PHASE SYNCHRONIZATION ANALYSIS OF EEG CHANNELS USING BIVARIATE EMPIRICAL MODE DECOMPOSITION

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ABSTRACT

The paper presents a novel concept implementing a phase locking value index estimation in application to brain-computer interfacing (BCI) motor imagery paradigm. We propose to decompose first the pairs of EEG channels using a bivariate empirical mode decomposition (BEMD) method. Next, the phase locking values (PLV) are estimated for the obtained intrinsic mode functions resulting in discriminating features drawn from EEG channel pairs representing the two different lateral hemispheres. Numerical results suggest that the PLV induced from BEMD can effectively detect phase synchrony between electrodes and is a promising feature for BCI implementation.

***Index Terms*—** BCI, EEG signal processing, bivariate EMD, phase synchrony, multivariate signal processing

1. INTRODUCTION

The state of the art brain–computer–interfaces (BCI) rely mostly on visual and imagery paradigms [1], which depend on EEG amplitude information that is unfortunately very sensitive to electrode impedance variability. Recent research reports have proposed to utilize EEG signal phase information [2, 3, 4, 5, 6] in order to avoid the signal amplitude related problems. To detect the phase synchronization, the so-called phase locking value (PLV) has been widely used [2]. To calculate the PLV, the observed EEG is decomposed into narrow-band signals by time-frequency analysis such as wavelets, and the phase difference between the EEG signals at two electrodes is evaluated. If two narrow-band signals are fully synchronized, the PLV has the value of unity.

This idea has been exploited to extract features aiming at BCI [3, 7, 8, **?**, 9, 10, 11]. In [3, 12, 7, 8, 10], the PLV is extensively used and studied as a feature of mental tasks such as motor-imagery. However, there is a limitation of detecting the phase-synchrony by using the PLV, when using time-frequency transformations. The signal component synchronized at different areas in the brain is rarely a narrow-band signal, since the frequency and the amplitude slightly fluctuate. Therefore, the synchronizing component can be decomposed into multiple narrow-band components, where the PLV cannot well quantify the phase synchrony.

A very efficient method for decomposing a signal into amplitude- and frequency-fluctuating functions (intrinsic mode functions (IMFs)) is the empirical mode decomposition (EMD) [13]. To solve the aforementioned problem, the EMD is utilized for obtaining the PLV through the instantaneous phase to evaluate the phase synchronization during motor-imageries [11]. However, in [11], the EMD is independently applied for each electrode, and therefore it can generate the different number of IMFs at different electrodes. This implies that IMFs of the same index number at two electrodes span totally different sub-bands.

To solve this problem, we propose to analyze EEG phase locking value (PLV) with utilization of data–driven bivariate empirical mode decomposition (BEMD) [14] method. In order to do so, we first decompose the pairs of recorded signals into the so called intrinsic mode functions (IMF) with utilization of the BEMD technique. Next we analyze the PLV indexes for the pairs of IMFs originating from between different EEG channel pairs. Finally we identify those PLV results which allow for discrimination of movement imagery patterns on the classical left/right hand movement paradigm.

From now on the paper is organized as follows. First we introduce the EEG recording experiment details. Next we discuss the BEMD signal decomposition leading to the pairwise PLV indexes analysis of the band limited and accurate instantaneous phase containing components. Finally we present the very encouraging results of inter–hemispheres PLV indexes variability allowing for the movement imagery patterns detection and lateral discrimination. The results discussion concludes the paper.

2. METHODS

The experiments reported in this paper have been conducted on voluntary bases in the Advanced Brain Signal Processing Laboratory of RIKEN Brain Science Institute, Japan. The experimental paradigm was a classic movement imagery task [1]. The subject imagined sequentially left and right hand oscillatory movements for about four seconds each. The EEG electrodes were connected to the head channels $C1$, $C2$, $C3$, $C4$, $C5$, $C6$, $T7$, $T8$, $CP1$, $CP2$, $CP3$, $CP4$, $CP5$, and $CP6$, as in extended $10/20$ EEG recording systems. The EEG signals were sampled with 512 Hz frequency. The electrode impedance was maintained below 10 kΩ using the g.USBamp biosignal amplifier. A single experiment consisted of a sequence of relaxation, followed by left and right hand movement imageries, respectively. The number of individual left hand and right hand trials was set to five. The recorded and analyzed signals were artifact free (visual inspection). The recorded data were used next to derive phase locking value based features to distinguish different motor imagery stages (relaxation and left vs. right). We propose a data adaptive multi–band approach to observe the phase synchrony of different EEG channels using bivariate empirical mode decom-

