Capturing Intra-and Inter-Brain Dynamics with Recurrence Quantification Analysis

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Abstract

We investigated the application of non-linear analysis techniques for capturing stability of neural oscillatory activity within and across brains. Recurrence Quantification Analysis (RQA), a technique that has been applied to detect stability and flexibility of motor performance, was extended to observe and quantify changes in patterns of non-linear neural activity. Participants synchronized their finger-tapping with a confederate partner who tapped at two different rhythms while neural activity was recorded from both partners using electroencephalography (EEG). Auto-recurrence (intra-brain) and cross-recurrence (inter-brain) of EEG activity were able to distinguish differences across tapping rhythms in stability of neural oscillatory activity. We also demonstrated the efficacy of RQA to capture how both period and phase changes in neural dynamics evolve over time.

Keywords: joint action; neural dynamics; electroencephalography; recurrence quantification analysis

Introduction

Researchers have become increasingly interested in capturing complex oscillatory signals common to human behaviors, and which often show non-linearities that evolve over time. This can be seen in individual motor behaviors like postural sway and finger-tapping (Schmit, Regis & Riley, 2005; Schmit, Riley, Dalvi, Sahay, Shear, Shockley, & Pun, 2006; Scheurich, Zamm, & Palmer, 2018), and in joint motor behaviors like conversational speech and music performance (Dale & Spivey, 2006; Demos, Chaffin, & Kant, 2014). One way in which these complex signals can be represented is through Recurrence Plots (RPs), which display the points in time at which an individual returns to previous behavioral states (i.e., self-similarity), or the points in time at which two individuals visit the same behavioral state (i.e., similarity between individuals; Eckmann, Kamphorst, & Ruelle, 1987). RPs are useful tools for observing transitions between states in a system and can be further quantified using Recurrence Quantification Analysis (RQA). These quantifications give insights into the behavioral dynamics of one or more systems over time through measures such as recurrence rate: how often a system returns to previous states or two systems visit the same state; and mean diagonal line length: the time over which one or more systems are stable (Marwan, Romano, Thiel, & Kurths, 2007; Marwan & Webber, 2015). One advantage of RQA is that it can be applied both within individuals during solo tasks (i.e., auto-recurrence) and between individuals during joint tasks (i.e., cross-recurrence; Marwan, Romano, Thiel, & Kurths, 2007; Marwan & Webber, 2015). Thus, these tools have been useful for characterizing dynamics of motor behaviors over time both within and across individuals during a variety of solo and joint behaviors (e.g., Schmit, Regis, & Riley, 2005; Schmit, Riley, Dalvi, Sahay, Shear, Shockley, & Pun, 2006; Romero, Fitzpatrick, Schmidt, & Richardson, 2016; Demos & Chaffin, 2017; Scheurich, Zamm, & Palmer, 2018).

Complex oscillatory signals are not unique to behavior, but are also observed in human brain activity. This can be seen, for example, in the oscillatory neural activity that underlies rhythmic auditory-motor behaviors (e.g., Nozaradan, Zerouali, Peretz, & Mouraux, 2013; Nozaradan, 2014; Morillon & Baillet, 2017; Zamm, Debener, Bauer, Bleichner, Demos, & Palmer, 2018). However, common methods for examining oscillatory neural activity supporting these kinds of behaviors often do not measure dynamics over time, but instead assume stationarity of the signal. RQA has been applied to oscillatory neural activity, as measured through electroencephalography (EEG), in a limited scope. This has been primarily in clinical settings, in which outcomes such as recurrence rate and mean diagonal line length, which provide information about the stability of neural activity, have been used successfully to classify periods of epileptics' EEG activity as normal, pre-ictal, and ictal activity (Acharya, Sree, Chattopadhyay, Yu, & Ang, 2011). Furthermore, RQA outcomes have been applied for monitoring consciousness of patients undergoing anesthesia (Becker, Schneider, Eder, Ranft, Kochs, Zieglgänsberger, & Dodt, 2010). In addition to its clinical applications, researchers have proposed RQA as a method for studying event-related potentials (ERPs). Although traditional methods of studying ERPs require averaging over many trials to obtain a clear waveform, RQA allows for the use of single trials to identify changes in ERP components, as demonstrated in an auditory perception experiment using the auditory oddball paradigm (Marwan & Meinke, 2004). No research, to our knowledge, has yet applied RQA to capture oscillatory neural activity that distinguishes different rhythmic auditory-motor behaviors.

