An Attempt to Visualize and Quantify Speech-Motion Coordination by Recurrence Analysis: A Case Study of Rap Performance

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Abstract

Recently, cognitive science researchers have revealed that human cognition involves the body and is a kind of self-organization phenomenon emerging from dynamic interaction across body-brain-environment. Some of the data obtained from such cognitive, behavioral, or physiological activities are often complicated in terms of non-stationarity and nonlinearity. Researchers have proposed several analytical tools and frameworks. *Recurrence analysis* is one of the nonlinear data analyses developed in nonlinear dynamics. It has been applied to various research fields, including cognitive science, for language (categorical) data or motion (continuous) data. However, most previous studies have applied recurrence methods individually to categorical or continuous data. We aimed to integrate these methods to investigate the relationship between speech (categorical) and motion (continuous) directly. To do so, we added temporal information (a time stamp) to categorical data and applied the joint recurrence analysis methods to visualize and quantify speech-motion coordination during a rap performance. Our pilot study suggested the possibility of visualizing and quantifying it.

Keywords: Visualization; Quantification; Recurrence Analysis; Speech-Motion Coordination; Rap

Introduction

Cognition as a Self-Organizing Phenomenon

Recent studies have revealed, theoretically and empirically, that we cannot separate cognition from the body and its environment, which are interdependent (e.g., Anderson, Richardson, & Chemero, 2012; Riley, Shockley, & Van Orden, 2012). This notion is called *embodiment*. From the viewpoint of embodiment, cognitive processes related to language and communication interact with bodily motion and behavior (e.g., Richardson, Dale, & Shockley, 2008; Shockley, Richardson, & Dale, 2009). We can consider cognition to be a complex phenomenon that emerges from the body-brain-environment interaction (e.g., Dale, Fusaroli, Duran, & Richardson, 2013; Richardson, Dale, & Marsh, 2014).

Research has shown that the body is not only connected to cognitive processes, but also to linguistic processes. Since McNeill (1992) found the significant relationship between gestures and speech, both in production and comprehension, the number of studies on co-speech gestures has increased. Previous research has shown that co-speech gestures facilitate the speaker's speech process. For example, when participants were asked to not move their hands while speaking, the proportion of unfilled pauses (Graham & Heywood, 1975) or fillers (Rauscher, Krauss, & Chen, 1996) increased. These findings suggest that speech is closely linked to meaningful hand movements.

To deal with such a complex phenomenon, the *dynamical systems approach* (DSA) has been widely applied to human movement science, developmental psychology, and cognitive science. Compared to the traditional approach, assuming internal computation in the brain, DSA focuses more on interactions between the body (including the brain), environment, and task. The DSA has provided both a theoretical framework and analytical tools based on the nonlinear dynamics theory (e.g., Van Orden & Riley, 2005).

Visualization and Quantification

Recurrence Plot (RP): A RP is a two-dimensional graph visualizing recurring patterns of dynamical systems, in which the matrix elements correspond to those times at which a state of a dynamical system recurs in the phase space (Marwan, Carmen Romano, Thiel, & Kurths, 2007). It is an advanced technique of nonlinear data analysis and was originally developed in the fields of descriptive statistics and chaos theory (Eckmann, Kamphorst, & Ruelle, 1987).

Recurrence Quantification Analysis (RQA): RQA is a method of nonlinear data analysis that quantifies the number and duration of recurrences of a dynamical system (Marwan et al., 2007). It was originally developed to uncover subtle time correlations and repetitions of patterns, and is relatively free of assumptions about data size and distribution (Zbilut & Webber, 1992). RQA can provide researchers with some useful measures to quantify self-organizing dynamical system behavior.

RP and RQA have been applied to both continuous data, for example, a numeric value obtained by sensor devices, and categorical data, for example, a letter or word sequence in literature pieces (Coco & Dale, 2014). However, most previous studies have applied these recurrence methods (categorical or continuous) separately. We aimed to integrate the two within the same recurrence analytical framework in order to visualize and quantify speech-action coordination/coupling.

