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Neural dynamics of closed-loop alpha wave modulation via phase-locked visual feedback

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Abstract— **Compared with the conventional self-regulated EEG neurofeedback strategy, a closed-loop feedback strategy can provide a more precise and robust brain wave modulation. By detecting a participant's instantaneous phase of EEG alpha oscillation and delivering phase-locked visual stimuli to the participant, a new closed-loop feedback paradigm, named phase-locked visual feedback modulation (PLVFM), has been developed to modulate his/her amplitude and frequency of alpha oscillation. However, the underlying neurodynamic mechanism of the PLVFM technique is still not clear, which limits the developments of precise and individualized applications of this new neural modulation technique. In this study, a neural dynamical model based on the limit cycle attractor has been proposed for alpha wave simulation to explore the neurodynamic mechanism of PLVFM. Results show that the simulated dynamic behaviors are consistent with the real results of online EEG modulation. The external stimuli at a specific phase change the instantaneous radius and phase of alpha oscillation. The repeated phase-locked stimuli stabilize the alpha oscillation in a new trajectory in the phase space and further induce the change of the amplitude and peak-frequency of alpha wave. The current study improves our understanding of the visual-modulated alpha wave, which is an important step towards precise modulation of EEG activity for the modulation of sensory and cognitive states.**

I. Introduction

Different rhythms of electroencephalographic (EEG), such as alpha, beta and theta, are highly related with cognitive functions [1, 2] and memory performance [3, 4]. The modulations of brain waves were found to be related to various mental diseases such as attention deficit hyperactivity disorder [5, 6], anxiety [7] and depression [8, 9]. Based on visual or auditory feedback of the instant information of the brain states, neurofeedback technique provides participants a way to improve their mental state through self-regulation [10]. However, in the absence of well-designed experiments and the possibility of placebo effects, the efficacy of neurofeedback remains a point of great controversy [11]. Furthermore, neurofeedback, as a type of endogenous method for brainwave modulation, depends on the user's active participation. It would take a period of time for training, and there are still a certain proportion of users who are not able to regulate their brain wave after training [12]. Hence, a new exogenous neuromodulation is highly desired.

A phase-locked feedback system [13] has been developed for exogenous alpha rhythm modulation via visual natural sensory pathway. In this system, alpha oscillation is modulated by phase-locked stimulus at a specific phase, and its amplitude and frequency are clearly modulated. Considering different evoked dynamic responses by visual stimulus at different phases of alpha wave [14], Huang et al. [13] modeled the alpha oscillation as the motion trajectory of a simple pendulum. In simple pendulum system, the visual stimuli are treated as an external force, which is exerted at a specific phase with the constant magnitude and direction. If the external force is in the same direction of the motion of simple pendulum, the amplitude of the simulated alpha oscillation would be increased. Otherwise, if the force is against to the direction of the motion, the amplitude would be decreased. The experiment results showed that the output of the phase-locked feedback system was agreed with the simple pendulum model assumption, that the amplitude of the alpha wave can be increased or decreased obviously when visual stimulus is exerted at a certain phase (Fig. 1a). The modulation effect on the amplitude presents a clear periodicity increasing along with an increase of the stimulus phase. The repeatability of the performance was verified in the independent work [13]. Comparing with large inter- and intra-individual variability on the other exogenous neuromodulation methods, such as transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation (TMS) [15], the results from the proposed phase-locked feedback system were consistent across almost all participants in the two replications in different days [13]. Further, the external noninvasive stimulus from TMS and tDCS would inevitably bring artifact to EEG signal, which makes the analysis of the brain rhythm during the stimulation difficult. The natural sensory pathway stimulus in phase-locked feedback system makes it possible to investigate the neural entrainment to the visual stimulus during the modulation.