The current study applies RQA to capture the dynamics of oscillatory neural activity during a 2-person rhythmic tapping task. Participants tapped at two different rhythms with a confederate partner while EEG was recorded from each partner. In one rhythm condition, the confederate tapped at twice the frequency of the participant. In the second rhythm condition, the confederate tapped at half the frequency of the participant. The neural activity at the participant's (constant) tapping frequency was compared across rhythm conditions. Only activity at the constant frequency was examined to identify changes in oscillatory neural activity related to changes in tapping ratios between partners as opposed to changes in absolute frequency. Auto- (intra-brain) and cross-recurrence (inter-brain) analyses of EEG activity were expected to reveal greater stability of oscillatory neural activity when the participants' tapping frequency was the dominant frequency (i.e., more auditory feedback at that frequency).

Methods

Participants

Data from eight adult musicians aged 18-30 years old with at least 6 years of private music instruction on an instrument other than percussion were taken from a larger study. Their duet tapping trials met a performance cut-off of at least 75% error-free trials (i.e., no missed taps) for each condition in which partners performed live together. Other conditions included in the larger study in which participants performed with pre-recordings of their partner were not examined in the current paper. A single confederate experimenter (more than 6 years of piano instruction) tapped with each participant to maintain consistent timing properties of live and pre-recorded conditions as well as social presence across participants. All participants and the confederate were right-handed and had normal hearing (< 30 dB HL threshold, 125 – 750 Hz) as determined by an audiometry screening. Participants and the confederate reported no current psychiatric or neurological conditions and were not taking medication affecting the central nervous system at the time of testing.

Equipment and Materials

Participants' hearing was assessed with a Maico MA40 audiometer. Participants tapped on a Roland A500s MIDI keyboard and the confederate tapped on a Yamaha PSR 500m MIDI keyboard. Auditory feedback was delivered in a sine tone timbre generated by a Roland Sound Canvas, amplified to a comfortable listening level using a Behringer Headphone Amplifier, through EEG-compatible earphones (Etymotic ER-1, Etymotic Research Inc.). Participants' auditory feedback was presented at pitch G4 (392.00 Hz), and the confederate's auditory feedback at pitch E5 (659.25 Hz). MIDI data were collected using FTAP software (Finney, 2001). FTAP was modified to integrate Lab Streaming Layer (LSL; Kothe, 2014) similar to Zamm, Palmer, Bauer, Bleichner, Demos, & Debener, 2017. This modification allowed for keystroke, metronome, and time triggers from FTAP on a Dell computer running Linux to be sent over the local area network and received by a second Dell computer running Windows 7, where LSL synchronized the keystroke and EEG data collection from both partners (Zamm et al., 2017).

EEG Data Recording

EEG data were recorded from each partner at a 512 Hz sampling rate via two separate but synchronized 64-channel BioSemi Active-Two systems (BioSemi, Inc.). Electrodes were positioned according to the 10-20 system. Data were recorded using a common mode sense (CMS) active electrode and driven right leg (DRL) passive electrode which formed the reference (http://www.biosemi.com/faq/cms&drl.htm). External electrodes were placed above and below the right eye to detect eyeblinks, on the outer corner of each eye to detect lateral eye movements, and on the mastoids to detect muscle artefacts.

Stimulus Materials and Design

Each stimulus was constructed of an approximately 40-second series of taps generated by the Participant and Confederate. Each pair (Participant and Confederate) completed the joint tapping tasks in a within-subjects design with 2 rhythm conditions: 1-2 (Confederate-Participant) and 4-2 (Confederate-Participant). In the 1-2 condition, the confederate tapped at half the rate (~0.95 Hz) of the Participant (~1.89 Hz). In the 4-2 condition, the Confederate tapped at twice the rate (~3.78 Hz) of the Participant (~1.89 Hz). Thus, the Participants' tapping frequency was constant across conditions. Each pair completed one practice trial and 12 experimental trials in each rhythm condition. Rhythm was blocked within pair, and blocks were counterbalanced across pairs. The dependent variables were auto- (intra-brain) and cross-recurrence (inter-brain) outcomes of Recurrence Rate, describing how much of the RP is occupied by recurrent points (how often a single system returns to previous states in auto-recurrence, or two systems visit similar states in cross-recurrence), and Meanline, describing the average diagonal line length (the mathematical stability of the system(s); see **RQA Application to EEG**).

