Published in final edited form as:

Neurosci Lett. 2016 March 11; 616: 204–210. doi:10.1016/j.neulet.2016.01.066.

Complexity Matching Effects in Bimanual and Interpersonal Syncopated Finger Tapping

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Abstract

The current study was designed to investigate complexity matching during syncopated behavioral coordination. Participants either tapped in (bimanual) syncopation using their two hands, or tapped in (interpersonal) syncopation with a partner, with each participant using one of their hands. The time series of inter-tap intervals (ITI) from each hand were submitted to fractal analysis, as well as to short-term and multi-timescale cross-correlation analyses. The results demonstrated that the fractal scaling of one hand's ITI was strongly correlated to that of the other hand, and this complexity matching effect was stronger in the bimanual condition than in the interpersonal condition. Moreover, the degree of complexity matching was predicted by the strength of short-term cross-correlation and the stability of the asynchrony between the two tapping series. These results suggest that complexity matching is not specific to the inphase synchronization tasks used in past research, but is a general result of coordination between complex systems.

Keywords

Fractal scaling; Complexity matching; Syncopation; Finger Tapping

1. Introduction

Contrary to traditional assumptions in the behavioral sciences, the behavior of natural systems does not, as a rule, vary randomly over time, but instead tends to obey *power-law* or *fractal* scaling [1,2]. Fractal scaling in time-evolving behavior refers to a scale invariant pattern of variation wherein smaller fluctuations are nested within larger fluctuations in a self-similar fashion [3]. Ample research has confirmed that fractal scaling characterizes many different human time series, including a variety of neurological signals [4]. Fractal

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patterns have been uncovered in ion channel behavior [5], spike trains from individual neurons [6], the collective activity of neural networks [7], and the distribution and organization of synaptic connections [8]. Finding fractal scaling at these different levels of organization is consistent with the idea that the brain is organized to promote information flow and to minimize energetic costs [9]. These scaling relations not only describe the operation of the human brain, but also many other human physiological and behavioral processes [10]. The ubiquity of this particular form of variation is therefore thought to reflect universal physical laws of energy dissipation and information flow that constrain all kinds of natural and adaptive systems [11,12,13].

Despite the findings indicating that fractal patterns characterize the normal, “intrinsic” functioning of brain and behavior [14], research has also shown that fractal scaling can be altered by several factors. For example, in human physiological processes, the fractal, “pink noise” signal (Fig. 1A, top) of inter-heartbeat intervals in healthy subjects shifts toward more random, “white noise” scaling (Fig 1A, middle) in subjects with congestive heart failure [15]. In the case of human behavioral processes, the normally pink noise in reaction time series shifts toward white noise scaling when random variation is injected into the task stimuli [16]. These shifts in fractal scaling can be quantified using a fractal time series analysis. Loosely speaking, detrended fluctuation analysis (DFA) works by plotting the relationship between the degrees of variation in the series against the associated timescales on a DFA plot (Fig 1B). The slope of the regression line fitting the DFA plot estimates the Hurst exponent (H), which quantifies fractal scaling in a single value. Thus, shifts from pink noise scaling ($H \approx 1$) toward white noise scaling ($H \approx 0.5$) are captured by a reduction in the Hurst exponent.

In the kinds of finger tapping tasks employed in the current study, changes in fractal scaling can be even greater. Several studies have shown that unconstrained, self-paced rhythmic finger tapping typically produces pink noise scaling in the series of inter-tap intervals [17,18,19]. If participants tap in synchrony with a metronome stimulus [20], however, the scaling in the inter-tap interval series shifts past white noise toward strongly anti-persistent, “blue noise”, while the asynchrony series continues to display pink noise scaling ($H \approx 0$; Fig. 1A and 1B, bottom), indicating a functional re-organization of the behavioral system [10,21].

Recent research has shown that the fractal scaling of human performances is not only altered by certain experimental manipulations, but also tends to closely match the scaling of other, coupled processes. More specifically, this research has clearly demonstrated that the Hurst exponents defining the behavior of two interacting systems tend to be strongly correlated. This phenomenon, called *complexity matching* (CM), has been found between interacting individuals engaged in many joint action tasks, such as finger tapping [22], pendulum swinging [23], treadmill walking [24] and conversational interaction [25], and has also been shown to occur between participants and computer-generated stimuli, as well as between two different effectors of the same participant [26]. In their seminal work, Stephen and colleagues [27] had participants synchronize their finger taps to beats of a chaotic metronome. They found the scaling of the participants’ inter-tap intervals was strongly correlated to that of the metronomes’ inter-onset intervals. More interestingly, this effect did

not seem to reflect a strong short-term correlation between the two time series. Thus, they concluded that the participants' behavior had become tuned to the "global", higher-order patterns of variation in the metronome without being strongly matched to the "local", sample-to-sample variation of the metronome.

