

Article

Study of EEG Inter-brain Synchrony during Nonverbal Facial Communication Games

Hao-Teng Hsu ¹, Yuri Shelepin ² and Po-Lei Lee ^{1,*}

¹ Department of Electrical Engineering, National Central University, Taoyuan City, 32001, Taiwan; fifaworld91@g.ncu.edu.tw

² Laboratory of Physiology of Vision, Pavlov Institute of Physiology, Russian Academy of Sciences, St. Petersburg, 199034, Russia; yshelepin@yandex.ru

* Correspondence: pllee@ee.ncu.edu.tw

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Abstract: Inter-brain synchrony can arise from task cooperation, neural mirroring, social interaction, or shared attention and perception. This study investigated brain synchrony between individuals with different linguistic backgrounds playing nonverbal facial communication games. Two eight-channel EEG systems were used to simultaneously measure participants located in different countries. Twelve participants in six groups were recruited to play an Easy and a Difficult nonverbal facial communication game, and their EEG signals were analyzed using two-layer empirical mode decomposition. Phase-locking values were obtained for frequency-modulated and amplitude-modulated intrinsic mode functions, and comparisons were made between the Easy and Difficult conditions. The results showed that as the number of execution times increased, the phase-locking values in the frontal cortex were significantly higher in both the alpha and beta bands under the Difficult condition. This study demonstrated inter-brain synchrony in brain waves when two participants were engaged in a more challenging nonverbal cooperative game.

Keywords: Electroencephalography, Empirical mode decomposition, Hyperscan

1. Introduction

The phrase “being on the same wavelength” typically refers to thinking or behaving similarly, although it does not specifically refer to brainwaves. For successful cooperation, two individuals can exhibit synchronized neural activity during the cooperation of a task, known as inter-brain synchrony. This inter-brain synchrony can be measured from the simultaneous recording of neural activities from two brains. Researchers have attempted to measure inter-brain synchrony as a neural biomarker for cooperative behaviors, and they defined the inter-brain synchrony as the coupling of brainwaves measured from two individuals’ brains [1]. Synchronous neural patterns can occur when the two brains are coupled through a physical stimulus, such as light, sound, or mental pressure. Inter-brain synchrony can be caused by various factors, such as cooperation in task engagement, social interaction, emotional contagion, neural mirroring, or shared attention and perception [2]. Recent studies on social coordination tasks have found that the brainwaves of two cooperating participants show increased synchrony [3]. For instance, during the takeoff and landing phases of flying, interconnections between the brains of two pilots were denser when they worked cooperatively than during cruising [4]. Inter-brain synchrony has also been observed in many different contexts.

Inter-brain synchrony can be observed in the communication of different individuals, especially when integrating different sensory information, to achieve better communication effectiveness. Schroeder et al. (2008) conducted a study on the use of visual cues during communication, specifically the observation of mouth movements, which has been shown to enhance speech comprehension and improve brain signals in the listener's brain [5]. Stephens et al. (2010) conducted an analysis on functional magnetic resonance imaging (fMRI) data and found that successful communication results in spatially and temporally coupled neural response patterns between speakers and listeners, particularly in auditory and parietal areas, and inferior frontal gyrus (IFG). [5,6]. These enhanced neural couplings during communication are suggested to be associated with anticipatory neural responses, leading to better comprehension in communication. Additionally, Schippers et al. (2010) investigated the brain activities during the observation of gesture communication using functional MRI. They discovered the involvement of both the putative mirror neuron system (pMNS) and the ventral medial prefrontal cortex (vmPFC) in mentalizing and resonating with the gestures performed by others [7]. However, due to the space limitation of MRI, many researchers have employed electroencephalography (EEG) to achieve more flexible research designs in investigating brain activity during social communication. Dumas et al. studied inter-brain neural activities during communication using EEG and found alpha-band inter-brain synchrony (9-14 Hz) in the right centro-parietal region

[8,9]. The alpha-band synchrony was linked to social tasks [10] and interpersonal coordination [11], which demonstrates the significance of alpha-band synchrony in social communications.

Brain synchrony has also been found in other EEG frequency bands during the execution of various cooperative tasks. Babiloni et al. found a correlation between alpha waves in the IFG and empathy during joint music making [12,13]. Sanger et al. (2013) discovered increased directed connection strengths within and between brains in the alpha and beta frequency bands when the leader and followers were engaged in playing music [14]. Szymanski et al. (2017) discovered the delta-band synchrony was linked to better task performance during joint visual search [2]. Mu et al. (2017) discovered the gamma-band synchrony was associated with better coordination during threat detection [15]. Although there have been some studies on brain synchrony related to speech, mirroring movements, and social movement interaction, the EEG research on brain synchrony during communication using facial expressions has not been studied yet. Therefore, the purpose of this study is to investigate the inter-brain synchrony during communication based on facial expressions.

This study aimed to design a novel cooperative game based on facial expressions to investigate the inter-brain synchrony of social communication. Cooperative games are commonly utilized in a more formal setting to study social interaction [16,17]. Multiple studies using EEG have utilized cooperative games to investigate the neural basis of social interaction [3,17,18]. Theory of mind (ToM), which involves reasoning about others' beliefs, intentions, and desires, is an essential cognitive process in social interaction [16]. The structures that support ToM are referred to as mentalizing networks, including the medial prefrontal cortex (mPFC) [7,16], the temporo-parietal junction (TPJ) [16,19,20], and the anterior cingulate cortex (ACC) [16,17,21]. In some cooperative games, specific parts of the mentalizing network appear to synchronize. Increased connections have been shown between the brains in the prefrontal cortex (PFC) and ACC during cooperation across multiple frequency bands [17]. Similarly, greater alpha and beta synchronization was demonstrated in the PFC and precentral regions during a cooperative game task when participants faced each other compared to when they could not see each other [22]. Further, greater beta and theta band synchronization was found in the PFC and orbitofrontal regions during cooperation [3,18], and PFC alpha connectivity was shown to be greater during successful periods than during unsuccessful periods in a cooperative card game [23]. Based on the aforementioned studies, communication and face-to-face interactions have increased in synchronization within the PFC, ACC, and TPJ [22,24] across various frequency bands. This synchrony appears to be linked to tasks involving the consideration of each other's intentions, such as ToM tasks. However, the aforementioned studies analyzed brainwave coherence in specific frequency bands using linear approaches (e.g. Fourier transform), which may overlook the nonlinear and non-stationary characteristics of brain waves. Therefore, investigating brainwave synchrony using nonlinear signal processing approaches may provide an opportunity to shed light on the mechanisms of inter-brain synchrony.