Procedure

After giving informed consent upon arrival to the lab, participants completed an audiometry screening. Then both the participant and the confederate were outfitted with EEG caps and electrodes. The participant and confederate were taken to the testing room where the confederate was introduced to participants as an experimenter who served as the partner in each pair to maintain consistency of interactions across pairs. The participant and the confederate were seated at two separate keyboards across from one another with a barrier placed between the keyboards such that the partners could only see one another above the shoulder.

The participant and confederate then completed the two tapping tasks together at the two different rhythmic ratios. They were instructed to tap with the index finger of their right hands on a single key of the keyboard while minimizing eyeblinks and eye movements. The participant and confederate were first presented with separate recorded examples of each tapping part in isolation, and then they were presented with a recorded example of how the two parts sounded together. After listening to the examples, the participant and confederate were instructed that they would hear a four-beat metronome cue sounded at the participant's prescribed rate at the beginning of each trial, and they were presented with a recorded example of how their parts sounded together with the metronome cue. The participants were instructed that they should synchronize with the confederate's tapping while maintaining the rate cued by the metronome, and the confederate was instructed to maintain a steady pulse. After completing a practice trial, pairs completed 12 experimental trials. This procedure was repeated for each rhythm condition. After completion of the tasks, participants were debriefed and received a small compensation. The whole experiment lasted approximately three hours.

EEG Preprocessing

EEG data were preprocessed in EEGLAB (Delorme & Makeig, 2004). Data were first prepared for artefact correction with Independent Component Analysis (ICA), using a procedure adapted from Zamm et al. (2017). Data were concatenated across all trials in all experimental tapping tasks, and re-referenced to the common average across electrodes. Electrodes reflecting poor signal quality were identified by visually inspecting electrode distributions of deviations from mean activity for each subject. Electrodes with very large deviations from mean activity were identified as noisy, and electrodes with no deviation from mean activity were identified as flat. These electrodes were removed, and data were subsequently filtered between 1 Hz and 40 Hz using a Hanning windowed sinc FIR filter (high and low pass filter order = 1000). Filtered data were then segmented into 1-second epochs, pruned for non-stereotypical artefacts, and submitted to extended infomax ICA. ICA components representing eyeblinks and lateral eye movements were visually identified and removed from the unfiltered data. After removing bad components, previously rejected electrodes with poor signal quality were spherically interpolated.

RQA Application to EEG

Power Spectral Density (PSD) estimates of ICA-corrected EEG activity were then computed similar to Zamm et al. (2017). PSD gives the amount of power present in the EEG signal at component frequencies. Preprocessed EEG data were high then low pass filtered using a Hanning windowed sinc FIR filter (high pass filter order = 1000, cutoff = 0.1 Hz; low pass filter order = 1000, cutoff = 20 Hz) and segmented into 3 10.56-second epochs (to control for tapping frequency drift). PSD was estimated for each electrode and epoch, and then was log-transformed before averaging across epochs and then trials. The electrode with maximal power on average across conditions, tapping frequencies, and participants was identified as electrode C1 (central and left-lateralized). This electrode is commonly identified as showing maximal activity in auditory-motor behaviors (e.g., Nozaradan, Zerouali, Peretz, & Mouraux, 2013; Nozaradan, 2014). Data from this electrode were used as input to auto- and cross-recurrence analyses.

ICA-corrected data from electrode C1 for participants and the confederate were then prepared for auto- and cross-recurrence analyses. First, the data were filtered at the participants' observed tapping frequencies. The filter frequency cutoffs were tailored per participant and confederate pair and rhythm condition to account for any deviations in expected tapping frequency. The data were high then low pass filtered using a Hanning windowed sinc FIR filter (high and low pass filter orders = 1000) with cutoff frequencies ± 2 standard deviations around the observed participant tapping frequency. Data were then segmented into 3 10.56-second epochs (for computational tractability) and *z*-scored per epoch.