Subsequent research on CM has revealed several interesting findings, but also led to disparate conclusions. In particular, there is disagreement concerning the extent to which CM relies on local coordinative processes [22,23,26,28]. Several studies have cited the lack of substantial short-term cross-correlation during CM as evidence against the local coordination account [23,25,29,30]. Other studies, however, have clearly demonstrated that the degree of CM and patterns of cross-correlation observed in empirical data can be captured by models based on short-term error correction processes [22,31]. It has also been suggested that the "local" processes underlying CM should not be defined by the cross-correlation between two interval series, but instead by the real-time, relative phase coordination between two movements [28]. There are, however, other findings that complicate a local coordination account. For instance, Rhea and colleagues [29] have recently shown that participants sustain the fractal scaling embedded in a metronome stimulus after they discontinue interacting with it. Thus, the nature of the coordinative processes underlying CM is still an open and important question [26].

To date, CM research has also almost exclusively relied on synchronization tasks, in which the participants' goal is to synchronize their behaviors with the behaviors of another participant or a computer-generated stimulus. There are, however, other modes of coordinating one's behaviors with other events, and these modes do have consequences for the dynamical structure of the performance [32,33]. In continuous rhythmic movements the "antiphase" mode of coordination (i.e., one oscillator moves in time with another, but in the opposite direction) is known to be less intrinsically stable than the "inphase" mode (i.e., two oscillators move in time with one another in the same direction). The antiphase mode reveals greater variability in the index of coordination (e.g., relative phase) and also tends to break down under conditions (e.g., high movement frequencies) in which the inphase mode remains stable [34,35]. Studies of discrete timing movements, such as finger tapping, have also revealed differences in the stability of "syncopation" (e.g., when taps fall between metronome beats) and synchronization [36,37]. More importantly, research has also shown that the fractal scaling of performance is influenced by the mode of coordination [38]. Specifically, Chen and colleagues [20] showed that the fractal scaling of the asynchrony series was closer to ideal pink noise ($H = 1$) when participants tapped in syncopation with a metronome than when they tapped in synchronization.

In summary, the behavior of natural systems tends to display fractal patterns of variation, but several factors can influence the scaling of these behaviors, including the scaling evident in coupled systems. Relatedly, CM has deep theoretical implications for understanding how complex systems (including human agents) exchange information and adapt to ongoing environmental events. The study of CM in human performances is still in its early development and, in particular, there is little agreement on the nature of the coordinative processes that support the attunement of the higher-order patterns of variation (i.e., fractal scaling) between interacting systems. The fact that previous work on CM has been limited to

synchronization tasks is an important limitation, as past research has consistently shown that the mode of coordination between two systems has consequences for the dynamical structure of task performance, including its fractal scaling. Thus, an essential next step for research on CM is to examine the fractal scaling of two interacting systems during modes of coordination other than inphase synchronization.

Accordingly, the current study was designed to meet this goal by investigating CM in a syncopated tapping task. Participants either produced syncopated taps bimanually, using the index fingers of left and right hands, or produced syncopated taps interpersonally with a partner, with each participant contributing one hand. The participants also heard metronome stimuli during the task, which constrained the taps on the left, on the right, on both sides, or on neither side. Finding CM in a syncopated task is theoretically interesting, as it demonstrates that the phenomenon is not exclusive to the kind of “anticipatory” processes involved in synchronizing one’s behavior with other events [27], but instead is a product of coordinating one’s behavior with other processes more generally. That is, this task entails less rigorous constraints between the interacting systems [10], and one system’s behavior is (potentially) freer to realize a different pattern of variation around this midpoint than the pattern embedded in the coupled system’s behavior. Thus, it was possible that CM would be weaker in the current syncopated task than in the past observations in synchronization tasks. Alternatively, to the extent that sustaining syncopated behavior involves making local adjustments to one’s behavior based on the behavior of the coupled system [38], it was possible that CM might be equally strong in the current experiment. The potential differences between the bimanual and interpersonal conditions are also theoretically important, particularly with respect to the relationship between CM and the time-dependent correlations between the tapping behaviors. The manipulation of the metronome condition in the current experiment was expected to influence the coupling between two interacting participants, as the need to attend to one another’s behavior in order to maintain coordination would differ based on the available task constraints. In contrast, the coupling between the two effectors was unlikely to be affected by the available external task constraints when they were coupled via a common nervous system. Thus, differences in the strength of CM, and any associated differences in the time-dependent correlations between the two tapping series, would provide insights about the underlying coordinative processes.