In this study, a collaborative game utilizing facial expressions as a form of nonverbal communication was proposed to examine the level of inter-brain synchrony. Considering the nonlinear and non-stationary characteristics of brain waves, we used a two-layer empirical mode decomposition (EMD) method to extract the brain wave signals in the alpha and beta bands, and focused on exploring the degree of brainwave synchrony under two different levels of game difficulty. The EMD-based method is an effective approach for noise removal that can be applied to EEG systems with fewer channels [25,26]. In comparison to other multichannel methods, such as independent component analysis, which requires the number of EEG channels to be greater than the number of signal sources. The intrinsic mode functions (IMFs) obtained through EMD are decomposed from a specific channel; thus, the proposed EMD-based method allows the EEG features in each channel can be separately analyzed and compared. To explore the level of inter-brain synchrony, we utilized the phase-locking value (PLV) to analyze the phase synchrony between IMFs. Taking advantage of the two-layer EMD in extracting the features of frequency modulation (FM) and amplitude modulation (AM) [25,27], we were able to compute PLV on the FM and AM signals. By analyzing the FM and AM characteristics of EEG through EMD, the two-layer EMD analysis method can extract the FM and AM characteristics of EEG, thereby providing more comprehensive information on inter-brain synchrony in the PLV analysis method. The organization of this paper is as follows: In Section II, the brainwave synchrony approach is presented; in section III, the experimental results are listed; and Sections IV and V present the discussion and conclusions.

2. Materials and Methods

2.1. Subjects and Experiments

This study recruited 12 participants who were between 20 and 25 years old and had no history of neurological diseases that might affect their brain function. The study comprised six groups, with each group consisting of one Mandarin-speaking student and one Russian-speaking student. The Mandarin-speaking students were from National Central University in Taiwan, while the Russian-speaking students were from the Pavlov Institute of Physiology, Russian Academy of Sciences. In this study, each pair of participants completed two sets of games. The conditions of the games alternated between having a "visible target" on the monitor

of the “Questioner” and not having one. The two sets of studies were identical except for the roles of “Questioner” and “Guesser” which were reversed in the second set. All subjects gave informed consent, and the study was approved by the Ethics Committee of the Institutional Review Board, Taipei Veterans General Hospital, Taiwan (TYGH108042).

In this study, EEG signals were recorded using an eight-channel dry-electrode EEG recorder (InMEX EEG, WellFulfill Co., Taiwan), as shown in Fig. 1. The recorder includes an integrated analog front-end chip ADS1299 (Texas Instruments Co.), an ultralow-power microcontroller MSP430F5438a (Texas Instrument, United States), and a Bluetooth module for wireless data transmission. Dry EEG electrodes, each constructed with 10 spring-loaded copper pins and designed in disk shape with a 1 cm diameter, were placed on F3, Fz, F4, C3, C4, P3, Pz, and P4 positions according to the international 10-20 system [28]. The EEG signals were pre-filtered (3rd-order Butterworth IIR filter) within 0.5-50 Hz and recorded at 1 kHz with 24-bit resolution. Figure 2 shows the experimental setup of this study. Both participants were equipped with an eight-channel dry-electrode EEG recorder and collaborated in a game through a video conferencing system using Google Meet. The video conferencing system displayed a grid that was used during the cooperative game. During the cooperative game, participants guessed the answers by clicking on boxes on the screen using a mouse. During the cooperative game, the participants' brainwave data were transmitted via WI-FI to the server for subsequent analysis.



Fig. 1. The eight-channel wireless EEG system. The system comprises three components: (a) The EEG hat, (b) The dry EEG electrode used to mount on the EEG hat, and (c) The eight-channel InMEX EEG recorder.

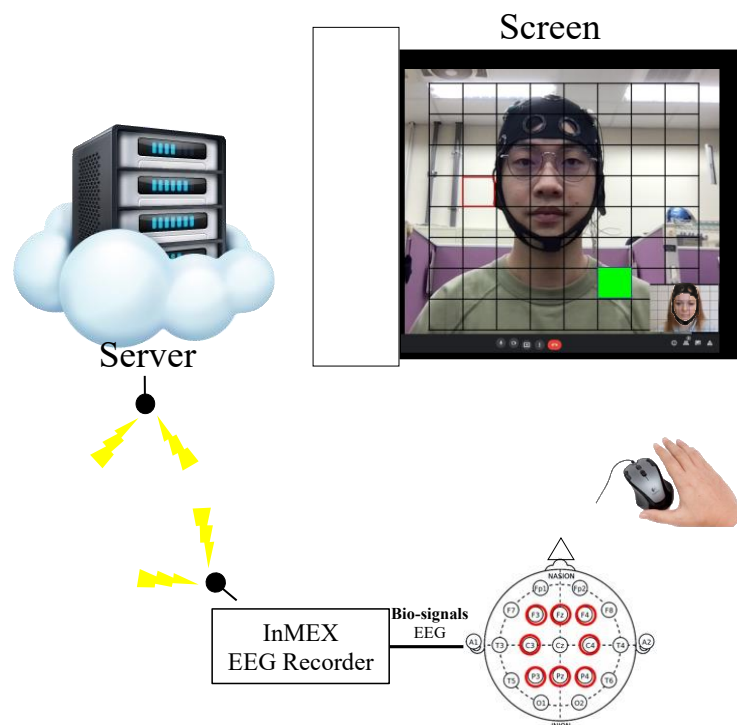


Fig. 2. The system architecture of our experiments setup. Both participants were equipped with an eight-channel dry-electrode EEG recorder. They were asked to collaborate in playing a game through a video conferencing system using Google Meet. The “Guesser” had to guess the answers set by the “Questioner” (the green box) by clicking on the boxes.

2.2. Nonverbal based Facial Communication Game

A remote interactive cooperative game was developed, which included two roles: “Questioner” and “Guesser”. The program was installed in Taiwan and Russia, and remote video connections were made through a paid VPN service, while the game was simultaneously played. Before the game started, the computer’s IP address and port number were entered, and the network transmission latency was tested. To avoid network congestion, we chose to play the game from 3 am to 5 am Taiwan time and 10 pm to 12 am Russia time. All connections used a paid VPN and required a transmission latency of less than 100 ms.

