088)	0.944 (0.160)
Correlation $\alpha$ DFA	0.986	0.982	0.963	0.991
Mean relative asynchrony (%)	6.363 (1.760)	10.583 (2.863)	4.227 (0.647)	8.240 (2.764)
SD of relative asynchronies (%)	5.406 (1.972)	10.319 (4.715)	3.316 (0.614)	5.758 (1.327)

Fisher scores. These standardized scores were point-by-point averaged and the means were then backward transformed in correlation metrics. As proposed by Roume et al. (2018) we tested the signs of averaged coefficients with two-tailed location  $t$ -tests, comparing the obtained values to zero. The code we used for the WDCC algorithm, written under Matlab R2015a, has been published in Roume et al. (2018).

A first application of WDCC revealed evident leader/follower relationships within dyads. Considering that the positions A and B were randomly assigned during the experiment, we reorganized the positions in the dyads so that participant A was systematically the follower and participant B the leader, and we computed again the WDCC functions.

## Results

We present in Table 1 the descriptive the means and standard deviations for the abovementioned descriptive statistics.

The ANOVA on intervals revealed a main effect of Task ( $F(1,19) = 208.824$ ,  $p < .01$ , partial  $\eta^2 = 0.917$ ). The interval means were significantly longer in oscillation than in tapping. We also obtained a main effect for Condition ( $F(1,19) = 32.430$ ,  $p < .01$ ; partial  $\eta^2 = 0.631$ ), indicating that interval means were significantly longer in digital conditions than in full conditions. The interaction effect was significant as well ( $F(1,19) = 59.352$ ,  $p < .01$ , partial  $\eta^2 = 0.758$ ). Post-hoc Sheffé tests revealed that the interval means produced in digital oscillations were longer than those produced in all other conditions. Note that in the oscillation task, in digital

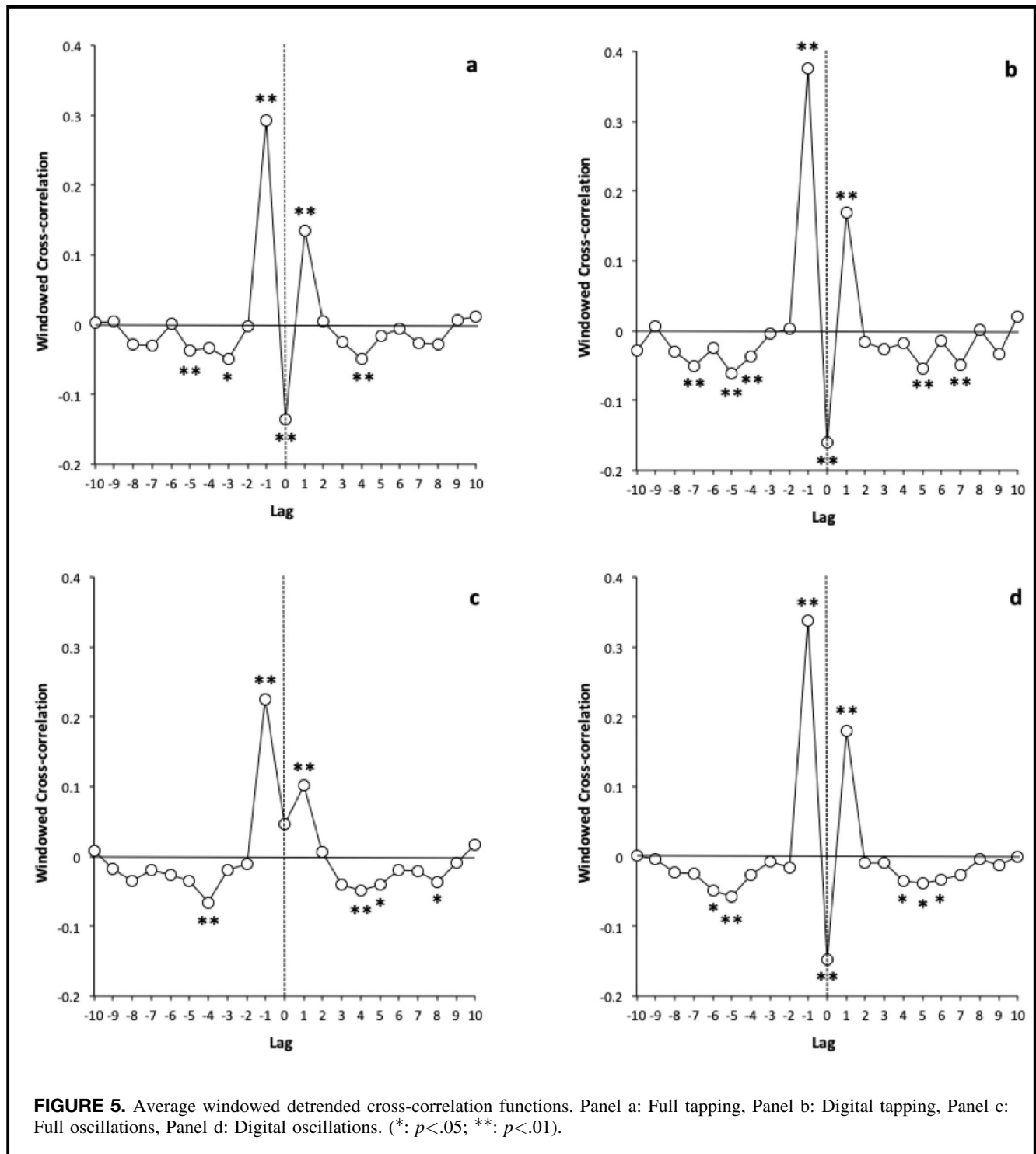
condition, series were often characterized by linear drifts, revealing a progressive increase of frequency.

