Recurrence Quantification as an Analysis of Temporal Coordination with Complex Signals

Charles A. Coey, Auriel Washburn and Michael J. Richardson

Abstract Ample past research demonstrates that human rhythmic behavior and rhythmic coordination reveal complex dynamics. More recently, researchers have begun to examine the dynamics of coordination with complex, fractal signals. Here, we present preliminary research investigating how recurrence quantification techniques might be applied to study temporal coordination with complex signals. Participants attempted to synchronize their rhythmic finger tapping behavior with metronomes with varying fractal scaling properties. The results demonstrated that coordination, as assessed by recurrence analyses, differed with the fractal scaling of the metronome stimulus. Overall, these results suggest that recurrence analyses may aid in understanding temporal coordination between complex systems.

1 Introduction

Human behavior is structured in both obvious and non-obvious ways. It is readily apparent when someone runs to catch a train before it leaves the station that their behavior is coordinated (i.e., non-random with respect) to the environment. But, there are more subtle layers of structure in behavior, such as the complex patterns of variation in the intervals between the runner's strides. Despite the imperceptible nature of this fine-grained structure, research shows it is an essential characteristic of human behavior and that it too might be coordinated with the environment and the behaviors of other actors.

Repeated measurements of human behavior, from simple motor performances (e.g., rhythmic finger tapping), to basic perceptual processes (e.g., visual search), to cognitive operations (e.g., choice reaction times), to attitudes and emotions (e.g., self-esteem ratings), all tend to show fractal, power-law structure. That is, the measurement series bears a dependency wherein the size of a fluctuation (S) in behavior scales as a constant power of how often fluctuations of that size occur (*f*), $S(f) = 1/f^{\alpha}$. Typically, in natural and healthy behavior, the scaling exponent (α) falls near 1,

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indicating an inverse proportionality between the size and frequency of fluctuations which is scale free, much like geometric fractal objects. Changing the frequency by a constant amount results in a constant change in power regardless of the exact frequencies examined [1]. Unlike a truly random, 'white noise' signal ($\alpha = 0$), such 'pink noise' scaling involves a dynamic pattern of variation in which successive observations are not independent of one another. Instead, pink noise is said to be 'persistent' and entails long-range correlation such that observations are positively correlated over considerable lengths of time. Interestingly, many research projects have shown that experimental manipulations, and other psychologically-relevant factors, can reliably alter this scaling and shift α toward random variation or even further toward an 'anti-persistent', 'blue noise' pattern of fluctuation ($\alpha = -1$).[1]

More recently, several research projects have found that the scaling properties of two interacting systems tend to match one another (e.g., [2–6]). Remarkably, this 'complexity matching' effect seems to only be partially accounted for by tight coordination at the immediate timescale. That is, although the scaling exponents of the two systems are highly correlated, the two series are not strongly synchronized with each other. These findings naturally have led to questions as to the form of the temporal coordination underlying complexity matching [3, 7, 8]. How exactly can two systems, interacting through an exchange of energy or information, match one another's 'global', fractal structure without strong, 'local' synchronization?

Further investigation of complexity matching critically depends on techniques to assess the nature and degree of coordination between two behavioral series. Most recently, researchers have begun to explore techniques capable of capturing both short- and long-range dependencies, as well as the scaling relations defining the co-variation of two series [5, 6]. Here, we present some preliminary research investigating how cross-recurrence quantification analysis (CRQA) may aid in understanding temporal coordination between two complex systems. CRQA is a highly-articulated technique that provides analysis of how two signals co-evolve through the same abstract phase space over the entire span of measurement. CRQA also provides an abundance of (albeit potentially redundant) information about the coordination of the two series in its various outcome measures. For these reasons, we thought CRQA might serve as an advantageous compliment to the other techniques employed as analyses of the complexity matching phenomenon. It is important to note at the outset, however, that these recurrence analyses *do not* assess the complexity (i.e., power-law scaling) of behavior (see [9] for an analogous argument). Rather, these analyses quantify aspects of the *variability* of behavior in phase space. Although the complexity and variability of behavioral signals are likely related in empirical data, the outcomes of the recurrence analyses may not be taken to speak to complexity directly.

[1] There are ample resources available for those readers interested in the details of fractal analyses [1, 10, 11] and the current theoretical debates [12–14].