This game allows two players to play the roles of either the “Questioner” or the “Guesser”. When successfully connected to the game program, the same grid was displayed on the screens of both players, but only the Questioner’s screen displayed the target (represented by a green rectangle). The green rectangle did not appear on the Guesser’s screen. To find the target, the Guesser clicked between the cells while observing the Questioner’s screen, based on nonverbal cues (such as facial expressions). In this study, participants who engaged in facial communication were only able to judge the correct orientation and position of the grid by observing the facial expressions of the other person. The participants were instructed not to communicate through with hints through eye or mouth movements. As shown in Fig. 3 for the visual representation of the grids generated by the program, each pair of participants was requested to play the 8×8 (easy) and 20×20 (difficult) grid games. Each pair of participants was required to perform the easy (8×8 grids) and difficult (20×20 grids) games ten times. Throughout the game, brainwave signals were synchronously measured.

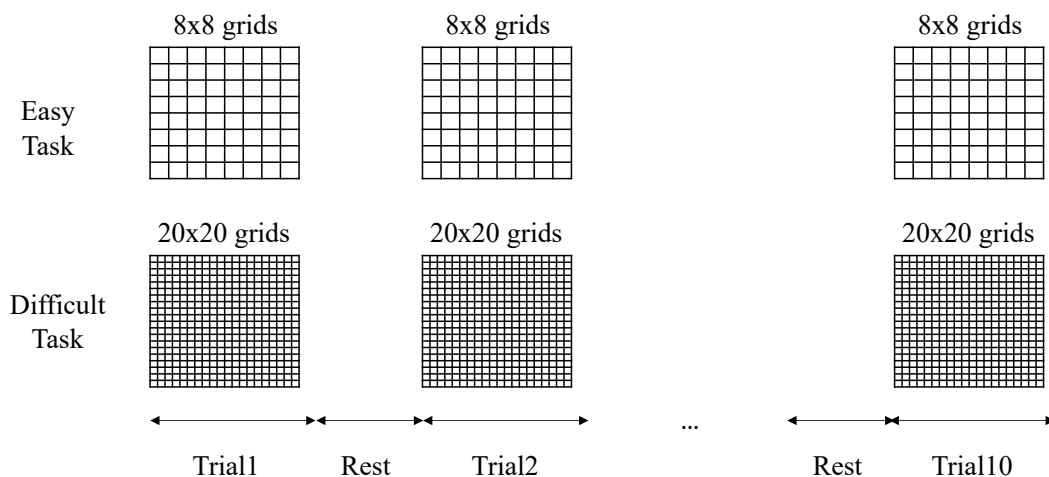


Fig. 3. Each pair of the participants were asked to play an Easy and a Difficult nonverbal facial communication game. The Easy game was set up with 8×8 grids, while the Difficult game was set up with 20×20 grids.

2.3. Signal Processing of EEG Signals

In this study, we used the game time as the event mark on the time axis of the EEG data, with the aim of identifying the EEG characteristics related to the response event during the continuous answering process. We extracted the EEG data from the beginning to the end of each trial (as shown in Fig. 4) and conducted a signal analysis using a two-layer EMD [29]. The two-layer EMD is a non-linear filtering tool that can remove unnecessary noise and effectively analyze the non-linear and non-stationary properties of the EEG. In our previous studies, we used the two-layer EMD technique to analyze the amplitude modulation and frequency modulation characteristics of the EEG in the motor area [25].

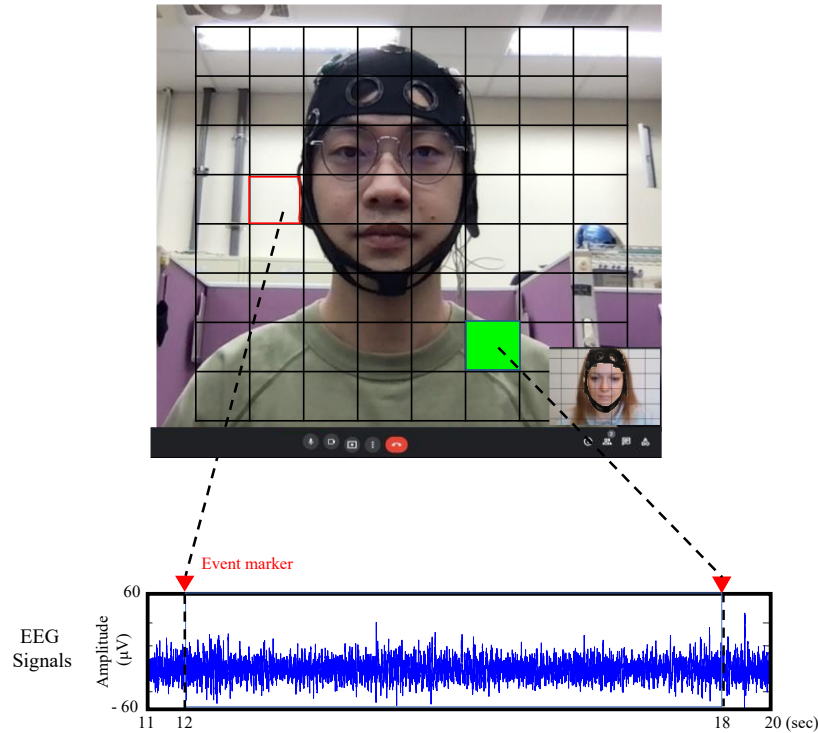


Fig. 4. The eight-channel EEG data were recorded continuously, and EEG segments (indicated by shaded pink color) were extracted based on the event markers (marked by inverted red triangle), from the beginning to the end of each trial. These segments were then subjected to subsequent two-layer empirical mode decomposition (EMD) processing.

The EEG signal was first separated into a set of FM IMFs, referred to as IMF_{FMS} , in the first layer. This was achieved by using a dyadic filter bank to effectively classify the frequency characteristics into distinct FM modes. The upper envelopes of these IMF_{FMS} were then decomposed into a group of AM IMFs, known as IMF_{AMS} , in the second layer of the EMD. The two-layer EMD allowed for the analysis of inter-mode interactions among the IMF_{FMS} . To determine the carrier-wave frequency FM and envelope-modulation frequency AM frequencies, an instantaneous frequency analysis technique was employed to calculate the instantaneous frequencies of both IMF_{FMS} and IMF_{AMS} . In this study, the IMF_{FMS} and their corresponding IMF_{AMS} located in the alpha (8 Hz - 12 Hz) and beta (12 - 20 Hz) bands were used for subsequent analysis. The EEG features decomposed from the two-layer EMD were also compared to the results obtained using the traditional filtering method (three-order Butterworth IIR filter).

