

## Research Article

# Neural Dynamics of Inter-Brain Phase Synchronization in EEG During Coordinated Rhythmic Interaction

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## ABSTRACT

Investigating how neural synchronization emerges during joint movement is essential for understanding interpersonal coordination dynamics. This study investigated inter-brain phase synchronization as pairs of individuals performed rhythmic arm movements during various phases of a game. Electroencephalography (EEG) signals were simultaneously recorded from both individuals as they performed a rock-paper-scissors game initiated by a synchronized arm swing. Particular attention was given to transitions from uncoordinated to coordinated states. Temporal analysis techniques have been applied to capture dynamic changes in inter-brain connectivity linked with the emergence of coordinated behavior. The proposed approach provides a quantitative framework for evaluating neural coupling and may offer potential information for designing adaptive human-robot interaction systems.

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## 1. Introduction

The ability to coordinate actions with others is fundamental to everyday social functioning. In dyadic movement synchronization, individuals must continuously adapt their own movements while interpreting their partner's actions and intentions.

Recently, multimodal “two-person neuroscience” approaches, integrating EEG hyperscanning, motion capture, and gaze tracking, have become a hot topic for elucidating the neural mechanisms underlying subjective experience during interactive tasks [1][2][3][4]. Different metrics have been suggested to characterize EEG phase synchronization, including the phase locking value (PLV) [5], phase lag index (PLI) [6], and comparable measures. Among these, the weighted phase lag index (wPLI) is widely used since it mitigates the impact of volume conduction [7] and provides a more reliable estimate of phase interactions [8][9]. However, the neural mechanisms underlying such phase synchronization, as well as its temporal dynamics, remain insufficiently understood. This

study focused on the arm-swinging phase of the “Look This Way!” game [10], in which both participants concurrently moved their arms during the integrated rock-paper-scissors (RPS) task, with the objective of investigating the dynamics of inter-brain phase synchronization using the proposed PD-wPLI. Auditory and attentional processes were examined to characterize brain dynamics associated with arm swinging. During the second phase, each participant points one direction among up, down, right and left with their finger for the RPS loser and with their head for the winner. If directions match, the RPS winner is the final winner. This second phase is not used for this study.

## 2. Methodology

### 2.1. Participants

This experiment involved 12 pairs (24 participants). Informed consent was given according to the ethics committees' institutional guidelines before the experiment, and approval was obtained at Kyushu Institute of Technology.

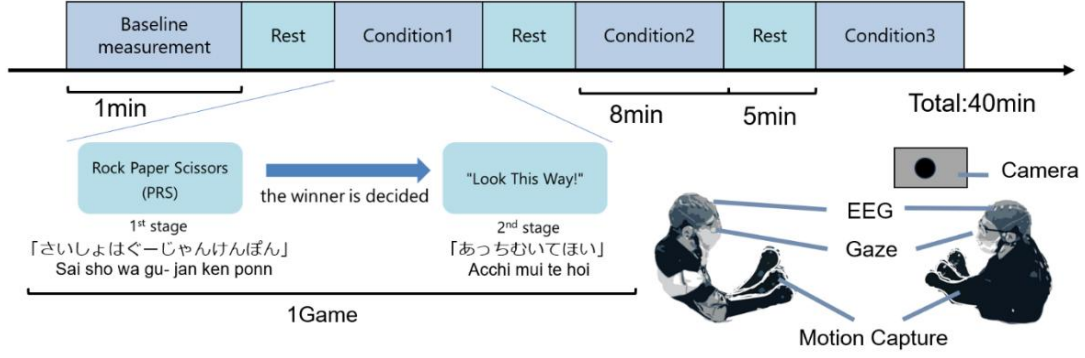


Figure 1 Experimental Paradigm and Timing Details of RPS Experiment

## 2.2. Phase Difference (PD) based Weighted Phase Lag Index

In this study, Phase Difference (PD) based wPLI (PD-wPLI) was used as a measure of the degree of phase synchronization. The proposed PD-wPLI is a phase-based variant inspired by the weighted phase lag index (wPLI) [7], which was originally proposed to reduce the influence of noise and volume conduction on phase synchronization estimates. Unlike the original formula, PD-wPLI is defined solely on phase differences, without applying any weighting, as it assumes the amplitude product of the two signals to be constant. A similar phase-based formulation has been used in previous studies [11]. PD-wPLI was computed from the sine of the phase difference between the two EEG signals. This metric was used as a reliable indicator of phase synchronization. The formula for calculating PD-wPLI has been shown in the following equation,

$$\text{PD-wPLI} = \frac{|E\{\sin PD\}|}{E\{|\sin PD|\}} \quad (1)$$

Here,  $PD = \phi_x - \phi_y$  represents the phase difference between  $x$  and  $y$  EEG signals.  $E$  denotes the expected value. In following sections,  $x$  and  $y$  correspond to specific channels either across subjects or within a subject, and their detailed specifications are provided according to the conditions described in each section. The value of PD-wPLI ranges from 0 to 1, where 0 indicates random phase delay or advance (no coupling) and 1 indicates consistent phase delay/advance (strong coupling).