2 The Experiment

The current study was conducted as a pilot experiment in a larger project designed to investigate complexity matching in finger tapping behavior. We first sought to determine if complexity matching was present when participants tapped to recordings of other participants' tapping behavior, as the extant research either had individual participants coordinate with mathematically-generated stimuli [4] or had two participants interact in real time under bi-directional coupling conditions [3]. Thus, we recorded tapping behavior from an initial sample of participants under different experimental conditions, and then used these series as metronome stimuli for a second sample of participants.

More specifically, in our initial sample, we had participants undergo two trials of tapping behavior. In the first trial, participants performed a continuation task in which they synchronized to a 500 Hz (2 bps) metronome for a short period (10 s), and then attempted to maintain that tapping interval after the metronome was discontinued. In the second trial, participants performed a synchronization task in which they simply synchronized their taps to the metronome for the entire trial. The inter-tap interval (ITI) series from both trials were submitted to two fractal analyses. Consistent with the past research on fractal scaling in tapping behavior (see [15]), both fractal analyses showed the ITI series tended toward persistent, 'pink' scaling during continuation tapping ($\alpha \approx 0.75$) and toward anti-persistent, 'blue' scaling in synchronization tapping ($\alpha \approx -0.60$).

From this initial sample, we selected a set of 11 series to serve as metronome stimuli for our second sample of participants. It is important to note that only the variation in the onset of taps was retained in the inter-onset interval (IOI) of the resulting metronomes. All variation in the length of the taps was eliminated by equalizing the duration of each tone in the resulting metronome series. Five series from the synchronization condition formed a set of 'blue' metronomes ranging from strong ($\alpha = -0.80$) to mild ($\alpha = -0.41$) anti-persistent structure. Six series from the continuation condition served as 'pink' metronomes ranging from strong ($\alpha = 1.06$) to mild ($\alpha = 0.41$) persistent structure. Participants in the second sample also completed continuation and synchronization trials. During synchronization, however, they heard 1 of the 11 fractal metronomes. We collected 33 participants, with 3 in each of these 11 possible metronome conditions.

The design of this experiment allowed us to investigate the extent to which the recurrence analysis can capture the dynamics underlying temporal coordination with complex stimuli. Specifically, we examined if auto-recurrence quantification analysis (RQA) would suggest different dynamics in the participants ITI series as a function of the metronome type (i.e., pink vs blue), whether these differences in recurrence actually did (albeit indirectly) reflect the complexity of the ITI series (as assessed by fractal analyses), and what cross-recurrence analysis between the ITI and IOI series might suggest as to the nature of the coordination between the participant and metronome systems.

3 The Results

We have tried to provide sufficient detail here about the specifics of the many analyses we conducted, but there are a number of technical points that have been omitted due to the limited available space. Where possible, we have provided references for the reader interested in learning more about these analyses.

3.1 Fractal Scaling and Complexity Matching

As a first step, we thought it necessary to demonstrate the complexity matching phenomenon was present in our series. To this end, we used two standard fractal analyses; power spectral density (PSD) and detrended fluctuation analysis (DFA). The outcomes of these techniques are generally equivalent, but as they do operate in different ways [16] we used both to corroborate our results.[2] The outcome of PSD is the scaling exponent (α) as described above, but DFA instead outputs Hurst exponents (H). To directly compare these two analyses we rescaled the Hurst exponents (where $2(H - 0.5) = \alpha$; see [17]). In keeping with standard practice, every ITI series was integrated prior to submission to DFA (see [1, 6]).

It is also important to note that, at this stage, the participants' ITI series were initially treated separately from the metronome IOI series. That is, the ITI series, from both the continuation and synchronization conditions, first underwent several pre-processing steps (e.g., outlier removal, linear detrending). The final processed series were submitted to fractal analysis and their scaling exponents compared across tapping conditions and to the scaling of the metronome IOI series.