2. Materials and Methods

A total of 48 undergraduate students were recruited from the Psychology Department’s research pool at the University of Cincinnati and successfully completed the experiment. A group of 14 of these students participated in a “solo” condition, in which they completed the experimental task on their own. The remaining 34 students participated in a “joint” condition, in which they were randomly paired ($n = 17$), and completed the task together. The data of one solo participant and one of the joint pairs were excluded from analysis, as these participants had extensive musical training that differentiated them from the rest of the sample.

Participants were seated at a table facing two, side-by-side MIDI keyboards (± 5 ms error). They were instructed that their task was to maintain stable syncopated finger tapping on the

two keyboards at a specified period (800ms between successive taps on each keyboard; 400ms between taps). In the solo condition, the individual participants tapped on the left and right keyboards with their two hands. In the joint condition, participants seated on the left tapped the left keyboard with their left hand and participants seated on the right tapped the right keyboard with their right hand. All participants wore headphones, through which they heard auditory metronome stimuli. In the *full metronome* condition, the metronome consisted of alternating low- and high-frequency tones presented at the specified tapping period (800 ms between successive tones of each type; 400 ms between tones). The participants were instructed that the low tone was to guide taps on the left keyboard and the high tone to guide taps on the right keyboard. In the *left metronome* and *right metronome* conditions, the metronome presented the full pattern of alternating low and high tones only for the first ten seconds of the trial, to allow participants a short time to stabilize the syncopated pattern of tapping. After ten seconds, one of the tones was discontinued and the other continued for the duration of the trial. It is important to note that for participants in the joint condition only one participant heard metronome tones in the left and right metronome conditions. That is, the headphones of the participant who's taps were not guided by the metronome (e.g., right participant in the left metronome condition) did not hear any sounds at all through the headphones after the initial ten second period¹. Finally, in a *baseline metronome* condition, the full metronome stimulus played for the first ten seconds of the trial and then both tones were discontinued, so that the participants had to maintain the syncopated pattern of tapping without any external timing constraints.

Each participant (or pair) completed one trial in each one of the four metronome conditions. All participants first completed their baseline trial to avoid carry-over effects from the metronome-paced trials. Participants then completed the remaining three, metronome-paced trials in a randomized order. Each trial lasted eight minutes and resulted in approximately 300 taps on each keyboard.

The keyboards were connected to a computer running Ableton Live (v. 8.2) software (Ableton, Berlin Germany), which both presented the metronome stimuli and recorded the participants' tapping behavior. To ensure that the recorded tapping behavior met a minimal criterion for syncopation, a custom Matlab algorithm processed the series of key-press times from each keyboard and removed non-alternating observations. The series was then differenced to yield an inter-tap interval (ITI) series separately for each keyboard. Additionally, the times between the successive taps on the two keyboards were differenced to yield an asynchrony (ASY) series, which was used to assess the stability of the coordination. Next, in keeping with standard practice [3], outlier observations were removed. Specifically, an ITI observation was considered to be an outlier if it was shorter than 400ms or longer than 1200ms. When an outlier in either ITI series was eliminated, the corresponding observations in the other ITI series and the ASY series were also eliminated. Finally, each series was truncated to a standard length (256 observations). If after the outlier removal process the series was only slightly shorter than the standard length (246 observations), the series was zero-padded to the standard length [3].

¹The results of the experiment were not meaningfully different for joint participants who could hear one another's metronome tones during the left and right metronome conditions.

