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# Learning curve of a short time neurofeedback training: Reflection of brain network dynamics based on phase locking value

Ze Wang, Chi Man Wong, Wenya Nan, Qi Tang, Agostinho C. Rosa, Peng Xu, and Feng Wan

***Abstract*—Neurofeedback (NF) training is a type of online biofeedback in which neural activity is measured and provided to the participant in real time to facilitate the top-down control of specific activation patterns. To improve the training efficiency, an investigation on the learning of EEG regulation and effect on neural activity during NF is critical. This paper attempts to analyze the learning curve and the dynamics of the phase locking value (PLV)-based brain network for a short time EEG-based NF, in which 28 participants carried out alpha down-regulating NF training in 2 consecutive days. The results reveal that participants could successfully construct the related learning network to achieve the training goals in the first day training and the beginning of the second day training. Moreover, the learning plateaus were discovered from the results of the relative amplitude and the functional brain network in the middle of the second day training. These findings could be helpful for better understanding of the learning process in NF from the functional connectivity viewpoint and would contribute to building a more efficient learning protocol for NF training.**

***Index Terms*—Neurofeedback training, Alpha down-regulation, Learning curve, Functional brain network dynamics, Phase locking value.**

## I. Introduction

NEUROFEEDBACK (NF) training is a psychophysiological procedure in which a closed-loop training technique is applied to help participants learn the self-regulation of their brain activity [1]. It has demonstrated benefits on cognitive and behavioral performance as well as the treatment of symptoms in brain disorders [2]–[5]. However, as the core mechanism of the NF training, the learning of the EEG self-regulation has not been understood well. The learning curve and changes of brain networks are explored in this study to investigate the learning process during the NF training, which could be helpful for improving the training protocol. The training protocols in most recent studies require more than 20-min training time per day and need to be repeated for a number of days [6]–[8]. Such long training time easily leads participants to over-learning, fatigue, and consequently to learning plateau [1], [9]. Based on the good understanding of the learning curve during the NF training, tailored protocols with short training time could be designed to maintain participants' attentions and improve the efficiency of training by avoiding the learning plateau.

The learning curve is literally a graphic record of the performance and self-control in the field of learning [10]. For a statistical pattern of the learning curve, when the number of repetitions is increased, there is a stagnation of learning the task [11], [12]. Results of the theta/beta NF for ADHD patients illustrated an increment in performance during the beginning of the training phase, a stagnation in the middle training phase, and a subsequent increase in the final training phase [13]. A flattening of the learning curve following a strong initial improvement also reported in the NF for treating tinnitus [14]. For healthy participants, NF training has also reported a plateau with a subsequent stagnation [15]–[17]. These findings illustrate that optimizing the NF training protocol for EEG regulation by studying the brain activities to avoid the learning plateau is required and important for maximizing the efficiency of the NF training. Many recent studies focused on analyzing factors influencing the EEG learning but from the activities in isolated brain regions [18]–[21]. Some researches tried to build the relationships between the learning processes of the NF and the brain functions to explain these changes of the training parameters in the NF training [10], [22], [23]. Although these studies showed the learning curves of the NF and hypothesized these observations as the training fatigue or over-learning, they did not consider the short time NF training and did not provide evidences from the modulation of neural activation patterns to explain the learning curves and to verify their hypotheses. To fill these knowledge gaps and better reveal the underlying neural functions, the functional connectivity method is introduced.

The functional connectivity elucidates the relationship between the topological structures of the brain networks and the processes appearing in those networks [24]. Recently, the graph theories are applied in several studies to obtain better understanding of the brain functions [25]–[27]. These studies suggest that the brain networks are correlated with

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the cognitive functions, and thus provide new insights into the brain activities during the NF training. The functional connectivity has been considered as the feedback in the NF training [1], [28], [29]. Besides as the feedback method in the NF training, it also could reflect the changes of neural functions due to the NF training. Most existing studies focused on analyzing the functional connectivities in resting states and differences between functional connectivities in pre/post-training conditions, which can reveal the rough trends of the brain networks before and after NF training [25], [30]–[33]. However, the detailed dynamics during the NF training cannot be disclosed in this case. Some researchers applied the functional magnetic resonance imaging (fMRI) to investigate dynamics of functional connectivity networks during the NF training [34], [35]. However, fMRI that is known for relatively poor temporal resolution could not be able to tell the detailed brain network dynamics. On the contrary, the EEG technique can provide high temporal resolution for investigating the functional connectivity network changes [26], [36], [37]. The EEG based functional connectivity analysis has been applied to study the fatigue states [38]–[40]. Among the measurements of the synchronization in the functional connectivity analysis, the phase synchronization has a key role of studying the integration and the brain networks of reciprocal interactions and providing the neuronal machinery underlying behavioral-level phenomena [41]–[44]. The phase locking value (PLV) method can separate the phase component from the amplitude component in EEG signals and is a fundamental method of quantifying the phase synchronization [45], [46]. Compared with different synchronization measures, the PLV is mathematically simple and theoretically fast to use and implement while keeping the same informational level as more complex measures [47], [48]. In literature, the PLV has been shown to reveal important aspects of brain function in different tasks, such as emotion processing, cognitive tasks, and motor imagery [49]–[54].

The alpha brainwave plays important roles in cognitive, memory and motor functions as well as physiological conditions [55]–[57], so that the alpha NF training becomes a common protocol in literature [6], [7], [58]–[61]. Moreover, the alpha frequency band has a large inter-individual difference, and thus it was suggested to adjust the frequency band of alpha individually [57]. The protocol of the NF training applied in this study is to down-regulate the relative individual alpha frequency band (IAB) amplitude. In our previous work [62], the effects of the alpha NF training were illustrated; however, due to the limited numbers of subjects and EEG channels therein, only the BCI performances before and after the NF training were compared, and the relationships among EEG signals in different channels were not explored. This study first analyzes changes of the NF training performance to obtain a learning curve, and then focuses on analyzing changes of the phase synchrony to further verify the learning curve and exploring changes of the brain networks during this short time NF training. It can be found that different brain network patterns were evoked in different stages of NF training. Such analysis of the brain network dynamics can provide better understanding of the learning process of NF training. In the first day, the participants successfully constructed phase synchrony networks. In the second day, they can rebuild the similar brain networks quickly and enhance these brain networks before achieving the NF learning plateaus. Then, there were significant trend changes of the PLV functional connectivity network after achieving the learning plateaus. These findings can be helpful for optimizing the NF training protocols and improving the effectiveness of the NF training in future applications.

## II. Material and methods

### A. Participants

A total of 28 healthy volunteers (age: $25.1 \pm 3.2$ years; 9 females) participated in the experiment. All subjects were normal or corrected to normal vision and did not have self-reported chronic medication/substance intake/neurological diseases such as epilepsy. They signed an informed consent form before experiment and received monetary compensation for their participation after experiment. The protocol was in accordance with the Declaration of Helsinki and approved by the local Research Ethics Committee (University of Macau).