The analysis of Local Variance showed a main effect of Task ( $F(1,19) = 19.801$ ,  $p < .01$ , partial  $\eta^2 = 0.510$ ): Local Variance was higher in oscillation than in tapping tasks. We obtained a significant effect for Condition ( $F(1,19) = 28.552$ ,  $p < .01$ ; partial  $\eta^2 = 0.600$ ): Local variance was higher in digital than in full conditions. Finally the interaction effect was also significant ( $F(1,19) = 21.207$ ,  $p < .01$ , partial  $\eta^2 = 0.527$ ). The Scheffé test indicated that Local Variance was higher in digital oscillations than in the three other conditions.

The computation of the scaling exponents  $\alpha$ DFA revealed in all conditions the presence of  $1/f$  fluctuations, with  $\alpha$  values close to 0.9. There was no effect for Task ( $F(1,19) = 0.301$ ,  $p > .05$ ), nor for Condition ( $F(1,19) = 1.637$ ,  $p > .05$ ), nor interaction effect ( $F(1,19) = 1.818$ ,  $p > .05$ ). Finally, in all conditions, we observed a close correlation between the  $\alpha$  exponents characterizing the series produced by participants A and B.

The analysis of relative asynchrony revealed a main effect for Task ( $F(1,9) = 14.765$ ,  $p < .01$ , partial  $\eta^2 = 0.621$ ): Asynchronies were higher in tapping than in oscillation tasks. The Condition effect was significant ( $F(1,9) = 36.409$ ,  $p < .01$ , partial  $\eta^2 = 0.802$ ): Relative asynchrony was lower in full conditions than in digital conditions. The interaction effect was not significant ( $F(1,9) = 0.018$ ,  $p > .05$ ).