For this purpose, we developed the *categorical recurrence analysis* and applied the *joint recurrence analysis* methods (see "Data Analysis" section under "Method"). If we can integrate these different types data within the same analytical framework, we are of the view that recurrence analysis can be extended widely to visualize and quantify various complex phenomena in cognitive science. As a first attempt to explore such a possibility, the current pilot study focused on a speech-motion coordination/coupling during a rap performance. Because rap or hip-hop music has a relatively obvious rhythm structure, and because mind-body coordination/coupling is important in rapping behavior, we assumed that this relationship would be relatively easy to extract using recurrence methods.

Method

Participants

A professional rapper (male, 30 years old, right-handed) participated in our experiment. He has more than 15 years of rapping experience and was the champion of a national freestyle rap battle. He has also released his tunes as a professional musician. The participant signed an informed consent form, agreeing to participate in this study.

Apparatus

We used a 3D motion capture system (OptiTrack Flex13, Natural Point, Inc.) to measure the participant's body movements (sampling frequency was 120 Hz) (Figure 1). Twelve reflective markers were attached to the participant's body (head, both shoulders, both elbows, both wrists, hip, both knees, and both toes). We used Motive (Natural Point) to process the time series data, MATLAB (R2017b, MathWorks) and RStudio (1.1.423) to analyze the data. We also used a video camera (HDR-PJ720, Sony) (frame rate of 50 FPS) and a headset microphone (Hafone). To analyze the audio data, we used Audiacity (2.2.2) after down-sampling at 25 FPS.

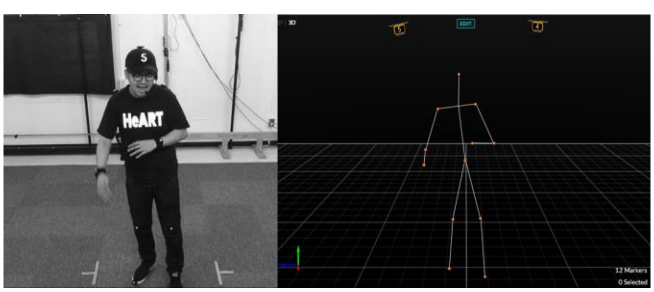

Figure 1: An experimental situation and the motion capture system.

Procedure

We required a professional rapper to perform parts of his rap song, which included an Introduction, Verse, and Hook (totaling one minute). Before recording, we attached twelve reflective markers and a microphone to his body, and we asked him to stand in front of the camera. We then instructed him to perform naturally, as if he were presenting a live performance. After sound checking, we started the recording. In this presentation, we report the results of our analysis of part of the tune (from the first Verse and Hook).

Data Analysis

To visualize and quantify the rhythmic structure and coordinated behavior between the rap (speech) and body movement (motion), we applied *recurrence analyses* (for tutorials, refer to Wallot, 2017; Webber & Zbilut, 2005). We briefly describe these recurrence methods, and we introduce the *joint recurrence method* (Marwan et al., 2007) to integrate them as described in the following paragraph.

In the case of continuous data, time series data are embedded, their trajectory is reconstructed in a higher dimensional phase space, and the distances between all possible combinations of each vector are calculated and distributed within a distance matrix (Webber & Zbilut, 2005). All elements in the distance matrix with distances at or below the threshold (i.e., radius) are said to be *recurrent* (recurrence point) and are included in the recurrence matrix, while all other elements are excluded from it. Such calculations and definitions are used to construct a *recurrence plot* (RP), a method of visualization that shows the dynamic properties and temporal patterns of the system as a two-dimensional representation (Eckmann et al., 1987). A *recurrence quantification analysis* (RQA) allows researchers to quantify and assess the properties of a dynamical system, based on RP or the phase space trajectory (more detail in Webber & Zbilut, 2005). This study reported four RQA measures, namely, the *recurrence rate* (***RR***), *percent determinism* (***DET***), *maxline* (***maxL***) and *mean line* (***L***). ***RR*** is the density (percentage) of recurrence points in a RP; ***DET*** is the percentage of recurrence points forming diagonal lines in the recurrence plot given a minimal length threshold; ***maxL*** is the length of the longest diagonal line; ***L*** is the average of the diagonal line's length (Coco & Dale, 2014). The units of these lines are indicated in time (e.g., seconds). If the length of these lines is long, it means that the system repeats the same state persistently for a long time. These measures have been interpreted as indexes related to stability or complexity of human motor/posture systems (e.g., Pellecchia, Shockley, & Turvey, 2005; Riley, Balasubramaniam, & Turvey, 1999).