### B. EEG signal acquisition

EEG signals were collected from 16 standard Ag-AgCl electrodes placed at Fpz, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, PO3, POz, PO4, O1, Oz, and O2 based on the international EEG 10-20 system with respect to the ground electrode at the forehead and the reference electrode at the left mastoid. These signals were amplified through the g.USBamp amplifier (Guger Technologies, Graz, Austria) with a sampling rate of 256 Hz. The impedances were kept below 10 k$\Omega$. The on-line filters including a bandpass filter between 0.5 Hz and 60 Hz and a 50 Hz notch filter enabled in the amplifier as well as the off-line filters including the Butterworth bandpass filter between 0.5 Hz and 30 Hz and the blind source separation (BSS)-canonical correlation analysis (CCA) method based filter were applied to filter out the high-frequency noise, the baseline drift, the power line interference, and EOG/EMG artifacts [63], [64]. In addition, data points with absolute amplitude exceeding 75 $\mu$V were regarded as noise and removed in time domain.

### C. Experiment design

For the NF training process, each participant performed 1 session with 5 blocks per day. Each block had three 1-min trials with an interval of 5 s between two consecutive trials. Resting EEG signals were recorded before and after training. Each baseline consisted of two 1-min epochs with eye open and two 1-min epochs with eye closed. There were 10-s intervals between epochs. The protocol of the NF training is shown in Fig. 1.

Since the occipital lobe is the visual processing center of the human brain [65], [66], this study utilized the Oz channel for the visual feedback based alpha down-regulation NF training. Due to large individual differences in the alpha frequency, the NF training focused on the IAB ranged from the low transition frequency (LTF) to the high transition frequency (HTF) where

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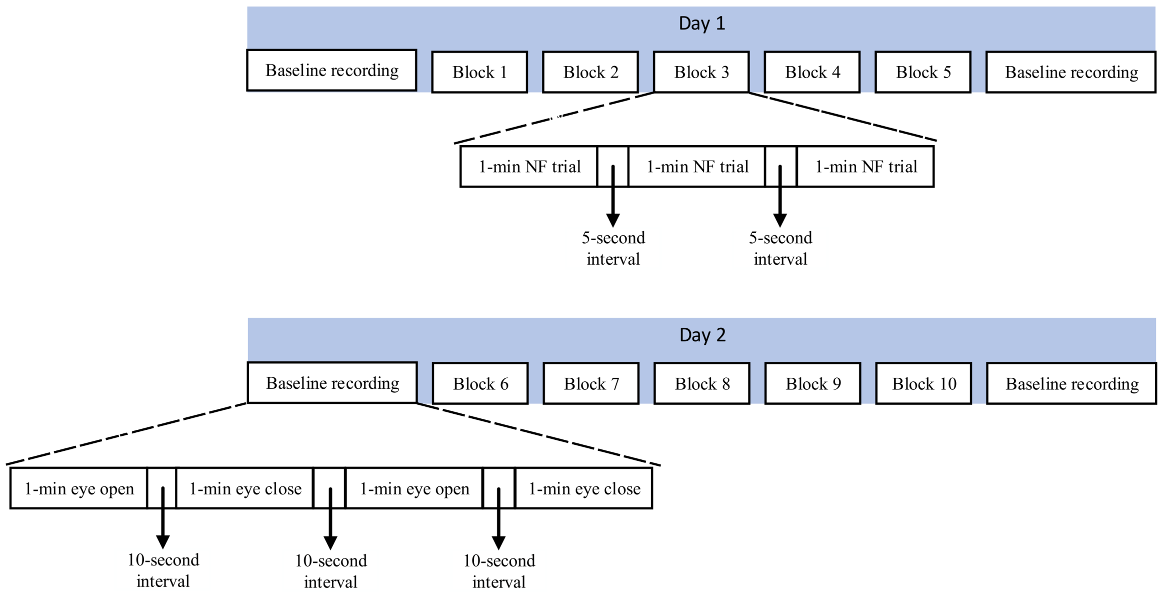


Fig. 1. Experimental protocol of the NF training on two days.

the LTF and the HTF were determined for each subject through the amplitude band crossing of the eye-open and eye-closed baseline recordings [62].

The training parameter was the relative amplitude of the IAB calculated by

$$\text{Relative IAB amplitude} = \frac{\sum_{k=\text{LTF}/\Delta f}^{\text{HTF}/\Delta f} X(k)}{\text{HTF} - \text{LTF}} \Bigg/ \frac{\sum_{k=0.5/\Delta f}^{30/\Delta f} X(k)}{30 - 0.5}, \tag{1}$$

where $X(k)$ is the frequency spectrum amplitude calculated by the fast Fourier transform (FFT) with a 1-s sliding window that shifted forward every 0.125 s, $\Delta f$ is the frequency resolution of the FFT, and $k$ is the spectrum index [62].

The real-time visual feedback contained a sphere and a cube that displayed on a computer screen. The radius of the sphere reflected the real-time feedback of the training parameter. If the training parameter was below the pre-defined threshold, the sphere changed its color from white to purple and increased its size, which is denoted as Goal 1. In addition, the height of the cube increased when the feedback parameter stayed below the threshold for more than 2 s, which is denoted as Goal 2. Participants were asked to achieve these two goals for their alpha reduction by applying spontaneous mental strategies [62]. In the experiments, we did not prescribe any specific strategies. Participants could perform any kind of mental strategies they like. Only one cognitive strategy should be performed in each trial, but it could vary between trials if a current strategy was not being successful.

### *D. Network calculations and graph theoretical analysis*

The functional connectivity between a pair of electrodes is measured by the PLV that is frequently used to characterize the phase synchronization between two narrow-band signals [67], [68]. Considering a pair of real signals $s_1(t)$ and $s_2(t)$ that have been filtered to the frequency range of interest, and their analytic signals in the form of $z_i(t) = A_i(t)e^{j\phi_i(t)}$ obtained from

$$z_i(t) = s_i(t) + j\text{HT}\{s_i(t)\}, \tag{2}$$

where $i = \{1, 2\}$, $j = \sqrt{-1}$, and $\text{HT}\{\cdot\}$ is the Hilbert transform, the PLV calculated as

$$\text{PLV} = \left| \frac{1}{T} \sum_{t=1}^{T} e^{j[\phi_1(t) - \phi_2(t)]} \right|, \tag{3}$$

where $T$ is the total number of samples, and $\phi_i(t)$ is the phase of $z_i(t)$ [46], [68]. When calculating the functional connectivity, the sliding window acted as a filter method. In each trial, one-min EEG signal was analyzed using a non-overlapping sliding window of one-second length and was divided into sixty windows. In each window, (3) was applied to compute the PLV values of all channel pairs. Then, we calculated the averaged PLV matrices of all windows in one trial as the PLV matrix of the corresponding trial. Finally, the PLV matrices of 3 trials were averaged as the functional connectivity of the corresponding block. The estimated functional connections are normally non-zero. These non-zero estimations of connectivity in the absence of true neuronal interactions are known as the spurious estimates [46]. To reduce the number of spurious edges, a threshold was applied in this study. We selected top $80\%$ connection strengths and set rest edges to 0. With this method, the resulting networks had the same number of edges.

