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Detection of Phase Synchronization in EEG With Bivariate Empirical Mode Decomposition

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Abstract— **In recent years, the phase synchronization phenomenon in the electroencephalograph (EEG) has been widely used to observe interactions between separate areas of the cortex. However, the traditional coherence to measure the phase synchronization need target signals to be stationary. In this paper, we propose a technique to measure the phase synchrony of non-stationary signals by the Phase Locking Value (PLV) with Hilbert transform and the Bivariate Empirical Mode Decomposition (BEMD). We analyzed the phase synchronization of EEG signals which were recorded during Dynamical Dot Quartet (DDQ) tasks using the conventional method and the proposed method. The analysis result suggests that proposed method more suitable for detecting the phase synchrony during the DDQ tasks than the conventional methods.**

I. Introduction

A brain has different functions in each cortex. Some brain activities associated with certain mental tasks are observed at several cortices at the same time [1]. Such brain activities that occur at several cortex are called cooperative brain activities. A recent study [2] has suggested that cooperative brain activities can be measured by the phase synchronization of electroencephalograph (EEG) signals.

The coherence [3] is a classical method for quantifying the phase synchronization. However, by definition the coherence assumes the stationarity of EEG signals which is not a practical assumption. The Phase Locking Value (PLV) evaluates the synchrony of two signals by the instantaneous phase difference that is extracted by a time–frequency analysis. Unlike the coherence, the PLV does not need to assume the stationary of signals.

To calculate the PLV, the instantaneous phase of the signal should be estimated. Well-known classical methods to extract the phase are short-time Fourier transforms and wavelet transforms [4]. Such a time–frequency analysis provides instantaneous phases of the target signal [5]. However, these methods have a trade-off between the temporal resolution and the frequency resolution [4]. Moreover, these methods are not suitable for analyzing components that have frequency fluctuations, which can be decomposed into several narrow-band components, even though the signal contains only one synchronized component.

To avoid this, we propose to use the Bivariate Empirical Mode Decomposition (BEMD) [6], [7] followed by the Hilbert transform [8] to obtain the instantaneous phase. The BEMD decomposes two target signals into the signals called Intrinsic Mode Functions (IMF), which are amplitude/frequency-modulated (AM/FM) waveforms. Therefore, even though the target component in the observed signal has a single oscillating mode with slightly fluctuating frequencies, it can be represented as a single IMF. Moreover it should be noted [6], [9] that the IMF well-defines the instantaneous phase by using the Hilbert transform. In [10], a synchrony analysis using the ordinary univariate EMD [9] was reported. However, the UEMD generates different numbers of IMFs for two different channel signals. This yields the difficulty of the synchrony analysis.

We analyzed the EEG signals recorded during Dynamical Dot Quartet (DDQ) tasks where the two dots are shown to subjects [11]. It has been found [11], when the subjects perceive that the dots move horizontally, the phases synchronizes between left and right visual cortex. Previous works showed the relation between the phase synchronization and the perception using the coherence [11] and wavelet transforms with the PLV [12]. We demonstrated that the proposed method is more suitable for detecting the phase synchrony than the conventional methods. We also analyzed the variation of the PLV over time in the relation between the phase synchronization and the perception using the proposed and the conventional methods.

II. Phase Synchrony Detection Using Single-Trial Phase Locking Value

The phase locking is defined as the constant phase difference. Given a pair of signals $x(t)$ and $y(t)$, the phase locking is defined [13] as

$$\left|\phi_x(t) - \phi_y(t)\right| = \text{const.}, \tag{1}$$

where $\phi_x(t)$ and $\phi_y(t)$ are instantaneous phases of $x(t)$ and $y(t)$, respectively. Even if the phase of two signals is locked, the phase difference of practical observed signals is not exactly constant. Thus, to quantify the phase difference, the Single-trial Phase Locking Value (SPLV) can be used [13]. The SPLV is defined as the time-average of the phase component:

$$\mathrm{SPLV}(f,t) = \left|\frac{1}{T}\int_{t-T/2}^{t+T/2} \exp(i(\phi_y(f,t) - \phi_x(f,t)))dt\right|, \tag{2}$$

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where $i = \sqrt{-1}$ is the imaginary unit, $\phi_x(f,t)$ and $\phi_y(f,t)$ are the instantaneous phases of narrow-band signals with the center frequency of f, and T is the length of a time window, which controls the temporal resolution of the analysis. SPLV ranges from 0 to 1, and 1 indicates the strongest phase-locking. When the length of the smoothing window is short, the temporal resolution is considered high. The short length of a smoothing window can lead to the SPLV close to unity.