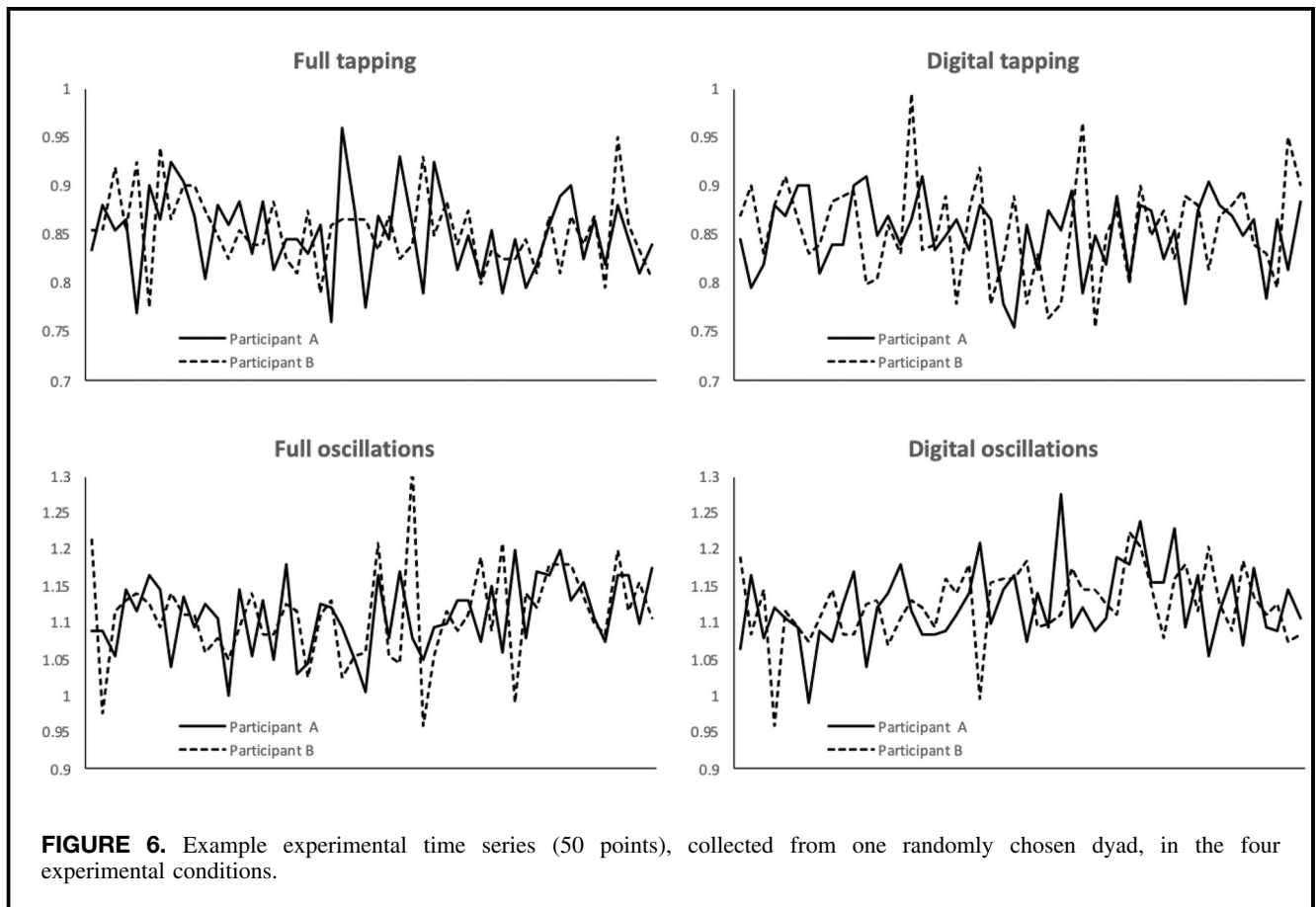
Finally, for the variability of relative asynchronies, we obtained a main effect for Task ( $F(1,9) = 28.983$ ,  $p < .01$ , partial  $\eta^2 = 0.763$ ): Asynchronies were more variable in tapping than in oscillation tasks. The Condition effect was significant ( $F(1,9) = 14.484$ ,  $p < .01$ , partial  $\eta^2 = 0.617$ ), showing that asynchronies



were more variable in digital conditions. There was no interaction effect ( $F(1,9) = 2.197, p > .01$ ).

We present in Figure 5 the windowed cross-correlation functions, for each experimental condition. The most important observation is that in all conditions we obtained positive peaks at lags 1 and -1. For full tapping WDCC lag-1 = 0.30 ( $t = 8.20, p < .01$ ) and WDCC

lag 1 = 0.13 ( $t = 5.01, p < .01$ ), for digital tapping WDCC lag-1 = 0.40 ( $t = 9.89, p < .01$ ) and WDCC lag 1 = 0.17 ( $t = 7.48, p < .01$ ), for full oscillations WDCC lag-1 = 0.23 ( $t = 10.51, p < .01$ ) and WDCC lag 1 = 0.10 ( $t = 4.12, p < .01$ ), for digital oscillations, WDCC lag-1 = 0.36 ( $t = 8.17, p < .01$ ) and WDCC lag 1 = 0.18 ( $t = 5.58, p < .01$ ). These results show that in all



conditions, synchronization involved mutual adaptation processes.