After the mean functional connectivity of each block was calculated, the network properties were evaluated by adopting the theoretical graph analysis to measure the brain networks. In this study, we focused on the weighted network analysis. Each weight that is the PLV between two channels indicates the connectivity strength and reflects a difference in the capacity and intensity of the connectivities between nodes [69]. Three network properties, i.e. the network clustering coefficient (CC), the characteristic path length (CPL), and the

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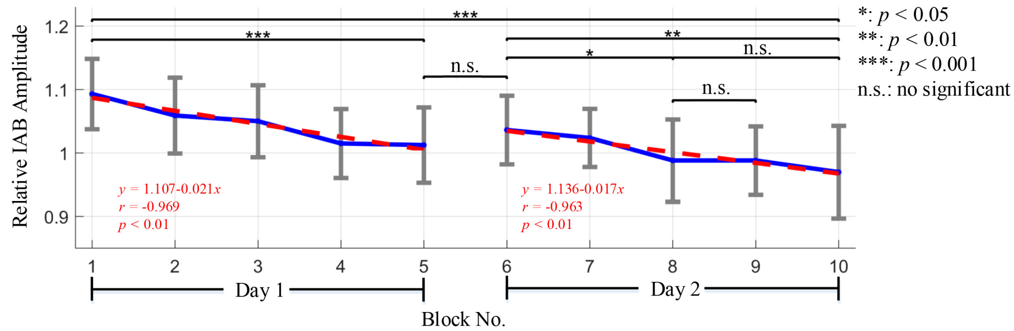


Fig. 2. Relative IAB amplitude at Oz during the NF training.

global efficiency (GE), were calculated by using the Brain Connectivity Toolbox [70].

In an $N$-by-$N$ weighted network, the CC denotes the extent of the density or cliquishness of the network [71], and can be calculated as

$$\text{CC} = \frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{j,h\in\mathbb{N}}\left(w_{ij}w_{ih}w_{jh}\right)^{1/3}}{k_i\left(k_i-1\right)}, \tag{4}$$

where $\mathbb{N} = \{1, 2, \cdots, N\}$, $w_{ij}$ is the weight between node $i$ and node $j$, and $k_i$ is the degree of node $i$.

The CPL of a network measures the global communication efficiency of a network by the harmonic mean length between pairs, and can be computed as

$$\text{CPL} = \frac{1}{\frac{1}{N(N-1)}\sum_{\substack{i,j\in\mathbb{N}\\ i\neq j}} 1/L_{ij}}, \tag{5}$$

where $L_{ij}$ is the shortest path length between two nodes, and the length of each edge is defined as the inverse of the weight [72]–[74].

The GE measures the global efficiency of parallel information transfer in the network. It is defined by the inverse of the harmonic mean of the shortest path length between each pair of nodes, and can be computed as [73], [74]

$$\text{GE} = \frac{1}{N\left(N-1\right)}\sum_{\substack{i,j\in\mathbb{N}\\ i\neq j}} 1/L_{ij}. \tag{6}$$

Comparing equations Eq. (5) and Eq. (6), the GE is the inverse of the CPL [73]. This study does not focus on exact values but focuses on relationships between temporal changes of network properties. Therefore, to avoid obtaining extreme values and keep the inverse relationship of the GE and the CPL, the GE is calculated as $\text{GE} = 1 - \text{CPL}$.

### E. Statistical analysis method

To verify the effect of blocks for the NF training performance and the network properties, an one-way repeated measures ANOVA with Block as within-subject factor is applied. The null hypothesis of the one-way ANOVA is that the average values of the tested index in different blocks. Moreover, to further evaluate the significances of local changes between blocks, the paired $t$-test is applied, while the $p$-value is corrected by the Bejnamini-Hochberg false discovery rate (FDR) procedure [75]. The null hypothesis of the paired $t$-test assumes that the mean difference of the tested index in two specific blocks is equal to zero. In statistics, the null hypothesis is rejected when the $p$-values are smaller than 0.05.

## III. Results

This study analyzes the short time NF training from three aspects. First, the training performance and the learning curve of the short time NF protocol during the training process is evaluated by using the relative IAB amplitudes. Then, the dynamics of the functional connectivity networks based on the PLV are computed to investigate the phase synchrony changes during the EEG learning process. In addition, these changes are quantified by network properties for better understanding of the mechanism of the NF training. Finally, the relationship between the training performance and the network properties are verified.

### A. Dynamics of relative IAB amplitude during NF training

In this study, the NF training protocol is designed to down-regulate the relative IAB amplitude at Oz. Therefore, the relative IAB amplitude at Oz is first analyzed, which can be applied to evaluate the training performance and the learning curve in this study. It is calculated for each subject in each block, and the averages in each block across subjects are illustrated in Fig. 2. The blue piecewise lines connect the mean relative IAB amplitude in each block. The red straight lines denote the linear regression result of the mean relative IAB amplitudes and the block numbers. It can be seen that the relative IAB amplitudes have a decrease trend over two-days training periods. In these two days, there are significant negative correlations between the mean IAB amplitudes and the block numbers (first day: $r = -0.969$, $p = 0.007$; second day: $r = -0.963$, $p = 0.009$). According to the analysis result of one-way repeated measures ANOVA, the Block factor has a significant effect on the relative IAB amplitudes ($F(9, 270) = 3.54$, $p = 0.0004$). In the first day, the relative IAB amplitude in block 5 is significantly smaller than that in block 1 ($t(27) = 3.612$, $p = 0.0006$). In the second day, the reduction of the relative IAB amplitude in block 10 is significant compared to the relative IAB amplitude in block 6 ($t(27) = 2.855$, $p = 0.004$).

From Fig. 2, differences between the trends in the first and second days can be observed. The mean relative IAB amplitudes of 5 blocks have significant differences between two days ($t(27) = 3.96$, $p = 0.0002$). From Fig. 2, we can see that the differences between the trends in the first and second days are mainly due to the stagnation of the decreasing trend in the second day. According to the paired *t*-test results, the relative IAB amplitude in block 8 is significantly smaller than that in block 6 ($t(27) = 2.454$, $p = 0.010$). However, such significant change is not continued from block 8 (change from block 8 to block 9: $t(27) = 0.0004$, $p = 0.500$; change from block 8 to block 10: $t(27) = 1.074$, $p = 0.146$). The mean relative IAB amplitude even slightly increases from block 8 to block 9.