## 2.3. Experimental Design

This experiment involved 12 pairs (24 participants) who performed “Look This Way!” game, including RPS, while facing each other. EEG, body movements, gaze, and view camera were recorded for approximately 24 minutes (three task types  $\times$  8 minutes each) excluding the resting time. The experimental paradigm has been presented in the following Figure 1.

The arm-swinging motion of particular interest begins a few seconds before the initial “rock” position. It is repeated until the participant chooses one of the three gestures (rock,

paper, or scissors) during RPS phase. The call for RPS was made by a fixed participant (left side in Figure 1), while the call for “Look This Way!” was made by the participant who won the RPS round. This study focused on the EEG phase synchronization between participants during the arm-swinging within the standard “Look This Way!” task. In our simultaneous measurement of EEG-Gaze-Motion [12], Tobii Pro Glasses2 (with scene camera), g.USBamp (sampling rate: 512 Hz) and Perception Neuron 2.0 were used for gaze, EEG, and motion recording, respectively. A scene camera and a standing video were installed to monitor two persons, allowing the whole behavior of the players to be analyzed. All the (video) cameras have the capability to capture frames at 25 fps (frame interval 0.04 s). In this experiment, 16 electrodes of EEG channels (Anterior Frontal Region: AF3, AF4, F3, F4, FC3, FC4; Centroparietal Region: C3, Cz, C4, CP3, CP4; Parietal and Parietooccipital Region: P3, Pz, P4, PO3, PO4) were used for each subject (32 channels in total for two persons). The electrode used for reference (Ref) was positioned on the right earlobe, whereas the ground electrode (GND) was positioned on the forehead (FPz). Event information for the experiment was extracted manually by examining the view camera data frame by frame. Event data was categorized into four stages ( $P_1$ : Initial “Rock”,  $P_2$ : Judgment of RPS,  $P_3$ : Pointing,  $P_4$ : Make direction), and within the  $P_2$ , it was further classified into three types ( $P_{2A}$ : Winner was A,  $P_{2B}$ : Winner was B,  $P_{2D}$ : Draw), including the outcome of the match. This study analyzed phase synchronization of brain activity around the  $P_1$  stage. MATLAB R2024a (Math-Works, Inc., Natick, MA) and the EEGLAB library have been used for the EEG measurement and analysis [13].

## 2.4. EEG Signal Preprocessing

A band-pass filter ranging from 1 to 50 Hz was applied to the EEG data after configuring the data structure in EEGLAB. Noisy channels were automatically identified and eliminated utilizing the “pop\_rejchan” function in EEGLAB, predicated on the kurtosis of each channel’s amplitude distribution. The kurtosis values were normalized across channels using Z-score normalization, and a threshold of 5 standard deviations was applied. Any channel whose Z-scored kurtosis exceeded this threshold was identified as artifactual and excluded from further analysis. For other segments with prominent artifacts,

partial correction was performed using artifacts subspace reconstruction (ASR) [14], and the eliminated channels were restored using spherical spline interpolation. Subsequently, the EEG data were downsampled from 512 Hz to 256 Hz, and components identified as noise were removed using independent component analysis (ICA). Finally, epoching of  $[-2, 2]$  s centered on the  $P_1$  events were extracted (epoching is performed again during phase analysis processing).

### 2.5. Phase Analysis

EEG signals were decomposed into frequency components using 1 Hz wide band-pass filters across the 1-50 Hz range. Using a wide bandwidth allows multiple frequency components to coexist, which reduces the accuracy of instantaneous phase estimation. Therefore, this study used narrowband conditions suitable for phase analysis. Subsequently, since some trials became invalid during EEG preprocessing due to noise removal, only trials valid for both subjects were used to enable comparisons between conditions. Next, the instantaneous phase was determined by applying the Hilbert transform to each frequency band. To remove artifacts near the band-pass filter edges, the first and last 0.5 s of each epoch were discarded.

During the computation of the phase difference between the two EEG signals, an apparent phase difference arises as the phase transitions from  $\pi$  to  $-\pi$ , potentially introducing noise. Therefore, unwrapping processing was applied to ensure phase continuity and correct these discontinuities. This preprocessing step was applied to improve robustness for obtaining reliable estimates of PD-wPLI.