Figure 5 shows the demonstration case of a 10-s EEG data using the two-layer EMD analysis in this study. First, the 10 s EEG signal from subject S1 was processed by the first layer EMD to obtain six sets of IMF_{FMS} . The center frequencies of these six IMF_{FMS} are 69.08, 21.97, 15.80, 8.98, 4.55, and 2.30 Hz. To analyze the envelope modulation in IMF_{FMS} located in the alpha and beta bands, we conducted a second layer EMD on the third (with a center frequency of 15.80 Hz) and fourth (with a center frequency of 8.98 Hz) IMF_{FMS} , and obtained their corresponding IMF_{AMS} .

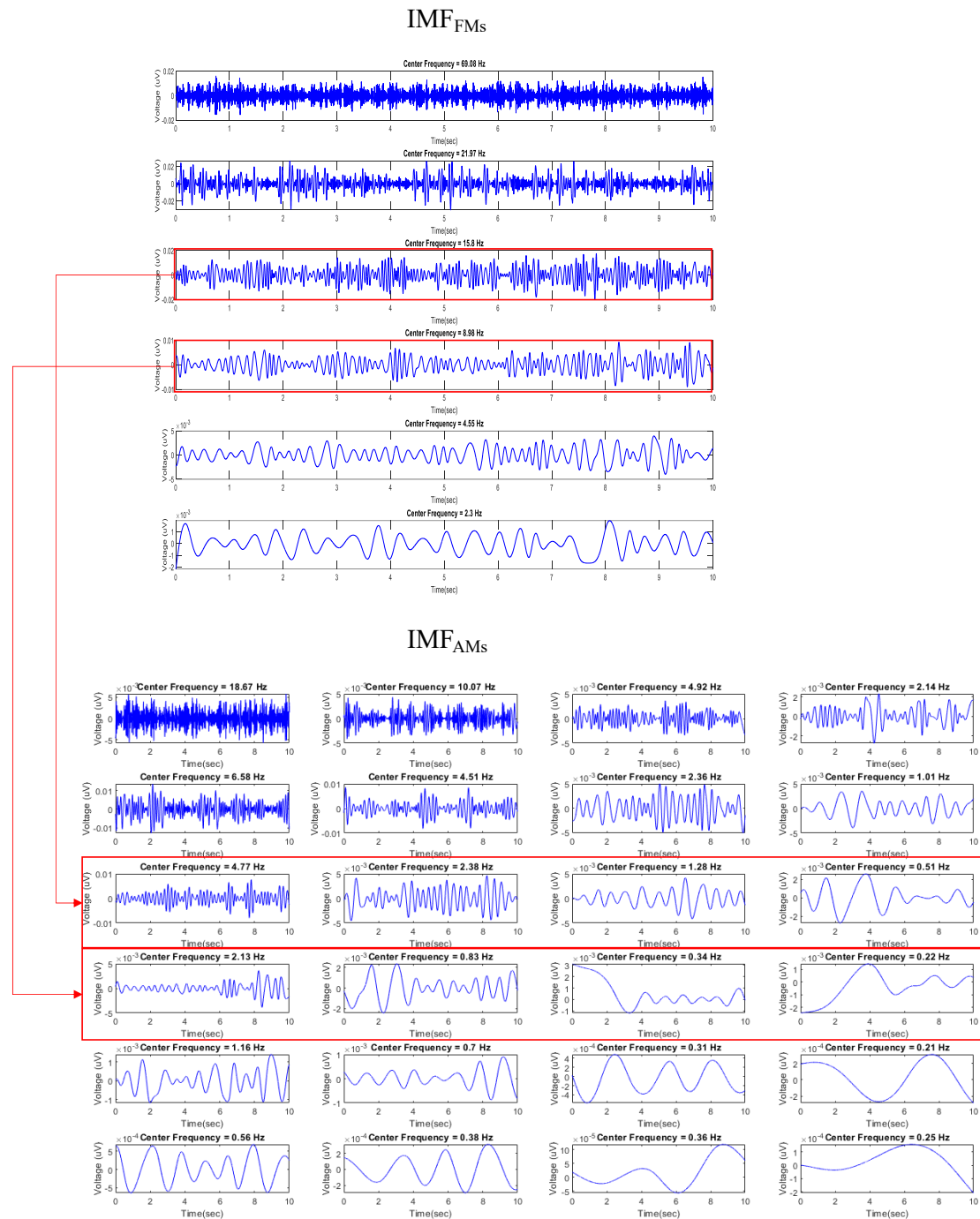


Fig. 5. The illustration of an EEG segment processed using the two-layer EMD. The IMFFMs were extracted in the first-layer EMD, and the IMFFMs located within alpha-band (center frequency at 8.98Hz) and beta-band (center frequency at 15.8Hz) were selected and subsequently processed by the second-layer EMD to obtain IMFAMs.

2.3. Signal Processing of EEG Signals

2.4. Phase Locking Value

To calculate the PLV between two simultaneously collected signals, $x_1(t_l)$ and $x_2(t_l)$ ($l = 1, 2, \dots, N$) of length N , their corresponding instantaneous phase series, $\phi_1(t_l)$ and $\phi_2(t_l)$, are first computed using Hilbert transformation [30]. The PLV, originally proposed by Lachaux *et al.* [31], is then defined as the measure of the consistency of the phase difference between the two signals. The equation of PLV between $x_1(t_l)$ and $x_2(t_l)$ is shown below.

$$PLV_{12} = \frac{1}{N} \left| \sum_{l=1}^N \exp(j(\Delta\phi_{12}(t_l))) \right|, (1)$$

where $\Delta\phi_{12}(t_l) = \phi_1(t_l) - \phi_2(t_l)$ is the instantaneous phase difference between x_1 and x_2 , and j represents the imaginary unit. The resulting PLV ranges between 0 and 1, with 0 indicating a random distribution of $\Delta\phi$ on a unity circle (i.e., no phase locking) and 1 indicating a constant $\Delta\phi$ (i.e., perfect phase locking).

In this study, the PLVs were obtained from the IMF_{FMS} and IMF_{AMS} located at the alpha and beta bands of each trial.

2.5. Statistical Analysis

In this study, each participant went through 10 rounds of Easy-condition and Difficult-condition games. The PLVs were calculated, and the differences in the PLVs between Easy-condition and Difficult-condition for the same trial number were tested. The Wilcoxon signed-rank test was used to analyze whether there were significant differences in the PLVs between the Easy-condition and Difficult-condition for the same trial number.