Auto- and cross-recurrence analyses were run using the Cross Recurrence Plot Toolbox (Marwan, Romano, Thiel, & Kurths, 2007). Optimal auto- and cross-recurrence parameters were determined per epoch; final selected parameters were determined by examining the distribution of parameters across epochs. The optimal delay parameter was determined by computing Average Mutual Information (AMI). AMI gives the amount of information a time series shares with itself at different time delays, with the delays at which it shares least information with itself being optimal for RQA. The first delay at which shared information of the C1 time series with itself reached a minima was selected (selected delay = 68 samples, corresponding to 1/4 cycle of the participant tapping frequency). The optimal number of embedding dimensions was determined by computing False Nearest Neighbors (FNN). FNN gives the amount of false neighbors in phase space as a function of the number of embedding dimensions (copies of the time series at the specified delay). The number of embedding dimensions at which number of false nearest neighbors was minimized and adding more dimensions no longer reduced number of false nearest neighbors was selected (selected embedding dimensions = 4). Finally, the maximum phase space diameter, corresponding to the standard deviation of the time series, was computed using the selected delay and embedding dimensions. The optimal threshold for which points in phase space are considered recurrent was determined by computing 10% of this value (selected threshold = 0.49; Schinkel, Dimigen, & Marwan, 2008). For auto-recurrence, the Thieler window, minimum diagonal line length, and minimum vertical line length were set to 34 samples (corresponding to 1/8 cycle of the participant tapping frequency). For cross-recurrence, the Thieler window was set to 0 samples and the minimum diagonal and vertical line lengths were set to 34 samples.

Results

Auto-recurrence Outcomes

We first investigated how auto-recurrence (intra-brain) outcomes changed with Rhythm, and whether these patterns held or changed across Partners within each pair. Separate two-way ANOVAs were run on Recurrence Rate and Meanline with Rhythm (1-2 and 4-2) and Partner (Participant and Confederate) as factors and pair as random variable. Results are summarized in Table 1 and sample RPs are shown in Figure 1. There was a significant main effect of Rhythm on Recurrence Rate: Recurrence Rate was higher for the 1-2 Rhythm (in which the participant tapped at twice the rate of the confederate) than for the 4-2 Rhythm. There was no significant main effect of Partner, $F(1, 7) = 0.012$, $p = 0.92$, or significant interaction between Rhythm and Partner, $F(1,7) = 0.415$, $p = 0.54$, on Recurrence Rate. There was also a significant main effect of Rhythm on Meanline: Meanline was higher for the 1-2 Rhythm than for the 4-2 Rhythm. Again, there was no significant main effect of Partner, $F(1,7) = 0.017$, $p = 0.90$, or significant interaction between Rhythm and Partner, $F(1, 7) = 0.582$, $p = 0.47$, on Meanline. These effects were replicated with mixed models in which random effects of Partner and Rhythm were allowed to vary as a function of the pair.

To ensure that the main effect of Rhythm on Meanline was not a function of differences in Recurrence Rate across Rhythms, we also examined the outcome of Meanline when Recurrence Rate was fixed to 10% across Rhythms during the process of computing the RQA. A two-way ANOVA was run on Meanline with Rhythm and Partner as factors and pair as random variable. The main effect of Meanline held when Recurrence Rate was fixed across Rhythms, $F(1, 7) = 17.577$, $p = 0.004$. Meanline was higher for the 1-2 Rhythm than for the 4-2 Rhythm. There was no significant main effect of Partner, $F(1, 7) = 0.001$, $p = 0.97$, or significant interaction between Rhythm and Partner, $F(1, 7) = 0.579$, $p = 0.47$.

Table 1: Auto-recurrence main effects of Rhythm.

Outcome	1-2	4-2	F	η^2	p
Recurrence Rate	3.06%	2.59%	23.03	0.79	0.002
Meanline	136.26	126.44	20.32	0.77	0.003

Figure 1 shows RPs for an example epoch from one participant for each Rhythm. As can be seen in these examples, there are more recurrent points and longer diagonal lines in the 1-2 RP (when the participant's tapping frequency is the dominant performance frequency) than the 4-2 RP. The white space between the diagonal lines on each plot corresponds approximately to the participant tapping frequency (1.89 Hz or approximately 271 samples).

