Article

Musical Collaboration in Rhythmic Improvisation

Shinnosuke Nakayama [1], Vrishin R. Soman [1] and Maurizio Porfiri [1,2,*]

[1] Department of Mechanical and Aerospace Engineering, New York University Tandon School of Engineering, 6 MetroTech Center, Brooklyn, NY 11201, USA

[2] Department of Biomedical Engineering, New York University Tandon School of Engineering, 6 MetroTech Center, Brooklyn, NY 11201, USA

* Correspondence: mporfiri@nyu.edu

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Abstract: Despite our intimate relationship with music in everyday life, we know little about how people create music. A particularly elusive area of study entails spontaneous collaborative musical creation, in the absence of rehearsals or scripts. Toward this aim, we designed an experiment in which pairs of players collaboratively created music in rhythmic improvisation. Rhythmic patterns and collaborative processes were investigated through symbolic recurrence quantification and information theory, applied to the time-series of the sound created by the players. Working with real data on collaborative rhythmic improvisation, we identified features of improvised music and elucidated underlying processes of collaboration. Players preferred certain patterns over others, and their musical experience drove the musical collaboration when the rhythmic improvisation started. These results unfold prevailing rhythmic features in collaborative music creation, while informing complex dynamics of the underlying processes.

Keywords: collaboration; information theory; music; recurrence; symbolic dynamics

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1. Introduction

Across cultures, along history, music has always been a universal part of human life [1]. Whether it is pursued as a form of art to express ourselves or as a therapeutic tool to address emotional, cognitive, physical, and social needs, we all are familiar with the nature and value of music [2]. However, little is known about the process of creating music, even in simple rhythmic improvisation comprised of a few notes.

Igor Stravinsky stated that a musical form is "far closer to mathematics than to literature—not perhaps to mathematics itself, but certainly to something like mathematical thinking and mathematical relationships" [3]. For example, Ernîo Lendvai identified the presence of Fibonacci numbers and golden ratios in many of Béla Bartók's pieces [4]. Musical structures can be visualized and quantified by studying self-similarity over time from recurrent patterns [5–7] or constructing networks based on pitch and duration of notes [8]. Predictably, the mathematical elements of music can be uncovered through machine learning, which could be used to detect a temporal structure of music [9] and even to compose music [10,11].

From a mathematically-principled analysis of musical structures within a single piece, one may attempt to compare pieces by different musicians. For example, a popular approach to the comparison of musical structures is to measure the distance between recurrence plots constructed on musical features [12]. Although the approach could, in principle, be extended to the study of musical collaboration, the literature in this field is scarce. To the best of our knowledge, the application of recurrence quantification methods to musical collaboration is limited to [13], which evaluated the dependency of two acoustic signals in collaborative music creation through cross recurrence quantification. The area of spontaneous synchronization of beats shares some similarities with musical creation [14,15], but music is generally more complex than synchronization on an emerging pattern.

A unique setting to experimentally study musical collaboration is improvisation, where music spontaneously emerges from unstructured dynamical interactions between players who embrace a sequence of decisions toward their sense of music [16]. Without rehearsals or scripts, music can be created through cognitive efforts that involve short- and long-term memory [17] and communication based on calls and responses [18]. In this context, understanding processes and outcomes of musical improvisation may offer a deeper insight into human nature of musical cognition. However, little effort has been directed toward the application of mathematically-principled approaches to elucidate how people interact during improvisation and what music they create.

In this study, we investigate processes and outcomes of collaborative musical improvisation. We focus on situations where people without professional training create music together through rhythm, which constitutes a fundamental element of music that humans are wired to appreciate [19,20]. In two improvisation sessions, participants with various musical expertise were randomly paired to freely create music using velocity-sensitive drum pads that generated percussive sound. Each participant was provided with only two notes of marimba. Without rehearsals or scripts, players were asked to create music. Participants were allowed to interact only through the music they heard and created, thereby eliminating visual cues that may otherwise contribute to musical collaboration [21,22]. In this sense, the outcomes of the collaboration were also the means that supported the processes of collaboration, through sharing and transfer of information.