In this study, we used only the hip and right wrist movements data in a vertical direction as continuous data (a collective marker of whole-body movement at the macro scale and a specific marker of rap-related rhythmic movement at the micro scale, respectively). After each time series was smoothed, it was then down-sampled at 25 Hz to integrate it with the categorical data.

In the case of categorical data, researchers generally need not to embed the data in a phase space, but to define the level or unit of analysis (e.g., a word or letter). Each unit is converted into numeric categorical sequence (e.g., 1, 2, 3, …). Researchers can create a recurrence point when the two series (original and self-copied sequential series) share the same state (i.e., the same word/letter) in time. Thus, the same RQA measures can be calculated and they provide meaningful indexes that can be considered *dynamic natural language processing*; for example, ***DET*** and ***RR*** are associated with *compressibility ration* and *co-occurrence* respectively (Dale, Duran, & Coco, 2018).

We obtained sequential data by analyzing the lyrics and converting each voice unit into a Japanese vowel (*a/i/u/e/o*), a syllabic nasal (*n*), or an assimilated sound (*x*). We chose a vowel as a main unit of analysis, because rap lyrics tend to rhyme (match rhyming words at vowel level) more often in hip-hop music, generally. We then categorized vowels into numbers as follows: *a*(1), *i*(2), *u*(3), *e*(4), *o*(5), *n*(6) and *x*(7). To analyze the audio data, we imported the audio file into a software, played the voice at each frame (25 FPS), and judged how the voice sounded. If there was no voice, we categorized the frame into *no-voice* (0); If there was a voice, we categorized it according to each vowel, a syllabic nasal, or an assimilated sound as described above (1, 2, 3, 4, 5, 6, 7). After categorization, we obtained two categorical data: first, sequential data of seven categories without any time information, and, second, time series data that included temporal information (i.e., a time stamp at 25 Hz) using eight categories from 0 to 7, as shown above.

Most previous studies have applied these recurrence methods (categorical or continuous) separately, but we integrated them within the same recurrence analytical framework in order to visualize and quantify speech-action coordination/coupling. For this purpose, we developed categorical recurrence analysis by adding temporal information (i.e., a time stamp) and applied the joint recurrence method.

The *joint recurrence analysis* was used to analyze two physically different time series (Marwan et al., 2007). A joint recurrence point can be considered as joint probability in which both systems have simultaneous recurrence points (more detail in Marwan et al., 2007). A *joint recurrence plot* (JRP) is a graph that shows all those times at which a recurrence in one dynamical system occurs simultaneously with a recurrence in a second dynamical system. In other words, the JRP is the Hadamard product of the recurrence plot of two systems (Marwan et al., 2007). JRPs capture the commonalities between two systems (i.e., signals or time series) as coinciding instances of recurrence between the individual RPs of those systems (Wallot, Roepstorff, & Mønster, 2016). First, each RP is constructed for each system, then their JRP can be computed by joining the plots together, so that common instances of recurrences are kept, but different instances between the two RPs are discarded (Wallot et al., 2016). JRQA measures such as ***RR*** and ***maxL*** as explained above (in **Data Analysis**) can be calculated from the JRP in the same way as auto/cross RQA. Originally, the joint method was proposed for two continuous time series, which can recur simultaneously in their individually reconstructed phase spaces, to compare two physically different systems at different units or dimensions. We extended this to compare continuous (motion) data with categorical data (rap).

We performed recurrence analyses using the MATLAB toolbox "CRP TOOLBOX," version 5.22 (Marwan & Kurths, 2002), and the R package "crqa," version 1.0.9 (Coco & Dale, 2014). We determined the optimal values for input parameters with reference to the standard guidelines for the RQA method (Webber & Zbilut, 2005) using *average mutual information* for determining the delay and *false nearest neighbor method* for determining the dimension (e.g., Marwan et al., 2007). As a result, for continuous data, we chose parameters of 10 for time delay, 3 for embedding dimensions, and 0.75 for the radius with *z-score* normalization, while for categorical data, we input 1 for time delay and embedding dimensions, and .001 for the radius.