In general, PSD and DFA showed the same pattern of results. Just as in the first phase of the study, ITI series during continuation tapping revealed persistent, pink noise scaling and showed a marked decrease in α during synchronization. Here though, there were also significant interactions (PSD: $p = 0.001$, $\eta_{p2} = 0.28$; DFA: $p = 0.013$, $\eta_{p2} = 0.18$) between the blue and pink metronome groups across the tapping conditions (Fig. 1). Whereas the blue metronome group showed a large decrease in α from continuation to synchronization (PSD: $p = 0.001$, $d = 1.10$; DFA: $p = 0.002$, $d = 0.96$), the decrease in α for the pink metronome group was marginally significant at best (PSD: $p = 0.079$, $d = 0.44$; DFA: $p = 0.122$, $d = 0.38$).[3]

[2] These two fractal analyses are frequently used in studies of human behavioral data, but there are also maximum-likelihood techniques that are superior for verifying actual power-law scaling (see [18, 19]).

[3] The primary difference between the two analyses is that, although both indicate the ITI series of participants synchronized with blue metronomes to be near-random on average ($\alpha \approx 0$), PSD estimated α in the remaining conditions to be substantially greater than DFA ($\alpha \approx 0.7$ versus 0.5). This difference, however, likely has little bearing on the further analyses described below.

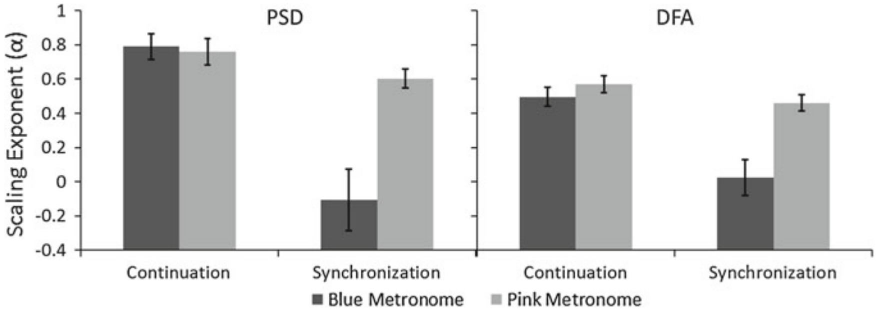

Fig. 1 Scaling exponents as a function of tapping condition and metronome group as estimated by power spectral density (*left*) and detrended fluctuation analysis (*right*)

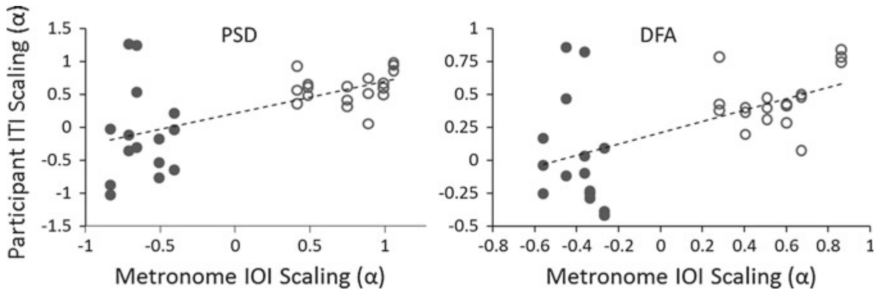

Fig. 2 Scatterplots for the relationship between participant ITI and metronome IOI scaling exponents for both power spectral density (*left*) and detrended fluctuation analysis (*right*) techniques. *Blue* metronomes are indicated by filled-in *circles* and *pink* metronomes by empty *circles*

Consistent with past research on complexity matching, we wanted to examine the correlation between the scaling of the participants' ITI series and the metronomes' IOI series. Simple correlations did reveal a moderate positive relationship for both PSD ($r = 0.58$, $p < 0.0005$) and DFA ($r = 0.57$, $p < 0.0005$). Interestingly, there seemed to be far greater variance in the participants' ITI scaling for the blue metronomes than for the pink metronomes (see Fig. 2). Given this heteroscedasticity, and the non-independence of observations sharing the same metronome stimulus, these correlations may not be the ideal statistical test for these data. Nonetheless, these results do suggest a considerable degree of complexity matching was present in our tapping task.

In order to examine the temporal coordination dynamics related to this complexity matching effect, we turned to the recurrence quantification techniques. Prior to submitting participant ITI and metronome IOI series to cross-recurrence analysis, however, we chose to examine the ITI series with auto-recurrence analysis in hope of relating recurrence outcomes (concerning variation within phase space) to the complexity of the series (as revealed by the fractal analyses).