Cross-recurrence Outcomes

Separate one-way ANOVAs were conducted on the same outcome measures (Recurrence Rate and Meanline) from cross-recurrence quantification analysis with Rhythm as factor and pair as random variable. Results are summarized in Table 2 and sample RPs are shown in Figure 2. There was a significant main effect of Rhythm on Recurrence Rate: Recurrence Rate was higher for the 1-2 Rhythm than for the 4-2 Rhythm. There was also a significant main effect of Rhythm on Meanline: Meanline was higher for the 1-2 Rhythm than for the 4-2 Rhythm. These effects were replicated with mixed models in which random effects of Rhythm were allowed to vary as a function of the pair.

To again ensure that the main effect of Rhythm on Meanline was not a function of differences in Recurrence Rate across Rhythms, we also examined the outcome of Meanline when Recurrence Rate was fixed to 10% across Rhythms during the process of computing the RQA. A one-way ANOVA was run on Meanline with Rhythm as factor and pair as random variable. The main effect of Meanline held when Recurrence Rate was fixed across Rhythms, $F(1, 7) = 14.264$, $p = 0.007$. Again, Meanline was higher for the 1-2 Rhythm than for the 4-2 Rhythm.

Table 2: Cross-recurrence main effects of Rhythm.

Outcome	1-2	4-2	F	η^2	p
Recurrence Rate	2.93%	2.53%	16.84	0.74	0.005
Meanline	131.22	122.78	16.81	0.74	0.005