Considering the average cross-correlation at lag 0, a negative peak was obtained for full tapping (WDCC lag 0 =  $-0.14$ ,  $t = -3.78$ ,  $p < .01$ ), for digital tapping (WDCC lag 0 =  $-0.17$ ,  $t = -3.91$ ,  $p < .01$ ), and for digital oscillations (WDCC lag 0 =  $-0.15$ ,  $t = -5.24$ ,  $p < .01$ ). In contrast, average cross-correlation at lag 0 was positive for full oscillation, albeit non significantly different from zero (WDCC lag 0 =  $0.05$ ,  $t = 1.37$ ,  $p > .05$ ).

In Figure 6, we present some example experimental time series (50 points), collected from one randomly chosen dyad, in the four experimental conditions. This figure highlights the presence of lagged crosscorrelation between series, in all conditions.

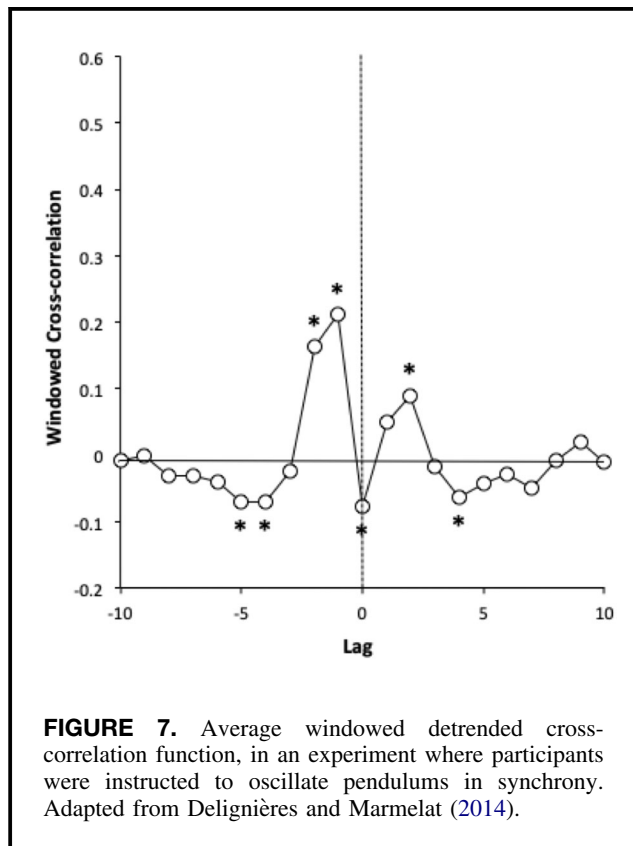
## Discussion

The analysis of the series produced by participants revealed that the mean interval was longer in oscillations than in tapping tasks. This suggests that tapping and oscillations movements possess different eigenfrequencies, and in both cases participants tend to adopt a

preferred tempo, corresponding to the performed task. Oscillation tasks, requiring more complex, to-and-fro movements within each cycle, have a lower preferred tempo than discrete tapping. The mean interval was also higher in digital conditions, and especially in the oscillation tasks, suggesting that limiting the amount of available information perturbs the maintenance of the prescribed tempo. Although we used local rather than global variance, we found similar effects concerning series' variability.

In contrast, asynchronies were lower and less variable in oscillations than in tapping tasks. As far as we know, this result was never reported in the literature. It could be related to the discreteness of the taps, which are supposed to be abruptly triggered on the basis of (cognitive) anticipatory processes. In contrast, oscillations allow more suitable adaptations, correction being distributed over a large part of the oscillators' cycle (Torre et al., 2010). Finally, asynchronies were larger and more variable in digital conditions, highlighting the essential role of visual information in synchronization.

The main result of this experiment is the systematic evidence for discrete error correction processes, whatever the task (tapping or oscillations) and the condition of



practice (full or digital). If one could expect this result in simultaneous tapping tasks (see Konvalinka et al., 2010), it appears more surprising in oscillation tasks (although a recently developed coupled oscillator model (Heggli et al., 2019) shows promise in describing this behavior, see below), when one knows the number of experiments that used the conceptual framework of coupled oscillators in this kind of tasks (e.g., Fine et al., 2015; Ouwehand & Peper, 2015; Peper et al., 2013; Schmidt et al., 1998). This result, however, is reminiscent of that obtained some years ago by Delignières and Marmelat (2014), in a task where participants had to synchronize the oscillations of pendulums. In this experiment, participants were seated side-by-side, between the two pendulums. Participant A held his/her pendulum with the right hand, and participant B with the left hand. Pendulums oscillated in the sagittal plane, they had a length of 0.48 m (from the bottom of the handle to the bottom of the pendulum), and a mass of 0.150 kg was fixed at the bottom of each pendulum. The authors reported a windowed cross-correlation function that also evidenced discrete correction processes, with positive peaks at lags  $-2$  and  $-1$ , and at lags  $1$  and  $2$ . In this situation, mutual corrections did not focus only on the previous asynchrony, but on the last two asynchronies (Figure 7). In these two different experiments, differing in the respective positions of the participants in the dyads (face-to-face vs side-by-