Furthermore, since analysis becomes difficult when channel configurations differ between participants, we confirmed the altered channel information resulting from reconstruction or channel removal. We extracted only the channels which are common to both participants and unified their order. Using this consistent data, we calculated the phase difference between participants and ultimately evaluated the PD-wPLI.

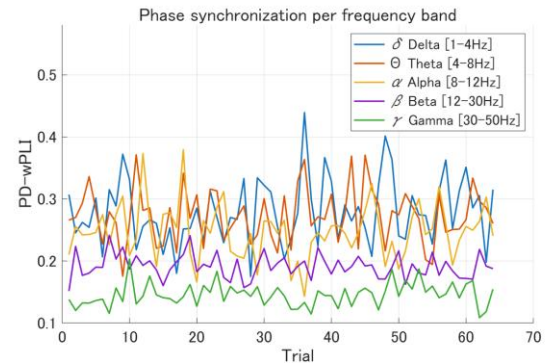
In this present study, only one pair of participants was analyzed because the extraction and annotation of behavioral event triggers from the recorded EEG data is a highly time-consuming process. In future studies, we plan to incorporate and analyze data from all participant pairs. For the analyzed participant pair, event-related data from 15 EEG channels were included across a total of 64 trials. The analyzed channels were distributed across multiple cortical regions: Anterior Frontal Region (AF3, AF4, F3, F4, FC3, FC4), Centroparietal Region (C3, C4, CP3, CP4), and Parietal and Parieto-Occipital Region (P3, Pz, P4, PO3, PO4), while Cz (noisy channel) was excluded from the analysis. The trials were divided into five non-overlapping slots to construct the time series: Slot 1 (Trials 1-13), Slot 2 (Trials 14-26), Slot 3 (Trials 27-38), Slot 4 (Trials 39-51), and Slot 5 (Trials 52-64). This segmentation was designed to minimize correlation between consecutive trials. The

number of trials in each slot was 13, 13, 12, 13, and 13, respectively. Subsequently, the average within each index was computed to represent the PD-wPLI values more clearly. PD-wPLI were compared in specific frequency bands: Delta ( $\delta$ ), Theta ( $\theta$ ), Alpha ( $\alpha$ ), Beta ( $\beta$ ) and Gamma ( $\gamma$ ) respectively defined as [1-4] Hz, [4-8] Hz, [8-12] Hz, [12-30] Hz, and [30-50] Hz. Differences among the five frequency bands were compared using the overall channel average.

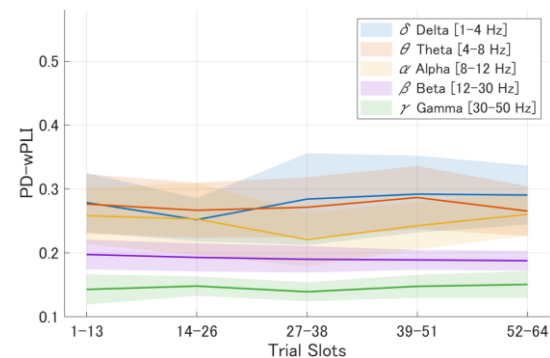
Additionally, focusing on auditory processing and attentional processing, we investigated whether each process might contribute to arm swing synchronization. In this study, channels related to auditory processing were defined as F3, F4, AF3, and AF4, with frequency bands being Delta ( $\delta$ ) ([1-4] Hz) and Theta ( $\theta$ ) ([4-8] Hz) [15]. Similarly, channels related to attentional processing were defined as Pz, P3, P4, F3, and F4 with the frequency band being Alpha ( $\alpha$ ) ([8-14] Hz) [16]. Besides, channels in the posterior region of the brain (Pz, P3, P4, PO3, PO4 channels) are also important for attention analysis [17]. The averages of the selected channels were compared with the overall channel average.

## 3. Experimental Results

### 3.1. Phase Synchronization across Brain Rhythms



a. PD-wPLI of Different Brain Rhythms across each Trial



b. PD-wPLI of Different Brain Rhythms across the Trial Slots

Figure 2 Phase Synchronization (PD-wPLI) Comparison of Delta ( $\delta$ ), Theta ( $\theta$ ), Alpha ( $\alpha$ ), Beta ( $\beta$ ) and Gamma ( $\gamma$ ) Waves related to Auditory Processing