### B. Dynamics of PLV functional brain network in IAB during NF training

After evaluating the NF training performance directly by using the feedback index that is the relative IAB amplitude in single channel, the functional connectivity network is adopted to investigate the dynamics of brain activities during the NF training from the multi-channel phase synchronization viewpoint. The functional connectivity strengths are assessed by the PLV for each subject in each block. Then, the paired *t*-test with the Benjamini-Hochberg FDR procedure is applied to verify the significances of the strength differences over blocks from two aspects. In this part, we focus on those connectivity links which have the significant changes ($p < 0.05$).

In the first aspect, the significant differences of the PLV connectivities between adjacent blocks within each day are investigated and illustrated in Fig. 3, which shows the local changes of the phase synchronization over blocks. As shown in Fig. 3A, the PLV connectivities between channels in the frontal region as well as those between channels in the frontal and occipital regions decrease in the beginning blocks, and then increase gradually in the succeeding blocks. In the second day, the rising trend is still maintained at the beginning blocks. However, after the block 8, most PLV connectivities are changed to a declining trend. The time of changing the trend is similar to the relative IAB amplitude as shown in Section III-A.

In the second aspect, the significant differences of PLV connectivities between the first block and the last block in each day, as illustrated in Fig. 4, show the global change of the phase synchronization within one day. There are large differences between the PLV connectivities in the first day NF training and the second day NF training. In the first day, most weights are significantly increased. However, in the second day, comparing the PLV connectivities in the first block (block 6) and the last block (block 10), most weights do not have significant changes. In addition, some weights in the parietal-occipital region are reduced. Since Fig. 3B illustrates a trend change of the PLV connectivity from block 8 in the second day, the differences of the PLV connectivities between block 6 and block 8 as well as those between block 8 and block 10 are also evaluated and shown in Fig. 4. It is clear that, in the second day, the rising trends of most weights are continued at the beginning blocks. The trends are changed from block 8, which matches the results of the relative IAB amplitude in Section III-A.

### C. Dynamics of network properties in IAB during NF training

After evaluating the functional connectivity strengths, three network properties are computed to quantify the states of the functional connectivity networks. These network properties are evaluated for each subject in each block. Averages of these network properties in each block across subjects are illustrated in Fig. 5. Blue piecewise lines connect the mean property values across all subjects in 5 blocks of each day. Red straight lines show the linear regression result of the mean property values and block numbers for all 5 blocks in each day. According to the results of the paired *t*-test, the averaged CC, CPL, and GE of 5 blocks have significant differences between two days (CC: $t(27) = -1.802$, $p = 0.0414$; CPL: $t(27) = 1.773$, $p = 0.0438$; GE: $t(27) = -1.817$, $p = 0.0402$). In the first day, the CC and GE show rising trends (CC: $r = 0.930$, $p = 0.022$; GE: $r = 0.933$, $p = 0.021$). The corresponding CPL shows a declining trend ($r = -0.926$, $p = 0.024$). However, such significant changes cannot be observed in the second day, which is mainly due to the trend changes between blocks.

According to the results of one-way repeated measures ANOVA, the Block factor has significant effects on the CC, the CPL and the GE (CC: $F(9, 270) = 3.15$, $p = 0.0013$; CPL: $F(9, 270) = 2.8$, $p = 0.0038$; GE: $F(9, 270) = 3.1$, $p = 0.0015$). From the results of the paired *t*-test, in the first day, the differences of the CC, the CPL, and the GE between block 1 and block 5 are all significant (CC: $t(27) = -1.820$, $p = 0.040$; CPL: $t(27) = 1.868$, $p = 0.036$; GE: $t(27) = -1.823$, $p = 0.040$). In the second day, the significant changes still can be observed from the differences of the CC, the CPL, and the GE between block 8 and block 1 (CC: $t(27) = -1.763$, $p = 0.043$; CPL: $t(27) = -1.713$, $p = 0.043$; GE: $t(27) = -1.825$, $p = 0.041$). However, the differences of the CC, the CPL, and the GE between block 10 and block 1 are not significant (CC: $t(27) = -0.445$, $p = 0.054$; CPL: $t(27) = -0.463$, $p = 0.052$; GE: $t(27) = -0.555$, $p = 0.051$).

Such trend changes in block 8 could be observed more clearly from the comparisons of the linear regression slopes. The 2-day NF training is divided into three stages. The first stage is the first day training from block 1 to block 5. The second stage is the second day training before block 8. The third stage is the second day training after block 8. For each participant, the linear regressions of three network properties in these stages are evaluated. The mean values and variances of the linear regression slopes across participants are illustrated in Fig. 6. Analysis results of three network properties are shown in three figures respectively. Three blue bars in one figure denote the averaged linear regression slopes of corresponding network properties in three stages. According to results of the paired *t*-test, the differences between the linear regression slopes from block 6 to block 8 and those from block 1 to