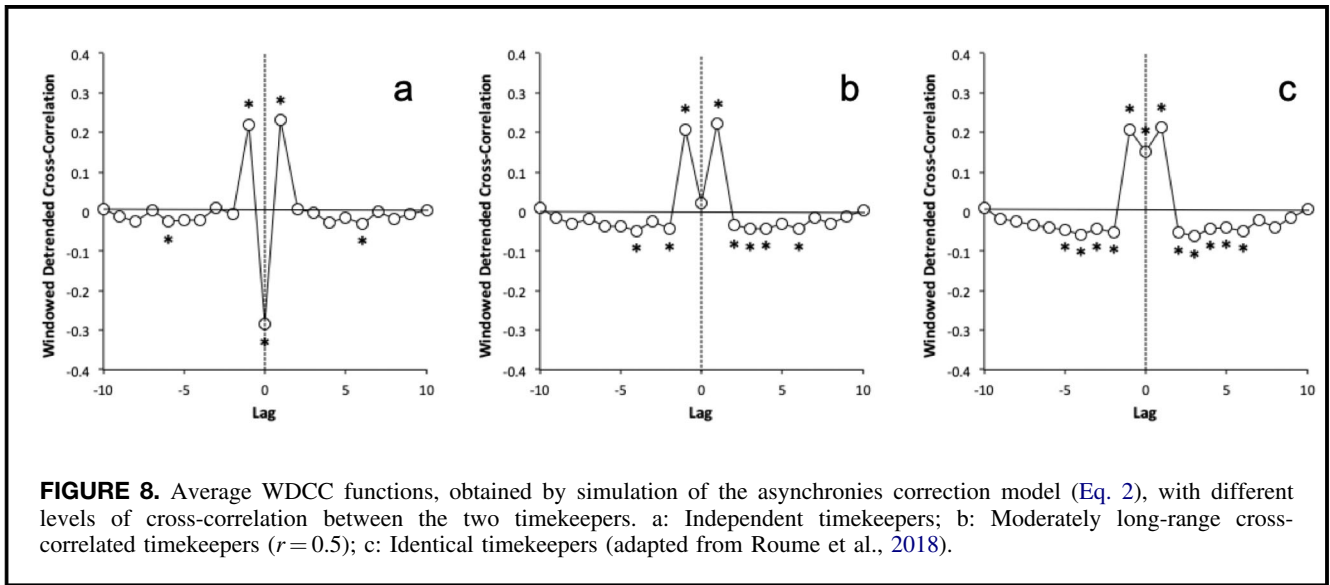
side), and by the nature of oscillations (small joysticks vs long pendulums), similar processes of discrete mutual correction were evidenced.

The coupled oscillator model states that the continuous coupling between oscillators represents the essential cause of synchronization. The coupling function, whose strength is modeled through  $a$  and  $b$  parameters in Eq. 3, and more precisely by the ratio  $b/a$ , allows competing against perturbations for maintaining a stable coordination between oscillators (Haken et al., 1985; Schöner et al., 1986). Then for a given perturbation strength (modeled by  $q_1$  and  $q_2$  in Eq. (3)), an increase of  $b/a$  yields an increase of lag 0 WDCC.

A number of papers studied frequency detuning, which represents a potential source of perturbation in coordination. Frequency detuning corresponds to a difference between the eigenfrequencies of the two oscillators (which could be modeled in Eq. (3) by the introduction of specific stiffness terms,  $\omega_1$  and  $\omega_2$ ,  $\Delta\omega = \omega_1 - \omega_2$ ). When  $\Delta\omega$  is small enough for being balanced by the coupling function, the expected coordination (e.g., the in-phase pattern) can be stably maintained. The model predicts that for larger values of frequency detuning, the coupling forces could be still able to ensue phase locking, but a typical phase lag between the two oscillators emerges that is proportional in size to  $\Delta\omega$ . This effect of frequency detuning has been evidenced in intra- as well in interpersonal coordination tasks (Amazeen et al., 1995; Schmidt & Richardson, 2008; Sternad et al., 1995). However, this typical phase lag, which emerges from the competition between frequency detuning and continuous coupling, cannot result in cycle-to-cycle dependencies, such as those disclosed in the present results.

