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Amplitude envelope correlations measure synchronous cortical oscillations in performing musicians

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A major question facing cognitive neuroscience is measurement of interbrain synchrony between individuals performing joint actions. We describe the application of a novel method for measuring musicians' interbrain synchrony: amplitude envelope correlations (AECs). Amplitude envelopes (AEs) reflect energy fluctuations in cortical oscillations over time; AE correlations measure the degree to which two envelope fluctuations are temporally correlated, such as cortical oscillations arising from two individuals performing a joint action. Wireless electroencephalography was recorded from two pianists performing a musical duet; an analysis pipeline is described for computing AEs of cortical oscillations at the duet performance frequency (number of tones produced per second) to test whether these oscillations reflect the temporal dynamics of partners' performances. The pianists' AE correlations were compared with correlations based on a distribution of AEs simulated from white noise signals using the same methods. The AE method was also applied to the temporal characteristics of the pianists' performances, to show that the observed pair's AEs reflect the temporal dynamics of their performance. AE correlations offer a promising approach for assessing interbrain correspondences in cortical activity associated with performing joint tasks.

Keywords: amplitude envelope; interbrain synchrony; music performance; joint action; temporal coordination

Introduction

Many joint actions, from ensemble music performance to team sports, require that multiple individuals coordinate the timing of actions with one another. Successful joint action coordination affords numerous social benefits, such as enhanced affiliation,[1] cooperativity,[2] and prosocial behavior[3] between group members. Deficits in the ability to achieve successful temporal coordination of joint actions have been observed in individuals with social and developmental disorders,[4] suggesting a neurobiological link between social behavior and action coordination. The neurophysiological bases of joint actions are not yet well understood, in part due to the numerous technical challenges involved in the simultaneous measurement of brain activity and behavior from multiple individuals.

Recently, a small body of electroencephalography (EEG) research has emerged that investigates the neural correlates of joint action in ensemble music performance.[5–10] This work focuses on identifying corresponding patterns of cortical activity between performing musicians while they synchronize their tone onsets. A general finding is that ensemble musicians show interbrain phase coherence of cortical oscillations in various frequency bands, such as delta (1–4 Hz) and theta (4–8 Hz).[5–7] This work provides evidence that interbrain synchronization of cortical oscillations occurs between performing ensemble musicians. Phase coherence

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is not the only form of neural synchrony: Cortical oscillations also show synchronous fluctuations of amplitude, which can occur independent of phase coherence measures.[11] Given that cortical amplitude dynamics are known to be modulated by the temporal dynamics of behavior,[12] it is likely that partners in joint tasks such as ensemble music performance also display interbrain synchrony of amplitude dynamics, a prediction that has not been explored.

One approach that measures synchrony of cortical oscillations *within individuals* is amplitude envelope correlation (AEC).[11,13,14] Amplitude envelopes (AEs)—defined as the absolute value of the Hilbert transform of a given cortical oscillation—reflect energy fluctuations in an oscillation over time; amplitude is high when energy is high. AECs are computed by correlating the amplitude (energy) envelopes of two oscillatory brain signals. High AEC values indicate synchronous AE fluctuations between oscillations or networks. AECs can detect synchrony between functional brain networks, both within and across frequency bands, independent of phase coherence.[11,13,14] Thus, AECs present a promising metric for assessing interbrain correspondences of amplitude dynamics between partners in joint action.

We provide the first application of AECs to interbrain neural dynamics between members of a joint task: duet piano performance. We measure amplitude dynamics of cortical oscillations at pianists' performed *musical beat frequency*, defined as the duet performance tempo measured in tones per second. The beat frequency is selected because cortical oscillations typically entrain to the produced beat frequency during musical rhythm production tasks, such as solo piano performance and rhythmic finger tapping.[15–17] AEs of cortical oscillations at the beat frequency are expected to reflect entrainment to the temporal structure of duet performances (i.e., exhibit higher amplitude when pianists produce tones at the beat frequency and lower amplitude when partners produce tones faster or slower than that beat frequency), and that these fluctuations will be synchronous (correlated) between duet partners.

The implementation of the AE method is described in detail for a case study of two pianists performing duets while EEG was recorded wirelessly. First, each pianist's multichannel EEG data was reduced to a single dimension representing cortical oscillations at the performed beat frequency. This was accomplished through application of spatial filters created by spatiospectral decomposition (SSD),[18,19] a technique for extracting cortical oscillations in a given frequency band. Second, AEs of each pianist's dimensionally reduced cortical oscillations were computed, and correlations were computed between the partner's AEs. Third, we assessed whether the AEs of cortical oscillations reflect the temporal structure of the duet performances by generating a continuous signal from each pianist's tone onset timing that can be directly correlated with their EEG AEs. Fourth, we demonstrate how the temporal structure captured by AEs is unique to specific performances of the same melody. Finally, chance estimates of the interbrain AECs and brain–behavior correlations are estimated from comparisons with simulated pairs. In sum, this method provides a new approach for assessing interbrain correspondences in joint tasks, and for assessing how intrabrain cortical amplitude dynamics are linked to the temporal structure of duet performance.