In addition to the amplitude modulation, frequency of alpha wave is also modulated. As shown in Fig. 1b, with the increase of stimulus phase, the peak frequency of the alpha wave is decreased, which is beyond the expectation of the simple pendulum model. Further, the simple pendulum model is not a stable system. Repeated stimulus would make the system divergence. Hence, a more precise model is desired to understand the mechanism of joint amplitude-frequency modulation by phase-locked feedback system. Jansen's neural mass model is a classical model to study the generation of alpha oscillations [16, 17]. In neural dynamics, neural mass model describes the alpha oscillations as a limit cycle attractor

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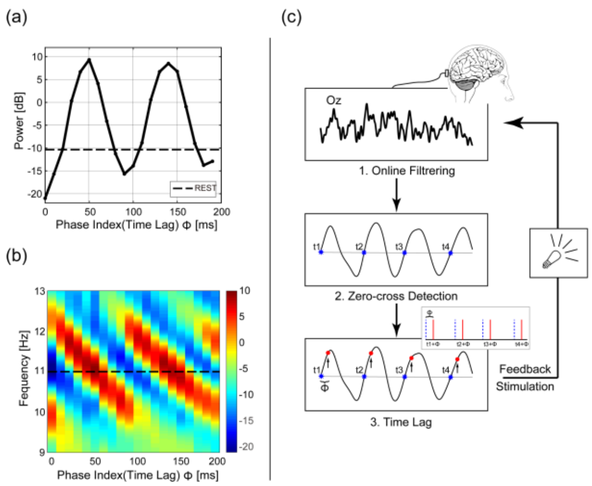

Figure 1. The exprementаl modulation results and the schema of the phase-locked feedback sysem. (a) The amplitude modulation function against the phase index (time lag) ϕ. (b) Power spectra of the system regulated by visual stimulus delivered at different values of ϕ. The dash line indicates the power and frequency without external stimulation. (c) The schema of the phase-locked feedback sysem.

in six-dimensional state space, which is a periodic trajectory that all neighboring trajectories would approach [16]. However, the six-dimensional state space and the nonlinear items in the neural mass model make it difficult for analysis and visualization. In this study, a two-dimensional limit cycle model is established to simulate the alpha oscillation to explore the neural dynamics mechanism for the phase-locked feedback system. The phase-locked feedback system and the simulation model is introduced in Section II. Then the simulation results are illustrated in Section III. The conclusion and discussion are given in Section IV.

II. Model and Method

A. The phase-locked feedback system

The process of the phase-locked feedback system [13] is shown in Fig. 1c, which is mainly divided into three steps. (1) EEG signal from channel Oz is online filtered by a 2-order 8-12Hz bandpass Butterworth filter to obtain the alpha wave. (2) The positive zero-crossing point is detected to identify the time point of alpha wave with phase of $3\pi/2$ (blue dot in Fig. 1c), which reaches a positive value from a negative value through a zero point. (3) A certain time lag ϕ is applied as the phase index to estimate the certain phases of alpha wave and generate a stimulus sequence (red line in Fig. 1c) to control stimulation feedback. Finally, the visual stimuli, which are controlled by the stimulus sequence and delivered by LED, is served as external stimuli to achieve stimulation feedback to EEG signal.

The entire system is a closed-loop phase-locked visual feedback system for EEG modulation. Since alpha wave results in different dynamic responses and modulation effects under a stimulation of different phases [14], the timely and accurate phase detection is the key of the phase-locked feedback system to guarantee modulation effect. In general, three strategies could be applied for phase estimation of real-time EEG signals: (1) zero-crossing point detection with a certain time lag, (2) an autoregressive (AR) model with Hilbert transform, and (3) machine learning. The last two methods could estimate the phase of ongoing alpha wave directly. The AR model achieve the phase estimation through predicting the future signal firstly, and then estimating the phases of signal by Hilbert transform. Several machine learning methods can be applied for phase estimation, such as multiple linear regression. However, the accuracy of phase estimation in these two methods depend on the stationarity of the signal. With external stimulus, the assumption of stationarity is not guaranteed. Hence, zero-crossing detection method with a certain time lag is applied for phase estimation in this study. By positive zero crossing, the $3\pi/2$ phase of alpha wave can be identified and a certain time lag ϕ is added to zero-crossing time point t_m to estimate the specific phase of alpha wave (Fig. 1c). This method is simple for online system implementation, and the low computation complexity can guarantee the real-time performance of the system.