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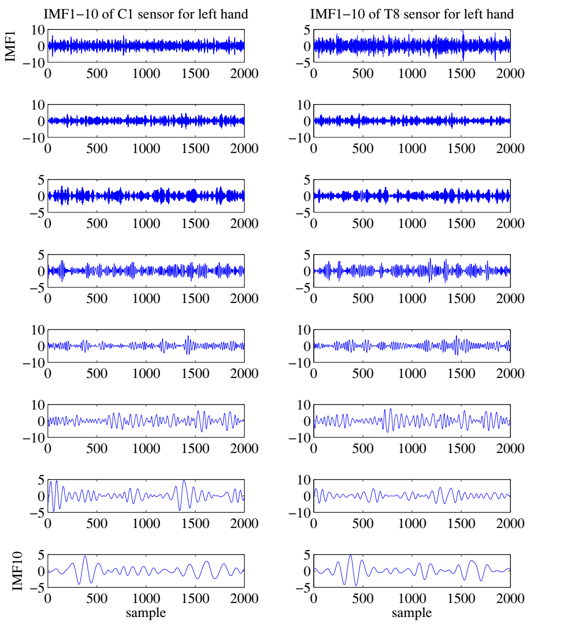


Fig. 1. The IMFs $(1-10)$ out of 14 of the EEG channels $C1$ and $T8$ obtained by applying BEMD.

position (BEMD) [14]. Each pair of the available EEG channels is decomposed together into a finite number of sub–bands taking into account their co-variation.

2.1. BEMD Analysis of EEG Signals

The Empirical Mode Decomposition (EMD) is a signal processing decomposition technique that decomposes the signal into waveforms modulated in both amplitude and frequency by extracting all of the oscillatory modes embedded in the signal [13]. The Complex Empirical Mode Decomposition (Complex-EMD) is an extension of the basic EMD suitable for dealing with complex value signals [15]. The motivation to extend EMD was that a large number of signal processing applications have complex value waveforms. In addition, this extension is applied to both real and imaginary parts simultaneously because complex valued signals have a mutual dependence between the real and imaginary parts. Thus, if the decomposition is done separately, the mutual dependency could be lost.

The Bivariate Empirical Mode Decomposition (BEMD) is a more generalized extension of the EMD to complex valued signals. The main difference between the BEMD and the Complex-EMD is that the latter uses the basic EMD to decompose complex signals, whereas the BEMD adapts the rationale underlying the EMD to a bivariate framework [14, 16]. In BEMD two variables are decomposed simultaneously based on their rotating properties. The BEMD algorithm, as proposed in [14], is as follows:

1) For $1 < m < M$,
   a) Project $x(t)$ on direction ϕ_m as: $p_{\phi_m} = Re(e^{-i\phi_m} x(t))$;
   b) Extract the maxima of $p_{\phi_m}(t)$ from: (t_i^m, p_i^m);
   c) Interpolate the set of $points(t_i^m, e^{i\phi_m} p_i^m)$ to obtain the partial envelope curve in direction ϕ_m named $e_{\phi_m}(t)$.

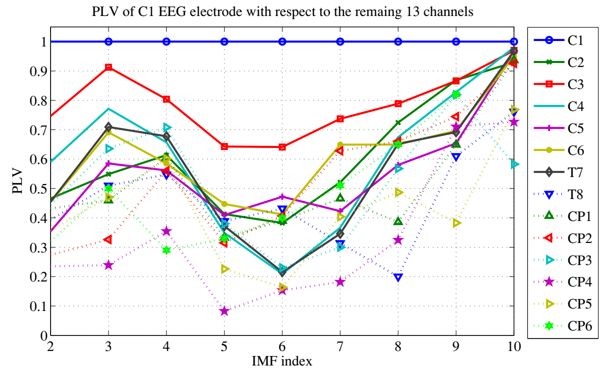


Fig. 2. The PLV of individual IMFs for 13 EEG channels with respect to the first one ($C1$ electrode).

2) Compute the mean of all tangents: $e(t) = \frac{2}{M} \sum_m e_{\phi_m}(t)$.
3) Subtract the mean to obtain $d(t) = x(t) - e(t)$.
4) Test if $d(t)$ is an IMF,
   – If yes, repeat the procedure from step 1 on the residual signal;
   – If not, replace $x(t)$ with $d(t)$ and repeat the procedure from Step 1.