3.2 Recurrence Quantification Analysis and Fractal Scaling

Recently many researchers have employed both recurrence quantification and fractal analyses [20–24]. Some have noted apparent associations between the results of the two methods [25]. Others have determined that the optimal models for classifying certain pathological conditions combine the outcomes of both methods [26–29]. Nonetheless, there has been relatively little exploration of the relationship between these two analyses in empirical data. With regard to the current study, validating that differences in recurrence measures actually are related to the complexity of the series is an important step, as many artifacts can influence recurrence analyses (see [30, 31]).

To begin, we performed auto-recurrence quantification analysis (RQA) on the very same participant ITI and metronome IOI series that we submitted to the two fractal analyses. As with the fractal techniques, there are several technical details that must be considered in preparing RQA (see [24, 32–34]). Most importantly, some preliminary analyses must be conducted in order to determine a few, critical parameter settings (i.e., delay, embedding dimension, radius). We followed the standard protocol in choosing these parameters (average mutual information, false nearest neighbors). It is also important to note that we used the integrated series (as submitted to DFA) in both the preliminary calculations and in the RQA. The preliminary steps suggested a delay of 25, an embedding dimension of 3, and a radius of 10 % the mean distance between points. We used these parameters and examined four of the possible outcomes from RQA: the total percent recurrence (REC), mean line length (MLL), percent determinism (DET), and entropy (ENT). We chose these four outcomes as they are relatively standard in analyses of human behavior, and ultimately to capture different (albeit highly interrelated) aspects of coordination between participant and metronome in the cross-recurrence analysis. In particular, REC was intended to capture the overall ‘amount’ of coordination, MLL and DET to capture the ‘stability’ of periods of coordination, and ENT to capture the ‘homogeneity’ in the periods of coordination.

Overall, all of the RQA outcomes revealed the same general pattern as found in the fractal analyses. That is, there was a very large decrease in all the outcomes from continuation to synchronization for those in the blue metronome group, and little to no decrease for those in the pink metronome group. One notable difference between the RQA outcomes is that REC and MLL showed sizable differences between the two metronome groups in the continuation conditions, whereas these group differences were not evident in DET and ENT (Fig. 3). As this effect was absent in the two fractal analyses, this finding suggested that DET and ENT might be more strongly related to the fractal scaling of the tapping behavior.

The convergence of the RQA results with those of the fractal analyses was also evident on a case-by-case basis. To this point, we calculated difference scores across the continuation and synchronization conditions, for each outcome variable, for every participant. We then computed correlations between the two difference variables for the fractal analyses (PSD-shift; DFA-shift) with the four difference variables

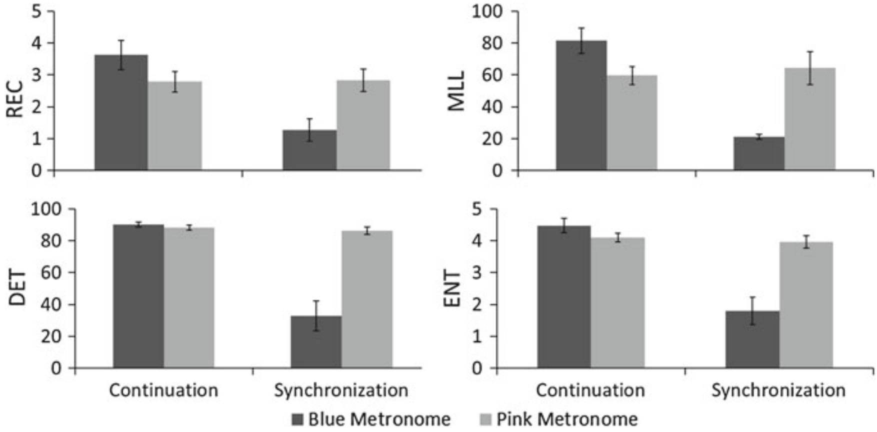

Fig. 3 Percent recurrence (*top left*), mean line length (*top right*), percent determinism (*bottom left*), and entropy (*bottom right*) as a function of tapping condition and metronome group

for the RQA outcomes (REC-shift; MLL-shift; DET-shift; ENT-shift). These tests all revealed a strong relationship ($0.72 \leq$ all r's ≤ 0.90, all p's < 0.0001) between the shift in fractal scaling and in the recurrence outcomes across the two tapping conditions. As before, the DET and ENT ($r \approx 0.85$) outcomes seemed to be more strongly related to the fractal scaling than REC and MLL ($r \approx 0.75$).