B. Limit cycle model

For simplicity of analysis, a two-dimensional limit cycle model is applied to simulate alpha dynamics in phase-locked feedback system, as follows

$$X' = F(X) + Ku(\tilde{y}, \phi), \tag{1}$$

in which $X = [x_1, x_2]^T$ is the state variable, $y = x_1$ is the observation variable (output signal) of the system, $\tilde{y}$ is the online filtered signal of y with 2-order 8-12Hz bandpass Butterworth filter and ϕ is the time lag, and $K = [3000,0]^T$ is a vector with only one dimension non-zero, which indicates the stimulus dimension and stimulus intensity. $F(X)$ describes the spontaneous EEG signal

$$F(X) = \begin{bmatrix} \frac{kx_1}{r} - kx_1 - cx_2 \\ \frac{kx_2}{r} - kx_2 + cx_1 \end{bmatrix} \tag{2}$$

with the parameters

$$k = 10, c = 60,$$

in which the limit cycle attractor trajectory is a circle with the radius of $r = \sqrt{x_1^2 + x_2^2}$, the value of k determines the rate of the system that converges to the limit cycle attractor, and c determines the angular velocity of the limit cycle attractor, which is constant. The external stimulus $u(\tilde{y}, \phi)$, depending on $\tilde{y}$ and ϕ, is the sum of impulse function and

$$u(\tilde{y}, \phi) = \sum_m \delta\big(t - (t_m + \phi)\big). \tag{3}$$

Firstly, the positive zero-crossing time point of the filtered signal $\tilde{y}$ is detected as t_m, with $\tilde{y} = 0$ and $\tilde{y}' > 0$. Then a time lag ϕ is added into t_m to perform the stimulus. Dirac delta function $\delta(t)$ is the unit impulse function with

$$\int_a^b \delta(t)dt = \begin{cases} 1, & a < 0 < b \\ 0, & otherwise \end{cases}. \tag{4}$$

Runge-Kutta method is applied to run the simulation [18] and the initial value is set as $X(0) = [1,0]^T$.

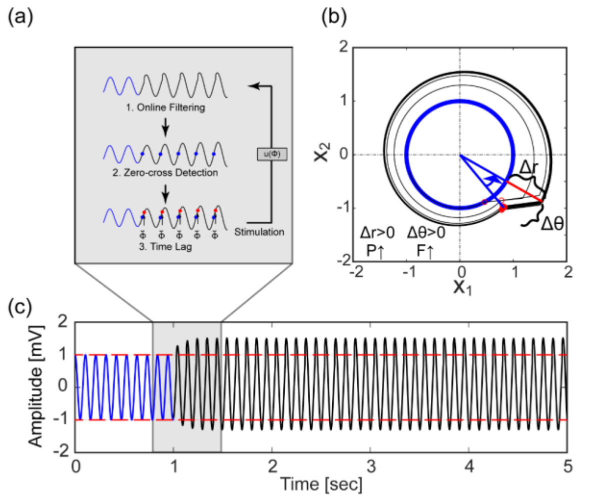

Figure 2. The simulation results of the phase-locked feedback system with external stimulus at phase index (time lag) $\phi = 10$ms. (a) The schema of the output signal modulation. The black dots indicates the positive zero-crossing point. The red dots indicates the actual stimulation point. (b) The modulation effect of the system in phase space. The red dots indicates the stimulation point. The angle of the blue arrow indicates the angle change of the system. The red line indicates the orbit redius change of the system. (c) The ouput signal of the system. The red dash line indecates the amplitude of the output signal without stimulating.

