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Phase shifts in alpha-frequency rhythm detected in electroencephalograms influence reaction time

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ABSTRACT

Although the phase shifts in ongoing oscillations seen in electroencephalograms (EEGs) and magnetoencephalograms are an important factor in discussions of phase dynamics, such as synchrony and reset, few studies have focused specifically on the phase shift. Here we investigate the relationship between phase shifts in alpha-frequency rhythms and reaction times during a visual simple reaction task by applying our previously described method (Naruse et al., 2013), which enables detection of phase shifts from a single EEG trial. In the left, parietal, and occipital areas, the reaction times in the trials in which phase shifts were detected before the button press were significantly longer than in those in which phase shifts were not so detected. These results indicate that phase shifts in the alpha and mu rhythms relate to variability in reaction times.

1. Introduction

The ongoing oscillations, i.e., alpha, beta, gamma, theta, and mu rhythms, seen in electroencephalograms (EEGs) and magnetoencephalograms (MEGs) exhibit a feature that has recently been gaining attention: they are synchronized (Lachaux, Rodriguez, Martinerie, & Varela, 1999; Mizuhara & Yamaguchi, 2007; Rodriguez et al., 1999; Varela, Lachaux, Rodriguez, & Martinerie, 2001) and reset (Makeig et al., 2002; Naruse, Matani, Hayakawa, & Fujimaki, 2006; Palva & Palva, 2007) by external stimuli. Although these oscillations include both amplitude and phase components, here we focus on the latter because phase is the most important factor in discussing synchrony and reset. In phase synchronization, the phases are shifted by external stimuli so that they are synchronized across more than two brain regions. In phase reset, the phases are rapidly changed by external stimuli. Thus, the ability to detect phase shifts is essential to understanding these phenomena.

To detect these shifts – in particular, phase resets – some previous studies have averaged data from many trials because of the low signal-to-noise ratio of EEG and MEG signals (Makeig et al., 2002; Naruse et al., 2006). The averaging method can detect only the phase-locking type of shifts that occur with similar timings over many trials. Other studies have detected phase shifts from single-trial data by using the Hilbert transform (Freeman, Burke, & Holmes, 2003; Kozma, Davis, & Freeman, 2012). However, phase shifts detected with this method have tended to concentrate in low-amplitude intervals (Freeman et al., 2003), raising the suspicion that they may be artifacts, perhaps caused by a loss of precision in the low-amplitude data. In an earlier study, we reported a novel statistical method that can detect phase shifts in the alpha rhythm from a single EEG trial (Naruse, Takiyama, Okada, & Umehara, 2013). This method uses state-space models (SSMs) and the line-process (LP) technique (Geman & Geman, 1984). The LP technique is a Bayesian method that can detect discontinuous changes in time series data. One important feature of our method is that it detects phase shifts most effectively when the amplitude is

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high and, accordingly, avoids false detections owing to imprecision in low-amplitude data (Naruse et al., 2013). However, the feature tends to increase the miss of the detection of the phase shift in low-amplitude data. The results from flash–response EEG data showed that there are non-phase-locking shifts that occur at differing times among trials, which cannot be detected by the averaging method. Our previous work mentioned only the dynamics of the phase shifts in the alpha rhythm; the functional role of these shifts in the alpha rhythm remains unclear.

Several studies have revealed the relationship between the phase of the alpha rhythm at stimulus onset and brain function, such as visual awareness (Mathewson, Gratton, Fabiani, Beck, & Ro, 2009), perceptual framing (Varela, Toro, John, & Schwartz, 1981), and reaction times (RTs) (Callaway & Yeager, 1960). In this study, we focus on the influence of the phase of the alpha rhythm on RTs because this problem has been outstanding since 1960. Callaway and Yeager first reported that the phase of the alpha rhythm at stimulus onset significantly influences RTs during a visual simple reaction task, and they concluded with the observation that "finer details of the relationship between alpha phase and reaction time must wait further investigation" (Callaway & Yeager, 1960). Decades afterward, the finer details are still unclear.

To our knowledge, there is no study that discusses the relationship between phase shifts in the alpha rhythm and RTs. By focusing on the influence of phase shifts on RTs, we expect that the functional role of these shifts can be elucidated. For instance, Freeman et al. have hypothesized that phase shifts represent state transitions in the brain (Freeman et al., 2003). If this is the case, then the RTs in a trial in which a phase shift is detected before a button press could differ from those in a trial that detects no such shift.

While the alpha rhythm occurs over the posterior regions of the brain, there is another rhythm at the alpha frequency (8–13 Hz) that occurs over the central or centro-parietal region, the mu rhythm, which relates to motor control (Chatrian et al., 1974). Phase shifts in the mu rhythm also may be connected to RTs. In this study, we investigate the relationship between phase shifts in the rhythms of alpha frequency and RTs during a visual simple reaction task.

2. Method

2.1. Phase-shift detection in a single trial

Our method for detecting phase shifts in a single trial was proposed in Naruse et al. (2013), to which we refer the reader for more details.