The bivariate EMD can now be expressed as:

$$x(t) = \sum_k d_k(t) + r(t), \tag{1}$$

where $d_k(t)$ denotes the k^{th} extracted complex empirical mode and $r(t)$ the residuum. The BEMD is employed to decompose a pair of EEG channels together. The IMFs 1–10 of $C1$ and $T8$ EEG channels for left hand movement motor imagery are illustrated in Fig. 1.

2.2. BEMD-Based EEG Phase Synchrony Detection

To determine the phase synchrony [5] two different EEG channels are decomposed into a finite number of IMFs using BEMD. A complex valued vector $x(t)$ is defined as: $x(t) = c_1(t) + jc_2(t)$; where $c_1(t)$ and $c_2(t)$ are two EEG channels. Each IMFs $d(t)$ obtained from Eq. (1) has real and imaginary components $y_R(t)$ and $y_I(t)$ respectively. The IMF's real part $y_R(t)$ corresponds the intrinsic mode of channel $c_1(t)$ and $y_I(t)$ of channel $c_2(t)$ respectively. The BEMD method is used as the preprocessor in face of the unwrapping problem in the Hilbert transform [13]. The instantaneous phase of a given signal $y(t)$ is computed as:

$$\tilde{y}(t) = \frac{1}{\pi}\Theta\left[\int_{-\infty}^{+\infty} \frac{y(\tau)}{t-\tau} d\tau\right] \tag{2}$$

$$\varphi(t) = \arctan\frac{\tilde{y}(t)}{y(t)} \tag{3}$$

where $\tilde{y}(t)$ is the Hilbert transform of $y(t)$, $\Theta[\cdot]$ implies the Cauchy principal value and $\varphi(t)$ represents the instantaneous phase of the signal $y(t)$. Since the calculation of the Hilbert transform requires integration over infinite time, 10% of the calculated instantaneous values are discarded on each side of the processing window.

Given a pair of IMFs $y_R(t)$ and $y_I(t)$, the phase difference is defined as $\triangle\theta(t) = m\varphi_R(t) - n\varphi_I(t)$; where m and n are small integers

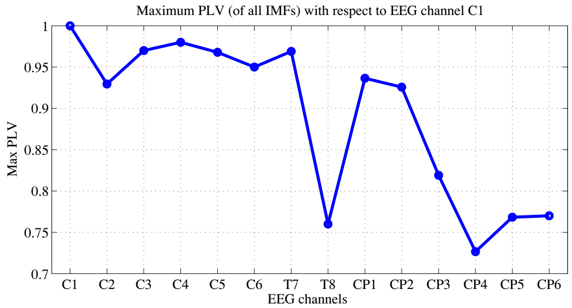


Fig. 3. The maximum PLV (among all IMFs) of all channels with respect to the first one (electrode $C1$).

that define the frequency equality $m\varphi_R(t) = n\varphi_I(t)$ of the coupled slow and fast oscillations (here $m : n = 1 : 1$), $\varphi_R(t)$ and $\varphi_I(t)$ are the instantaneous phase of $y_R(t)$ and $y_I(t)$ respectively. This phase difference is fluctuating and a statistical criterion is employed to quantify the degree of phase locking. Then phase locking value (PLV) δ can be defined as:

$$\delta = \left| \frac{1}{T} \sum_{t=0}^{T-1} e^{j\triangle\theta(t)} \right| \tag{4}$$

In the case when the two signals are completely synchronized, $\triangle\theta(t)$ is a constant and PLV equals the unity. Conversely, if two signals are unsynchronized, $\triangle\theta(t)$ follows a uniform distribution and PLV equals to zero.

3. EXPERIMENTAL RESULTS

After the first decomposition step of each EEG channel pairs, using the BEMD, into complex valued IMFs, each of them is next separated to real and imaginary vectors representing both processed EEG channel as shown in Fig. 1. The highest order (lower frequencies) IMFs are considered empirically to represent the artifacts (e.g. EOG) and hence not included in the subsequent PLV processing.

3.1. Maximum Phase Synchrony

The PLVs of individual IMFs of a pair of EEG channels are calculated using Eq. (4). The cross PLVs estimates of the 13 EEG channels with respect to the first channel ($C1$ EEG electrode) are illustrated in Fig. 2. It is shown there that the lower and higher order IMFs are more synchronized than the middle order.