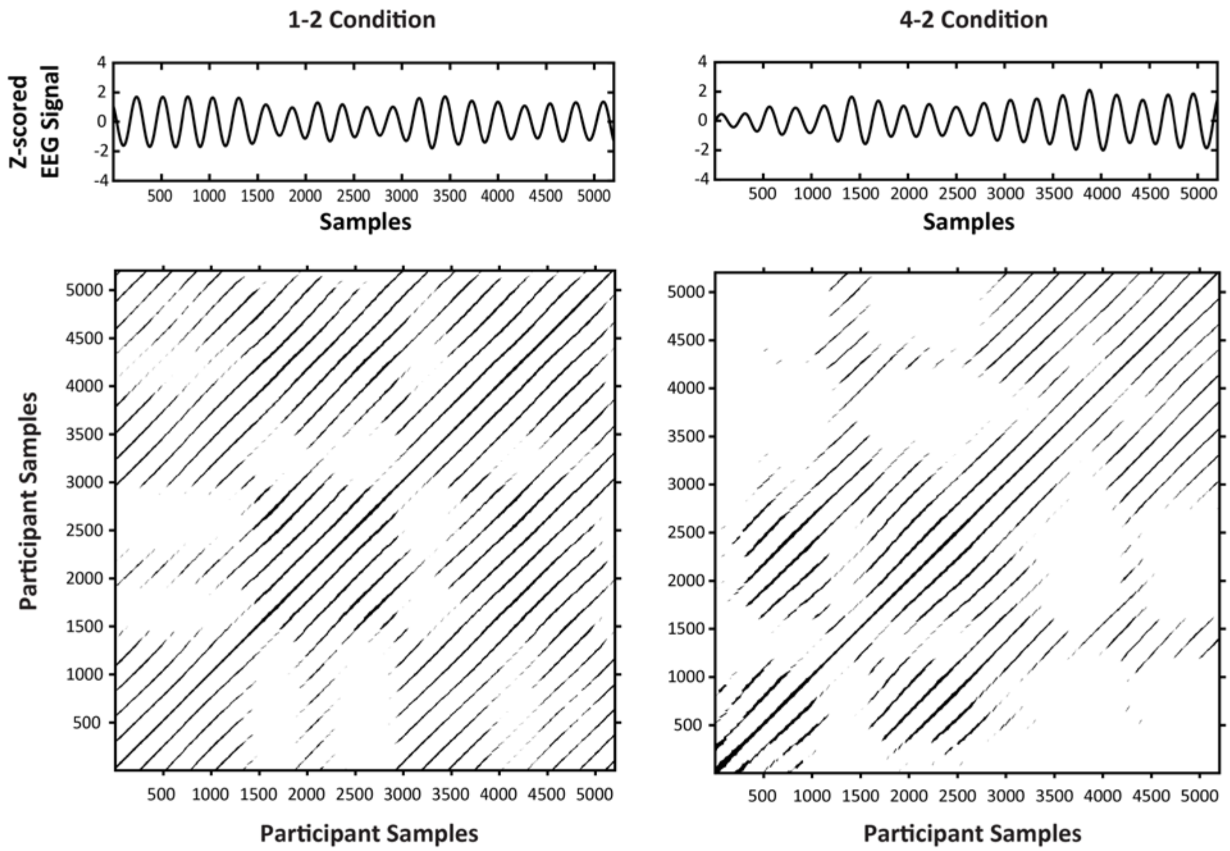

Figure 1: Time series and RPs with samples as a unit of time for one epoch from one participant for Rhythms 1-2 and 4-2. The time series shows the *z*-scored preprocessed signal from electrode C1.

Figure 2 shows example cross-recurrence plots (CRPs) for a single epoch from one pair for Rhythms 1-2 and 4-2 for the same trials shown in Figure 1. As can be seen in these examples, the 1-2 CRP is more densely occupied by recurrent points than the 4-2 CRP; these points also form longer diagonal lines than those in the 4-2 CRP. This indicates that the two signals overlap more often and for longer periods in phase space during the 1-2 Rhythm than the 4-2 Rhythm, indicating greater inter-brain stability. Furthermore, the white space between diagonal lines indicates the period at which the two neural signals recur with one another, and this period corresponds approximately to the participant tapping frequency (1.89 Hz or approximately 271 samples). Phase shifts between the two signals over time can also be observed by the degree of curvature in the diagonal lines in each CRP.

Discussion

The current experiment examined the application of RQA to neurophysiological data collected during a rhythmic tapping task between partners. Both auto- and cross-recurrence measures were sensitive to changes in stability of neural oscillations across tasks. Stability of neural oscillations at the participant tapping frequency was greater both within and across brains, as shown by larger recurrence rate and meanline outcomes from auto- and cross-recurrence, respectively, when there was more auditory feedback for both partners at the participants' tapping frequency.

We showed intra- and inter-brain recurrence that corresponded approximately to the participant tapping frequency. We also showed phase shifts in time as observed by the degree of curvature of the diagonal lines. Future work can further examine the time delay in recurrent points between two signals using quantifications such as the diagonal recurrence profile (e.g., Richardson & Dale, 2005; Dale, Kirkham, & Richardson, 2011), and subsequently relate this to behavioral performance. In contrast to other inter-brain metrics such as phase coherence, one advantage of cross-recurrence is the ability to show and subsequently quantify inter-brain dynamics when neural signals occupy the same phase space.

One limitation of the current experiment is that we only examined neural activity filtered at the participant tapping frequency. Future work can extend this technique to look at other stimulus frequencies to further examine the time evolution of neural dynamics in a joint motor task. We were also limited in our analyses by a small sample size. With more pairs, it could be possible to apply more sophisticated analysis methods to RQA outcomes such as an Actor-Partner Interdependence Model to examine how partners influence one another (Kenny, Kashy, & Cook, 2006). We also used PSD estimates for selecting a single electrode whose data were used for auto- and cross-recurrence