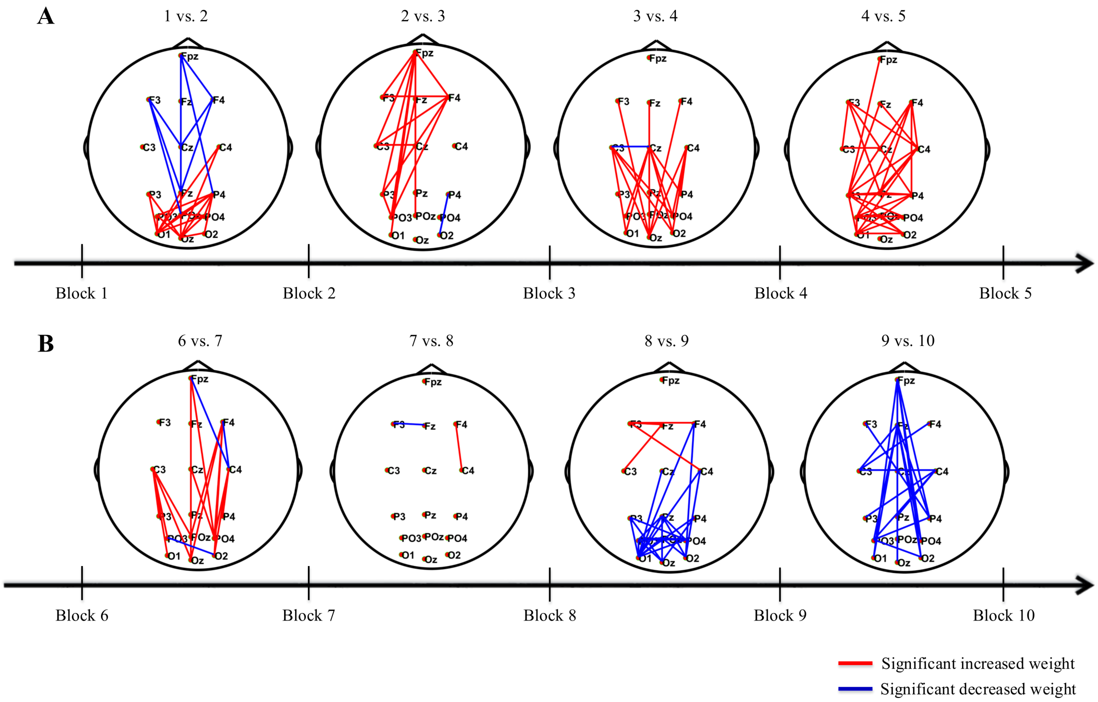


Fig. 3. Local changes in PLV functional connectivity weights of IAB between two consecutive blocks (A) in the first day and (B) in second day. The significance is verified by the paired *t*-test with the Benjamini-Hochberg FDR procedure. Red lines show the PLV connections that have the significant increases. Blue lines show the PLV connections that have significant reductions.

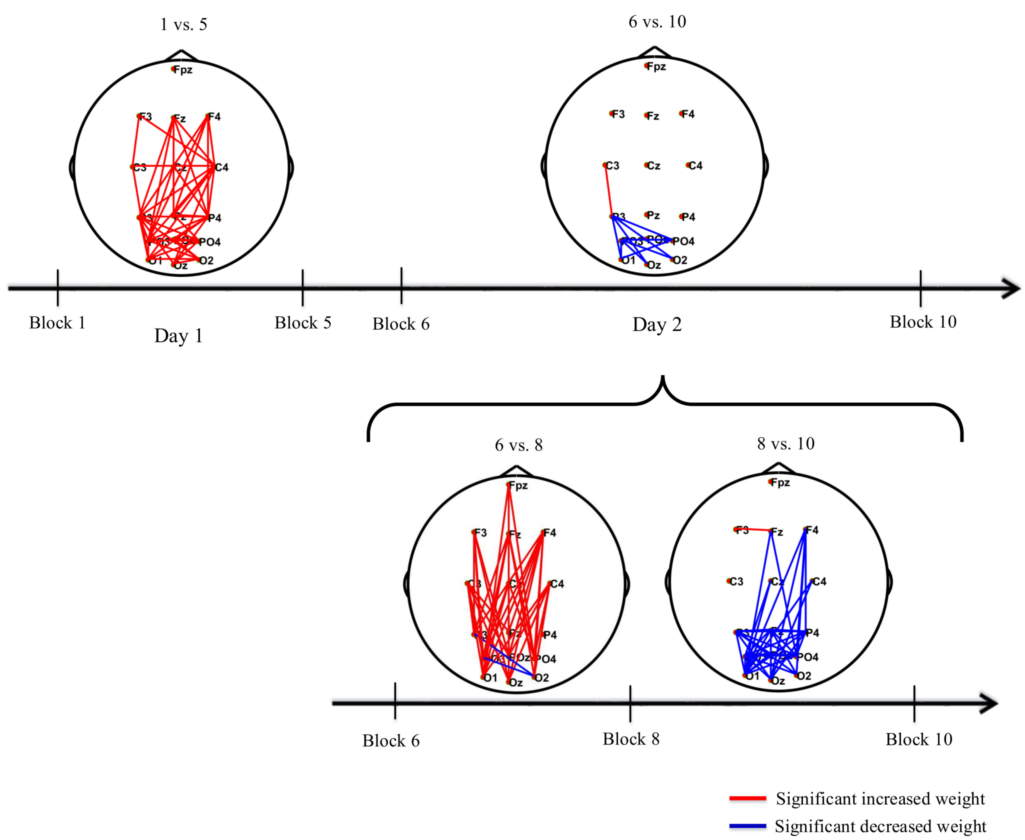


Fig. 4. Global changes in PLV functional connectivity weights of IAB in the first day, the second day as well as before and after block 8. The significance is verified by the paired *t*-test with the Benjamini-Hochberg FDR procedure. Red lines show the PLV connections that have the significant increases. Blue lines show the PLV connections that have significant reductions.

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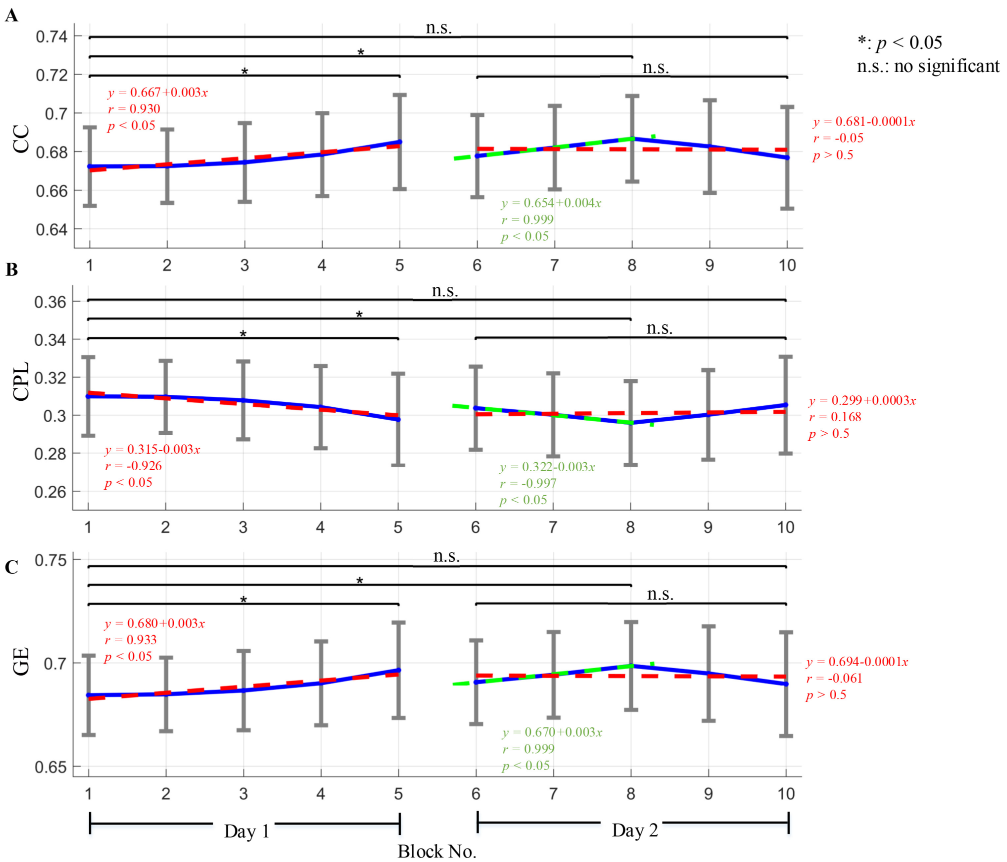


Fig. 5. Dynamics of (A) CC, (B) CPL, and (C) GE during NF training.