Methods

Participants

The methods are applied to music performances by a representative pair of experienced adult pianists, drawn from a larger sample of 40 pianists (see Ref. 15 for further details). The University of Oldenburg and McGill University ethics committees reviewed the study in which the pianists participated, and participants provided written informed consent according to the Declaration of Helsinki. Criteria for inclusion in the study were self-reported normal or corrected to normal vision, no current psychiatric or neurological conditions or use of medication affecting the central nervous system, right-hand dominance (confirmed using the Edinburgh handedness inventory[20]), and normal hearing ($<$20 dB binaurally) for the range of frequencies used in the stimulus melody (confirmed through a pure-tone audiometric screening test).

Stimulus materials

Participants performed the popular melody *Frère Jacques* ("Brother John") in duet with a partner; the melody, often performed as a round, was performed in unison (same pitches produced at the same time) as a synchrony task. Participants were instructed to perform with the right hand and suggested fingerings were indicated (based on recommendations of three skilled pianists not in the study) on notation provided to control for possible differences in motor movements across participants. Participants were sent the notation prior to the study, so that they could learn the melody with the fingerings in advance of arrival at the laboratory.

Equipment

Performance recordings. Duet partners performed the melody on two Yamaha P35B electronic DC-powered keyboards (Yamaha Corporation, Japan) that stood facing one another in the same room. Audio from each keyboard was delivered to participants through onboard speakers. Speaker volume was calibrated to equal sound level across keyboards. Musical instrument digital interface (MIDI) timing information associated with keystrokes was merged from the two keyboards via a MIDI–USB merger (Prodipe Corporation, France), and sent as two separate channels (one for each keyboard) to FTAP software[21] running on a Linux (Fedora) operating system computer. The Linux computer was connected to a network switch box (TP-Link GmbH, Germany) via Ethernet cable, allowing for data recorded in FTAP to be present on the local area network (LAN). FTAP was modified to incorporate the Lab Streaming Layer[32] (LSL; Kothe, 2012, https://github.com/sccn/labstreaminglayer/) library, so that keystroke triggers could be sent as a local network stream to LSL LabRecorder software (version 1.10), which also recorded EEG data (see below). Validation of this method of synchronizing MIDI and EEG data acquisition is described in Ref. 15.

EEG recording. EEG data from each participant were recorded with a 24-channel mobile EEG system (SMARTING mBrain Train LLC; http://www.mbraintrain.com/smarting/) attached to an elastic electrodes cap (www.easycap.de). Electrodes were positioned according to the international 10–20 system, with the reference electrode placed at the FCz site and ground electrode at the AFz site. Electrode impedance was kept below 20 kOhms before the recording started. A digital amplifier (weight = 60 g; size = 82 × 51 × 12 mm; resolution = 24 bits; sampling rate = 500 Hz) was attached to the back of each participants' cap (between electrodes O1 and O2). A Bluetooth dongle (BlueSoleil Inc., China) placed on the wall directly behind each participants' piano bench received digitized EEG data wirelessly from the amplifier. Bluetooth dongles were connected via USB extension to Windows 7 computers running SmartingLSL, which collected the data using the LSL library. SmartingLSL sent the data to LSL LabRecorder over the LAN, where MIDI data from piano keyboards was also recorded.

Task and procedure

Upon arrival at the lab, each pianist separately completed a melody memory test to ensure that they could perform the melody without pitch or rhythm errors in the absence of music notation; each member of the duet pair waited outside the testing room while their partner completed the memory test. The memory test comprised a single performance of the melody: Participants were allowed two attempts at the test. If participants failed after the second attempt, they and their partner were excluded from the study. After the melody memory test, pianists subsequently completed a solo piano performance task[15] in which they performed the melody at a natural and consistent rate in three trials, where each trial comprised four continuous repetitions of the melody (3 trials × 4 continuous repetitions = 12 total melody performances). Partners completed the solo task separately and did not hear one another's performances. The goal of the solo task was to capture the beat frequency at which each partner performed the melody for comparison with beat frequencies chosen by partners in the subsequent duet task. Furthermore, the solo task provided an independent EEG data set for generating spatial filters representing each pianist's topography of cortical oscillations at the beat frequency of music performance (see below).

Next, the partners completed the duet performance task together in which they performed the melody at a pace cued by one of the partners. There were two conditions: in the first condition, one partner cued the performance pace (Player A condition), and in the second condition, the other partner cued the pace (Player B condition). In each condition, the pianist who established the pace was instructed to choose a natural and consistent rate, as they had during the solo performances. Their partner was instructed to follow this pace and to synchronize their performance with the cueing pianist. The pianist responsible for cueing the pace performed the first eight tones of each trial alone to establish the pace, and was joined by their partner in unison on the ninth tone. Each duet condition comprised six trials: On each trial, partners performed the melody four times continuously, without stopping between repetitions, aiming for a consistent pace across trials. Thus, partners performed the duet melody 24 times total per condition (6 trials $\times$ 4 repetitions per trial). Pianists heard full auditory feedback from one another during the duet task. EEG was recorded during all piano performances.