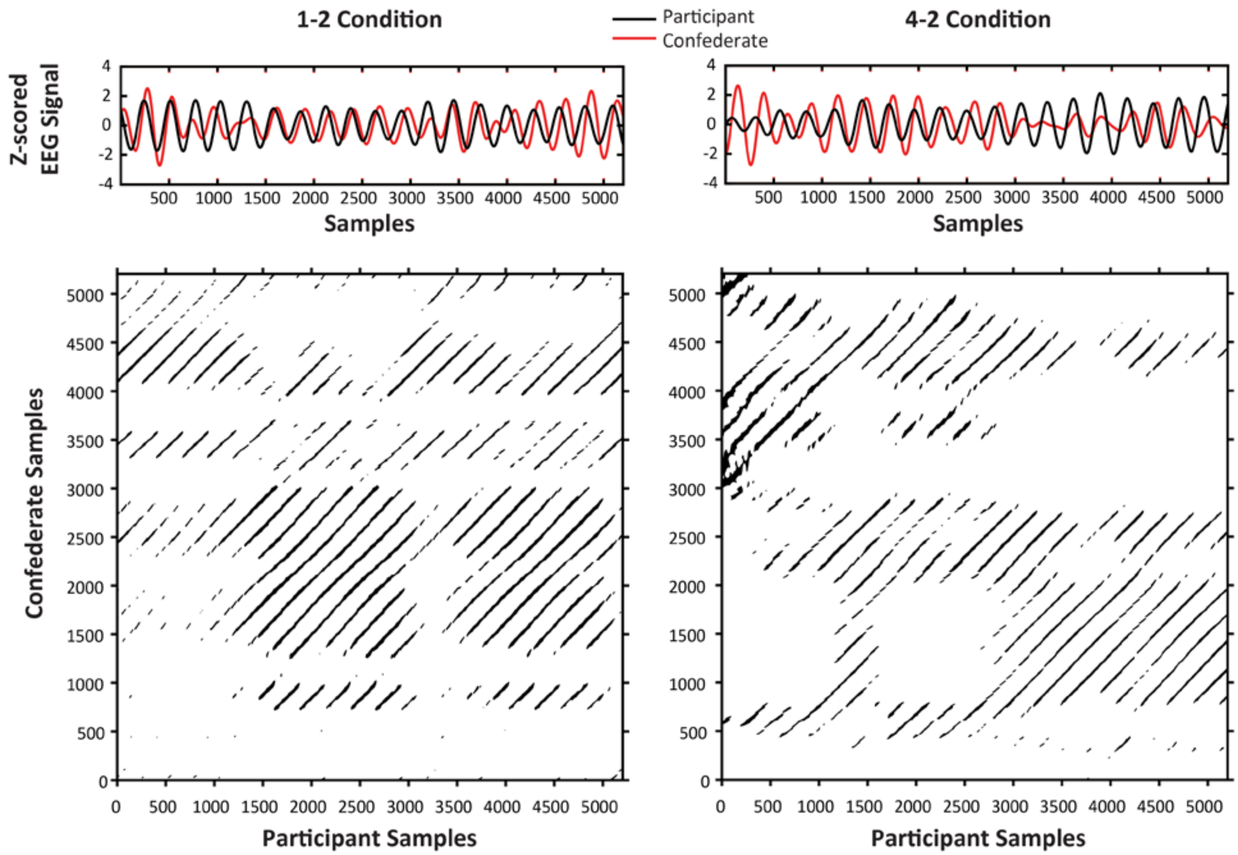

Figure 2: Time series and CRPs with samples as a unit of time for one epoch from one pair for Rhythms 1-2 and 4-2. Time series show the *z*-scored preprocessed signal from electrode C1 for the participant (in black) and the confederate (in red).

analyses. Future work can also extend this technique to identify regions of interest (i.e., multiple EEG electrodes) on which Multidimensional Recurrence Quantification Analysis (MdRQA) could potentially be applied (Wallot, Roepstorff, & Mønster, 2016).

In sum, recurrence quantification techniques were sensitive to changes in the dynamics of oscillatory neural activity that occurred during a joint rhythmic task. This is the first demonstration, to our knowledge, of RQA techniques to show consistent intra- and inter-brain differences in a joint auditory-motor task. These findings suggest that the sensitivity of RQA to stability of oscillatory neural activity might lend the technique to more fine-grained characterization of non-linearities in neural dynamics in a variety of behaviors and participant populations.

References

Acharya, U. R., Sree, S. V., Chattopadhyay, S., Yu, W., & Ang, P. C. A. (2011). Application of recurrence quantification analysis for the automated identification of epileptic EEG signals. *International Journal of Neural Systems*, *21*(3), 199-211.

Becker, K., Schneider, G., Eder, M., Ranft, A., Kochs, E. F., Zieglgänsberger, W., & Dodt, H. U. (2010). Anaesthesia monitoring by recurrence quantification analysis of EEG data. *PLoS One*, *5*(1), e8876.

Dale, R., Kirkham, N. Z., & Richardson, D. C. (2011). The dynamics of reference and shared visual attention. *Frontiers in Psychology*, *2*, 355.

Dale, R., & Spivey, M. J. (2006). Unraveling the dyad: Using recurrence analysis to explore patterns of syntactic coordination between children and caregivers in conversation. *Language Learning*, *56*(3), 391-430.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9-21.