One could obviously consider that in the digital condition, as visual information about the partner's behavior is not available, this continuous coupling cannot work, and synchronization is necessarily achieved on the basis of cycle-to-cycle asynchrony corrections. This was clearly expected in our hypotheses. In contrast, the presence of such discrete correction processes in the full condition was clearly not expected, and contradicts the basic assumptions of the coupled oscillator model.

We obviously considered the possibility of a possible effect of our experimental implementation of the oscillation task, which could perhaps have induced a particular salience of reversal points in joysticks oscillations (anchoring), yielding a more discrete form of synchronization. However, we found no convincing reason for justifying this kind of reserve, our experimental task being equivalent to those used in a number of related works, and the fact that a similar result was evidenced in clearly different experimental conditions by Delignières and Marmelat (2014) reinforces the plausibility of the present observation.

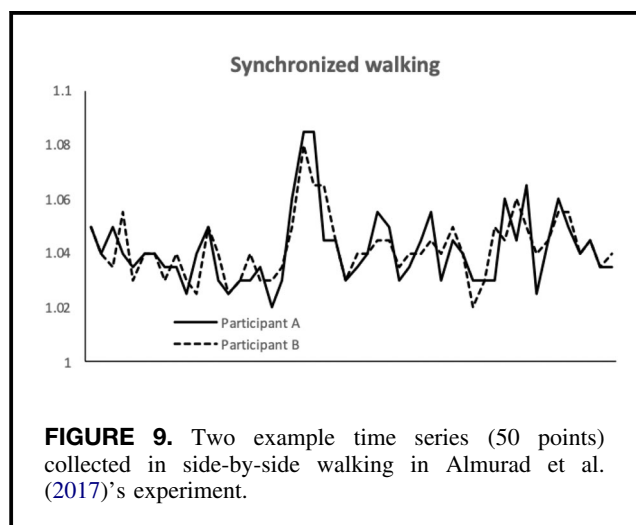


The present results suggest a discretization of synchronization processes in interpersonal oscillations coordination, as compared to the continuous character of synchronization in the intrapersonal case. The limitations of the original 2-coupled oscillator model have been highlighted by Beek et al. (2002), especially concerning its inability to generate the serial dependencies typical of rhythmic movements, and the inadequacy of the coupling function. They proposed a more encompassing model, involving a system of four coupled oscillators, two at the neural level and two at the effector level, which seemed able to overcome those limitations. More recently Heggli et al. (2019) also introduced a four-coupled oscillator model, each member of a dyad being abstracted as a unit consisting of two connected oscillators, representing intrinsic processes of perception and action, respectively. The authors showed that with certain combinations of coupling parameters (especially with a higher between-unit coupling than within-unit coupling), this model was able to produce the typical cross-correlation pattern of mutual adaptation (with positive correlations at lag-1 and lag 1). This kind of model offers interesting perspectives which could reconcile, in this domain of interpersonal coordination, the information-processing and the dynamical systems approaches (Beek et al., 2002; Heggli et al., 2019; Konvalinka et al., 2009). The present results obviously plead for this reconciliation.

The WDC functions present another intriguing result, for lag 0 CC, with negative coefficients for tapping tasks and for oscillations in digital condition, but positive (albeit not significant) in the full oscillations condition. We previously presented in Figure 1 the average WDC function obtained with series simulated with the asynchronies correction model (Eq. 2). In this simulation the two timekeepers  $I^*_1(n)$  and  $I^*_2(n)$  were modeled as

independent  $1/f$  sources. Roume et al. (2018) analyzed the effect of the simulation of various levels of cross-correlation between the two timekeepers. We present in Figure 8 some typical results they obtained. From the right to the left, this figure shows the WDC functions obtained (1) for independent timekeepers ( $r=0$ ), (2) for two moderately long-range cross-correlated timekeepers ( $r=0.5$ ), and (3) for identical timekeepers ( $r=1$ ). The lag  $-1$  and lag  $1$  cross-correlation coefficients were not affected by the manipulation of cross-correlation between timekeepers. In contrast, the cross-correlation at lag  $0$  was negative when timekeepers were independent, and progressively increased toward positive values as timekeepers became more and more cross-correlated.