In order to assess fractal scaling and CM, the ITI series were submitted to DFA. The ITI series were first cumulatively summed, which is an essential step for DFA to accurately estimate the fractal scaling of fractional Gaussian noise series [3]. The series were then broken into non-overlapping windows of a minimal size (16 observations), a local linear trend was found within each window, and the root mean square error of the data around the local trend was computed. The error scores were averaged across all windows to yield an “F” score for that window size. The window size was then increased by a certain amount (8 observations) and this process was repeated up to windows of a maximal size (128 observations). Finally, the F scores were plotted against the window sizes on a double-logarithmic DFA plot (see Fig 1B for example). The slope of the regression line fitting the DFA plot was the estimate of the Hurst exponent for the series. Correlations between the Hurst exponents for ITI series from the left and right keyboards were used to assess the strength of CM.

Windowed detrended cross-correlation (WDCC) provided a test of the short-term relationship between the ITI series from the left and right keyboards. First, each ITI series was broken into small windows (15 observations) and linear trends were removed from each window. Then the cross-correlation between the two series was computed within each window from time lags of -10 to 10 samples. Lastly, the cross-correlation functions were averaged across windows.

Detrended cross-correlation analysis (DCCA) provided a test of the multi-timescale relationship between the ITI series from the left and right keyboard. The DCCA technique is similar to DFA [see 34]. The two ITI series were broken into small windows (16 observations) and local linear trends were removed from each window. Whereas DFA assesses the variance in a single series around these local linear trends, DCCA assesses the covariance of two series around their respective linear trends. The covariance was averaged across all windows, and then was divided by the product of the averaged variances of the individual series to yield DCCA- ρ , which scales as a correlation coefficient (-1 to 1). As in DFA, the window size was iteratively increased by a small amount (8 observations) up to a maximal window size (128 observations). The outcome of this analysis was a DCCA- ρ function for each pair of ITI series, which displayed how the relationship between the two series changed over increases in timescale (i.e., window size). The DCCA- ρ function was expected to increase some asymptotic level across increasing timescales [34].

Additionally, it is good practice to compare the assessments of the dynamic relationship between the two ITI series (i.e., WDCC and DCCA) to randomized surrogate series. These surrogates were created by randomly shuffling the time position of all observations in the ITI series, thus eliminating any dynamic structure within the series and any dynamic relationship between the series. The surrogate series were submitted to WDCC and DCCA along with the empirical ITI series to provide a critical comparison condition.

3. Results

First, participants in the solo condition had considerably less trouble sustaining stable syncopated tapping than participants in the joint condition. Four pairs in the joint group

produced one trial marked by extremely unstable coordination, a high number of outlier observations, and time series too short for fractal analysis after outlier removal. In the interest of providing a fair comparison between the solo and joint groups, these pairs' data were excluded from the remaining analyses². The remaining 12 joint pairs still produced slightly more outliers per trial ($M = 7.0$, $SD = 5.2$) than did the 13 solo participants ($M = 1.0$, $SD = 5.2$).

The average ITI, from both left and right keyboards, was very close to the specified tapping period (800ms) in the three metronome-paced conditions, but the participants tapped faster in the baseline condition, $F(3,69) = 11.10$, $p < .0005$, $\eta_p^2 = .33$. Also, the solo participants ($M = 730.6$ ms, $SD = 65.4$) tapped faster than the joint participants ($M = 778.2$ ms, $SD = 42.7$) in the baseline condition, $F(1,23) = 4.23$, $p = .051$, $\eta_p^2 = .16$. The standard deviation of the ITI was smaller in the full metronome condition than in the other metronome conditions, $F(3,69) = 10.12$, $p < .0005$, $\eta_p^2 = .31$. Consistent with the ITI, the average asynchrony between taps on the left and right keyboards was close to the specified value (400ms) in the metronome-paced conditions, but was slightly faster in the baseline condition. Additionally, the solo participants ($M = 390.2$ ms, $SD = 20.2$) produced shorter asynchrony than the joint participants ($M = 416.8$ ms, $SD = 20.2$) in all the metronome conditions, $F(1,23) = 10.94$, $p = .003$, $\eta_p^2 = .32$. Lastly, the solo participants ($M = 37.5$ ms, $SD = 19.5$) produced much less variable asynchrony than did the joint participants ($M = 76.1$ ms, $SD = 19.5$) in all the metronome conditions, $F(1,23) = 24.5$, $p < .0005$, $\eta_p^2 = .52$.