3. Results

Figure 6 shows the average time taken by six participants to complete each trial in the Easy and Difficult-conditions of the game. As shown in the figure the average completion time for the Difficult-condition was significantly greater than that for the Easy-condition in each trial. The averaged completion time for Trial 1 and Trial 10 in Difficult-condition were 23.34 s and 14.56 s, respectively. Although in the Easy-condition, there was not much change in the completion time of the game across execution trials, in the Difficult-condition, the execution time of the game was significantly shortened with an increase in the execution trial number. Further, the completion time decreased with an increase in the trial number, indicating an improvement in the participants' nonverbal communication abilities. In our experiment, the completion time of Trial 6 or more was significantly shorter than the completion time of Trial 1, demonstrating that training can enhance nonverbal communication ability in our nonverbal communication game.

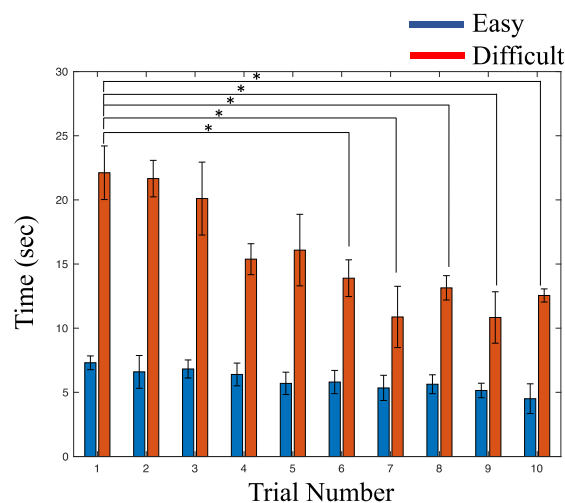


Fig. 6. The average time of completing each trial taken by the six pair of participants in the Easy and Difficult conditions of the game.

* indicates significant difference between conditions at $p < 0.05$.

Figure 7 shows the comparison of the PLVs and EEG topographic maps between Easy and Difficult-conditions in Trial 1 and Trial 10 within the frequency range of 8 - 12 Hz using the traditional filtering method (denoted as EEG_{filt, alpha}). In Fig. 7(a), the PLVs of Easy and Difficult-conditions in Trial 1 showed no significant difference in any of the eight EEG channels. Similarly, in Fig. 7(b) for Trial 10, no significant differences were observed in the PLVs between the Easy and Difficult-conditions in any of the eight EEG channels except for F3, Fz, and F4 channels, which showed significant differences ($p < 0.01$, Wilcoxon signed-rank test) in the Difficult-condition. The red box in the EEG topographic maps of alpha band indicates significant differences in the PLV for the F3, Fz, and F4 channels under the Difficult condition. Figure 8 shows the comparison of the PLV and EEG topographic maps between Easy and Difficult-conditions in Trial1 and Trial10 within the frequency range of 12-20 Hz using traditional filtering method (denoted as EEG_{filt, beta}). In Fig. 8(a), the PLVs of Easy and Difficult-conditions in Trial1 show no

significant difference in any of the eight EEG channels. However, in Fig. 8(b), for Trial 10 after filtering in the beta-band, only the F3 channel showed a significant difference ($p < 0.05$, Wilcoxon signed-rank test) in the Difficult-condition compared to the Easy-condition, while other EEG channels showed no significant differences. In the EEG topographic maps of beta band, the red box indicates significant differences in the PLV for the F3 channel under the Difficult condition. Fig. 7 and Fig. 8 showed that in the alpha band, F3, Fz, and F4, as well as F3 in the beta band, were the main regions responsible for learning nonverbal communication between the two individuals.

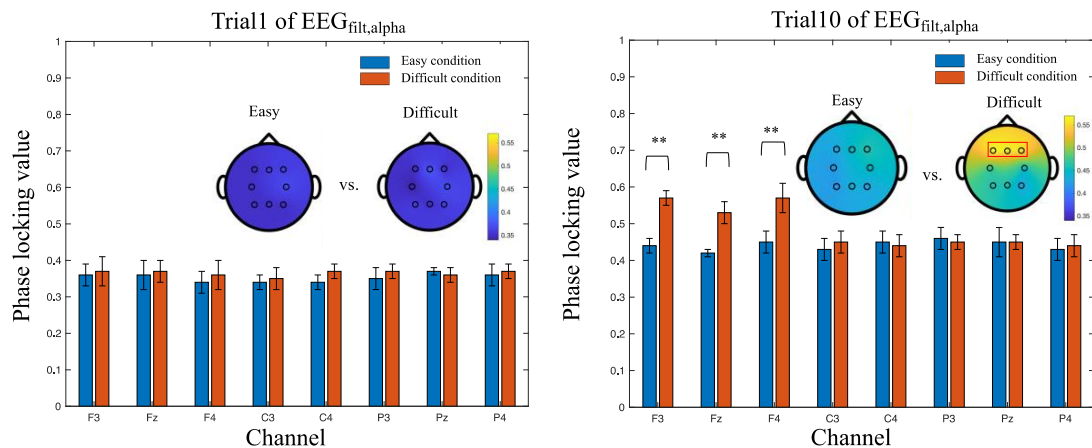


Fig. 7. The comparisons of PLVs and their EEG topographic maps for EEG_{filt, alpha} between Easy and Difficult-conditions during Trial1 and Trail10. (a) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial1. (b) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial10. ** indicates significant difference between conditions at $p < 0.01$.

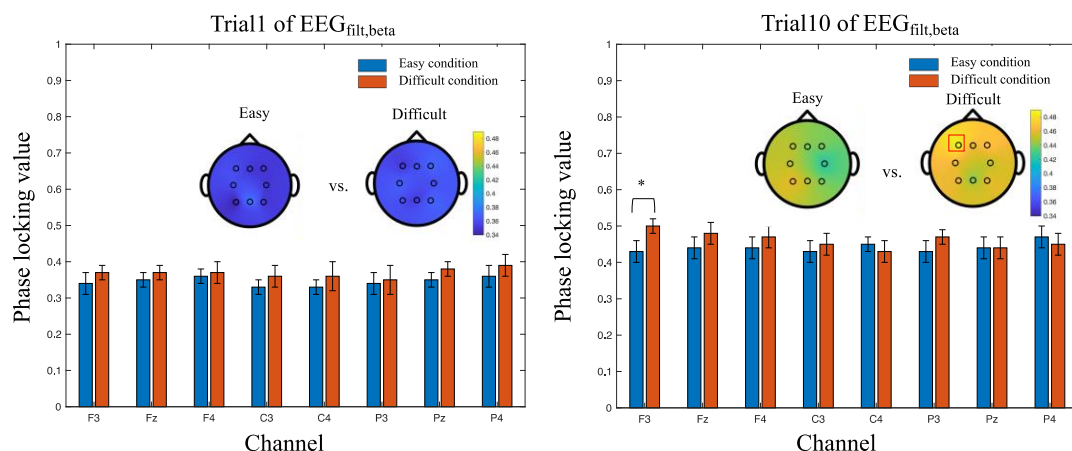


Fig. 8. The comparisons of PLVs and their EEG topographic maps for EEG_{filt, beta} between Easy and Difficult-conditions during Trial1 and Trail10. (a) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial1. (b) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial10. * indicates significant difference between conditions at $p < 0.05$.