By examining the sound data collected in the experiment, we study rhythmic patterns of improvised music through recurrence quantification, which offers a mathematically-principled approach for studying musical structures [7,12]. From the percussive sound produced by the two players, we form a symbolic time-series where each symbol identifies a specific ordinal pattern in the amplitude of consecutive sound samples. Each time-series is examined through the lens of recurrence quantification analysis to create colored symbolic recurrence plots, where the color of a point identifies the recurring symbol [23,24]. The more points populate the recurrence plot, the more repetitive the rhythm is and the higher the symbolic recurrence rate is. Entropy on symbolic recurrences is used to quantify preference for specific musical patterns that emerge during collaboration. Hence, low entropy values indicate a preference of the players for specific rhythmic patterns, while larger entropy values pertain to a less marked preference for patterns over others. We hypothesize the emergence of recurring patterns with a potential preference for specific musical patterns, as found in human solo drumming [25].

To elucidate the interaction between the players, we perform a multivariate recurrence analysis on the two time-series of the sound amplitudes produced by the players within each pair. From these time-series, we measure the amount of information that is shared and transferred between the two players through salient information-theoretic metrics on joint symbolic recurrence plots [24,26]. Mutual information is used to quantify the association between the rhythmic patterns of the two players, and transfer entropy is employed to measure the responsiveness of the players to their partners. We hypothesize that the process of collaboratively and spontaneously creating music is supported by strong information sharing and transfer between the players.

To explain the variation in the degree of interaction between the players, we inspect the expertise of the participants in playing music, acquired through independent surveys. Following the mental model on teamwork that emphasizes the importance of individual experience and skills on the outcome of collaboration [27], we hypothesize that the extent of information sharing and transfer within a pair is explained by the musical expertise of the pair.

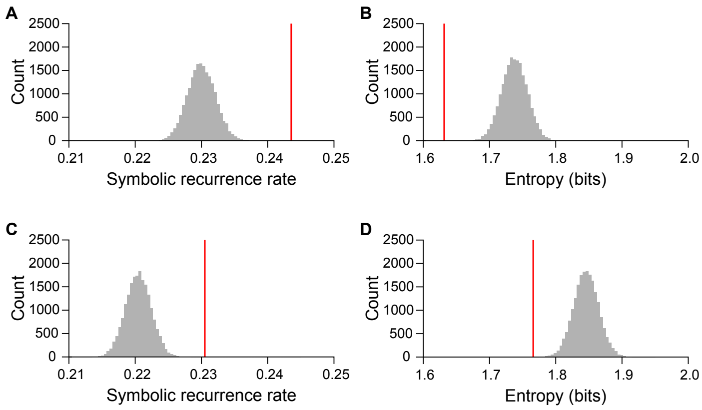

Figure 1. Mean observed recurrence metrics of the music created by a pair against the null distributions: music was characterized by rhythmic patterns and players preferred some patterns over others. (A) Symbolic recurrence rate in the first session, (B) entropy in the first session, (C) symbolic recurrence rate in the second session, and (D) entropy in the second session. Vertical red lines represent the observed means, and the grey areas indicate the null distributions of the means.

2. Results

2.1. Symbolic Recurrence Quantification of Music

For each of the two improvisation sessions, we characterized the music created by each pair in terms of symbolic recurrence rate (SRR) and entropy. We observed an SRR of 0.244 ± 0.034 (mean $\pm$ standard deviation) in the first session and of 0.231 ± 0.033 in the second one. The mean of SRR was significantly greater than chance (two-sided permutation test, $p < 0.001$ for both sessions; Figure 1). Overall, pairs showed consistent values of SRR between the sessions (Pearson's correlation, $r = 0.659, t = 4.638, d.f. = 28, p < 0.001$), but values were smaller in the second session (paired t-test, $t = 2.544, d.f. = 29, p = 0.017$). The recordings of the experiments with the lowest and the highest SRR are available at https://github.com/shinn1/music.

The entropy of the music was 1.632 ± 0.324 bits in the first session and 1.766 ± 0.309 bits in the second one. The mean of the entropy was significantly smaller than chance ($p < 0.001$ for both sessions; Figure 1). Entropy was correlated between sessions ($r = 0.693, t = 5.085, d.f. = 28, p < 0.001$), although pairs showed greater values in the second session ($t = 2.913, d.f. = 29, p = 0.007$).