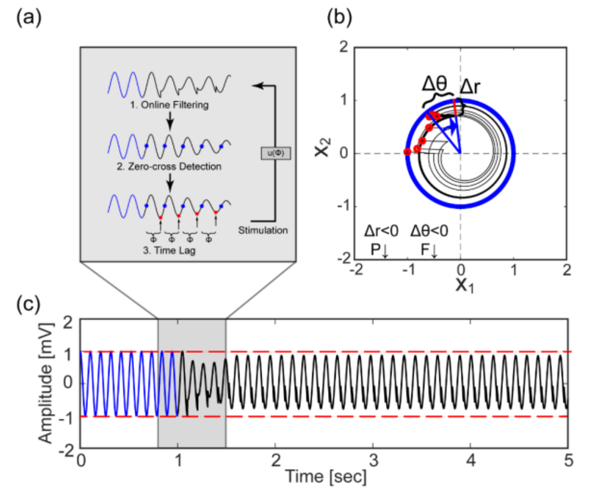

Figure 3. The simulation results of the phase-locked feedback system with external stimulus at phase index (time lag) $\phi = 80$ms. (a) The schema of the output signal modulation. The black dots indicates the positive zero-crossing point. The red dots indicates the actual stimulation point. (b) The modulation effect of the system in phase space. The red dots indicates the stimulation point. The angle of the blue arrow indicates the angle change of the system. The red line indicates the orbit redius change of the system. (c) The ouput signal of the system. The red dash line indecates the amplitude of the output signal without stimulating.

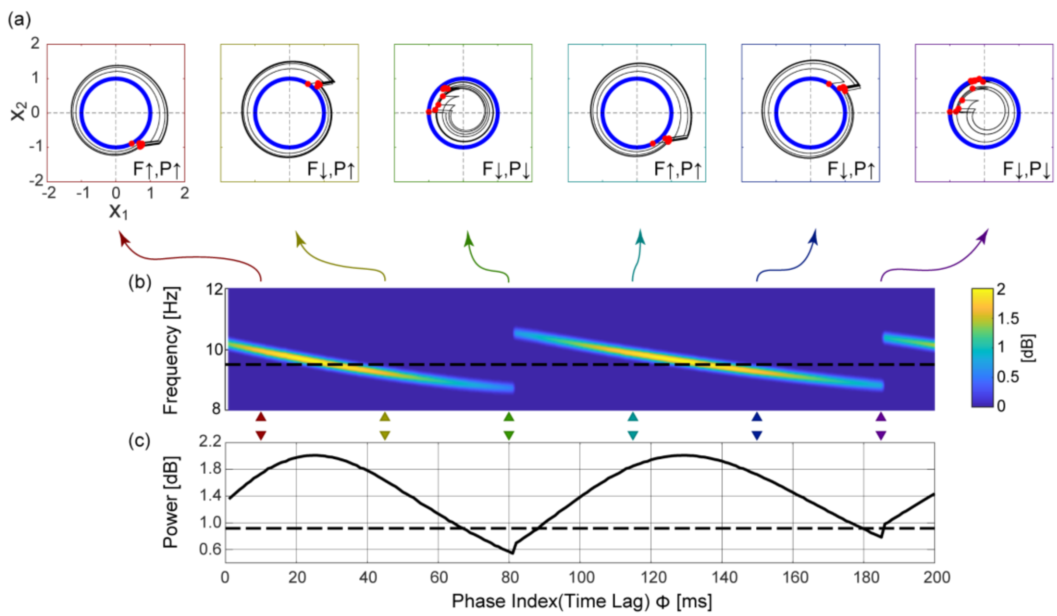

Figure 4. The simulation results of the phase-locked feedback system with external stimulus as time lag ϕ increasing from 0 to 200ms. (a) The modulation effect of the system in phase space, with phase index (time lag) of 10ms, 45ms, 80ms, 115ms, 150ms and 185ms, respectively (left to right). (b) Power spectra of the system regulated by impulse delivered at different values of ϕ. (c) The amplitude modulation function against the phase index (time lag) ϕ. The black dash line indicates the frequency and power without external stimulus.