Results

Data preprocessing

Behavioral data. Because performances with pitch errors often include timing errors,[22] analyses included only pitch-error-free performances of the melody. Of all duet melody repetitions, 97.9% were identified as error free (24 melody repetitions in the Player A condition, and 23 melody repetitions in the Player B condition).

EEG artifact correction. Preprocessing of EEG data was implemented in EEGLAB.[23] Independent component analysis (ICA) was used to correct EEG data for eye movement artifacts. To prepare data for ICA, data were concatenated across all trials and conditions, filtered between 1 and 40 Hz (Hanning windowed sinc FIR filter[24]), epoched into 1 s segments, and pruned for nonstereotypical artifacts. Data were subsequently submitted to ICA, and independent components representing typical artifacts associated with lateral movements, eye blinks, and non-cerebral artefacts were identified and removed. Corrected EEG data were subsequently common average re-referenced.

Calculation of beat frequencies for piano performances

The mean beat frequency (frequency at which pianists produced each quarter note duration) of solo and duet performances was determined by expressing the mean interonset interval (IOI in milliseconds) of each melody repetition at the quarter-note level (the most common IOI) in Hertz (1000/IOI, equivalent to number of quarter-note beats/second). To ensure that this estimate reflected the beat frequency, off-beat eighth notes were removed prior to IOI calculation, and half-notes were linearly interpolated. Beat frequency was computed over the first 9 s of each melody repetition (based on the duration of one melody repetition in the fastest performance of the melody in the larger sample of pianists from which the current pair was drawn) to ensure equivalent trial durations across performances.[15] The mean beat frequency, computed for the first 9 s and for the entire trial duration, differed by less than 1 ms (mean = 0.023 ms) across the two methods of calculation (maximum difference = 0.45 ms).

Calculation of EEG AEs

The multistep procedure used to compute AEs of EEG oscillations is illustrated in Figure 1 for a sample performance and described in detail below.

Dimensionality reduction through spatial filtering. First, each pianist's multichannel EEG data were reduced to a single dimension using a spatial filter that represented the unique topographical distribution of cortical oscillations at their beat frequency of performance. Spatial filtering was implemented for several reasons: first, spatial filters generated separately for each pianist take into account individual differences in topography associated with a given feature of interest—this case, cortical oscillations at each pianist's performance frequency; second, adequate spatial filters increase the signal-to-noise ratio; third, the problem of multiple comparisons is reduced by condensing information across electrodes into a single dimension.

Dimensionality reduction was achieved using spatial filters generated by the SSD algorithm.[18,19] SSD is a linear decomposition method that extracts a given frequency band of cortical oscillations from an EEG signal by optimizing the signal-to-noise ratio between the frequency band of interest, called the signal band, and neighboring frequency bands, denoted as noise bands.[18,19] Other traditional decomposition methods often fail to detect oscillatory source activity because they identify components based on nonnormality (e.g., kurtosis), whereas oscillatory EEG activity is generally close to Gaussian.[25] SSD produces a set of orthogonal components representing oscillatory activity within a frequency band of interest, defined as input parameters to the algorithm. Each component is associated with a spatial filter and corresponding spatial pattern that is the inverse of the spatial filter, representing the physiological distribution of a given component across channels. Spatial filters obtained from SSD can be multiplied with any EEG data set to produce a dimensionally reduced