2.2. Information Sharing and Transfer on Symbolic Recurrence

How players shared information with each other and how they responded to their partners were measured through mutual information and transfer entropy on symbolic recurrences, respectively. For each trial, we computed one value of mutual information and two values of transfer entropy (from the partner to the focal player, corresponding to the responsiveness of the focal player). We observed a mutual information of 0.145 ± 0.160 bits in the first session and of 0.119 ± 0.129 bits in the second one. The mean of mutual information was significantly greater than chance (permutation test, $p < 0.001$ for both sessions; Figure 2). Mutual information was similar between sessions ($t = 1.005, d.f. = 29, p = 0.323$), and pairs showed strong consistency across sessions ($r = 0.539, t = 3.389, d.f. = 28, p = 0.002$). The recordings of the experiments with the lowest and the highest mutual information are available at https://github.com/shinn1/music.

Transfer entropy was 0.038 ± 0.036 bits in the first session and 0.036 ± 0.024 bits in the second one. Again, the mean was significantly greater than chance ($p < 0.001$ for both sessions; Figure 2), and values were correlated between sessions ($r = 0.278, t = 2.201, d.f. = 58, p = 0.032$). There was no change between sessions ($t = 0.373, d.f. = 59, p = 0.710$).

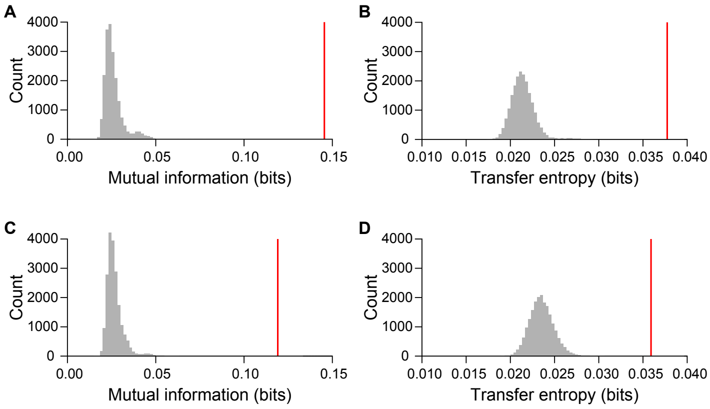

Figure 2. Mean observed recurrence metrics of interaction within the pair against the null distributions: the process of musical collaboration is underpinned by information sharing and transfer between the players. (A) Mutual information in the first session, (B) transfer entropy received from partners in the first session, (C) mutual information in the second session, and (D) transfer entropy received from partners in the second session. Vertical red lines represent the observed means, and the grey areas indicate the null distributions of the means.

2.3. Effects of Pair and Individual Traits on Information Sharing and Transfer

The survey revealed a wide range of musical expertise among the participants, measured through two independent variables. With respect to experience in playing music with others, 12 participants answered 'never' (score 0), 11 'rarely' (1), 17 'sometimes' (2), 13 'frequently' (3), and 7 'always' (4). The duration of practicing music ranged from 0 to 15 years (1st quartile: 0, 2nd: 3, and 3rd: 7 years).

These traits explained variation in mutual information among pairs in the initial phase of the improvised musical collaboration (Figure 3). Specifically, in the first session, mutual information was associated with the interaction between the within-pair sum of experience in musical collaboration and within-pair difference ($\chi^2_1 = 6.664, p = 0.010$). It was also marginally explained by the interaction between the within-pair difference in duration of practicing music and within-pair difference ($\chi^2_1 = 3.507, p = 0.061$) and by the within-pair difference ($\chi^2_1 = 3.030, p = 0.082$), but not by the within-pair sum ($\chi^2_1 = 0.643, p = 0.423$). In the second session, however, mutual information was not explained by the experience in musical collaboration ($\chi^2_1 = 0.054, p = 0.817$ for the sum; $\chi^2_1 = 0.256, p = 0.613$ for the difference; $\chi^2_1 = 0.497, p = 0.481$ for the interaction). The duration of practicing music did not explain the variation in mutual information, either ($\chi^2_1 = 2.199, p = 0.138$ for the sum; $\chi^2_1 = 0.042, p = 0.837$ for the difference; $\chi^2_1 = 0.975, p = 0.323$ for the interaction).