DFA revealed the expected effect of metronome condition on the fractal scaling of the ITI series, for both the left and right keyboards, wherein the baseline condition produced fractal, pink noise Hurst exponents ($M = 0.81$, $SD = 0.23$), and the full ($M = 0.20$, $SD = 0.16$), left ($M = 0.22$, $SD = 0.20$), and right ($M = 0.37$, $SD = 0.23$) metronome conditions produced Hurst exponents in the anti-persistent, blue noise range. There was no difference in the average scaling of ITI between the solo and joint groups. There was, however, a considerable difference in the strength of CM between the groups, with a much tighter fit between the Hurst exponents from the left and right keyboards, across all the metronome conditions, for the solo participants than for the joint participants (see Fig. 2). The strength of CM can be captured, on a case-by-case basis, by the absolute residual variation of the data from the regression line fitting the CM plot. There was no difference in these "CM scores" between the metronome conditions, but there were overall smaller scores for the solo than for the joint group, $F(1,23) = 16.38$, $p = .001$, $\eta_p^2 = .42$.

WDCC also revealed characteristic differences in short-term cross-correlations between the solo and joint participants (see Fig. 2). The modest peak correlation for the solo participants was consistent with the past CM research ($r \approx 0.3$), and was relatively equal across all metronome conditions. In contrast, the peak correlations for the joint participants were relatively equal in the baseline, left, and right metronome conditions, but the time lag location of the peaks differed. There was effectively no peak correlation in the full metronome condition, and this cross-correlation function was indistinguishable from that of

²Including these joint participants in the analyses, with scores in the problematic conditions provided by mean imputation, did not substantially alter the pattern of results.

the randomized surrogates. DCCA showed a similar pattern of effects (see Fig. 2). The asymptotic level of the DCCA- ρ functions (i.e., mean DCCA- ρ for windows of 64 to 128 observations) for the solo participants was relatively high (0.68 – 0.97) for all of the metronome conditions. In contrast, there were much larger differences between metronome conditions for the joint participants, with the highest asymptotic level in the baseline condition (0.78), substantially lower levels in the left (0.44) and right (0.47) conditions, and effectively no correlation in the full (0.03) metronome condition.

Examining the relationships between the time series analyses revealed that the strength of CM was related both to the stability of the coordination (asynchrony SD) and the strength of short-term correlation between the two ITI series (WDCC peak correlation). There was very little variability in the CM scores from the solo participants, as their CM was consistently very strong across all the metronome conditions. Consequentially, there were no relationships between CM and the asynchrony SD or the WDCC peak correlation for the solo group. These relationships were considerably stronger in the joint group, where there was substantially more variability in the CM scores (see Fig. 5). Specifically, stronger CM was associated with more stable coordination (lower asynchrony SD) and stronger short-term correlation (higher WDCC peaks). A hierarchical regression model confirmed that the asynchrony SD ($\beta = 0.46, p = .03$) and the WDCC peak ($\beta = -0.33, p = .03$) accounted for a significant amount of variance in the CM scores, and together they accounted for a significant amount of variance above and beyond that accounted for by the participant group alone ($R^2 = .28, p = .004$)³. The asymptotic value of DCCA- ρ was not related to the CM scores to any meaningful extent in either groups, but was moderately predicted by the WDCC peak both the solo ($r = 0.44$) and joint ($r = 0.47$) groups.

4. Discussion

The intent of the current study was to establish the presence of the CM effect in a syncopated task behavior and to gain insight into the coordinative processes underlying CM. The experiment required participants to produce syncopated finger tapping either bimanually or interpersonally. The series of inter-tap intervals were submitted to several time series techniques to assess the fractal scaling in the task performance (DFA) and the short-term correlation (WDCC) and multi-timescale correlation (DCCA).

Consistent with the past research on fractal scaling in finger tapping, DFA suggested a fractal, pink noise scaling in the ITI series when the participants' tapping was not constrained by a metronome stimulus (i.e., baseline condition), but an anti-persistent, blue noise scaling when the participants were constrained by the metronomes. More importantly, the fractal scaling values in the two ITI series were closely matched to one another, even though the participants tapped in syncopation. This finding is an important addition to the existing CM literature, as past research has consistently shown that differences in the mode of coordination (e.g., synchronization vs. syncopation) have consequences for the dynamical structure of the task behavior [32,33], including its fractal scaling [20]. Thus, finding

³This regression model was run only on the data from the baseline condition to avoid the dependencies between observations due to the within-subjects design. The baseline condition was chosen as it provided the most variability in the CM scores.

relatively strong CM in the current syncopated task supports the conclusion that CM is not specific to situations requiring anticipatory inphase synchronization with external events [27], but is a product of coordinated behaviors more generally [25].