Figure 9 shows the PLV comparison and EEG topographic maps of alpha-band IMF_{FM} brainwave signals in Trial 1 and Trial 10. Figure 9(a) displays the PLVs under the Easy and Difficult-conditions in Trial1, which showed no significant difference in PLVs between Difficult and Easy-conditions across the eight brainwave channels. Figure 9(b) shows the PLVs under the Easy and Difficult-conditions in Trial 10, with the PLVs of the Difficult-condition being significantly higher than that of the Easy-condition in channels F3, Fz, and F4 ($p < 0.01$, Wilcoxon signed-rank test). The red box in the EEG topographic maps of alpha-band IMF_{FM}s indicates significant differences in the PLV for the F3, Fz, and F4 channels under the Difficult condition. However, there was still no significant difference in the remaining brainwave channels. Figure 10 presents the PLV comparison and EEG topographic maps of beta band IMF_{FM} brainwave signals in Trial 1 and Trial 10. Figure 10(a) shows the PLVs under the Easy and Difficult-conditions in Trial 1, with no significant between PLVs of Difficult and Easy-conditions across the eight brainwave channels. Figure 10(b) displays the PLVs under the Easy and Difficult-conditions in Trial10, where the Difficult-condition's PLVs is significantly higher

than that of the Easy-condition in channels F3, Fz and F4 ($p < 0.05$ at F3 and Fz channels; $p < 0.01$ at F4 channel, Wilcoxon signed-rank test). In the EEG topographic maps of beta band IMF_{FM}s, the red box indicates significant differences in the PLVs for the F3, Fz, and F4 channels in the Difficult condition. There was no significant difference in the other brainwave channels. Notably as shown in Fig. 10(b), there were more brainwave channels (F3, Fz, and F4) showing significant differences. This may be because the PLVs were easily affected by noise, whereas the two-layer EMD processing improved signal quality, resulting in consistent analysis results between the beta band analysis in Fig. 10(b) and the alpha band analysis in Fig. 10(a).

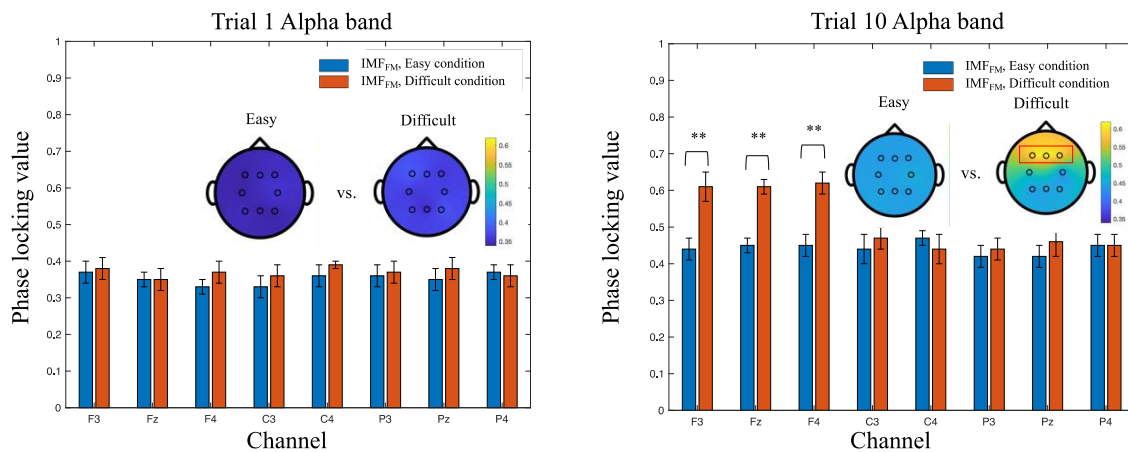


Fig. 9. The comparisons of PLVs and their EEG topographic maps for alpha-band IMF_{FM}s between Easy and Difficult-conditions during Trial1 and Trail10. (a) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial1. (b) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial10. ** indicates significant difference between conditions at $p < 0.01$.

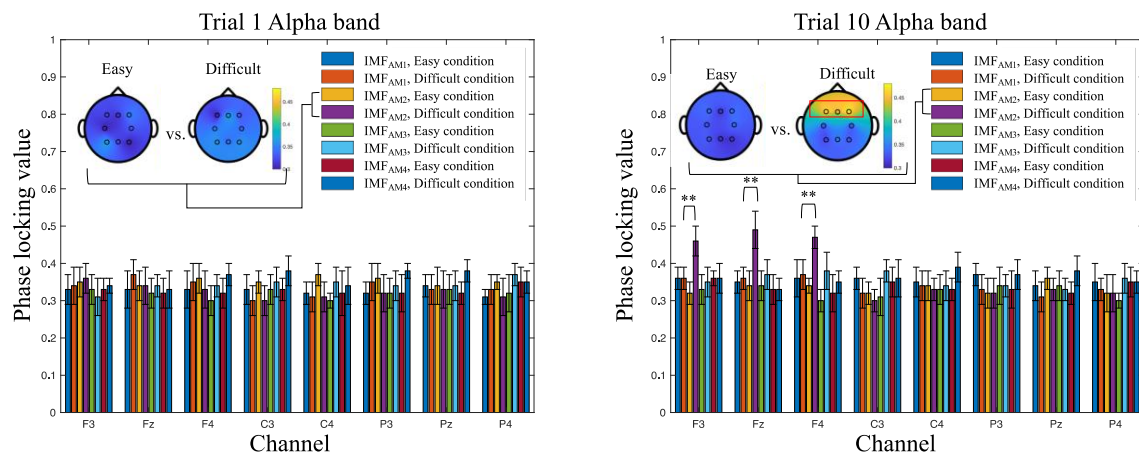


Fig. 10. The comparisons of PLVs for IMF_{AM}s extracted from alpha-band IMF_{FM}s between Easy and Difficult conditions during Trial1 and Trial10. (a) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial1. (b) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial10. The illustrated EEG topographic maps were generated based on the PLV values of IMF_{AM2}. ** indicates significant difference between conditions at $p < 0.01$.