III. Phase Component Extracting Method

A. Wavelet transform

The instantaneous phase is extracted from the coefficients of complex-valued wavelet transforms [4]. The wavelet transform is given as

$$W_x(\tau, f) = \int_{-\infty}^{\infty} x(t)\Psi^*_{\tau,f}(t)dt, \quad (3)$$

where $x(t)$ is the observed signal, $\Psi_{\tau,f}(t)$ is the wavelet function, τ is the center location, f is the target frequency, and $\cdot^*$ is the complex conjugate. The well-known complex Gabor wavelet is given as

$$\Psi_{\tau,f}(t) = \sqrt{f}\exp(i2\pi f(t-\tau))\exp\left(-\frac{(t-\tau)^2}{2\sigma^2}\right), \quad (4)$$

where σ is the standard deviation.

It follows that the instantaneous phase difference between $x(t)$ and $y(t)$ can be described with the wavelet coefficients as

$$\exp(i(\phi_x(\tau,f) - \phi_y(\tau,f))) = \frac{W_x(\tau,f)W^*_y(\tau,f)}{|W_x(\tau,f)W_y(\tau,f)|}, \quad (5)$$

where $\phi_x(\tau,f)$ and $\phi_y(\tau,f)$ are the phase components of $W_x(\tau,f)$ and $W_y(\tau,f)$, respectively.

B. BEMD

Empirical Mode Decomposition (EMD) [9], [14], [**?**] is a data-driven signal decomposition. This technique decomposes a signal into several waveforms modulated with both amplitude and frequency. Each decomposed waveform is called as Intrinsic Mode Function (IMF) [9], [14]. The important feature of the EMD is that the number of IMFs and the spectrum of IMFs are fully dependent on the original signal [9].

An extension of the EMD to bivariate data is the Bivariate Empirical Mode Decomposition (BEMD) which is suitable for dealing with a bivariate time series [6], [7]. The BEMD decomposes two signals to a pair of the same number of IMFs.

The algorithm of BEMD for two signals $x_1(t)$ and $x_2(t)$ can be given as follows [6]:

1) Compose a complex signal, $C(t) = x_1(t) + ix_2(t)$.
2) For $1 < m < M$,
   a) Project $C(t)$ on direction ϕ_m as $p_{\phi_m} = \Re(e^{-i\phi_m}C(t))$;
   b) Extract the maxima of $p_{\phi_m}(t)$ from (t^m_i, p^m_i);
   c) Interpolate the set of points $(t^m_i, e^{i\phi_m}p^m_i)$ to obtain the 3-dimensional envelope curve in direction ϕ_m named $e_{\phi_m}(t)$.
3) Compute the mean of all tangents $e(t) = \frac{2}{M}\sum_m e_{\phi_m}(t)$.
4) Subtract the mean to obtain $d(t) = C(t) - e(t)$.
5) Test if $d(t)$ satisfies the conditions of IMF,
   - If yes, repeat the procedure from the step 2 on the residual signal.
   - If not, replace $x(t)$ with $d(t)$ and repeat the procedure from step 2.