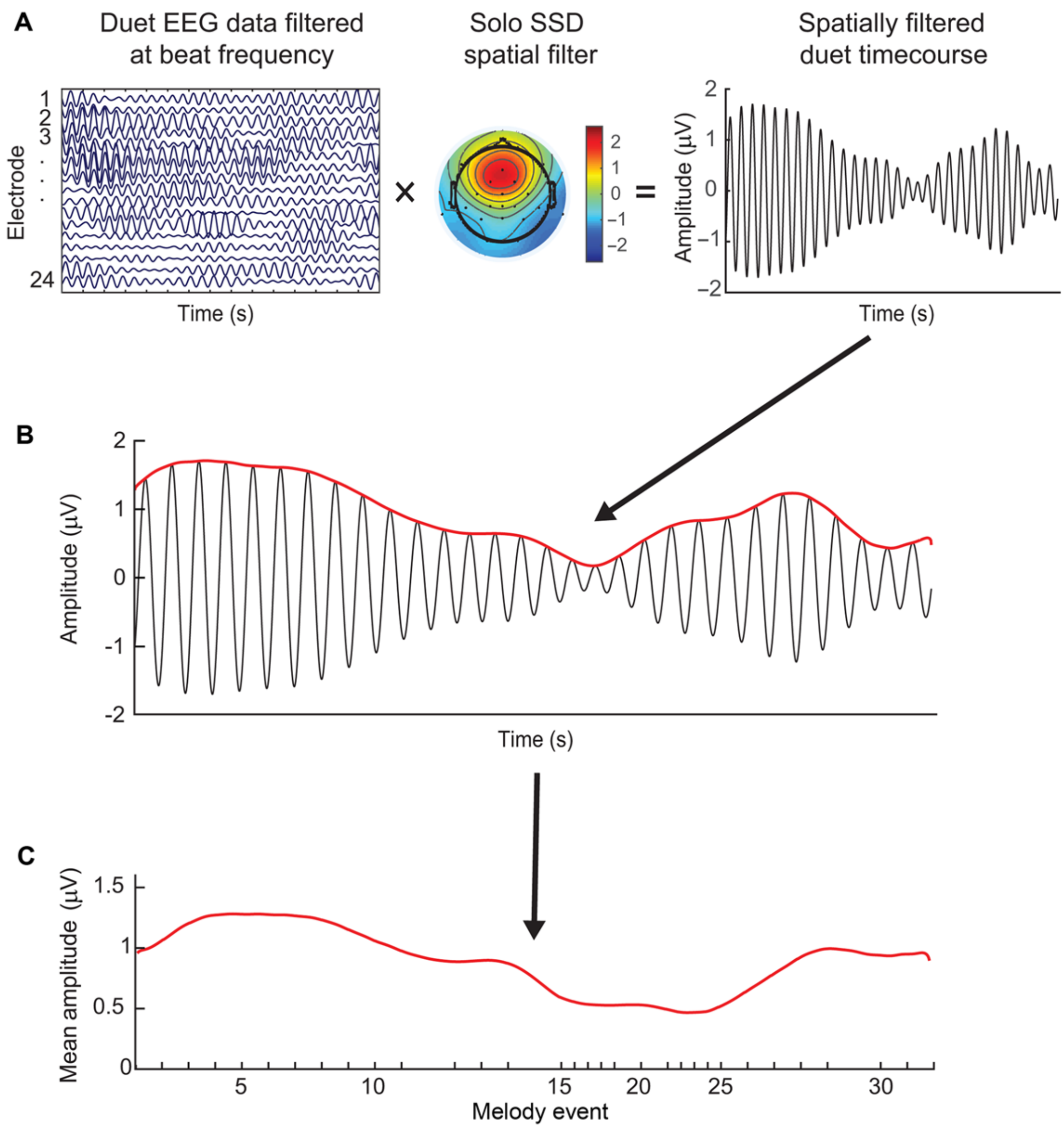

Figure 1. Analysis method for computing EEG amplitude envelopes. (A) One pianist's multichannel EEG signal (left) from a single melody performance (1 epoch) is filtered at their duet performance frequency, and multiplied with the spatial filter associated with the selected SSD pattern for the pianist's solo performance (middle). This yields a SSD time course representing oscillatory activity at the beat frequency (right). For the purpose of visibility, 18 channels of multichannel EEG are shown; all analyses were computed on 24 channels. (B) The amplitude envelope of the SSD time course is computed from the absolute value of the Hilbert transform. (C) Amplitude envelopes for each melody epoch are resampled (see section "Calculation of MIDI AEs") and averaged within a given duet condition for each pianist.

time course of activity, representing the linear combination of channel activity as weighted by the SSD filter. The SSD algorithm is described in detail in Refs. 18 and 19; the code is publicly available at https://github.com/svendaehne/matlab_SPoC/tree/master/SSD.

The SSD spatial filters and patterns were computed from EEG data associated with each pianist's solo performances, which represent an independent data set for a comparable task of performing the same stimulus melody with similar range of performed beat frequencies (see Supplementary

Material 1, online only, for validation tests that show comparable topography of solo and duet beat-related SSD patterns.)

Each pianist's solo EEG data, pruned for non-stereotypical artefacts, were submitted to the SSD algorithm using a signal band of 1.5–3 Hz, corresponding to the range of both solo and duet beat frequencies, spanning the delta frequency band (lower noise band = 0.5–1.49 Hz, upper noise band = 3.51–4.5 Hz). For each participant, the SSD component representing the most stereotypical sensorimotor delta topography was selected and the components were confirmed by the first and second authors. SSD eigenvalues for selected components were consistently first or second in the rank order of components. The grand average selected SSD spatial pattern across participants is shown in Figure 1 (top panel). SSD spatial filters were subsequently used to dimensionally reduce duet EEG data filtered at the performance frequency.

Frequency filtering and Hilbert envelope calculation. Each pianist's artifact-corrected multichannel duet EEG data were filtered narrowly around the frequency range of their performance (mean beat frequency ±0.183 Hz, signal bandwidth = 0.366 Hz) using the same frequency filter implemented by the SSD algorithm (second order Butterworth filter, butterworth.m in MATLAB), and multiplied with SSD spatial weights obtained from solo performances. This multiplication procedure yielded a single time course of cortical oscillations for each pair at their unique duet performance frequency, representing a linear combination of channel activity as weighted by the SSD filter. This time course was subsequently segmented into epochs corresponding to the duration of each melody repetition ±2.5 s and downsampled to 100 Hz (antialiasing FIR filter, pop_resample.m in EEGLAB) for the efficiency of subsequent calculations, which preserved the temporal resolution. The AE of the EEG signal within each epoch was then computed from the absolute value of the Hilbert transform of the SSD component time course; 2.5-second tails of each epoch were trimmed to avoid ringing artifacts of the Hilbert transform.