To more fully understand the relation between the complexity (fractal scaling) of the tapping behavior and the dynamic structure revealed by recurrence analysis, we also examined the ITI dynamics as embedded in phase space. To illustrate, we chose two example series from each metronome group (see Fig. 4). The difference between the series was not readily apparent 'by eye' in the raw ITI series. In fact, the series had similar overall variability (Blue: $SD = 9.48$; Pink: $SD = 10.74$), but the structure of that variability over time was very different between the two series (Blue: $\alpha = -0.03$; Pink: $\alpha = 0.75$). The long-term, coherent trends entailed in the persistent structure of the pink series, when cumulatively summed, led to much greater variability than the near-random blue series. This structure also translated into the trajectory of the series through phase space. Not only did the pink series show much greater variability, but also a more coherent (less 'noisy') trajectory through phase space. Thus, the differences in complexity revealed by the fractal analyses did reliably translate into differences in the dynamics assessed by RQA. The pink series accordingly yielded larger recurrence outcomes (REC = 1.88, MLL = 58.90, DET = 89.19, ENT = 4.16) than did the blue series (REC = 0.71, MLL = 6.50, DET = 26.69, ENT = 1.62).

Collectively, these analyses suggested that the recurrence outcomes did capture the different dynamics in the tapping behavior, particularly DET and ENT. Again, this is not to imply that the recurrence technique assesses the complexity of these series directly, but only that there was a reliable mapping between the two analysis techniques for the tapping behavior under study. Thus, we proceeded to the

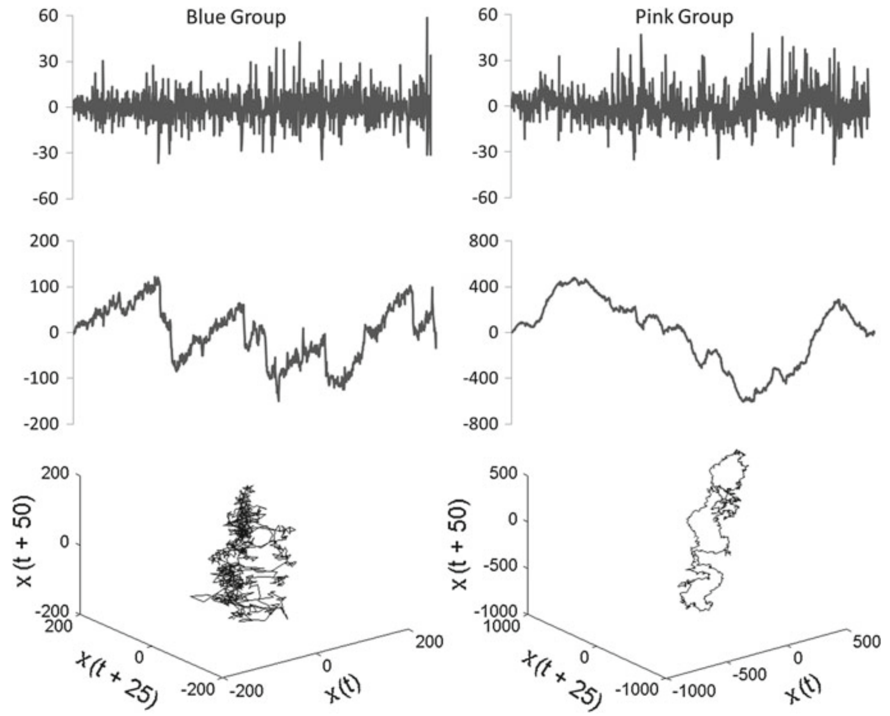

Fig. 4 Raw ITI series (*top row*), integrated series (*middle row*), and phase space trajectories (*bottom row*) for an example series from the *blue* and *pink* group. Note, although the scale is the same for the two raw series, it differs dramatically for the integrated series and the phase space

cross- recurrence analysis to examine the shared dynamical structure (i.e., coordination) between the participants' ITI series and the metronome IOI series.