Similarly, musical expertise explained variation in how people responded to their partners in the first session, but not in the second (Figure 4). In the first session, transfer entropy was associated with the interaction between the focal player and the partner in their experience in musical collaboration ($\chi^2_1 = 13.465, p < 0.001$) and in the duration of practicing music ($\chi^2_1 = 21.467, p < 0.001$). By contrast, in the second session, transfer entropy was not explained by the experience in musical collaboration ($\chi^2_1 = 1.906, p = 0.167$ for focal players; $\chi^2_1 = 0.498, p = 0.480$ for partners; $\chi^2_1 = 0.937, p = 0.333$ for the interaction). The duration of practicing music did not contribute to the model fit ($\chi^2_1 = 0.620, p = 0.431$ for partners; $\chi^2_1 = 0.877, p = 0.349$ for the interaction), with a marginal significance for the focal players' duration of practicing music ($\chi^2_1 = 3.592, p = 0.058$).

3. Discussion

This is the first study that elucidates processes and outcomes of collaborative musical improvisation through a mathematically-principled approach. Pairs created music characterized by repetitive rhythmic patterns with marked preference for specific patterns over others, and the formation of such musical characteristics was underpinned by information sharing and transfer

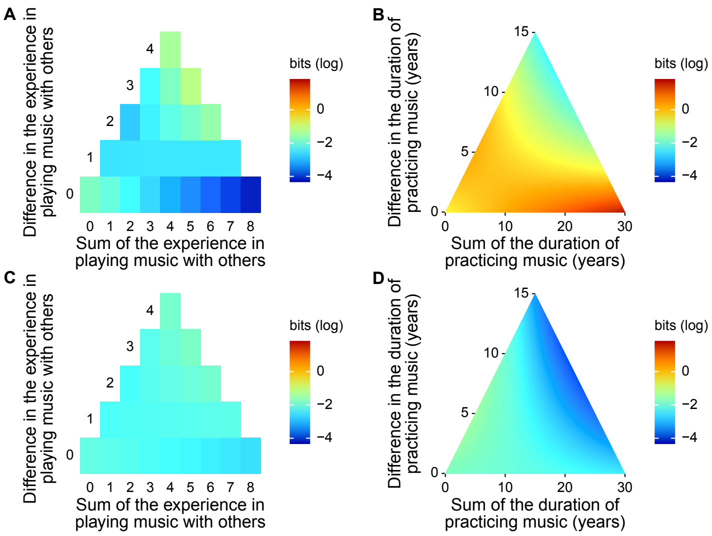

Figure 3. Effects of pairwise traits in musical expertise on mutual information: in the first session, information sharing is favoured by differences in experience in playing with others and similarities in duration of practicing music. (A) Experience in playing music with others in the first session, (B) duration of practicing music in the first session, (C) experience in playing music with others in the second session, and (D) duration of practicing music in the second session.

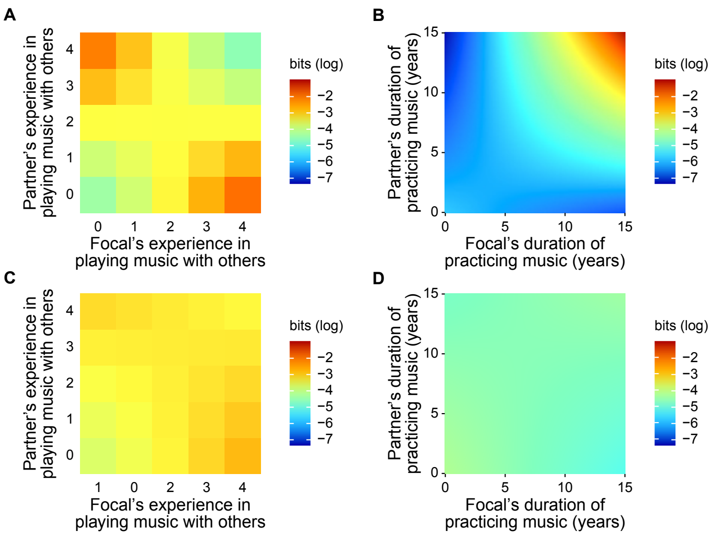

Figure 4. Effects of individual traits in musical expertise on transfer entropy (from the partner to the focal player): in the first session, information transfer is favoured by differences in experience in playing with others and similarities in duration of practicing music. (A) Experience in playing music with others in the first session, (B) duration of practicing music in the first session, (C) experience in playing music with others in the second session, and (D) duration of practicing music in the second session.