More importantly, the results supported the conclusion that a “local” coordinative process underlies CM. Consistent with past research, the overall strength of short-term cross-correlation was relatively small, and likely beneath the threshold for statistical significance [e.g., 23]. Nonetheless, the differences in the strength of CM across the experimental conditions were mirrored in the strength of the short-term and the multi-timescale correlations between the two ITI series. Moreover, the patterning of the relationships between the different time series analyses suggested that the degree of local correlation (WDCC peak) predicts both the strength of CM and the overall strength of the multi-timescale correlations between the two ITI series (DCCA asymptote). Consistent with the recent research suggesting it is the relative phase dynamics that best capture “local” coordination [28], the results also showed that the stability of the asynchrony between the two tapping behaviors also predicted the strength of the CM. Interestingly, both the strength of the short-term correlation between the two ITI series (WDCC peak) and the stability of the local coordination (asynchrony SD) seemed to account for a significant portion of *unique* variance in the CM scores. This finding suggests that the coordinative process underlying CM involves control of both the asynchrony and inter-event interval dynamics.

Lastly, as expected, the coordination (as assessed by WDCC peaks) was not influenced by the metronome condition in the bimanual (solo) case, but was in the interpersonal (joint) case. These results are intuitive and consistent with past research on bimanual and interpersonal rhythmic coordination [39]. The manipulation of the metronome task constraints does not greatly change in the coupling between the two effectors in the bimanual case, when they are coupled via a common nervous system, but does in the interpersonal case, when they are coupled via visual information. The current findings therefore raise an important question about what constitutes “complexity matching”. Several mechanistic models for timing behavior [e.g., 40], including those adapted for fractal scaling in synchronized and syncopated finger tapping [38,41] and for CM [22], assume the existence of a neurocognitive “timekeeper” process; an internal clock which generates behavioral intervals. Accordingly, the correlated fractal structures observed during bimanual coordination in the current experiment might not reflect CM *per se*, as the variability in both effectors is ultimately prescribed by the same timekeeper process. Nevertheless, these current results advance the existing literature on CM and also suggest a number of avenues for further research. Specifically, an important next step would be to integrate the existing mechanistic models of fractal scaling in syncopated tapping behavior [38] with those meant to capture CM [22] to address the results of the current experiment. At the same time, it is important to consider the “emergent” perspective [e.g., 23,27,28], and attempt to develop formal models that demonstrate how CM might spontaneously emerge from continuous coupling between interacting systems. Finally, it is very important to attend to the different task variables (i.e., ITI vs. asynchrony) and to carefully specify the system architecture [e.g., 21]. To this end, it would be advantageous to adopt a “behavioral dynamics” perspective

[42] to consider how to understand the CM phenomenon both as a product of two interacting (sub)systems and as a stable dynamic of their operation as a large, unified system.

5. Conclusion

The current experiment demonstrated the existence of CM in non-synchronous task performances and provided evidence that, at least for simple timing behaviors, CM is driven by “local” coordinative processes. Again, these results support the conclusion that CM is not exclusive to the anticipatory processes involved in the synchronization tasks of past research [e.g., 27] but instead concerns the exchange of information and coordination more generally [13]. Thus, these findings are a step toward better understanding the interaction of complex systems across spatial and temporal scales, including the multiscale coordination that exists between different brain structures [5] and between brain, body, and world [43].

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Highlights

- Investigated the complex dynamics of interpersonal syncopated coordination.
- The fractal scaling of the tap intervals were correlated (complexity matched).
- Complexity matching was related to the strength/stability of local coordination.

Figure 1.

(A) Example pink noise (top), white noise (middle), and blue noise (bottom) synthetic time series and (B) the associated scaling relations and Hurst exponents.

Figure 2.

The complexity matching correlations (top row), windowed detrended cross-correlation functions (middle row), and detrended cross-correlation functions (bottom row) for both the solo (left column) and joint (right column) participant groups.

Figure 3. The complexity matching (CM) scores as a function of the standard deviation of the asynchrony series (left panel) and the windowed detrended cross-correlation peak (right panel).