3.3 Cross-Recurrence and Temporal Coordination

It was, in principle, possible to simply submit the ITI and IOI series as they were to cross-recurrence quantification analysis (CRQA) by embedding both series in the same phase space. As noted above, however, this would have ignored the fact that the participant and metronome time series were initially treated separately. That is, the participant ITI series were pre-processed by a set of criteria that did not need to be applied to the metronome IOI series. The result was that there was no guarantee that, for a given trial, the 100th ITI in the participant series actually corresponded in real time to the 100th IOI in the metronome series. So, we utilized a different pre-processing procedure for the series submitted to CRQA. We paired each tap to its nearest metronome beat and eliminated any extraneous observations (i.e., taps for which the nearest metronome beat was nearer to another tap). The ITI and IOI series were calculated from these tap-beat paired series, respectively. Finally, the ITI series went through all the same pre-processing steps as before, and in cases where a particular ITI was to be eliminated (e.g., met outlier criteria) the paired IOI was also eliminated.

We conducted a number of preliminary analyses to ensure that this alternate method of pre-processing the data did not substantially alter the previous findings. The scaling exponents defining these new series were strongly correlated with the original scaling exponents (PSD: $r = 0.98$, $p < 0.0001$; DFA: $r = 0.97$, $p < 0.0001$) and there were small differences in exact values on average (PSD: 0.01; DFA: 0.002). As before, we also found strong correlations between the fractal scaling of these new ITI series and the accompanying IOI series for both PSD ($r = 0.69$, $p < 0.0001$) and DFA ($r = 0.67$, $p < 0.0001$). These findings showed that the fractal scaling and complexity matching revealed in the original analyses did not change for this new processing method, and so we proceeded to CRQA.[4] From our initial findings, we were most interested in DET and ENT. We did also examine REC and MLL, however, and the results were generally consistent with those of DET and ENT.

There were a number of possible analyses to assess the relationship between these CRQA outcomes and the degree of complexity matching. As seen above, one common method of assessing complexity matching is to simply correlate the scaling exponents of two time series. We knew from the preliminary tests that the scaling exponents from the participant and metronome were strongly correlated, but we also tested whether the two metronome groups differed in their degree of complexity matching. The blue metronome group showed weaker correlations (PSD: $r = 0.31$, $p = 0.27$; DFA: $r = -0.10$, $p = 0.72$) than did the pink metronome group (PSD: $r = 0.49$, $p = 0.04$; DFA, $r = 0.52$, $p = 0.03$). Moreover, the raw difference in the participant and metronome scaling exponents was greater for the blue metronome (PSD: $M = 0.47$, $SD = 0.58$; DFA: $M = 0.39$, $SD = 0.38$) than the pink metronome (PSD: $M = -0.18$, $SD = 0.24$; DFA: $M = -0.09$, $SD = 0.21$). Interestingly, these group differences are also apparent in the CRQA outcomes. The blue metronome group showed substantially lower DET ($M = 9.74$, $SD = 8.11$) and ENT ($M = 0.77$, $SD = 0.11$) than did the pink metronome group (DET: $M = 86.42$, $SD = 11.03$; ENT: $M = 4.37$, $SD = 1.16$). As above, these results suggested a reliable mapping between the CRQA outcomes and the complexity matching revealed by the two fractal analyses.

Although the relation between CRQA and the fractal methods held at the scale of group differences, we also wanted to consider a finer-grained scale. To do so, we calculated the absolute value of the difference between the scaling exponents for the participants and the metronome as a rudimentary 'complexity match' score. These scores showed generally significant correlations with the CRQA outcomes both for PSD (DET: $r = -0.37$, $p = 0.04$; ENT: $r = -0.32$, $p = 0.07$) and for DFA (DET: $r = -0.46$, $p = 0.01$; ENT: $r = -0.43$, $p = 0.01$), which suggested that greater differences between the scaling exponents of participant and metronome were associated with lower DET and ENT.

[4] Preliminary examination of the new ITI series suggested that the same parameter settings for delay (25), embedding dimension (3), and radius (10 % of the mean distance). Every series was also Z-scored prior to CRQA to ensure both series were on a standard scale.