between players. Musical collaboration was established in the initial phase through players' musical expertise, but the influence of musical expertise disappeared over time. These results unfold prevailing rhythmic features in collaborative music creation, while informing complex dynamics of the underlying processes.

An empirical study has demonstrated common structural regularities in rhythm when humans play a drum in solo [25]; our results reveal the emergence of such regularities in collaborative music creation. Improvised music collaboratively created by our participants was characterized by repetitive rhythmic patterns with marked preference for specific patterns over others, indicated by higher symbolic recurrence rates and lower entropy. Considering that the origin of music is rooted in social activities [28,29], humans may have an innate inclination to rhythmic patterns that are easy to learn and memorize [25]. Indeed, people are more likely to perceive rhythmic patterns as a division of sound duration by small integers [30]. Cross-cultural similarities in rhythmic patterns [31,32] further support the possibility. Unlike solo music, however, musical collaboration through improvisation requires social exchanges of musical motifs with dynamic responses and adjustments [16,18,33]. Our results indicate that humans are able to perform such complex tasks through acoustic cues toward collaboratively creating music.

Delving into variations in information sharing and transfer across trials, we confirmed our hypothesis that the players' expertise in playing music is responsible for the processes of musical collaboration. Musical expertise was measured in terms of both self-assessed level of experience in musical collaboration and the duration of practicing any musical instrument. In the first experimental session, participants were found to share more information when playing music with partners that had a different level of experience in musical collaboration. Hence, pairing experts with novices in musical collaboration favored information sharing compared to pairing players with moderate experience in musical collaboration. By contrast, similarities within the pair in the duration of practicing music were conducive to information sharing, although pairing experts in musical instruments led to stronger information sharing than pairing novices.

Variation in information sharing was partly associated with how individuals musically responded to their partners, quantified through transfer entropy on symbolic recurrence. Transfer entropy offers a mathematical tool to quantify directional influence between systems [34], with proven success in the study of climate networks [35] and human behavior [36]. In the initial phase of the musical collaboration, players' responses to their partners were explained by musical expertise of both players. Predictably, novices to musical collaboration will be influenced by partners who have experience in playing with others; these experienced partners, in turn, will be able to adjust their rhythm more when playing with novices. The extent of this feedback will depend on their relative training in music, whereby participants would respond more strongly when partnered with others who practiced music for a similar duration. In this way, participants adjusted acoustic responses to their partner without knowing their musical expertise.

The music created by pairs evolved over time, where the rhythms became less repetitive with more diverse patterns. These musical traits may suggest that participants attempted to invent new rhythmic patterns once they established communication, resulting in the creation of music that was more unpredictable. Although the extent of information sharing and transfer in the second session was correlated with those in the first session, musical expertise of the players no longer explained the variations. One possibility is that musical expertise played a role only until participants understood their partner's rhythmic inclinations and responses through learning [18]. We may also propose that as time progresses, players gained confidence in their own musical expression, living a unique moment of inspiration, independent of their musical expertise or that of their partner. Further study will be needed to fully understand the dynamics of improvised music over time and the underlying factors that contribute to the dynamics.

In this study, we did not appraise the quality of the improvised music, as the notion of music is elusive [28]. Although most music entails common traits in rhythms, such as a use of isochronous beats and a metrical hierarchy in meters [31], perception of music is largely shaped by enculturation [37–40]. Hence, people from different cultural backgrounds may exhibit disparate preferences [41–44]. For example, American infants prefer drum patterns with familiar Western meters (pulse duration ratio of 2:1:1) over unfamiliar Balkan meters (pulse duration ratio of 3:2:2), whereas Turkish infants who are familiar with both meters do not express preference [45]. Considering that participants in our study were from a student pool of a university that is home to students from diverse cultures, similarity in cultural backgrounds could also explain the extent of information sharing and transfer, in addition to their musical expertise.