Figure 11 shows the PLV comparison of four sets of IMF_{AM}s belonging to the alpha-band IMF_{FM} in Trial 1 and Trial 10. In Fig. 11(a), the PLVs of all IMF_{AM}s under Easy and Difficult-conditions in Trial1 are compared, and there is no significant difference between the Difficult and Easy-conditions in all the eight brainwave channels. In Fig. 11(b), the PLVs of all IMF_{AM}s under Easy and Difficult-conditions in Trial10 are compared, and the PLVs of IMF_{AM2} under the Difficult-condition are significantly higher than that under the Easy-condition in the F3, Fz, and F4 channels ($p < 0.01$, Wilcoxon signed-rank test). The averaged center frequency of IMF_{AM2} in the alpha band for all subjects was 0.76 ± 0.13 Hz. There was no significant difference in the remaining brainwave channels. Moreover, the PLVs of the IMF_{AM2} in the alpha band are shown on the EEG topographic maps, and the red box indicates significant differences in the PLV for the F3, Fz, and F4 channels in the Difficult condition. Figure 12 shows the PLVs

comparison of four sets of IMF_{AMS} belonging to beta-band IMF_{FM} in Trial 1 and Trial 10. In Fig. 12(a), the PLVs of all the IMF_{AMS} under Easy and Difficult-conditions in Trial1 are compared, and there was no significant difference between the Difficult and Easy-conditions in all eight brainwave channels. In Fig. 12(b), the PLVs of all IMF_{AMS} under Easy and Difficult-conditions in Trial 10 are compared, and the PLV of IMF_{AM3} under the Difficult-condition were significantly higher than that under the Easy-condition in the F3, Fz, and F4 channels ($p < 0.01$, Wilcoxon signed-rank test). The averaged center frequency of IMF_{AM3} in beta-band over all subjects was 1.14 ± 0.15 Hz. The EEG topographic maps show the PLVs of IMF_{AM3} in the beta band, with the red box indicating significant differences in the PLV for the F3, Fz, and F4 channels in the Difficult-condition. However, there is no significant difference in the remaining brainwave channels. Therefore, based on Fig. 11 and Fig. 12, we can conclude that in the Difficult-condition, the participant's ability to learn nonverbal communication improved with an increase in the number of test trials. The main brain regions involved in this learning process were the bilateral frontal areas (F3, Fz, and F4).

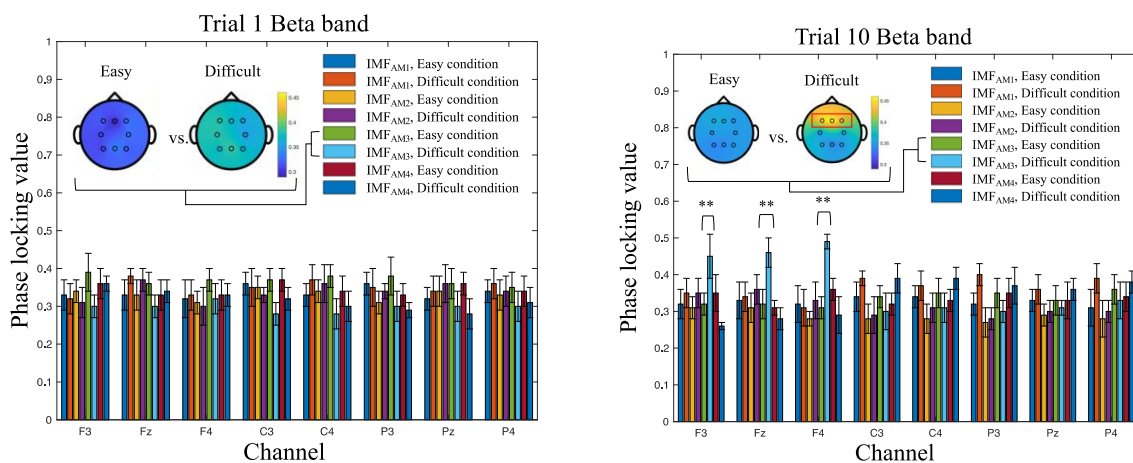


Fig. 11. The comparisons of PLVs for IMFAMs extracted from beta-band IMFFMs between Easy and Difficult conditions during Trial1 and Trial10. (a) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial1. (b) The PLV and EEG topographic maps between Easy and Difficult conditions in Trial10. The illustrated EEG topographic maps were generated based on the PLV values of IMFAM3. ** indicates significant difference between conditions at $p < 0.01$.

4. Discussions

The salient feature of this study is the design of a face-to-face nonverbal collaborative task and the application of this game to investigate inter-brain synchrony between two individuals with different linguistic backgrounds. Previous research has primarily focused on the connections between inter-brain synchrony and positive social outcomes through verbal [24,32,33] and bodily communication [7–9], with only limited research on inter-brain synchrony in face-to-face situations involving nonverbal interaction. Therefore, we expected that the participants in this study's game would exhibit subtle but sufficient signals to activate the mechanism for investigating brainwave synchrony.

We found that the completion time of the Difficult cooperative game decreased significantly as the number of trials increased, whereas the completion time of the easy cooperative game did not show significant changes (Fig. 6). During the Difficult game, participants needed to spend more time communicating through facial expressions. As the number of trials increased, the two participants gradually understood each other's communication cues, resulting in a decrease in game time. However, there was no significant difference in the game completion time for the last three trials, as the participants found a stable way to communicate through facial expressions. By contrast, since the difficulty of the easy cooperative game was relatively simple, the participants did not need to spend too much effort to bridge their communication which resulted in a more consistent completion time.

This study focused on examining the level of synchrony between the brains of two individuals playing collaborative games with varying levels of difficulty. Brain synchrony has been shown to be associated with interactive decision-making in the brain [34]. In social and cooperative interactions, previous studies have demonstrated the involvement of the alpha band EEG in integrating and processing social information [35,36], and its correlation with effective social coordination [37,38]. Brain interconnectivity in the prefrontal and central frontal regions has been found in various social interactions, such as cooperation [39], imitation [40], communication [41], and musical interaction [42]. Many research reports have indicated that the prefrontal and anterior frontal regions are associated with social cognition [42,43] and play an important role in the decision-making process.

The central prefrontal cortex is activated when participants infer, model, and predict the intentions of others [42,44,45]. Sinha *et al.* (2016) analyzed brain synchrony in collaborative and competitive settings, both in physical and virtual spaces, showed increased brain synchrony in the alpha and beta bands in the prefrontal region during collaboration compared to competition [46]. This effect was particularly pronounced in the virtual space. These findings revealed that the alpha and beta bands are the primary frequency bands associated with brain synchrony during collaborative processes. We found that the theta band was considered susceptible to eye movement artifacts, and that both theta and gamma bands were less responsive in terms of brain synchrony. Therefore, in this study, we primarily focused on the analysis of the alpha and beta bands.