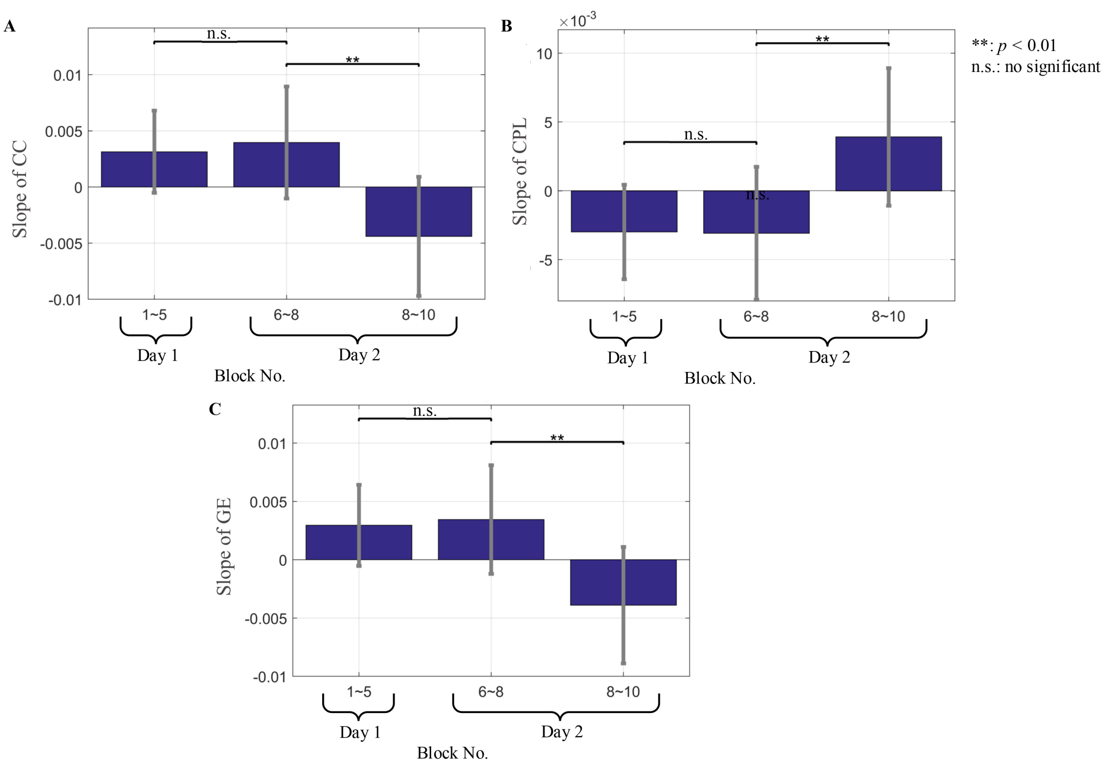


Fig. 6. Slopes of linear regressions of (A) CC, (B) CPL, and (C) GE during NF training.

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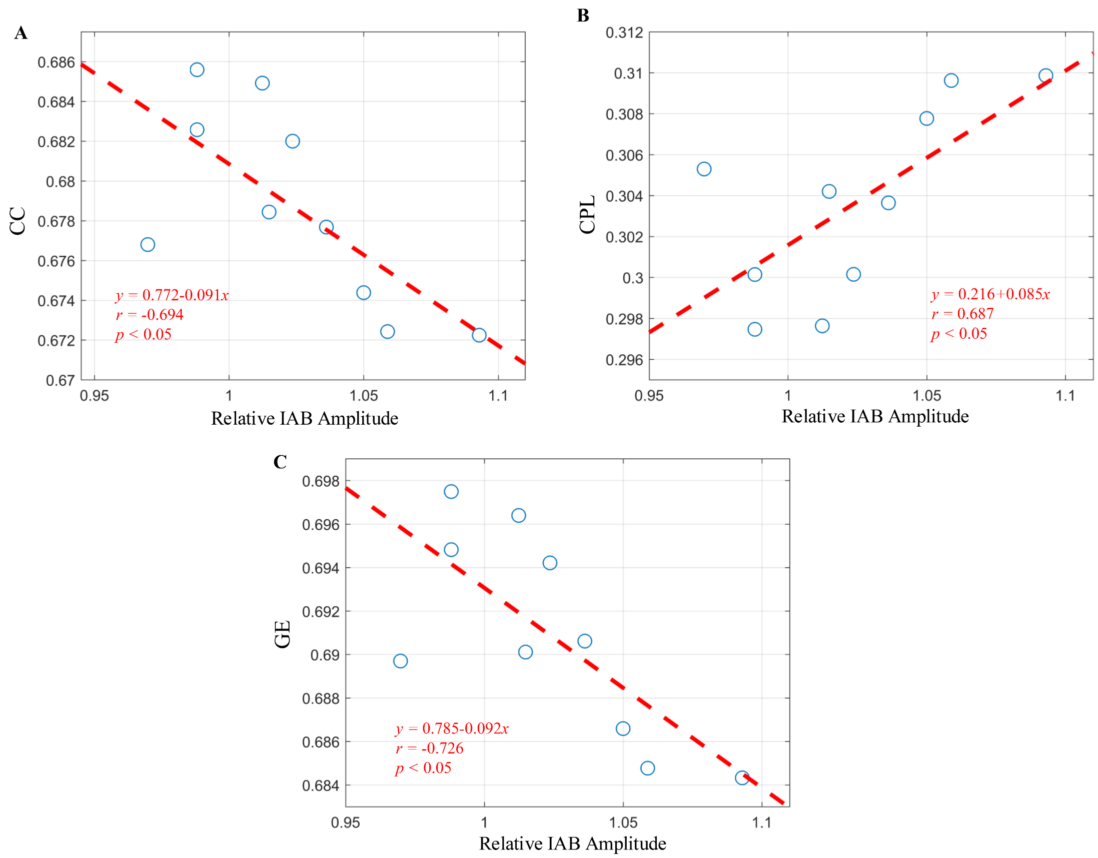


Fig. 7. Relationship between mean relative amplitude and mean values of (A) CC, (B) CPL as well as (C) GE during NF training. Blue circles denote the mean relative IAB amplitudes and the mean network properties of 10 blocks. Red straight lines indicate the linear regression results of the mean relative IAB amplitudes and the mean network properties.

block 5 are not significant (CC: $t(27) = -0.321$, $p = 0.375$; CPL: $t(27) = 0.0394$, $p = 0.484$; GE: $t(27) = -0.202$, $p = 0.421$). From block 8, the trends of the CC, the CPL, and the GE are changed to the opposite directions significantly (CC: $t(27) = 3.1746$, $p = 0.002$; CPL: $t(27) = -2.800$, $p = 0.0049$; GE: $t(27) = 2.951$, $p = 0.003$).