In conclusion, we studied processes and outcomes of musical collaboration in rhythmic improvisation through symbolic recurrence quantification and information theory. In reality, musical collaboration could be achieved through other elements of music, such as melody, harmony, timbre, and texture [46]. Further, there exist implicit rules that facilitate musical collaboration in jam sessions [47–49], including body gestures [22]. Nevertheless, our results shed light on a human ability of musical collaboration through rhythm, which constitutes a fundamental element of music from evolutionary and ethnomusicological perspectives [50,51].

4. Materials and Methods

4.1. Experimental Setup

The instruments provided to participants were MIDI controllers with pads (nanoPAD2, KORG, Melville, NY), digitally programmed with samples of a marimba sourced from the public domain library of University of Iowa Electronic Music Studios. The MIDI controllers fed velocity-sensitive information directly to the recording interface, via two sets of adjacent rubber pads. The recording interface was a standard digital audio production application (REAPER, Cockos Incorporated, New York, NY). This platform was chosen because of the customizable nature of the interface, audio routing capabilities, and compatibility with audio drivers and the MIDI instruments. The recordings were taken at 44,100 Hz, on a Windows laptop augmented with an external USB sound card in addition to inbuilt audio capabilities.

Within the REAPER interface, incoming MIDI signals were rendered as the sampled marimba audio signal and sent to both the participants' sets of headphones (ATH-AVC200, Audio-Technica, Tokyo, Japan). The MIDI controller was configured to play a set of two notes. MIDI recordings were performed in REAPER and saved as REAPER project files. Data was exported as WAV audio files for listening and further analysis.

Two players controlled four notes in an F major seventh chord (F, A, C, and E), one of the traditional chords in Western music that is frequently utilized within an improvisational context [52]. To promote collaboration, each player could only make a partial chord on their own, which would then be extended with the addition of their partners' complementary notes. Specifically, one player was assigned the fifth and seventh (C and E) of the chord, while the other player was assigned the first and third (F and A). This selection was also helpful for players to discriminate their sound from their partners'. Although F and E are dissonant, our participants showed preference for these keys over the middle ones (A and C) (see Supplementary materials).

4.2. Data Collection

Participants were recruited from the New York University community in the Brooklyn campus, NY, USA. Each trial consisted of a tutorial, followed by two experimental sessions. The tutorial was based off a classic one-note call-and-response exercise, toward introducing a standardized basis of collaboration and improvisation. Two participants sat in the same room, facing away from each other. The headphones of the participants were connected to two distinct audio outputs, and audio information was isolated between the participants during the tutorial. Through the headphone, the participants heard a short series of measure-long rhythms, each followed by two measures of rest, and progressively increasing in complexity. The experimenter instructed them to mirror what they heard exactly, using their respective base notes. Then, the participants were exposed to the same series of rhythms through their headphones and instructed to improvise a response, instead of merely repeating. The tutorial ended with a 30-s practice session, where they could use both the notes while listening to a pre-recorded drum backing track.

During a short intermission after the tutorial, participants were asked to complete a survey regarding their musical expertise. Specifically, they filled out their experience in playing music with others on the Likert scale (0: never, 1: rarely, 2: sometimes, 3: frequently, and 4: always) and duration of practicing music in years.

Upon completing the surveys, the participants began the experiment, which consisted of two improvisation sessions, each of 2 minutes in duration. Before commencing the session, the experimenter instructed the participants as follows: "Now you will be playing together and collaborating in your improvisation. Feel free to experiment, but remember to collaborate." Different from the tutorial, participants' headphones were connected to a single audio out port on the USB sound card using an audio splitter device so that they would hear the music they collaboratively created. The same drum backing track used in the tutorial was played for the first 15 seconds of each session, providing a starting tempo for the participants. After this initial 15 seconds, there was no accompaniment and the participants improvised for the duration of each two-minute session. Between sessions, the notes controlled by each participant were swapped to randomize the key assignment. In total, we collected data from 30 pairs. The experiment was approved by the Institutional Review Board of the University (IRB-FY2017-898).