Demos, A. P., & Chaffin, R. (2017). Removing obstacles to the analysis of movement in musical performance: Recurrence, mixed models, and surrogates. In M. Lesaffre, P-J. Maes, M. Leman (Eds) *The Routledge Companion to Embodied Music Interaction*. New York, NY: Routledge.

Demos, A. P., Chaffin, R., & Kant, V. (2014). Toward a dynamical theory of body movement in musical performance. *Frontiers in Psychology*, *5*, 477.

Eckmann, J. P., Kamphorst, S. O., & Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhysics Letters, 4*(9), 973-977.

Finney, S. A. (2001). FTAP: A Linux-based program for tapping and music experiments. *Behaviour Research Methods, Instruments, and Computers, 33*(1), 65-72.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Methodology in the social sciences (David A. Kenny, Series Editor). Dyadic data analysis.* New York, NY: Guilford Press.

Kothe, C. (2014). Lab streaming layer (LSL). *https://github.com/sccn/labstreaminglayer.*

Marwan, N., & Meinke, A. (2004). Extended recurrence plot analysis and its application to ERP data. *International Journal of Bifurcation and Chaos, 14*(2), 761-771.

Marwan, N., Romano, M. C., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports, 438*(5-6), 237-329.

Marwan, N., & Webber, C. L. (2015). Mathematical and computational foundations of recurrence quantifications. In C. Webber, Jr., N. Marwan (Eds) *Recurrence Quantification Analysis: Theory and Best Practices* (pp. 3-43). Cham, Switzerland: Springer International Publishing.

Morillon, B., & Baillet, S. (2017). Motor origin of temporal predictions in auditory attention. *Proceedings of the National Academy of Sciences, 114*(42), E8913-E8921.

Nozaradan, S. (2014). Exploring how musical rhythm entrains brain activity with electroencephalogram frequency-tagging. *Philosophical Transactions of the Royal Society B: Biological Sciences, 369*(1658), 20130393.

Nozaradan, S., Zerouali, Y., Peretz, I., & Mouraux, A. (2013). Capturing with EEG the neural entrainment and coupling underlying sensorimotor synchronization to the beat. *Cerebral Cortex, 25*(3), 736-747.

Richardson, D. C., & Dale, R. (2005). Looking to understand: The coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cognitive Science, 29*(6), 1045-1060.

Romero, V., Fitzpatrick, P., Schmidt, R. C., & Richardson, M. J. (2016). Using cross-recurrence quantification analysis to understand social motor coordination in children with autism spectrum disorder. In: Webber, Jr. C., Ioana, C., Marwan, N. (eds) *Recurrence Plots and Their Quantifications: Expanding Horizons*. Springer Proceedings in Physics, vol 180. Springer, Cham.

Scheurich, R., Zamm, A., & Palmer, C. (2018). Tapping into rate flexibility: Musical training facilitates synchronization around spontaneous production rates. *Frontiers in Psychology, 9,* 458.

Schinkel, S., Dimigen, O., & Marwan, N. (2008). Selection of recurrence threshold for signal detection. *The European Physical Journal Special Topics, 164*(1), 45-53.

Schmit, J. M., Regis, D. I., & Riley, M. A. (2005). Dynamic patterns of postural sway in ballet dancers and track athletes. *Experimental Brain Research, 163*(3), 370-378.

Schmit, J. M., Riley, M. A., Dalvi, A., Sahay, A., Shear, P. K., Shockley, K. D., & Pun, R. Y. K. (2006). Deterministic center of pressure patterns characterize postural instability in Parkinson's disease. *Experimental Brain Research, 168*(3), 357-367.

Wallot, S., Roepstorff, A., & Mønster, D. (2016). Multidimensional Recurrence Quantification Analysis (MdRQA) for the analysis of multidimensional time-series: A software implementation in MATLAB and its application to group-level data in joint action. *Frontiers in Psychology*, *7*, 1835.

Zamm, A., Debener, S., Bauer, A-K. R., Bleichner, M. G., Demos, A. P., & Palmer, C. (2018). Amplitude envelope correlations measure synchronous cortical oscillations in performing musicians. *Annals of the New York Academy of Sciences.*

Zamm, A., Palmer, C., Bauer, A-K. R., Bleichner, M. G., Demos, A. P., & Debener, S. (2017). Synchronizing MIDI and wireless EEG measurements during natural piano performance. *Brain Research.*