Figure 2 shows the channel-averaged PD-wPLI and its temporal changes across five brain waves: Delta ( $\delta$ ), Theta ( $\theta$ ), Alpha ( $\alpha$ ), Beta ( $\beta$ ) and Gamma ( $\gamma$ ). Relatively high PD-wPLI values were observed in the low-frequency bands: Delta ( $\delta$ ), Theta ( $\theta$ ), Alpha ( $\alpha$ ) bands compared to Beta ( $\beta$ ) and Gamma ( $\gamma$ ) bands. The Beta ( $\beta$ ) band is commonly associated with motor-related functions, whereas the Gamma ( $\gamma$ ) band is linked to active cognitive processing, movement execution, and neural integration. Given the elevated PD-wPLI values in the lower-frequency bands, subsequent analysis focuses on Delta ( $\delta$ ), Theta ( $\theta$ ), and Alpha ( $\alpha$ ) waves. No consistent trends in PD-wPLI values were observed across all five frequency bands based on trial slot classification.

### 3.2. Auditory Processing

Figure 3 shows the comparison of PD-wPLI values for auditory processing. Channels defined as related to auditory processing, F3, F4, AF3, and AF4 are suitable for

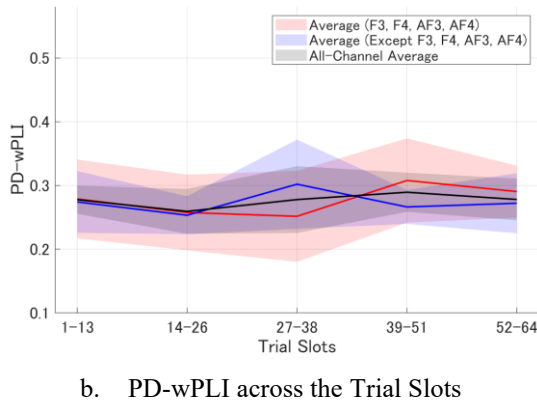
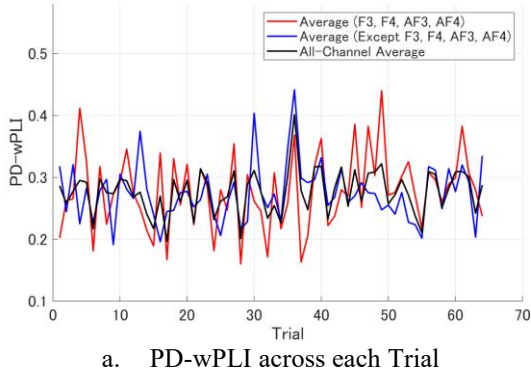


Figure 3 PD-wPLI Comparison of Delta ( $\delta$ ) and Theta ( $\theta$ ) Waves related to “Auditory Processing”

analysis [15]. The average of these four channels is compared with the overall channel average as well as the average of all channels except the channels related to auditory processing. Figure 3a shows the PD-wPLI values across each individual trial, where all three averages fluctuate within a comparable range of approximately 0.2 to 0.4 with no consistent separation between groups. Figure 3b shows the average PD-wPLI across trial slots, where auditory-related channels decrease in the middle

slots and then recover later. This pattern aligns with the observed game pace where participants performed slowly during the early trials, gradually accelerated through the middle trials, and settled into a faster, consistent rhythm toward the later slots. During the middle phase, the irregular and increasing rate of verbal cues may have disrupted Delta ( $\delta$ ) and Theta ( $\theta$ ) rhythms in frontal regions, as these oscillations tend to weaken under unpredictable auditory input [18]. As the faster pace became stable in the later slots, auditory synchronization recovered, consistent with evidence that prefrontal Delta ( $\delta$ ) and Theta ( $\theta$ ) waves synchronization strengthens when speech and verbal events are regular and predictable [19]. These results suggest that phase synchronization in auditory-related channels is influenced by the speed and regularity of verbal cues during the task.

### 3.3. Attention Processing

Figure 4 shows the comparison of PD-wPLI values for attentional processing.

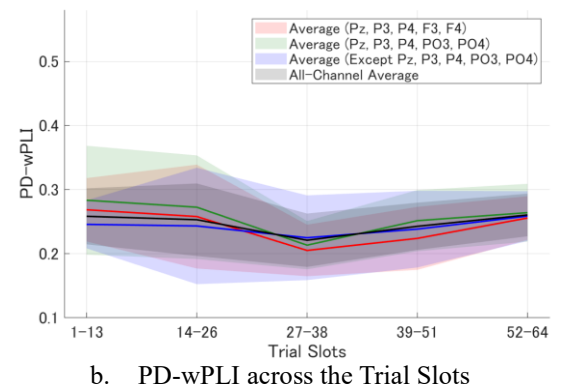
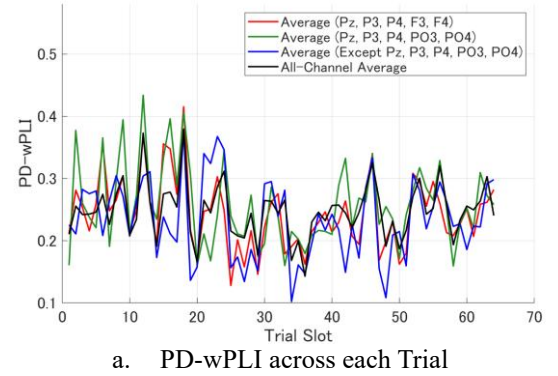