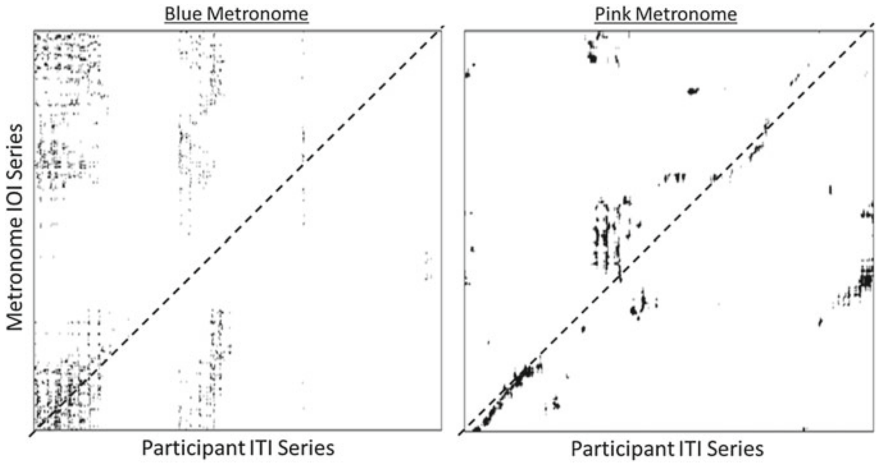

Fig. 5 Two example CR plots from the *blue* (*left*) and *pink* (*right*) metronome conditions. These plots reflect cases with near equal percent recurrence, but the plot for the *pink* metronome case reveals greater structure in the coordination between the participant and metronome

Collectively, these analyses suggested that the shared structure assessed by CRQA outcomes and the cross-recurrence (CR) plots might provide insight as to the nature of the coordination defining complexity matching. The two plots above (Fig. 5) represent two trials, one from each of the different metronome groups. These two cases are interesting because they are comparable in terms of their overall recurrence (Blue: REC = 1.32; Pink: REC = 1.27), but very different in the measures of the *structure* of that recurrence (Blue: DET = 28.13, ENT = 1.53; Pink: DET = 79.74, ENT = 3.30). This difference in the behavioral structure shared between the participant and the metronome is apparent in the CR plots.

Interestingly, the two instances reflected in these CR plots also are comparable in terms of their 'complexity matching' (i.e., simple difference in scaling exponents). That is, in both the blue and pink metronome case, the difference between the scaling of the participant ITI series and metronome IOI series was relatively small (PSD, α-difference $\approx$ 0.21; DFA, α-difference $\approx$ 0.14). This finding suggests that although coordination with a blue signal might yield 'bluer' behavior, and a pink signal to 'pinker' behavior, the actual *coordination* between signal and behavior might differ considerably. Specifically, coordination (i.e., instances of recurrence) with a blue metronome seemed to be less 'stable' (lower MLL and DET) and to be more homogeneous (lower ENT). Hence, these findings suggest that beyond the discussion of whether the complexity matching phenomenon is driven by local coordination there are questions as to the dynamical structure of that coordination.

As before, a fuller appreciation of these effects can be gained by examination of the dynamics as embedded in phase space. The participant ITI series and the metronome IOI series for the two example cases presented in the above CR plots are shown above (Fig. 6). Again, the long-term trends entailed in the pink noise pattern