### D. *Relationship between relative amplitude and network properties of IAB during NF training*

Besides the changes of the relative IAB amplitude and the functional network of the IAB, the correlations of the mean relative IAB amplitude across subjects and the mean network properties across subjects are evaluated and illustrated in Fig. 7. The blue circles show the mean relative IAB amplitudes and the mean network properties of 10 blocks of 2-day NF training. The red straight lines indicate the linear regression results of the mean relative IAB amplitudes and the mean network properties. The CC and the GE have significant negative correlations with the relative IAB amplitudes (CC: $r = -0.694$, $p = 0.026$; GE: $r = -0.726$, $p = 0.018$). In addition, there is a significant positive correlation of the CPL and the relative IAB amplitude ($r = 0.687$, $p = 0.028$).

## IV. Discussion

We adopt the relative IAB amplitude and the phase synchronization to investigate the dynamics of brain activities during 2-day NF training, and identify differences of constructing functional connectivity networks in these two days. These results show that (a) participants can successfully construct related brain networks to regulate their relative IAB amplitudes in the first day, (b) the similar networks can be reconstructed efficiently and enhanced in the second day, and (c) interestingly, the relative IAB amplitudes and functional connectivity networks both have stagnations started from the middle of the second day. According to these results, the whole process can be divided into three parts. The relative IAB amplitude can reflect the NF training performance. A rough learning curve can be observed from the following discussion of the changes of the NF training performance. In order to further verify this learning curve and find the relationships between the NF training performance and the mental states, the changes of the phase synchrony between channels will be further discussed. The learning stagnation in the second training day will be pointed out. Referring to the related literature as well as the relationships between the observations and the mental states, some possible reasons will be provided. Finally, some limitations of this study will be listed.

### A. *Learning curve of NF training performance*

In this study, the protocol is to down-regulate the relative IAB amplitude. According to the training goals, the performance of the NF training can be quatified by the measurements of the relative IAB amplitude, which reflects the learning curve of the NF training. The significant reductions of the relative IAB amplitude from block 1 to block 5 as well as those from block 6 to block 8 as shown in Fig. 2 indicate that participants can successfully learn the self-regulation of the NF training parameter over the first day training as well as can apply and further enhance the ability in the second training day. Moreover, after block 8, the declining change of the relative IAB amplitude becomes slow, which indicates the learning stagnation of the NF training.

A similar learning stagnation of the NF training with the down-regulation of the relative IAB amplitude can also be observed in our previous work [62]. In addition, other NF related studies also show the similar stagnation of the NF training performance. Due to different training protocols, e.g. training parameter, time intervals between blocks, and number or duration of blocks, the time points of such stagnations of the NF parameters may be different [6], [8], [15]–[17]. In order to observe the learning curve clearer and investigate the relationships between the observations and the changes of the brain activities, the PLV based functional connectivity networks are discussed below.

### B. Changes of phase synchrony and related mental states

The timing of activation processes is functionally related to the phase, which describes the time and direction of a change in inhibition or excitation process for information processing. According to previous studies, the phase synchrony is essential in the formation of transient neuronal assemblies, communication therein, and large-scale integration [42], [76]. Therefore, the understanding of the phase interaction can provide information about the functional significance of the alpha-frequency band oscillations [43], [76]. In addition, the top-down modulation can be mediated by the phase interactions of the alpha frequency band [41]. In particular, the phase dynamics of the alpha frequency band can figure out a direct and active role in the mechanisms of attention and consciousness [43].

Owing to these advantages, the dynamics of brain activities across 5 blocks in each day can be reflected by the phase synchrony between pairs of channels measured by the PLV. From block 1 to block 2, the weights around the occipital and parietal-occipital regions were significantly increased. The alpha activity in these regions are associated with the performance for visual task [77], [78]. Since participants were not familiar with the NF training, they would like to focus on the visual feedback and thus tried to construct the brain networks that support their visual tasks in the visual feedback. At the same time, parts of phase synchronizations between frontal and central regions were reduced. The phase synchrony in alpha frequency band in these regions is related to the memory-load and working-memory [79], [80]. The reason that the memory related functions was inhibited may lie in that, at the beginning blocks, participants paid more attention on the visual feedback and changed their mental strategies frequently to test which one was more suitable for achieving the training goals. Then, from block 2 to block 4, the weights between the frontal and occipital regions as well as those between the central and occipital regions were successively increased. Previous studies reported that the phase coupling between the prefrontal cortex and posterior sites is highly related to the attention [80], [81]. In particular, the attention related brain network is built by the prefrontal cortex and posterior regions together and might be controlled by the prefrontal cortex [82], [83]. Moreover, the topographic localization over central electrodes also reveals the involvement in the attention [84]. Therefore, the visual attention related brain networks enhanced from block 2 to block 4 may further support the visual tasks in the visual NF training. Besides the attention, some other complex cognitive tasks, such as manipulation or maintenance of information in the working memory, or perception of meaningful objects, can also increase the alpha phase coupling [85], [86]. [80] and [87] reported that the long-range phase synchrony, especially alpha phase coupling between fronto-parietal brain regions, is modulated by the attention or the working memory and can be applied to the prediction of the stimulus identification and the individual working memory capacity. The reason that the memory related functions were excited may lie in that, in this stage, participants needed recalling memories to avoid applying previous wrong mental strategies that did not lead to the training goals, and to actively apply previous right mental strategies that were helpful for achieving the training goals. In the final stage of the first day training, the increase of the PLV connectivities in the whole brain from block 4 to block 5 may indicate that participants successfully learned the abilities of adopting suitable brain functions to regulating their IAB. Moreover, these observations also revealed that the NF engaged more than one distinct neural networks or overlapping networks, which was also mentioned by [1].

For the second day training, comparing the beginning blocks in the first day and the second day, it can be found that the phase synchronization between the frontal region and occipital region was fired faster in the second day. Such fast increases of the PLV connectivities in the second day indicate that, through one night resting, subjects did not lose the ability of regulating their alpha EEG and can successfully apply and further improve it in the second day training to generate the visual attention and memory related brain networks quickly. However, such rising trend of the PLV connectivity was blocked gradually and turned to the opposite direction from block 8.