If $\delta_i(p, q)$ represents the PLV between channels p and q at i^{th} IMF, the maximum phase synchrony is defined as,

$$\hat{\delta}(p, q) = \max_{i=1,2,...K} \delta_i(p, q), \tag{5}$$

where K is the total number of IMFs used in PLV processing. It implies that one of the IMFs exhibits maximum phase synchrony between the EEG channels p and q. The maximum PLV (among all IMFs) between the first channel ($C1$) and q^{th}, ($q = 1, 2, \ldots, 14$) i.e. $\hat{\delta}(1, q)$, is shown in Fig. 3.

In [11], the PLV of the relaxation period is used as the reference PLV to construct the distinguishing features for different motor imagery stages. In this experiment, the EEG of the sequence of relaxation as well as left and right hand imagery are recorded. Three EEG data sets (14 EEG channels each) corresponding to relax, left and right hand imagery movement are extracted from the mentioned

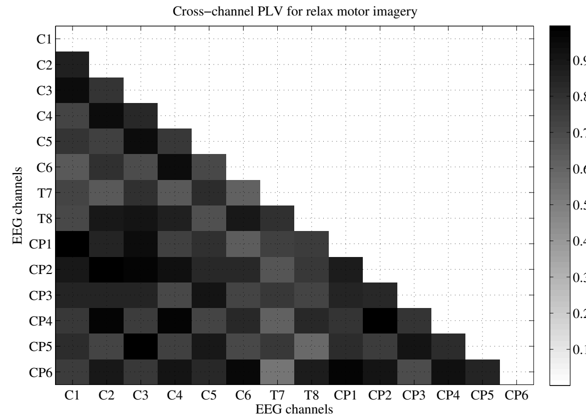


Fig. 4. Cross-channel PLV of relax stage for all possible pairs of the 14 EEG channels.

recordings. The cross-channel PLV matrices $\hat{\delta}_{relax}(1, q)$, $\hat{\delta}_{left}(1, q)$, and $\hat{\delta}_{right}(1, q)$ of individual motor events are computed first. The cross-channel PLV matrix (the all possible pairs of the 14 EEG channel set) with EEG of the relaxed stage is shown in Fig. 4.

Then the cross-channel PLV of motor imagery movement is next calculated (normalized) as follows:

$$\bar{\delta}(p, q) = \frac{\hat{\delta}_{left}(p, q) - \hat{\delta}_{relax}(p, q)}{\hat{\delta}_{relax}(p, q)} \times 100. \tag{6}$$

The normalized cross-channel PLV for left and right hand movement motor imagery $\bar{\delta}_L(p, q)$ and $\bar{\delta}_R(p, q)$ respectively is obtained using Eq. (6) and illustrated in Figs. 5(a) and 5(b), respectively.

3.2. Local PLV

To distinguish between left and right hand movement motor imageries the two pairs of electrodes $(T7, T8)$ and $(C1, T8)$ are selected as illustrative example. We observed that the mentioned pairs can significantly differentiate between left and right hand motor imageries in our experiments. A time window of 1 s is adopted for calculating the local PLV $\rho(t)$, where t represents the time window. The PLV within the specified time window t is calculated using Eq. (5). Then the local PLV is calculated in relation to the pre-task 4 s long relaxation period as:

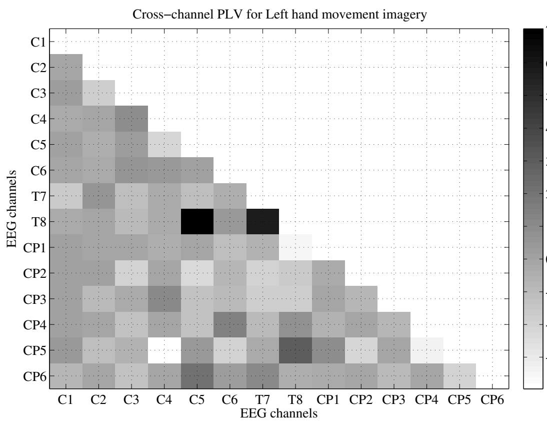
$$\rho_{ref} = \frac{1}{T} \sum_{t=1}^{T} \rho(t), \tag{7}$$