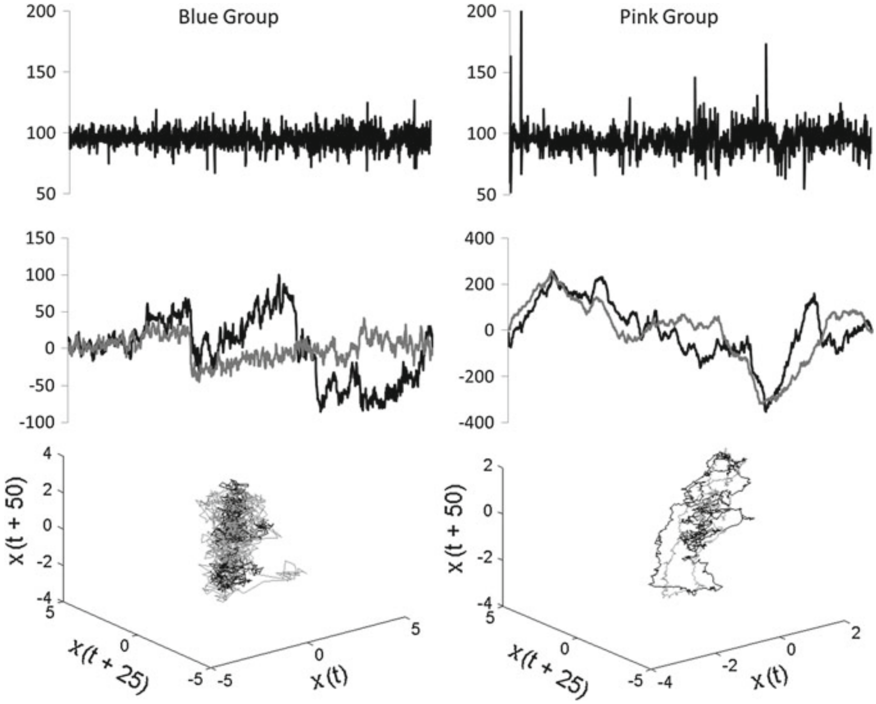

Fig. 6 The raw ITI series (*outliers included*) for the series portrayed in the example CR plots (*top row*), the pre-processed, integrated participant ITI (*black*) and metronome IOI (*grey*) series (*middle row*), and the Z-scored ITI and IOI series embedded in phase space (*bottom row*)

of variation yielded a more coherent trajectory through the phase space. With respect to coordination, these more coherent trajectories yielded to greater structure in cross-recurrence for the pink metronome group. That is, the ITI and IOI series tended to 'move together' through the phase space for longer periods, which ultimately led to longer lines of recurrence (MLL), more recurrent points on lines (DET), and a more heterogeneous distribution of line lengths (ENT).

4 Conclusion

The results of the current experiment suggest that the structure of the coordination between two complex systems might itself be characteristically different under different conditions. Although these findings do propose an interesting new idea, it is important to remember that these results are preliminary and that further testing and validation are imperative. We thus acknowledge some of the limitations of the current work below and suggest some directions for future research.

First and foremost, there is some question as to how precisely the outcomes of CRQA map onto the dynamical structure revealed by fractal analysis. Again, the recurrence techniques do not directly quantify the same complexity of a signal (i.e., power-law scaling) as fractal methods. As stated before, recurrence analyses are more readily understood as capturing the variability in phase space associated with the fundamental dynamics. Our analyses demonstrate that this variability does indeed reflect the complexity in our measured behavior, although generally complexity cannot be inferred from variability alone (see [9]). One must be mindful of this distinction when interpreting what the outcomes of recurrence techniques mean with respect to the complexity of a behavior.

Secondly, though the results of this introductory study are encouraging, further research is required to validate the use of CRQA to assess the coordination driving complexity matching. For instance, even within the context of finger tapping tasks, a more controlled and thorough study should be conducted to replicate these initial results, and a series of careful surrogate analyses should be run to substantiate the data from the experimental conditions. Moreover, these analyses should be applied to instances of complexity matching in different behavioral tasks to assess whether this use of CRQA can be reliably generalized.

Lastly, CRQA should be carefully compared to other possible analyses of the complexity matching phenomenon. For instance, joint recurrence analysis [24, 32] has several potential advantages in comparison to CRQA, and should be evaluated as an alternative. Similarly, recent research has explored detrended cross-correlation analysis in study of complexity matching [6], and these two techniques should be compared to ensure CRQA provides unique and helpful information.

Despite these limitations, we contend that recurrence techniques remain a viable option for researching the dynamics of temporal coordination underlying the complexity matching effect. First, recurrence analysis is a sensitive analysis with several different outcomes, each of which can provide information as to different aspects of coordination. Second, recurrence analysis is a flexible technique and it readily treats time series of different lengths, even those considerably shorter than those acceptable for fractal analysis. Third, there are several potential avenues within recurrence methods yet to be explored. Information concerning fractal scaling and complexity matching might be available in other quantifiable aspects of the recurrence plots, or in examination of the phase space itself. We do hope that future research will continue to survey this rich technique.

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