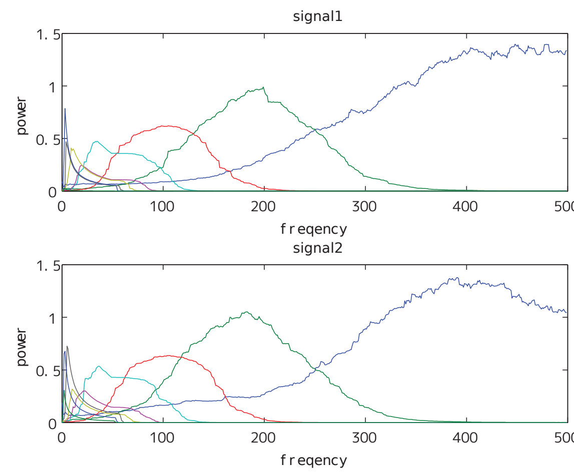


Fig. 1. Real and imaginary part of spectra of the IMFs obtained from two independent Gaussian white noises with the BEMD are indicated as signal1 (top) and signal2 (bottom). It can be observed that each IMF is almost band-limited.

In summary, the BEMD can be expressed as

$$C(t) = \sum_k d_k(t) + r(t), \quad (6)$$

where $d_k(t)$ is the $k-$th complex IMF and $r(t)$ is the residuum. An example of spectra of IMFs via BEMD is illustrated in Fig. 1.

C. Hilbert transform

From each component of $d_k(t)$, the instantaneous phase should be extracted. Indeed, we can obtain the instantaneous phase from an IMF as follows. A real signal can be expressed as

$$x(t) = a(t)\Re(\exp i\phi(t)), \quad (7)$$

where $a(t)$ is the instantaneous amplitude and $\phi(t)$ is the instantaneous phase, which are given as

$$a(t) = \sqrt{x^2(t) + (H[x(t)])^2}, \quad (8)$$

$$\phi(t) = \arctan\left(\frac{H[x(t)]}{x(t)}\right). \quad (9)$$

where $H[x(t)]$ is the Hilbert transform of $x(t)$ [8], yielding $z(t) = x(t) + iH[x(t)]$ called the analytic signal of $x(t)$. The derivative of $\phi(t)$ is the instantaneous frequency.

IV. Experimental Methods

A. Subjects and stimuli

We analyzed the EEG data during Dynamical Dot Quartet tasks, which were obtained in the Laboratory for Rhythm-Based Brain Information Processing Unit, RIKEN Brain

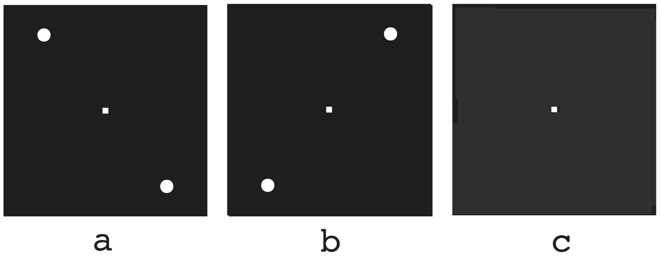


Fig. 2. Dynamical Dot Quartet (DDQ) stimulus layout [12]. a, b: Two diagonal tokens (filled white circles; diameter: 0.6875°). The horizontal and vertical distances between dots from center to center were 6.4101° and 7.8943°, respectively (aspect ratio, 1:1.2315). c: Fixation square.

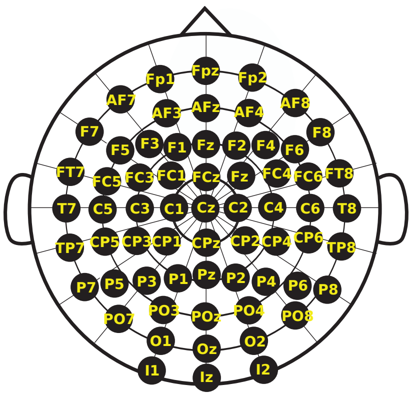


Fig. 3. The location of electrodes. (the international 10/10 system [15])

Science Institute. Sixteen healthy volunteers (age 20–43) took part in this experiment. The subjects were seated on a chair and watched a computer monitor.

The subjects tasks were given as follows.

1) The subjects gaze at a fixation square exhibited in the middle throughout each experimental run as shown in Fig. 2 for 10 sec.
2) Two diagonal tokens as illustrated in Fig. 2a were presented for 250 ms and were then replaced by the other tokens as illustrated in Fig. 2b for 250 ms. These two patterns of diagonal tokens were alternatively presented for 60 sec.
3) Subjects were asked to keep pushing a button only while the stimulus is perceived as moving horizontally.