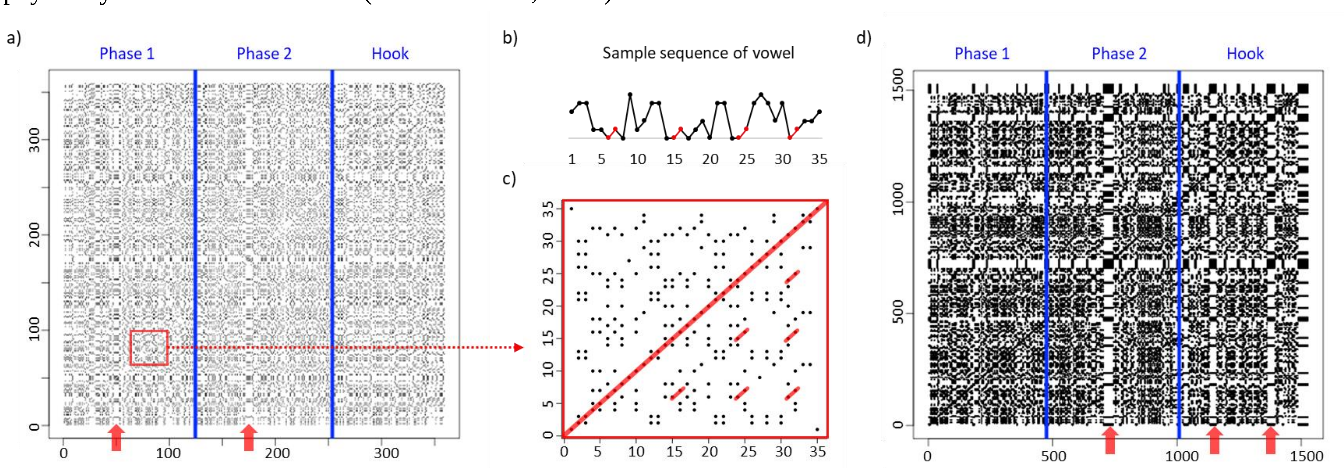

Figure 2: Categorical recurrence plot (CaRP) of rap.
a) Standard CaRP, b) Sample sequence of vowel, c) Part of CaRP, d) Proposed CaRP

Results and Discussion

Categorical Recurrence Plot: Rap Data

Figure 2a shows the categorical RP (CaRP) of the lyrics of the current rap song generated by the standard procedure (with neither temporal information nor a time stamp). Here, we report the partial result of analysis of the tune, the first Verse and the Hook. We indicated three phases consisting of the first part of the Verse (Phase 1), the latter part of the Verse (Phase 2), and the Hook by adding two blue lines (see Figure 2a). Using vowels as a unit of analysis, the lyric consisted of 359 units (Phase 1: 124, Phase 2: 129, Hook: 106). The CaRP does not have random dots, but a structured pattern across the phases. The white bands observed in Phase 1 and Phase 2 (red arrows in Figure 2a) visually represent successive vowels, then a constant value (i.e., "*a*" repeated four or five times).

Figure 2b presents a sample sequence of vowel units, while Figure 2c shows its CaRP, extracted from Figure 2a (red square). Red circle markers in Figure 2b indicate repetition (i.e., rhyming) of the same vowel units (i.e., *a-i*) four times in part of the lyric. The same part appears in Figure 2c as red lines parallel to the diagonal line in the center of CaRP. These parallel diagonal line structures can be interpreted as a rhyming structure, which appeared temporally. These results suggest that CaRP can provide a visualization of rhyming structure in musical lyrics.

Figure 2d presents the proposed CaRP with temporal information (i.e., a time stamp at 25 FPS). It has 1527 points (25 Hz, approximately 60 seconds) including vowels and a no-voice zero value. Accordingly, it is possible that the same value (e.g., "*a*") can appear successively; for example, "*a*" can repeat 25 times if the voice stays for one second. By adding such temporal information as a time stamp, we integrated categorical data with continuous data within the same framework (joint recurrence analysis), as discussed below. This new method seems to provide a more obvious structured pattern than the standard method, comparing Figure 2d and Figure 2a. For example, the transition point where the phase changed, or which was a *break* and *pause* in the tune, can be observed as a white band that indicates a no-voice state (red arrows in Figure 1d). These characteristics seem to express the original music (rap performance) and its temporal structure more clearly.