The results of the present experiment suggest that in tapping tasks, the two timekeepers remain independent, and that synchrony is essentially achieved through a mutual asynchrony correction. In contrast, the WDC function for the “full” oscillation task shows that the “timekeepers” are (moderately) cross-correlated, suggesting a slight complexity matching effect between the two participants. This cross-correlation remains quite moderate, however, and we are not sure that the continuous coupling function defined in the HKB model could be able to cope with this discrepancy between the systems in coordination (Torre et al., 2007). The idea of mixed models, combining discrete asynchronies corrections and complexity matching, has been already proposed by Roume et al. (2018). For example in side-by-side walking, synchronization seems mainly achieved through complexity matching, but a slight process of asynchronies correction is also detectable in WDC functions (see also Almurad et al., 2018). Synchronization appears *dominated* by one process, but secondary adjusted by a second. In the oscillation task, synchronization is clearly



dominated by asynchronies correction. Interestingly, the complexity matching effect disappeared when oscillations were performed in digital conditions, suggesting that a full access to the visual information relative to the partner's behavior is essential for the emergence of a (at least partial) complexity matching effect.

Finally, we found a close correlation between  $\alpha$ DFA exponents, in all conditions. This correlation was sometimes considered as a signature of complexity matching (Den Hartigh et al., 2018; Marmelat & Delignières, 2012; Stephen et al., 2008). However, Delignières et al. (2016) casted some doubts about the fact that this statistical matching between mono-fractal exponents could represent a non-ambiguous signature of genuine complexity matching. The present results confirm that the close correlation between  $\alpha$  exponents is just the consequence of synchronization, and does not provide information about the processes that underlie synchronization between systems. In contrast, obtaining a positive peak at lag 0 in the average WDCC function represents a non-ambiguous signature of the presence of a complexity matching effect (Roume et al., 2018).

Note that we never found in the present experiment the typical signature expected from a synchronization process dominated by complexity matching, as illustrated in Figure 3. To date, such a signature was only obtained in side-by-side walking (Almurad et al., 2017, 2018; Roume et al., 2018). Just for comparison, we present in Figure 9 two example time series collected in side-by-side walking in the experiment by Almurad et al. (2017). One can note the sharp contrast between this graph, highlighting immediate synchronization within the dyad, and those of Figure 6, suggesting a systematically delayed synchronization process.

This scarcity brings a number of questions. Most of the experiments carried out on interpersonal synchronization focused on simple and standardized laboratory tasks,

involving artificial movements, and focusing on manual effectors. And in most cases processes of discrete corrections have been highlighted. An unambiguous complexity matching effect only appeared in a more natural situation, implying more global movements, and with less accuracy requirements.

## Conclusion

The main result of this study is the ubiquity of mutual adaptation, based on asynchronies correction, in the four experimental conditions. This pattern of cross-correlation has been already described in previous experiments on interpersonal tapping (Konvalinka et al., 2010; Roume et al., 2018), but never for continuous, cyclical tasks (except Delignières & Marmelat, 2014). As the original coupled oscillators model has received considerable support in interpersonal experiments (Fine et al., 2015; Richardson et al., 2007; Schmidt et al., 1990, 1998; Schmidt & Richardson, 2008; Schmidt & Turvey, 1994), we invite our colleagues to apply our WDCC analysis on their original data sets, in order to check for the eventual presence of discrete asynchrony correction, and also to assess the level of lag 0 cross-correlation between their series.

The present results suggest that whatever the involved movements (discrete or rhythmic), mutual adaptation is a mandatory solution when the “timekeepers” of the two cooperating systems present too independent dynamics, which seems the case in interpersonal coordination. A theoretical effort seems necessary for conciliating those experimental observations into a reunified model (Heggli et al., 2019). Among all the situations studied to date, synchronized walking remains a very special case, the only one where a complexity matching effect emerges from the interaction between participants, allowing a more immediate synchronization between partners. Further research is necessary for understanding this specificity, which has not been observed in the present experiment.

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## Disclosure Statement

No potential conflict of interest was reported by the author(s).

## Data Availability

The data set associated with this paper is available at the following address: <https://mfr.osf.io/render?url=https%3A%2F%2Fosf.io%2Fk4urf%2Fdownload>

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