Each subject conducted these tasks twice. If the subjects never push the button at a trial, the data at that trial were removed.

B. Data acquisition

EEG signals were recorded with 64 Ag/AgCl electrodes at position illustrated in Fig. 3. The EEG signals were amplified by BrainAmp MR plus (Brain Products) and filtered in the frequency band of 0.1–100 Hz. Moreover, we subtracted reference EEG signals which were placed on the right and lef lobes. The sampling rate was 1000 Hz.

C. SPLV with Wavelet and BEMD: wPLV and iPLV

We calculate the SPLV values of a pair of signals by using the Gabor wavelet and the BEMD, as mentioned in the previous section. Referring to [11], we analyzed the phase synchrony in a pair of electrodes, P5–P6, P7–P8, PO7–PO8, and TP7–TP8.

With the complex Gabor wavelet, we apply the same method as [12], that is, we calculated wavelet coefficients for frequencies $f = 31, 32, \ldots, 45$ Hz, yielding SPLV(f, t). Then, we define a time series of SPLV as

$$\mathrm{wPLV}(t) = \frac{1}{15} \sum_{f=31}^{45} \mathrm{SPLV}(f, t). \tag{10}$$

By using the BEMD, we also calculate SPLV of the IMF that has the peak in the range of 31–45 Hz. This time series is denoted by iPLV(t). Note that there may exist more than one IMF that has the peak in this range of frequencies[1]. In this case, we choose one of those IMFs.

V. Results and Discussion

By this experiment, we would like to confirm the variation of PLV while subjects have the perception as the horizontal dots motion. It has been found [11], [12] that the PLV between electrodes on both hemisphere increases.

Our analysis suggested that iPLV(t) with BEMD works more efficiently in detecting the perception of horizontal movement than wPLV(t) with the Gabor wavelet. We chose $\sigma = 8/f$, and wavelet window length was 1000σ. Detailed results and discussions are given as follows.

Figure 4 shows the evolutions of the SPLV (iPLV(t) and wPLV(t)) for the 16-th subject. The shaded area indicates periods when the subject perceived the visual stimulus as horizontal motion, that is, when the subject kept pushing the button. We denote this period by HPn and the other period by OPn, where n is the index. In the case of Fig. 4, the 16th subject has the sequence of perception: OP1, HP1, OP2, HP2, OP3, HP3, OP4, HP4, OP5. In order to enhance the variation of SPLV, we plot in Fig. 5 the values of SPLV averaged over either HPn or OPn. For example, we denote the average of iPLV(t) over HPn by iPLV(HPn). In Fig. 5, we observe the increase of iPLV(HPn) at HP1, HP2, and HP4. On the other hand, wPLV(t) increased very slightly at only HP2.

The number of the increase of SPLV was counted in all experimental sessions for all subjects. Specifically, we counted the number of "successes" which are the cases where

$$\mathrm{SPLV}(\mathrm{OP}n) < \mathrm{SPLV}(\mathrm{HP}n).$$

Throughout all experimental runs for all the subjects, we observed the perception of horizontal motion 55 times. Figure 6 lists the ratio of the number of successes to 55 in percent. In both methods, we varied the length of the smoothing window, T, from 5 ms to 1000 ms. It can be seen that for all cases, SPLV with the BEMD (iPLV(t)) showed more accurate detection of the horizontal motion perception. The maximum percentage in the case of wPLV(t) was 58.1 %, when $T = 50$ ms and a pair of electrodes was P7–P8, while in the case of iPLV(t), the maximum was 83.6 %, when $T = 50$ ms and a pair of electrodes was P5–P6.

[1]Our experiment suggested that usually we obtained only one or at most two IMFs in this range.