Event-based envelope resampling. Musicians do not perform melodies with identical timing across tones,[26] and the number of EEG samples between corresponding melody tones performed by the pianists therefore differed across the performances; furthermore, the total duration of performances differed. To allow for comparison across performances within each duet condition, each pianist's AEs were resampled such that the number of samples between corresponding tone events was constant across different performances of the stimulus melody in each condition. Figure 2 illustrates the timing profile for two of the duet performances in terms of IOI deviations relative to the notated durations in a musical score, measured as performed IOI/categorical IOI (defined as the mean quarter-note duration for that performance). As shown in Figure 2, the temporal fluctuations of performances by each pianist differ across the Player A performance example (top) and the Player B performance (bottom), typical of human performances. Values greater than 1 indicate IOIs longer than average, and values less than 1 indicate IOIs shorter than average. To address the different number of EEG samples across performances, first the number of samples between tone onsets was determined by identifying the minimum number of samples between tone onsets across melody repetitions within the given pair/condition: IOIs were then resampled proportionally to this number of samples, such that eighth notes were equal to this number, quarter notes were twice this number, and half notes were four times this number. Resampling between each pair of tone onsets was implemented using shape-preserving piece-wise cubic interpolation (interp1.m in MATLAB, using "pchip" and "extrap" arguments), which fits a cubic polynomial between each set of interpolation points with the goal of preserving the original shape of the resampled signal. This procedure allowed AEs to be averaged across melody repetitions while ensuring that the data segments being averaged corresponded to the same tone onsets.

Calculation of MIDI AEs

Next, the same method for computing AEs was applied to the MIDI piano tone onset data. This method creates a continuous signal that captures the temporal patterning of tone onsets that can be directly compared with EEG AEs, to determine whether EEG oscillations track the temporal structure of pianists' performances. First, we computed the AEs from a series of impulse responses that represented the time course of pianists' MIDI tone onsets. As illustrated in Figure 3, MIDI tone onset

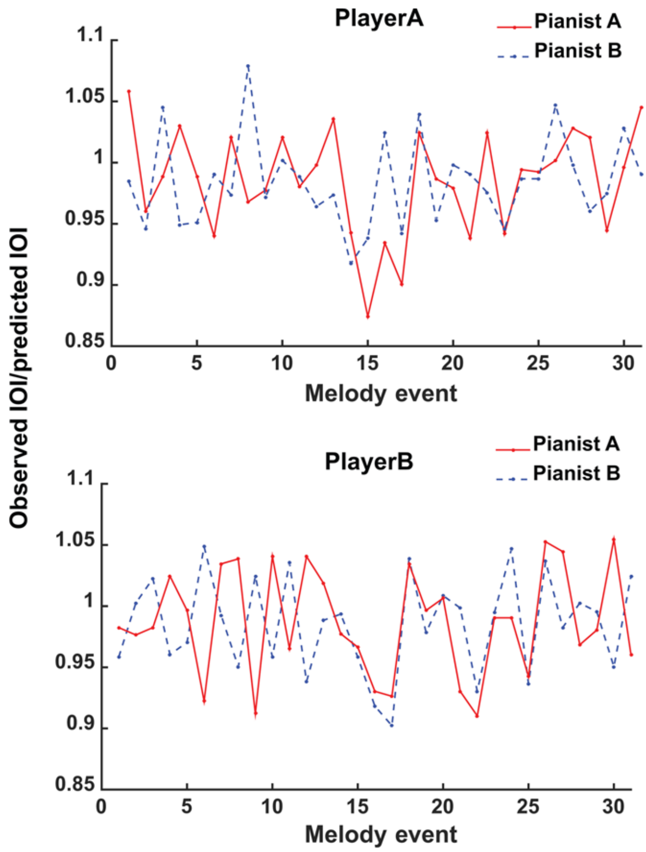

Figure 2. Temporal variability profiles of IOIs. Temporal variability profile (observed IOI/predicted IOI) for two sample performances of the melody; Partner A (solid red), Partner B (dashed blue). Top panel: Player A condition. Bottom panel: Player B condition.

times (recorded in milliseconds) were first converted to events at the same sampling rate as the EEG data. An impulse function was then created in which EEG samples within which a tone onset occurred were assigned a value of 1 and all other samples were assigned a value of 0. These MIDI impulse functions were subsequently concatenated with 5 s of zero padding between each melody repetition, and were submitted to the same Butterworth filter used on the duet EEG data, with a signal band corresponding to the mean beat frequency for the given pair/condition ±0.183 Hz (bandwidth = 0.366 Hz). This filter output was a continuous signal representing the temporal patterning of MIDI tone onsets. The AE of this continuous signal, referred to here as a MIDI AE, was then computed using the same procedure as for the EEG data: The signal was downsampled to 100 Hz (antialiasing FIR filter, pop_resample.m in EEGLAB), and the absolute value of the Hilbert transform was computed for each epoch ±2.5 s; 2.5-s tails were subsequently trimmed to remove edge artifacts. The same resampling procedure described in section above was then implemented, to permit averaging of MIDI AEs across melody repetitions, while ensuring that data segments being averaged were associated with the same tone onsets. As shown in Figure 3 (bottom panel), the MIDI AEs filtered at the beat frequency reflect how pianists produced the musical rhythm: highest amplitude is observed at the beginning of the melody, when pianists performed a series of quarter-note events at the beat frequency, and amplitude decreases in the second phrase, containing a series of eighth-note events (some of which are associated with the beat frequency).