4.3. Symbolic Recurrence Quantification

Given a scalar time-series $\{x_t\}_{t=1}^{T}$ of T samples, we construct the symbolic time-series of $m!$ symbols based on ordinal patterns of length m, $\{S^x(\bar{x}_t)\}_{t=1}^{\bar{T}}$, where $\bar{T} = T - m + 1$, $\bar{x}_t = (x_t, x_{t+1}, \ldots, x_{\bar{T}})$ is the phase space vector at time t, and $S^x(\cdot)$ is the symbolization mapping. For example, if $m = 3$, we have an alphabet Γ^x of six symbols, each identifying a specific pattern for three consecutive readings in the time-series, from a sequence of three numbers that continuously decrease to three that instead steadily increase. From the symbolic time-series, we assemble a symbolic recurrence plot [23] to encode the recurrence of each symbol of the alphabet in time, that is,

$$SR^x_{ts}(\pi^x) = \begin{cases} 1 & \text{if } S^x(\bar{x}_t) = S^x(\bar{x}_s) = \pi^x, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The symbolic recurrence rate of the generic symbol π^x is computed by counting the total fraction of recurring symbol, that is,

$$SRR(\pi^x) = \frac{1}{\bar{T}(\bar{T}-1)} \sum_{\substack{t,s=1 \\ t \neq s}}^{\bar{T}} SR^x_{ts}(\pi^x). \tag{2}$$

This quantity estimates the probability of recurrence of π^x. By summing these partial rates, we calculate the symbolic recurrence rate SRR, which measures the overall extent of recurrence, without discriminating whether it pertains to few or many symbols that are repeating in time. For reference, an independent identically distributed time-series will have a symbolic recurrence rate of $1/m!$.

To afford further quantification of recurrence in the phase space, we examine the entropy of the symbolic recurrence plot [26]. By exclusively focusing on the portion of the recurrence plot that encodes recurrence, we estimate the probability of recurrence of the generic symbol π^x as the fraction of its recurrences over the total number of recurrences, that is,

$$P^x(\pi^x) = \frac{SRR(\pi^x)}{SRR}. \tag{3}$$

Hence, the entropy is

$$H(x_t) = -\sum_{\pi^x \in \Gamma^x} P^x(\pi^x) \log P^x(\pi^x), \tag{4}$$

where we use the logarithm to the base 2 so that we measure entropy in "bits." Again, for an independent identically distributed time-series, the entropy should be $\log(m!)$.

When looking at two or more time-series, we can study a multivariate form of the symbolic recurrence plot, in which we examine a phase space vector in the higher dimensional space given by the Cartesian product of the original phase spaces. In this vein, the symbolic recurrence plot of two time-series $\{(x_t, y_t)\}_{t=1}^{T}$, with ordinal patterns of length m, will track $(m!)^2$ symbol pairs. From this symbolic recurrence plot, we compute mutual information between the time-series as

$$I^{xy} = H(x_t) + H(y_t) - H(x_t, y_t). \tag{5}$$

Similarly, we can examine the symbolic recurrence plot of the multivariate time-series $\{(x_{t+1}, x_t, y_t)\}_{t=1}^{T-1}$ to compute transfer entropy on symbolic recurrences as

$$TE^{y \to x} = H(x_{t+1}|x_t) - H(x_{t+1}|x_t, y_t). \tag{6}$$

With respect to the focal time-series $\{x_t\}_{t=1}^{T}$, this value quantifies the directional influence of the other time-series $\{y_t\}_{t=1}^{T}$.

Throughout the study, we down-sample the time-series at a rate of 150 ms, mirroring typical auditory reaction time [53]. This yields a total of $T = 800$ samples for each trial. To capture the complexity of the time-series while balancing the limited length of the time-series, we use $m = 3$ for the symbolization. In Supplementary materials, we illustrate the robustness of these choices by examining the cases of down-sampling at 100 ms with $m = 3$ and down-sampling at 150 ms with $m = 2$.