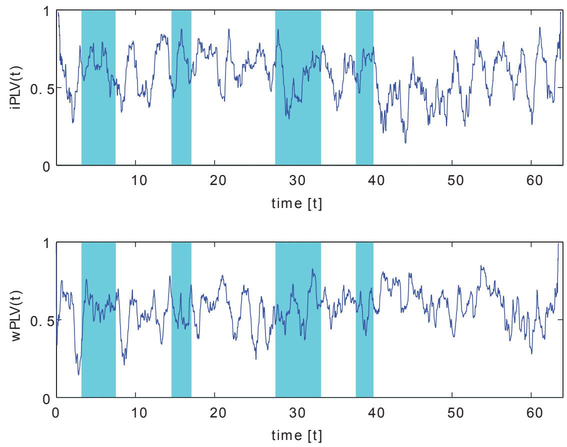


Fig. 4. Time evolution of SPLV for the second trial data of the 16th subject. Shaded sections indicate the period for horizontal perception, HP*n*. The upper panel shows iPLV(t), and the lower panel shows wPLV(t). The length of the smoothing window was 500 ms, and the pair of electrodes was P5–P6.

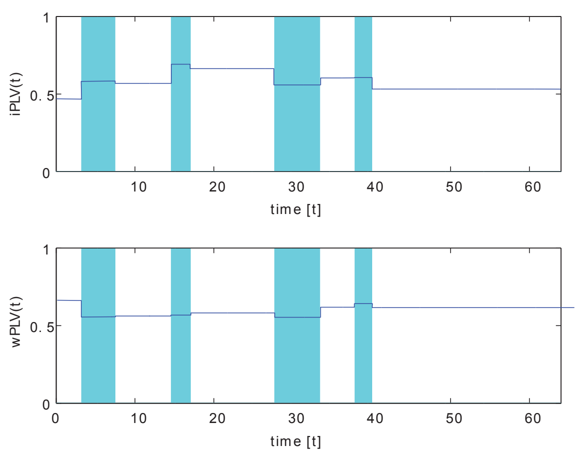
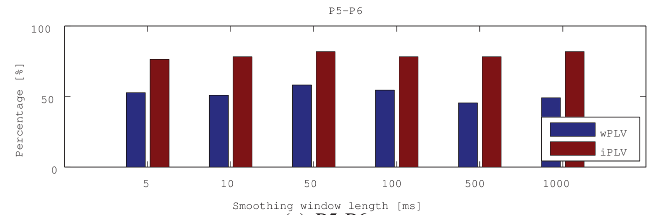
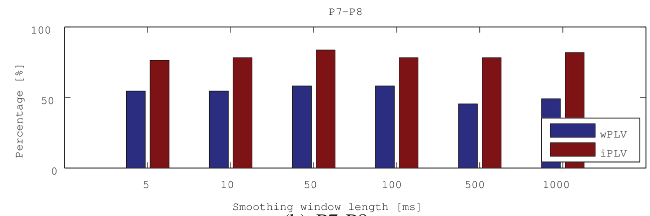


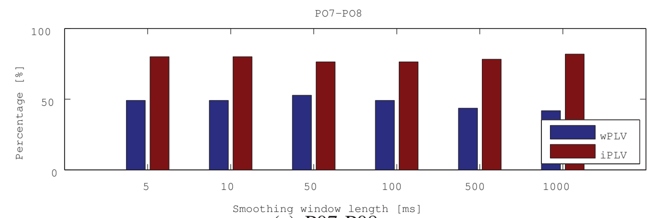
Fig. 5. The averaged values of iPLV(t) and wPLV(t) over each period for the data shown in Fig. 4. The upper panel shows the averages for iPLV(t), and the lower panel for wPLV(t).



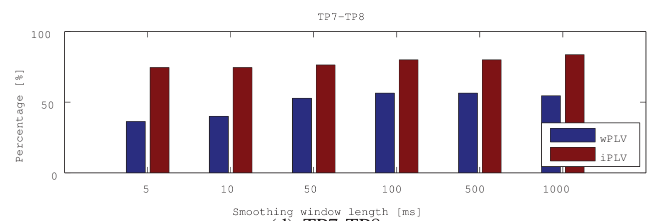
(a) P5-P6



(b) P7-P8



(c) P07-P08



(d) TP7-TP8

Fig. 6. Percentage of the number of "successes." SPLV with the Gabor wavelet is indicated by gray bars, and that with the BEMD is illustrated by white bars. For all window lenths, $p < 0.01$ as a result of t test.

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