The EEG data at the sampling point k is denoted by y_k. We assume that y_k includes the alpha-frequency rhythm and independent observation noise between sampling points. Thus, it is expressed as $y_k = a_k \cos x_k + \xi$, where x_k and a_k denote the instantaneous phase and amplitude of the rhythm of the alpha frequency at sampling point k, respectively, and ξ denotes the observation noise. Note that the domain of the phase is $[0, 2\pi)$ and that of the amplitude is $[0, \infty)$. Here we assume the noise is Gaussian, and hence the likelihood function is

$$p(y_k|a_k, x_k, \alpha) = \sqrt{\frac{\alpha}{2\pi}} \exp\left[-\frac{\alpha}{2}(y_k - a_k \cos x_k)^2\right], \tag{1}$$

where α is a hyperparameter that controls the strength of the observation noise. We define the prior distribution of the phase using the von Mises distribution and the SSM as

$$p(\boldsymbol{x}, \boldsymbol{l}^p|\beta, \omega, \kappa) = \frac{\exp\left\{\sum_{n=1}^{N-1}[(1 - l_n^p)\beta \cos(x_{n+1} - x_n - \omega) - l_n^p \kappa]\right\}}{Z_p(\beta, \kappa)}, \tag{2}$$

where $\boldsymbol{x} = \{x_1, x_2, \ldots, x_N\}$, $\boldsymbol{l}^p = \{l_1^p, l_2^p, \ldots, l_{N-1}^p\} \in \{0, 1\}^{N-1}$, and $Z_p(\beta, \kappa)$ indicate the instantaneous phase, the parameter for the phase shift based on the LP technique, and the normalization constant of $p(\boldsymbol{x}, \boldsymbol{l}^p|\beta, \omega, \kappa)$, respectively. The hyperparameters β, ω, and κ control the amount of phase fluctuation, the individual alpha frequency, and the frequency of the phase shift, respectively. N is the number of sampling points; $l_k^p = 1$ indicates the occurrence of a phase shift in the time bin between the kth and $(k+1)$st sampling points, and $l_k^p = 0$ indicates a smooth phase change.

Similarly, we define the prior distribution of the amplitude using the Gaussian distribution and the SSM as

$$p(\boldsymbol{a}, \boldsymbol{l}^a|\gamma, \lambda) = \frac{\exp\left(\left\{\sum_{n=1}^{N-1}\{(1 - l_n^a)\left[-\frac{1}{2}\gamma(a_{n+1} - a_n)^2\right] - l_n^a\lambda\}\right\}\right)}{Z_a(\gamma, \lambda)}, \tag{3}$$

where $\boldsymbol{a} = \{a_1, a_2, \ldots, a_N\}$, $\boldsymbol{l}^a = \{l_1^a, l_2^a, \ldots, l_{N-1}^a\} \in \{0, 1\}^{N-1}$, and $Z_a(\gamma, \lambda)$ indicate the instantaneous amplitude, the parameter for the amplitude shift based on the LP technique, and the normalization constant of $p(\boldsymbol{a}, \boldsymbol{l}^a|\gamma, \lambda)$, respectively; the hyperparameters γ and λ control the magnitude of the amplitude fluctuation and the frequency of the amplitude shift, respectively. Similarly to the case of the phase shift, $l_k^a = 1$ indicates the occurrence of an amplitude shift and $l_k^a = 0$ indicates a smooth amplitude change at the time bin between the kth and $(k+1)$st sampling points.

Assuming that the prior distributions of the phase and amplitude are independent, we can express the posterior distribution based on Bayes' theorem as

$$p(\boldsymbol{a}, \boldsymbol{x}, \boldsymbol{l}^p, \boldsymbol{l}^a|\boldsymbol{y}, \alpha, \beta, \gamma, \omega, \kappa, \lambda) = \frac{p(\boldsymbol{y}|\boldsymbol{a}, \boldsymbol{x}, \alpha)p(\boldsymbol{x}, \boldsymbol{l}^p|\beta, \omega, \kappa)p(\boldsymbol{a}, \boldsymbol{l}^a|\gamma, \lambda)}{Z(\alpha, \beta, \gamma, \omega, \kappa, \lambda)}, \tag{4}$$

where $Z(\alpha, \beta, \gamma, \omega, \kappa, \lambda)$, which is equal to $p(\boldsymbol{y}|\alpha, \beta, \gamma, \omega, \kappa, \lambda)$, is the normalization constant of $p(\boldsymbol{a}, \boldsymbol{x}, \boldsymbol{l}^p, \boldsymbol{l}^a|\boldsymbol{y}, \alpha, \beta, \gamma, \omega, \kappa, \lambda)$.

We estimated the hyperparameters on the basis of type II maximum likelihood estimation. Their estimated values are

$$\{\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\omega}, \hat{\kappa}, \hat{\lambda}\} = \arg\left[\max_{\{\alpha,\beta,\gamma,\omega,\kappa,\lambda\}} \prod_{h=1}^{H} Z_h(\alpha, \beta, \gamma, \omega, \kappa, \lambda)\right], \tag{5}$$

where H indicates the number of trials.

When marginalizing the posterior distribution between sampling points k and $k+1$, we can calculate the probabilities of four states:

(S1) Both the phase and amplitude are smooth $[p(l_k^p = 0, l_k^a = 0) = p(l_k^p = 0) \times p(l_k^a = 0)]$;
(S2) Only the phase is shifted $[p(l_k^p = 1, l_k^a = 0) = p(l_k^p = 1)p(l_k^a = 0)]$;
(S3) Only the amplitude is shifted $[p(l_k^p = 0, l_k^a = 1) = p(l_k^p = 0)p(l_k^a = 1)]$; and
(S4) Both are shifted $[p(l_k^p = 1, l_k^a = 1) = p(l_k^p = 1)p(l_k^a = 1)]$.

By comparing the probabilities of these four states, we can estimate the state at each time bin. In this study, we focus on the phase shift, and therefore, we define a phase shift to have been detected in the bin between sampling points k and $k+1$ if S2 or S4 has the highest probability among the four states.

2.2. EEG experiments

We used the data described in Naruse, Takiyama, Okada, and Murata (2010). EEG data from six clinically normal adult volunteers with their eyes closed were recorded. None of the subjects had any history of relevant neurological or visual disorders. All