Our results show that CaRPs can extract a repetitive structure or recurrence pattern of the lyric and rap performance. Our proposed method can visualize the RPs in a more informative way by including temporal information. In the future, quantification and analytical indexes of rhyming structure should be explored.

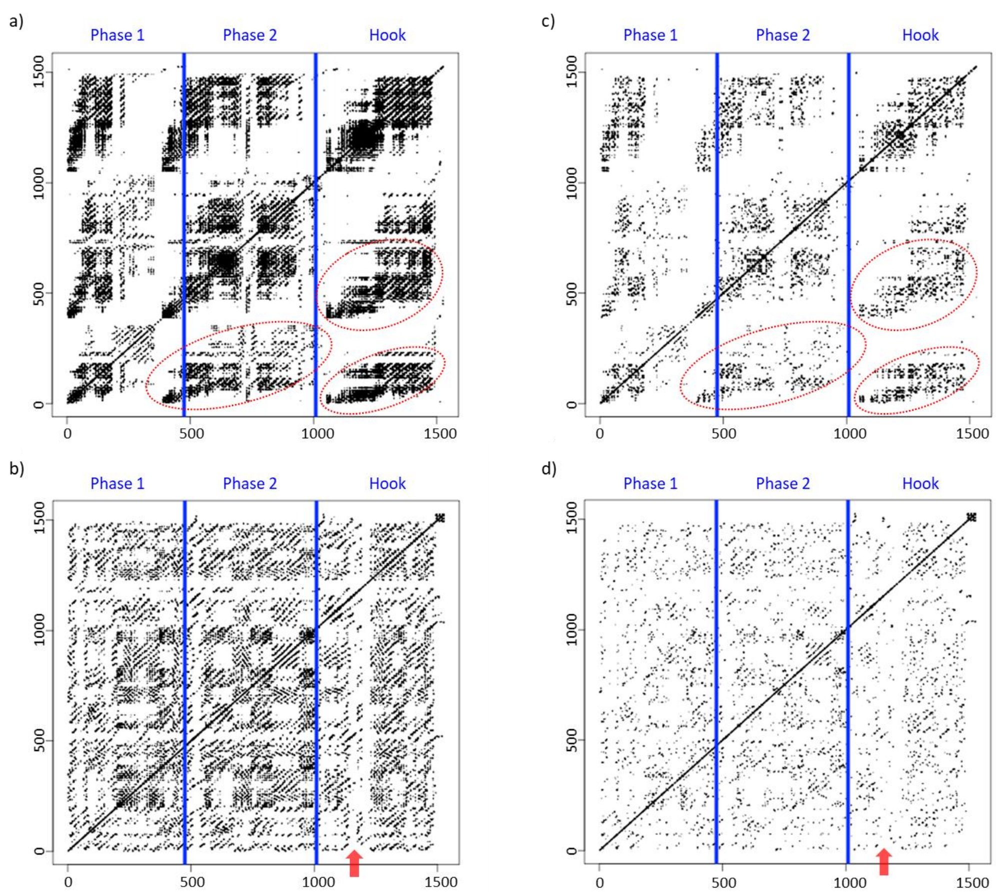

Figure 3: Continuous recurrence plot (CoRP) of rap and Joint recurrence plot (JRP).
a) CoRP of hip, b) CoRP of hand, c) JRP of rap-hip, d) JRP of rap-hand

Continuous Recurrence Plot: Motion Data

Figure 3a represents the continuous RP (CoRP) of hip motion in the vertical direction. Blue lines separate the phases again. We assumed that the vertical hip motion could represent whole-body rhythm. The CoRP shows a recurrence pattern at the macro level, but not random dots. Interestingly, a white band can be observed at the center of the CoRP like the proposed CaRP (the first red arrow in Figure 2d). We could observe the change in bodily rhythm at this break point in the actual video data. In each phase, recurrence points are shown as a whole-body beat rhythm repeatedly. Furthermore, a similar recurrence structure can be found in the red areas (i.e., Phase 1-Phase 2, Phase 1-Hook, and Phase 2-Hook). These results suggest that the participant beat out a rhythm with whole-body movement and that similar/common rhythm patterns can be found across the phases.