As measurements of the brain networks, the changes of these two day training can be observed more clearly from the network properties. In literature, a shorter CPL and a higher GE indicate more efficient parallel information transfer and integration in the brain [72]. A larger CC indicates larger information processing [71]. Moreover, the high attentional performance is related to the high efficiency of the brain network [88], [89]. Changes of the GE, CC, and CPL in the first day suggest that participants tried to enhance the efficiency of the network organization and thus increase the attention for achieving the training goals. Starting from the middle of the second training, participants cannot keep increasing the efficiency of the brain network. From the block 8, the

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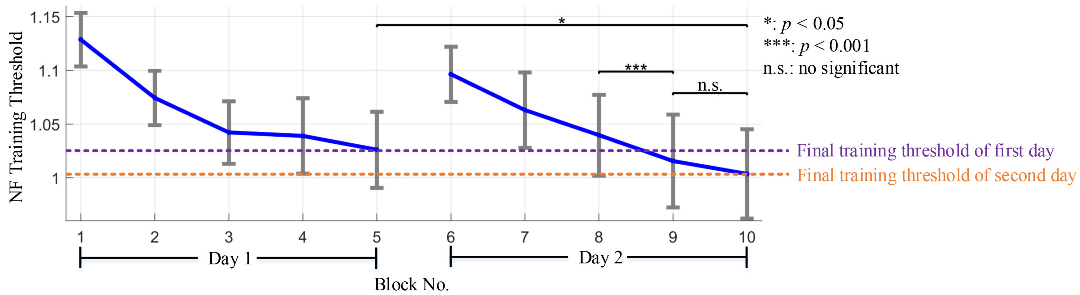


Fig. 8. Threshold setting during the NF training.

trends of the CC, the CPL, and the GE are changed to their opposite directions. These observations match the changes of the relative IAB amplitudes in Fig. 2 and above analysis of dynamics of brain networks. It should be noticed that the learning plateau in the second day training has large effects on the training performance from the network property point of view since it counteracts the changes of the network properties in the beginning blocks of the second day.

To explain the trend changes of the PLV connectivities in the second day, two possible reasons could be proposed. The first possible reason for the trend changes of the relative IAB amplitude and PLV connectivities is that, participants restarted the optimization process of achieving the related brain functions to achieve the difficult training goals in the second day training. From the first day training, participants already obtained the ability of regulating their alpha EEG. In the second day training, they just needed to further consolidate and practice this ability, and thus could directly adopt the related brain functions to achieve the training goals efficiently. After they achieved the old training goals that were set for the first day training, the threshold of the NF training was further adjusted as shown in Fig. 8 that illustrates the threshold settings during the NF training. It can be seen that, before block 8, the thresholds in the second day were higher than the final threshold of the first day. After block 8, since participants could achieve the training goals, there was a significant decreasing of the mean thresholds from block 8 to block 9. In addition, the final threshold of the second day was significantly lower than that of the first day. Participants needed to resume their learning processes in order to achieve the new training goals in the second day. The similar possible reason related to practicing newly acquired skills beyond the point of initial mastery was also mentioned by [90] and [17]. The second possible reason for the trend changes of the relative IAB amplitude and PLV connectivities is that participants could not concentrate on the NF training from the middle of the second day. In the experimental results, the decreases of the phase coupling between the prefrontal cortex and posterior sites from block 8 to block 10 are related to the attention loss [80], [81]. From the first day training, participants had already been familiar with the training protocol and consequently they lost their attention in a shorter time in the second day training. The similar possible reason related to the attention losing during the NF training was also mentioned by [16], [17] and [23]. These two possible explanations indicate that participants were able to get the experience or even obtain the ability of down-regulating their alpha EEG from the first day short time NF training, and would achieve their learning plateaus in the second day training. Therefore, the training protocol could be further optimized to avoid the learning plateau. Moreover, besides the NF training, the similar overtraining phenomenon affecting the effectiveness of learning can also be found in other self-regulatory process, such as studies and sport training [91]–[93]. These evidences support that a careful time management is essential for creating a focused approach in the self-regulatory process.

### *C. Relationship between relative amplitude and phase synchrony of IAB*

The negative correlation of the alpha amplitude and alpha phase synchrony for the top-down mental processing, especially for the attention, has been reported in literature. [94] verified that there is clearly higher alpha amplitude at sites ipsilateral to the attended location than contralateral to it. The alpha amplitude related studies [77], [95] and the inter-areal alpha phase synchrony related studies [96], [97] show that the alpha amplitude and alpha phase synchrony have opposite correlations with cortical excitability and task performance in sensory cortices. In addition, an accumulating data directly shows that the alpha amplitude suppression is associated with a concurrent increase in alpha band phase synchrony [85], [98], [99]. The results in this study further confirm the negative correlation between the relative IAB amplitude and the phase synchronization during the NF training.

### *D. Limitations*

In this study, the phase synchrony is only evaluated by the PLV that has the problems caused by the volume conduction. Since the volume conduction in two blocks with performing the same NF training protocol affects the connectivity in a similar way, which can be treated as a common error [46], the experimental contrasts between blocks measuring the temporal changes of the PLV is immune to the volume conduction influence. In the future, other measures, like phase lag index (PLI) [100], phase slope index (PSI) [68], [101], and pairwise phase consistency (PPC) [102], can be applied to further verify findings in this study as well as explore the

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detailed information of the functional connections during the NF training.

Moreover, we investigated functional connectivity changes across all participants in this experiment. Due to individual differences, it cannot rule out that there were different functional connectivity changes for all participants. Furthermore, this study focuses on analyzing the dynamics of brain activities during the short time NF training. The effects after this NF training, e.g. the baseline changes and the long-term effects, can be investigated in the future.

The lack of the control group is another limitation of this study. The NF training protocol applied here is based on our previous study, in which the down-regulating IAB activity was found to enhance the performance of the subjects in using the SSVEP-based BCI by comparing the control and experimental groups [62]. However, how the learning progressed was not explored due to the limited numbers of subjects and EEG channels therein. By following the NF training protocol and procedures, the NF training results in this work were found consistent with its predecessor. As the main objective is to study how the learning progresses and how the brain networks change during the NF training, the control group was not considered for simplicity in this study. However the control group should be included to further confirm whether the effect comes from the NF rather than other factors such as some tasks or reward or mistaken learning.

## V. Conclusions

In this paper, the functional connectivity method is applied to illustrate the brain network dynamics and analyze the learning curve during 2-day NF training for down-regulating IAB EEG. Experimental results of the relative IAB amplitude and the PLV-based brain network show that participants were able to construct more than one distinct or overlapping suitable neural networks to down-regulate their IAB amplitude, and successfully applied this learned ability for the second day training to achieve a more efficient training process. Moreover, the stagnation of the learning curve for the relative IAB amplitude in the second day short time NF training was identified. Based on the relationships between brain functions and corresponding brain network dynamics, possible reasons for the trend changes of the learning curve are discussed. The observed learning curve and PLV brain network dynamics indicate the effectiveness and cost-efficiency of the self-organization in the NF training could be further improved by optimizing the parameter design of NF training. From this study, a better understanding of the detailed brain network dynamics during the NF training can be obtained, which would be helpful for establishing more efficient learning protocol of the NF training.

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