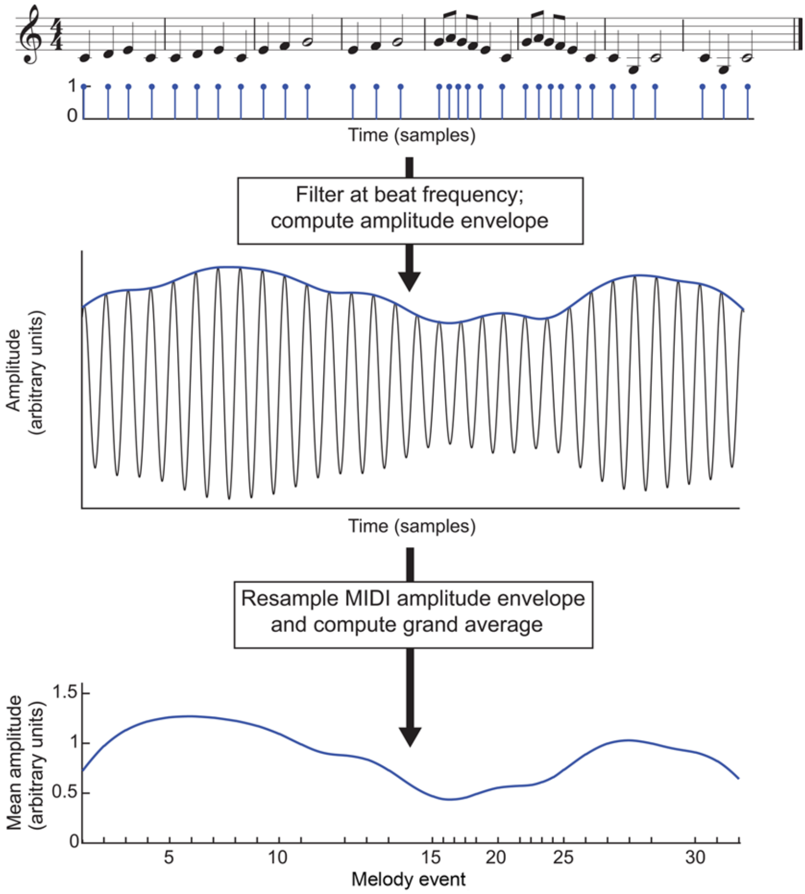

Figure 3. Analysis method for computing MIDI amplitude envelopes. Top panel: Musical notation indicating ideal temporal patterning of tone onsets. Below the musical notation is an impulse response representing the time course of performed tone onsets in the melody (1 epoch), where vertical lines indicate MIDI keystrokes associated with tone onsets (drawn to exemplify unequally spaced MIDI tone onsets typical of pianists' performances). Middle panel: The impulse response is filtered at the mean beat frequency of the pianist's duet performance, and the amplitude envelope of the filtered signal is computed from the absolute value of the Hilbert transform. For comparison with the EEG envelopes shown in Figure 1, the pianist's mean MIDI envelope values shown in the bottom panel are linearly rescaled to the min/max of the same pianist's mean EEG envelope values (Fig. 1). Bottom panel: MIDI amplitude envelopes for each melody epoch are resampled and averaged within a given duet condition for each pianist.

Intraindividual correlations of EEG and MIDI AEs

Within-pianist correlations were then computed between the EEG and MIDI AEs associated with the same duet performances. The first melody repetition of each duet trial was excluded from analysis because the first eight tones were performed by only one member of the duet pair ($n = 6$ excluded melody repetitions). Pearson correlation values were converted to Fisher's z values to ensure normality, and then averaged within pianist and across conditions for each repetition in cases where no melody repetitions were excluded due to errors. The mean correlation between EEG and MIDI AEs was then computed for each pianist and converted back to Pearson correlation coefficients.

Chance estimation for intraindividual correlations of EEG and MIDI AEs

To determine whether the EEG-MIDI AE correlations were unique to the temporal patterning of the specific duet performances, a chance measure of the correlations was computed. First, the time series of MIDI tone onsets for each performance were randomly shuffled in each melody repetition. Then an impulse function was created from this vector using the same method as for the original MIDI performances, in which samples corresponding to tone onsets were assigned a value of 1 and all other samples assigned a value of 0. This impulse function was then submitted to the same procedure used to compute the Hilbert transform and AE of observed MIDI time series (see above). The resulting AEs of the shuffled MIDI performances were then correlated with the observed EEG AEs for each melody repetition, yielding a chance distribution of 18 values per condition (number of melody repetitions included in the analysis, because first repetition in each trial was excluded, per section above) for each pianist. These values were converted to Fisher's r to z scores to ensure normality, and then converted back to Pearson correlation values. Critically, this chance estimate method preserves the mean beat duration of the original performance.