Figure 3b shows the CoRP of hand (i.e., right wrist) motion in the vertical direction. Blue lines separate the phases again. We chose the right wrist marker motion for analysis, because the participant was right-handed and showed specific hand movements, such as beating or gesturing, during the rap performance. Compared with hip motion, hand motion seemed to be more closely related to rap performance and to have a high frequency. As a result, its RP (Figure 3b) shows a more detailed recurrence pattern at the micro level than that in Figure 3a. The white band in Hook phase (red arrow) corresponded to no-voice part, and the right hand stopped at this moment.

Joint Recurrence Plot

Figure 3c and Figure 3d depict the joint RP (JRP) of rap-hip coordination and rap-hand (i.e., right wrist) coordination. Blue lines separate the phases again. Compared to the CoRP of hip motion (Figure 3a), the JRP of rap-hip coordination seems to hold a common recurrence pattern at the macro level (red circles in Figure 3c). This suggests that the whole-body rhythm was coupled with rap rhythm. Similarly, the JRP of rap-hand coordination (Figure 3d) seems to hold a common recurrence pattern with the RP of hand motion at the micro level (Figure 3b). This can also be considered rap-hand coupling. These results indicate that JRPs can visualize speech-motion coordination/coupling during rap performance.

Recurrence Quantification Analysis

Table 1 shows the RQA measures quantified from each RP.

Categorical RQA: The proposed method provided higher values in ***DET*** and ***maxL*** than the standard method. This came as a result of adding temporal information at 25 Hz, because it can realize successive value.

Continuous RQA: The total hip RQA measures were higher than hand RQA measures. These results suggest that the participant maintained a stable whole-body rhythm, although he moved his dominant hand rhythmically, but in a complicated manner, synchronizing with the rap lyric and beat during rap performance. To address this possibility, the relationship between hand movement (e.g., gesture) and rap lyrics can be researched in more detail in future studies.

Joint RQA: While ***RR*** and ***DET*** were higher in rap-hip coordination than in rap-hand coordination, interestingly, ***maxL*** was higher in rap-hand coordination than in rap-hip coordination. This suggests that hand movement is likely to couple with rap performance more sustainably and is involved in the content of the lyrics. We found that the right hand of the participant seemed to express the lyric contents, match with the rap tempo (e.g., beating rhythm) and correlate with rapping.

Table 1: Recurrence quantification analysis measures.

	Rap standard	**Rap** proposed	**Hip** vertical	**Wrist** vertical	**Joint** rap-hip	**Joint** rap-hand
RR	19.68	17.22	7.91	3.77	1.68	0.79
DET	36.20	91.85	94.23	76.89	76.84	61.35
maxL	18	60	435	229	16	35
L	2.28	3.74	4.35	2.88	2.82	2.66

General Discussion

In this report, we introduced temporal information (i.e., a time stamp) to the standard categorical recurrence analysis. We showed the possibility of revealing the lyrical structure and the temporal structure (i.e., rhythm) of rapping (singing) or beat (music) itself more clearly. Furthermore, we applied the joint recurrence method to integrate categorical data (rap) with continuous data (bodily motion). By employing such integration, we showed the applicability of the joint recurrence method to the investigation of the speech-motion coordination/coupling and suggested the possibility of visualizing and quantifying it.

Our current pilot study focused on hip-hop music, a music genre that has a relatively obvious rhythm and a repetitive/recurring structure (i.e., rhyme) in its lyrics, which helped us to investigate speech-motion relationship. We guessed that this relationship would be relatively easy to extract using the joint RP and RQA. Some similarities between rap dynamics and motion dynamics were found because common auditory information (i.e., a musical track) might affect these dynamics.