Figure 4 PD-wPLI Comparison of Alpha ( $\alpha$ ) Wave related to “Attention Processing”

Among the defined channels, Pz, P3, P4, F3, and F4 are suitable for analysis [16]. Besides, posterior regions of the brain (Pz, P3, P4, PO3, PO4 channels) are also important for analysis [17]. Figure 4a shows the PD-wPLI values across each individual trial, where all groups fluctuate within a moderate range with no clear consistent separation. Figure 4b presents the PD-wPLI averaged across trial slots. In the early trial slots, both of the attentional channel groups exceeded the all-channel average, indicating relatively higher phase synchronization at the beginning of

the task. However, as the trials progressed, the PD-wPLI values of these channels dropped below the overall average in the later slots. This decreasing trend suggests that the demand for attentional processing gradually reduced as participants became more familiar with the rhythm of the task. As the game pace increased from slow to fast, participants likely internalized the motor rhythm of arm swinging, reducing the need for explicit attentional monitoring over time [20] [21]. This result indicates that reduced attentional demand may have been associated with rhythmic coordination as the task progressed.

#### 4. Discussion

This study analyzed the dynamics of EEG synchronization during arm-swinging movements. As shown in Figure 2, no clear trend in PD-wPLI values was observed over time. However, the experiment included auditory processing during rock-paper-scissors, suggesting that these auditory stimuli may have influenced synchrony. Additionally, our results by frequency band showed that in the Beta ( $\beta$ ) band, commonly associated with motor-related processing, phase synchronization was relatively lower than the other frequency bands. In contrast, relatively high PD-wPLI values were obtained in the low-frequency waves [Delta ( $\delta$ ), Theta ( $\theta$ )] and [Alpha ( $\alpha$ )] waves. These rhythmic components are recognized to be involved in auditory processing [15] and attentional processing [16], respectively. Under the experimental conditions of this study, it is possible that auditory stimuli and attentional demands, rather than the movement itself, were reflected in the synchronization patterns. For auditory processing, the average value for channels related to this processing (F3, F4, AF3, and AF4) was higher than the overall average in the later trials. For attention processing, a lower-than-average value was observed in the latter half, possibly indicating reduced need for attention as the task progressed. Although this analysis used only one pair, the dynamics of synchronization suggest that the observed synchronization may influence both auditory and attention processing. Moving forward, it is required to increase the number of analyzed pairs and statistically evaluate how auditory processing, attention processing, and motor processing relate to EEG signals of motor and synchrony.

#### 5. Conclusion

This study investigated the dynamics of EEG synchronization during simultaneous arm-swinging between two participants in a game. The game included a rock-paper-scissors task and the “Look This Way!” task. Instantaneous phase was calculated from EEG data recorded before and after the initial rock-throwing timing. The phase synchronization over time was evaluated using the PD-wPLI index. Analysis revealed no consistent trend in phase synchronization across all channels average, showing moderate to low agreement. The underlying neural dynamics provided deeper insight into auditory and attentional processing. For auditory processing, a temporary decrease in PD-wPLI was observed in the middle trial slots, followed by a recovery in the later slots.

This fluctuation pattern was associated with the observed change in game pace, where participants played slowly in the beginning and gradually shifted to a faster pace, causing Delta ( $\delta$ ) and Theta ( $\theta$ ) waves in auditory-related frontal channels to temporarily weaken during the transitional phase and recover once the faster tempo stabilized. For attentional processing, PD-wPLI values in the attentional channels initially exceeded the overall average but declined below it in the latter trial slots, suggesting that as participants became more familiar with the arm-swinging rhythm and interpersonal coordination became more automatic, the demand for explicit attentional monitoring gradually reduced. These findings suggest that both auditory cue regularity and attentional demand dynamically shaped inter-brain phase synchronization during the task, rather than motor movement alone. Future work requires increasing the number of analyzed pairs to statistically evaluate how auditory processing, attentional processing, and motor processing each contribute to synchronization.

#### Acknowledgements

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