Interindividual correlations of EEG AEs

Interbrain correlations of partners' EEG AEs were computed to test whether amplitude fluctuations of oscillations at the beat frequency are time-locked between partners during performance. Specifically, correlations were computed for each melody repetition within each duet condition. For the first melody repetition in each trial, correlations were computed over data occurring after the 8th tone (during which both partners were performing). Interbrain AECs were subsequently converted using Fisher's r to z values to ensure normality, and averaged across repetitions within duet condition. A single correlation value representing mean interbrain synchrony of EEG AEs for the pair, computed across duet conditions, was converted back to a Pearson r value.

AEC chance estimates based on white noise envelopes

To assess whether observed EEG AE correlation values were higher than would be expected between two stochastic signals of equivalent duration to the observed data, the observed EEG AECs were compared with a chance distribution of correlations based on white noise AEs. AEs of white noise signals were generated with signal duration values and filter frequency bands that matched the signal durations and filter frequency bands applied to the obtained pianists' data in each duet condition. The white noise envelopes were then correlated to create a distribution of chance correlations, for comparison with the obtained values (see Supplementary Materials, online only, for further details).

Results

MIDI measures of performance tempo and synchrony

Mean IOIs, representing the tempo (beat frequency), for each pianist during solo performance were 557.19 ms (the leader in Player A condition condition) and 473.64 ms (the leader in Player B condition); these values are equivalent to 1.79 Hz (tones per second) and 2.11 Hz, respectively. Mean IOIs during the pair's duet performances were 533.10 ms (leader in Player A condition) and 498.74 ms (leader in Player B condition), equivalent to 1.88 Hz (Player A condition) and 2.01 Hz (Player B). To confirm that the duet pair successfully coordinated the timing of tone onsets intended to be simultaneous, we computed tone onset asynchronies over the same 9-s window used to compute IOIs. The mean tone onset asynchrony for the duet pair was = 17.80 ms (Player A condition = 18.92 ms, Player B condition = 16.60 ms), consistent with the range of tone onset asynchronies reported in previous studies of duet piano performance.[27,28]

Intraindividual correlation of EEG and MIDI envelopes

Figure 4 shows pianists' mean EEG and MIDI envelopes from the Player A condition. As can be observed, these envelopes showed a similar pattern of amplitude fluctuations (see Supporting information, online only). Correlations between EEG and MIDI envelopes within each pianist's performances were compared with chance estimate correlations between observed EEG and shuffled MIDI envelopes. The observed correlation for Pianist A was higher than 17 of 18 correlations between observed EEG and shuffled MIDI envelopes (binomial tests, $P < 0.001$, observed Pianist A mean $r = 0.59$; mean chance estimate $r = 0.05$), and the observed correlation for Pianist B was higher than 18 of 18 chance correlations (binomial tests, $P < 0.001$, observed Pianist B mean $r = 0.56$, mean chance estimate $r = -0.09$). Thus, the binomial tests indicated that the observed brain–behavior correlations for both pianists were significantly higher than the chance estimates (see supporting information, online only).

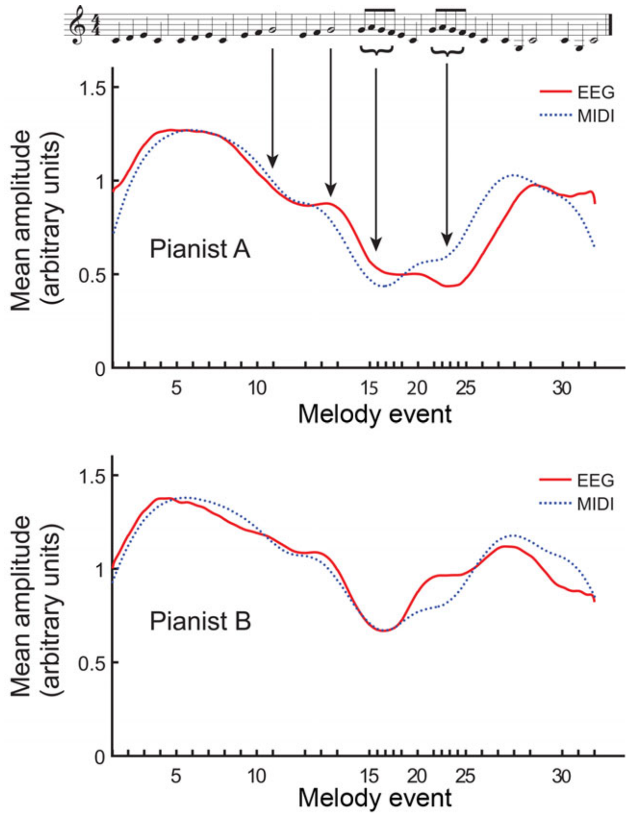

Figure 4. Comparison of EEG and MIDI amplitude envelopes. Mean EEG (solid red) and MIDI (dashed blue) amplitude envelopes (AEs) for Pianist A (top panel) and Pianist B (bottom panel) in the sample pair across all melody repetitions within the Player A duet condition. Each pianist's MIDI envelope values are linearly scaled to the minimum–maximum of that pianist's mean EEG envelope in this figure, for comparison.