Future Direction

Given that we analyzed only one sample in this study, it needs to be confirmed whether our findings are robust by collecting and analyzing further data. If we could collect other rappers' data, it would be possible to compare original data to virtual pair data of rap-motion coordination/coupling generated from other rappers' performance data. This analysis would show that the current result was not produced by an artifact or possible random matching in terms of surrogate data method (e.g., Shockley, Baker, Richardson, & Fowler, 2007). It would heighten the applicability of the joint method that integrates categorical data (rap) with continuous data (motion). Although the present study focused on an intrapersonal coordination between speech and motion, interpersonal coordination across participants can also be examined within the same framework as investigated by previous studies that have applied the recurrence analysis to various joint action tasks (e.g., Fusaroli, Konvalinka, & Wallot, 2014; Shockley & Riley, 2015). The proposed method should be applied to not only ready-made songs but also improvisational freestyle performance, including various music genres. Improvisational performance is more like everyday social interaction, in the sense that it also has complex aspects emerging from real-time interaction (Walton et al., 2018). The complex dynamical systems methods (e.g., recurrence analysis) are also expected to reveal the creative process in detail using more advanced techniques (e.g., the windowed sliding method; Coco & Dale, 2014; Kodama, Tanaka, Shimizu, Hori, & Matsui, 2018). We also aim to apply the framework not only to experimental situations but also to more ecological situations, such as the practical field of artistic performance, and daily natural conversations involving speech-motion coordination in the future (D'Ausilio, Novembre, Fadiga, & Keller, 2015; Sekine & Kita, 2015; Shimizu & Okada, 2018).

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References

Anderson, M. L., Richardson, M. J., & Chemero, A. (2012). Eroding the Boundaries of Cognition: Implications of Embodiment. *Topics in Cognitive Science*, 4(4), 717–730. https://doi.org/10.1111/j.1756-8765.2012.01211.x

Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: an R package. *Frontiers in Psychology*, 5, 510. https://doi.org/10.3389/fpsyg.2014.00510

D'Ausilio, A., Novembre, G., Fadiga, L., & Keller, P. E. (2015). What can music tell us about social interaction? *Trends in Cognitive Sciences*, 19(3), 111–114. https://doi.org/10.1016/j.tics.2015.01.005

Dale, R., Duran, N. D., & Coco, M. I. (2018). Dynamic Natural Language Processing with Recurrence Quantification Analysis, 1–22. http://arxiv.org/abs/1803.07136

Dale, R., Fusaroli, R., Duran, N. D., & Richardson, D. C. (2013). The Self-Organization of Human Interaction. In H. R. Brian (Ed.), *Psychology of Learning and Motivation - Advances in Research and Theory* (Vol. 59, pp. 43–95). Academic Press. https://doi.org/10.1016/B978-0-12-407187-2.00002-2

Eckmann, J.-P., Kamphorst, S. O., & Ruelle, D. (1987). Recurrence Plots of Dynamical Systems. *Europhysics Letters* (EPL), 4(9), 973–977. https://doi.org/10.1209/0295-5075/4/9/004

Fusaroli, R., Konvalinka, I., & Wallot, S. (2014). Analyzing social interactions: the promises and challenges of using cross recurrence quantification analysis. In *Translational recurrences* (pp. 137-155). Springer, Cham. https://doi.org/10.1007/978-3-319-09531-8_9

Graham, J. A., & Heywood, S. (1975). The effects of elimination of hand gestures and of verbal codability on speech performance. *European Journal of Social Psychology*, 5(2), 189–195. https://doi.org/10.1002/ejsp.2420050204

Kodama, K., Tanaka, S., Shimizu, D., Hori, K., & Matsui, H. (2018). Heart Rate Synchrony in Psychological Counseling: A Case Study. *Psychology*, 9(07), 1858. https://doi.org/10.4236/psych.2018.97108

Marwan, N., Carmen Romano, M., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports*, 438(5–6), 237–329. https://doi.org/10.1016/j.physrep.2006.11.001

Marwan, N., & Kurths, J. (2002). Nonlinear analysis of bivariate data with cross recurrence plots. *Physics Letters A*, 302(5–6), 299–307. https://doi.org/10.1016/S0375-9601(02)01170-2

McNeill, D. (1992). *Hand and mind: what gestures reveal about thought*. University of Chicago Press.