III. Results

In this section, the neural dynamics of the phase locked feedback system is shown with two different values of the time lag ϕ. Then the result of joint amplitude-frequency modulation is shown as the phase increases from 0-200ms.

Fig. 2 shows the dynamic of the system modulated by an external stimulus with time lag $\phi = 10$ms. In the first second, there is no external stimulus, and the spontaneous EEG is illustrated in blue curves. As is shown in Fig. 2a, the simulated raw signal is firstly online filtered by 2-order 8-12Hz bandpass Butterworth filter. Then the positive zero crossing point is detected to get the time point of simulated signal with the phase of $3\pi/2$ (blue dot in Fig. 2a). Thirdly, a certain time lag, as $\phi = 10$ms here, is added to phase estimation (red dot in Fig. 2a) and generate a feedback stimulus sequence, which is used to control the impulse to achieve feedback stimulation. With the external stimulus, the system would take less than one second into a stable state, in which the power of the oscillation is increased and the frequency of the oscillation is also increased (Fig. 2c). By investigating the phase portrait in Fig. 2b, it is found that the external stimulus creates the radius of the trajectory increasing ($\Delta r > 0$), hence the power of the oscillation increasing ($P \uparrow$). Furthermore, the external stimulus also causes the change of instantaneous phase angle. The increased phase angle ($\Delta\theta > 0$) makes the frequency of the oscillation increasing ($F \uparrow$).

Fig. 3 shows the dynamic of the system modulated by the external stimulus with time lag $\phi = 80$ms. As is shown in Fig. 3a, the whole processing is similar as it is in Fig. 2a. But the time lag ϕ increases from 10ms to 80ms. In result, the power of the oscillation is decreased and the frequency of the oscillation is also decreased (Fig. 3c). Due to the stimulus in different phase (Fig. 3b), it is found that the external stimulus creates the radius of the trajectory decreasing ($\Delta r < 0$), hence the power of the oscillation decreasing ($P \downarrow$). Furthermore, the external stimulus also causes instantaneous phase angle change. The decreased phase angle ($\Delta\theta < 0$) makes the frequency of the oscillation decreasing ($F \downarrow$).

Fig. 4 shows the joint amplitude-frequency modulation effect. With the time lag ϕ increasing from 0 to 200ms, the peak-frequency decreased and presents a clear periodic (Fig 4b) and the power shows a sinusoidal-like with the time lag ϕ (Fig 4c). The phase portrait with time lag $\phi = 10, 45, 80, 115, 150,$ and 185ms is illustrated in Fig. 4a. The change of power and frequency mainly depends on instantaneous change of the trajectory radius r and phase angle θ by the external stimulus. If the change of angle $\Delta\theta > 0$, corresponds to the increasing of frequency for output signal. On the contrary, if $\Delta\theta < 0$, the frequency of output signal is decreased. If the change of trajectory radius $\Delta r > 0$, corresponds to the increasing of amplitude for output signal. On the contrary, if $r < 0$, the amplitude of output signal is decreased.

IV. Conclusion

In this paper, a limit cycle model has been established for EEG alpha oscillation simulation. The dynamic behavior in the simulation is consistent with the real online EEG modulation results [13], which indicates that the proposed limit cycle model can well describe the dynamic mechanism of phase-locked feedback stimulation. The repeated external stimulus at specific phase make the simulated alpha wave stabilize in a new trajectory. The change of the trajectory radius leads to the modulation of amplitude. Meanwhile, the angular velocity is constant in the proposed system, the change of instantaneous phase by external stimulus would lead to the modulation of peak-frequency eventually.

The neural dynamic study of the phase-locked feedback system in this work deepens our understanding on the mechanism of brainwave entrainment with the external stimulus. The proposed two-dimensional limit cycle model, allows us thoroughly explore the influence of different factors on the effect of EEG modulation, and what kind of dynamic structure would have a joint amplitude-frequency modulation phenomenon. Based on these investigations, a new EEG modulation protocol can be further developed.

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