Interindividual correlation of EEG envelopes

Next, the interbrain AECs were computed by correlating the EEG AEs of the two partners within each melody repetition and then averaging Fisher's z values first within duet conditions and then across conditions. Finally, the Fisher's z values were converted to a Pearson r value; the mean observed correlation was $r = 0.3102$ (Fisher's $z = 0.3208$). The mean observed correlation for each duet condition was $r = 0.30$ for the Player A condition (Fisher's $z = 0.304$) and $r = 0.325$ for the Player B condition (Fisher's $z = 0.337$). These observed interindividual correlations were compared with a chance distribution of correlations based on white noise AEs, to assess whether observed correlations were higher than would be expected between simulated stochastic signals with the equivalent sample duration and sampling rate (see Supplementary Material 3, online only, for full details). The 95th percentile correlation value from 100 simulations of 24 correlations among the white noise AEs (matching the 24 observed melody repetitions) were compared with the observed EEG AECs. Observed mean EEG AECs for both duet conditions (converted to r values) were higher than the 95% chance estimates (Player A condition: observed $r = 0.30$, chance $r = 0.106$; Player B: observed $r = 0.325$, chance $r = 0.100$). Thus, observed correlations of partners' beat-related EEG AE fluctuations were higher than would be expected between stochastic signals of equivalent duration processed using the same analysis pipeline, indicating that the correlations were not simply a function of the sampling rate.

Discussion

We described a novel application of AEs for assessing temporal fluctuations of beat-related cortical (EEG) oscillations between musicians during duet performance. To extract cortical oscillations at the beat frequency of each duet performance, a spatial filter procedure (SSD) was first applied,[18,19] which allows for identification of spatial weights representing the topographical distribution of a given cortical oscillation. EEG data from pianists' solo performances—which represent well-matched independent measures to the same pianists' duet performances—were used to identify SSD spatial filters associated with cortical oscillations at the pianists' beat frequencies, corresponding to tempo. Each pianist's spatial filters were then applied to the EEG data from their duet performances to extract a single time course on which the AEs could be computed. The mean correlation between partners' EEG AEs was significantly higher than chance estimates computed from simulations of white noise envelope correlations. Thus, the current method of AEC provides a promising new measure for assessing synchronous cortical oscillations between individuals engaged in joint action.

Correlations among interbrain AEs also allow comparisons of oscillatory dynamics across people who perform tasks at a range of rates. The same methodology of aligning data performed at different rates could be extended across numerous contexts. For example, the AEC method outlined here could be used to investigate the neural correlates of gait, in tasks that measure walking at one's natural frequency. Participants' EEG measures could be sampled relative to walking "events" (such as the timing of heel strikes) that permit direct comparison of interpersonal synchronization among side-by-side walkers.[29]

This method was also applied to identify brain–behavior correspondences for each pianist by using AEs to compare EEG oscillations with MIDI-based tone onset patterns. To generate a continuous measure of each pianist's tone onset timing, we created an impulse function representing the time course of MIDI keystrokes and submitted this impulse function to the same filter methods used for the EEG data. The AE derived from each pianist's MIDI keystroke data was then directly correlated with the AE of each pianist's cortical oscillations; these values were highly correlated. To confirm that those correlations were a function of the unique temporal patterning of each pianist's performed tone onsets, the MIDI keystroke timing in the original performances were randomly shuffled and then converted to a continuous signal and re-correlated with the pianist's original EEG AEs. This chance estimate method preserves the mean beat duration of the original performance but alters the temporal patterning. The shuffled MIDI signals did not correlate significantly with observed EEG AEs for either duet partner, confirming that the observed EEG–MIDI amplitude envelope correlations for each pianist indeed reflect the unique temporal patterning of each pianists' produced tone onsets.

The proposed method of using AEs to assess both the temporal structure of music performance and the temporal structure of neural oscillations offers a promising approach to investigating the neural correlates of interpersonal coordination during joint action. Most measures of interbrain correspondences associated with joint action focus on *phase synchrony* of partners' cortical oscillations; the proposed methods address *amplitude alignment*, which can occur independent of phase alignment and may be particularly useful in cases where measurement noise can introduce phase jitter between partners' EEG measurements in joint action tasks. The methods described here can be extended to measure correlations between oscillations at different frequencies,[30] and possibly to assess brain-to-brain cross-frequency coupling.

An important future direction is to establish whether interbrain correspondences in AE fluctuations are correlated with behavioral synchrony of joint actions. The duet pair under study was highly synchronized, with tone onsets occurring within 18 ms of each other on average. Future empirical studies may recruit duet partners with a wider range of synchronization abilities to address the relationship between behavioral synchrony and interbrain correspondences of AE fluctuations. Another critical question is how amplitude fluctuations of cortical oscillations are related to other measures of interpersonal coordination, such as fluctuations in the power of beta and alpha oscillations that are typically time-locked to motor initiation.[31] The current study provides a set of methods that should facilitate answers to these fundamental questions on the neural organization of joint action.

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Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. SSD spatial patterns computed from each pianist's Solo (left) and Duet (right) EEG data for Pianist A (top) and Pianist B (bottom).

Figure S2. Grand mean amplitude envelope across 500 simulated white noise signals.

Competing interests

The authors declare no competing interests.

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