Considering the influence of noise on traditional PLV calculations for brain synchrony, we adopted a two-layer EMD approach. In the first layer of EMD, brainwave signals were decomposed into several meaningful frequency bands. In the second layer of EMD, IMF_{AMS} extracted from IMF_{FMS} were analyzed to investigate the presence of phase locking. The purpose of calculating the phase-locking relationship in IMF_{AMS} is to extract meaningful signal envelope information from IMF_{FMS} and compute their phase-amplitude coupling (PAC). In the first layer of EMD, we utilize EMD for feature extraction, allowing signals with oscillatory activity to be well-preserved and reducing interference from external noise sources. The advantages of our two-layer EMD approach can be observed in the results, compared to those obtained from the traditional filtering method. Comparing the EEG_{filt, alpha} with the IMF_{FMS} in alpha band, both the EEG_{filt, alpha} and alpha-band IMF_{FMS} of frontal channels (F3, Fz, and F4) showed significantly higher PLVs in the Difficult-condition than those in the Easy-condition. In the beta band, only the EEG_{filt, beta} at F3 showed a significant increase in the Difficult-condition compared to the Easy-condition. By contrast, the beta-band IMF_{FMS} located at F3, Fz and F4 exhibited a significant increase in the Difficult-condition compared to the Easy-condition. EMD is an adaptive data-driven processing method that is suitable for decomposing measured signals into meaningful oscillatory modes. It has a greater ability to suppress noise during the extraction of oscillatory activity, leading to an effective improvement in the signal-to-noise ratio (SNR) [47,48]. Consequently, the EMD analysis enabled the observation of brain synchrony in the Fz and F4 channels, which was not seen in the results obtained from the traditional filtering method.

Other researchers have also found that frontal alpha synchronization showed increased values when cooperative games entered a successful tacit coordination phase [3,17,22,23] which is consistent with our findings. Figure 10(b) shows that the beta-band IMF_{FM} located at the F3, Fz and F4 positions showed greater PLVs in Difficult-condition than in the Easy-condition. This is also consistent with the findings proposed by Jahng *et al.* [22], which reported greater beta-band synchronization in the prefrontal cortex and precentral regions during a cooperative game task when participants faced each other compared to when they could not see each other, which is echoed by the results of the beta-band synchronization analysis in this study.

One noteworthy feature of this study is the finding of phase-synchrony in IMF_{AMS}. In [49], the spectral coherence measure reportedly deviated substantially from the expected phase locking. We extracted IMF_{AM} features from the envelopes of IMF_{FMS} and calculated their PLVs, which essentially measure the PAC within the same frequency band across different participants. PAC has previously been applied to sensory signal detection [50], attentional selection [51], and memory processes [52,53] to emphasize cross-frequency coupling features. Additionally, some studies have attempted to analyze brain waves during cooperative tasks using spectral coherence but found that spectral coherence often fails to robustly reflect changes in synchrony-mediated information flow between neural networks. Therefore, many researchers suggest reconstructing instantaneous phases and analyzing the PLVs between different signals.

This study demonstrated the phase synchrony of IMF_{AMS} among different participants. Figure 11(b) shows that the IMF_{AM2} of the alpha-band IMF_{FM} at the F3, Fz, and F4 positions showed significantly greater PLVs than that under the Easy-condition. Similarly, Fig. 12(b) shows that the IMF_{AM3} of the beta-band IMF_{FM} located at F3, Fz, and F4 positions had greater PLVs under the Difficult-condition than that under the Easy-condition. Further investigation of the frequency involved in phase locking within AM brainwaves. In the alpha-band, the IMF_{AM2} with a center frequency of 0.76 ± 0.13 Hz exhibited the most significant increase in PLV during the Difficult-condition compared to that in the Easy-condition. In the beta-band, the IMF_{AM3} with a center frequency of 1.14 ± 0.15 Hz showed a significant increase in PLV in the Difficult-condition compared to the Easy-condition. This might demonstrate that the brainwave synchrony operates through the inter-scale coupling of brain signals. When participants are engaged in a more challenging cooperative game, their brains require many activation and decoupling processes, resulting in increased brainwave synchrony in the frontal cortex. Considering that some studies suggest that working memory load may interfere with brainwave synchrony [], we designed a game that only requires face-to-face nonverbal communication, without complex verbal communication or body behavior. With this tacit coordination task, it is possible to separate individuals' neural signals related to coordination from those related to other social cues. In [54], brainwave coherence was found to be unaffected in a collaborative task with a high cognitive load, even though the coordination performance was reduced. This is consistent with our research results which indicate that the brainwave synchrony features in IMF_{AMS} may come more from the collaborative task of the paired participants than from the working memory load.

5. Conclusions

This study designed a novel face-to-face nonverbal communication collaborative game and aimed to explore the brainwave characteristics of inter-brain synchrony. Several key findings were found in this face-to-face nonverbal communication study. First, our novel face-to-face nonverbal communication collaborative game that enabled the participants to engage in face-to-face collaboration tasks without the interference of verbal interaction. Second, we used traditional methods to extract the brainwave features in the alpha and beta bands, revealing frequency-dependent inter-brain synchrony in the prefrontal brain region. Third, we employed a two-layer EMD to extract the IMF_{FMS} and IMF_{AMS} of the brainwaves, demonstrating inter-brain synchrony was found in the IMF_{FMS} of the alpha and beta bands, as well as in their IMF_{AMS}. This indicates important information regarding inter-brain synchrony in FM and AM modulation signals during the playing of nonverbal communication games. Fourth, we showed that the brain synchrony at the frontal region can be enhanced with increase in collaboration trials. Fifth, our findings indicate a positive correlation between the level of inter-brain synchrony in the frontal area and the challenging level of the cooperative game, which shows the important role of the frontal area in human nonverbal communication tasks. In future research, more advanced brain imaging and brain connectivity technologies will be adopted to explore the subtle dynamics of operation mechanism of inter-brain synchrony in this nonverbal communication study. One limitation of the two-layer EMD method is its high computational complexity. In future studies, advanced decomposition methods, such as variational mode decomposition (VMD) [55] and successive variational mode decomposition (SVMD)[56], can be considered as they offer more efficient feature extraction and lower computational complexity. Further, one aspect worth considering in the future is the contribution of racial and cultural differences, which was not taken into account in this study. More research is needed to investigate the issues of cultural diversity and to explore variations among different cultures.

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