4.4. Analysis

To test whether musical improvisation brings about an emergence of recurring patterns with marked preference for certain patterns, we compared SRR and entropy of the music created by pairs against random values (Figure 5). To that end, for each session, we generated the sound data of 30 pairs by randomly shuffling partners and merging their individual sound data in a new pair, thereby simulating the sound data in the case where players within a pair could not acoustically communicate with each other. We computed the mean value of SRR and entropy of the shuffled 30 pairs for 20,000 times and compared the null distributions against the observed means (two-sided permutation test).

Similarly, we tested whether players exhibit a greater extent of information sharing and transfer within pairs, by comparing mean mutual information of 30 pairs and transfer entropy of 60 players against random values. We computed the mean value of mutual information and transfer entropy for 20,000 times and compared the null distributions against the observed means (one-sided permutation test). Further, we investigated the difference between sessions and consistency within pairs in the musical characteristics and extents of information sharing and transfer. Specifically, SRR, entropy, mutual information, and transfer entropy were compared between sessions using a paired t-test. Similarly, within-pair consistency in these values were investigated using Pearson's correlation.

Next, we investigated the musical expertise of each player as a possible factor for the variation in the extent of information sharing and transfer among pairs. For information sharing, we characterized pair traits with the sum of the experience in playing music with others (score 0–8) and the difference (score 0–4), as well as the sum and difference of duration practicing music (in years). Mutual information was fitted into a generalized linear model with a gamma error distribution and a log link. The interaction terms of the sum and difference were also included in the model. For information transfer, transfer entropy that focal players received from their partners was fitted into a generalized linear model, with the musical expertise of a focal player and its partner as explanatory variables. The

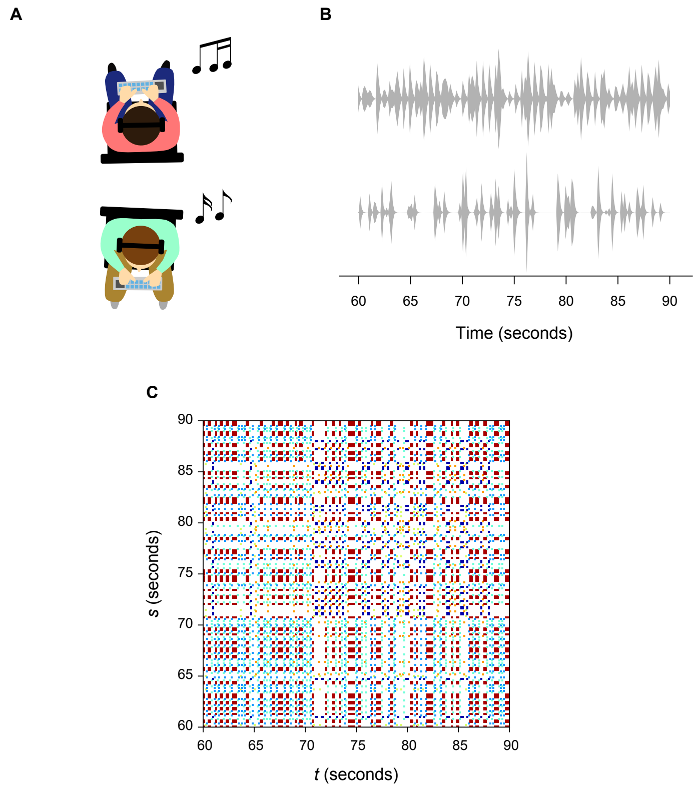

Figure 5. Flow of the study. (A) Two participants create music together by improvising, while acoustically communicating with each other. (B) Amplitudes of the sound are extracted (2 minutes $\times$ 2 sessions, excluding the first 15 seconds with a backing track from each session). (C) Recurrence plots of the music are created from sound amplitudes, by symbolizing following ordinal patterns. Colored areas of a recurrent plot indicate the recurrence of a symbol at time t and s, with colours representing which one of the symbol is recurring. A portion of the recurrence plot is shown for clarity.

model was specified with a gamma error distribution and a log link. The interaction terms of focal players' and their partners' musical expertise were also included in the model.

All data analyses were performed using base R ver. 3.6.0 [54], R package 'seewave' ver. 2.1.4 [55], 'car' ver. 3.0-3 [56], and Python package 'NumPy' ver. 1.17.2 [57].

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