Pellecchia, G. L., Shockley, K. D., & Turvey, M. T. (2005). Concurrent cognitive task modulates coordination dynamics. *Cognitive Science*, 29(4), 531–557. https://doi.org/10.1207/s15516709cog0000_12

Rauscher, F. H., Krauss, R. M., & Chen, Y. (1996). Gesture, Speech, and Lexical Access: The Role of Lexical Movements in Speech Production. *Psychological Science*, 7(4), 226–231. https://doi.org/10.1111/j.1467-9280.1996.tb00364.x

Richardson, D. C., Dale, R., & Shockley, K. D. (2008). Synchrony and swing in conversation: coordination, temporal dynamics and communication. In I. Wachsmuth, M. Lenzen, & G. Knoblich (Eds.), *Embodied Communication in Humans and Machines* (pp. 75–94). Oxford University Press,. https://doi.org/10.1093/acprof:oso/9780199231751.003.0004

Richardson, M. J., Dale, R., & Marsh, K. L. (2014). Complex Dynamical Systems in Social and Personality Psychology. In *Handbook of Research Methods in Social and Personality Psychology* (pp. 251–280).

Riley, M. A., Balasubramaniam, R., & Turvey, M. . (1999). Recurrence quantification analysis of postural fluctuations. *Gait & Posture*, 9(1), 65–78. https://doi.org/10.1016/S0966-6362(98)00044-7

Riley, M. A., Shockley, K. D., & Van Orden, G. C. (2012). Learning From the Body About the Mind. *Topics in Cognitive Science*, 4(1), 21–34. https://doi.org/10.1111/j.1756-8765.2011.01163.x

Sekine, K., & Kita, S. (2015). The parallel development of the form and meaning of two-handed gestures and linguistic information packaging within a clause in narrative. *Open Linguistics*, 1, 490–502. https://doi.org/10.1515/opli-2015-0015

Shimizu, D., & Okada, T. (2018). How Do Creative Experts Practice New Skills? Exploratory Practice in Breakdancers. *Cognitive Science*, 42(7), 2364–2396. https://doi.org/10.1111/cogs.12668

Shockley, K. D., Baker, A. a, Richardson, M. J., & Fowler, C. A. (2007). Articulatory constraints on interpersonal postural coordination. *Journal of Experimental Psychology. Human Perception and Performance*, 33(1), 201–208. https://doi.org/10.1037/0096-1523.33.1.201

Shockley, K. D., Richardson, D. C., & Dale, R. (2009). Conversation and Coordinative Structures. *Topics in Cognitive Science*, 1(2), 305–319. https://doi.org/10.1111/j.1756-8765.2009.01021.x

Shockley, K. D., & Riley, M. A. (2015). Interpersonal couplings in human interactions. In C. L. Webber & N. Marwan (Eds.), *Recurrence Quantification Analysis Theory and Best Practices* (pp. 399–421). Springer. https://doi.org/10.1007/978-3-319-07155-8-14

Van Orden, G. C., & Riley, M. A. (Eds.). (2005). *Tutorials in Contemporary Nonlinear Methods for the Behavioral Sciences*. National Science Foundation.

Wallot, S. (2017). Recurrence Quantification Analysis of Processes and Products of Discourse: A Tutorial in R. *Discourse Processes*, 54(5--6), 382–405. https://doi.org/10.1080/0163853X.2017.1297921

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(NOV), 1–13. https://doi.org/10.3389/fpsyg.2016.01835

Walton, A. E., Washburn, A., Langland-Hassan, P., Chemero, A., Kloos, H., & Richardson, M. J. (2018). Creating Time: Social Collaboration in Music Improvisation. *Topics in Cognitive Science*, 10(1), 95–119. https://doi.org/10.1111/tops.12306

Webber, C. L., & Zbilut, J. P. (2005). Recurrence quantification analysis of nonlinear dynamical systems. In M. Riley & G. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 26–94).

Zbilut, J. P., & Webber, C. L. (1992). Embeddings and delays as derived from quantification of recurrence plots. *Physics Letters A*, 171(3–4), 199–203. https://doi.org/10.1016/0375-9601(92)90426-M