with $\rho_r(t)$ obtained from

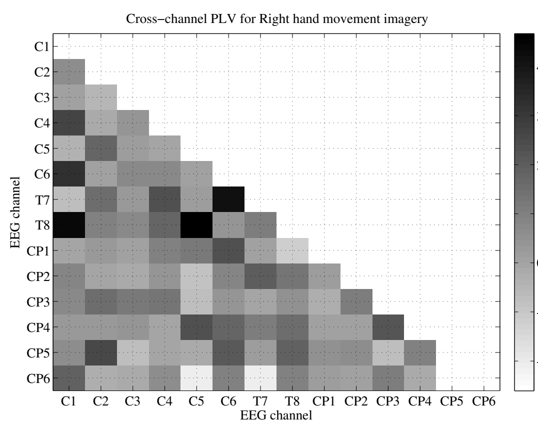
$$\rho_r(t) = \frac{\rho(t) - \rho_{ref}}{\rho_{ref}} \times 100\ [\%]. \tag{8}$$

where ρ_{ref} is the mean local PLV of the reference (relaxation) period and $\rho_r(t)$ is the PLV as shown in Fig. 6(a). Note that the local PLV of the mentioned two pairs of electrodes can differentiate properly the left and right hand motor imageries.

To justify the use the proposed method we compared the BMED with an univariate EMD (UEMD) EEG preprocessing for the same dataset as that used in the upper panel of Fig. 6(a). The result is presented in Fig. 6(b). Note that the classical UEMD preprocessing did not allow for the discrimination of PLV indexes in the movement imagery experiment.



(a) Left hand movement



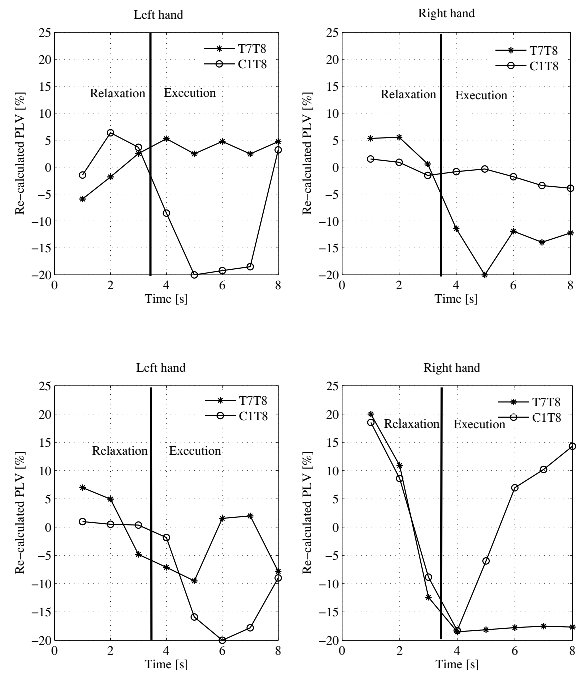
(b) Right hand movement

Fig. 5. Normalized cross-channel PLV for hand movement motor imagery.

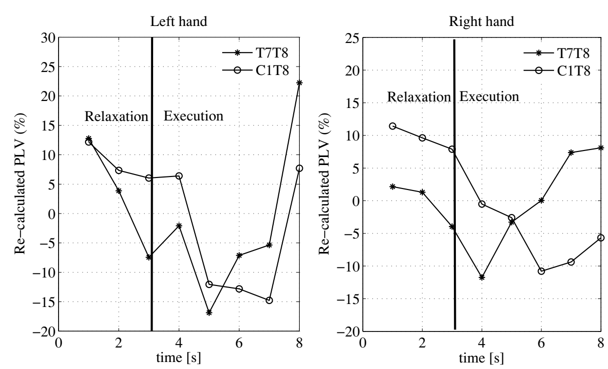
4. CONCLUSIONS

In the presented paper we have proposed a novel method to analyze EEG signals in BCI movement imagery paradigm using the phase locking information instead of the classical signal amplitude or power classification, which is very sensitive to the recording condition variability (unstable electrode impedance, etc.). The data–driven signal decomposition method BEMD has been applied for the pairwise EEG channels decompositions leading to the resulting PLV based phase synchrony analysis. The resulting PLV indexes illustrating the dynamic phase relationship dynamics allowed us to distinguish among relax and left/right movement imagery stages, taking into account EEG electrodes originating from the two different lateral brain hemispheres. We also have compared the proposed method based on BEMD EEG preprocessing with the UEMD case, which has also shown the superiority of the proposed approach. Preprocessing with UEMD did not result with satisfactory discrimination of PLV indexes for various movement imageries.

The presented research is a step forward in EEG multivariate signal processing leading to the robots and phase information based BCI application approaches. We plan the further online application of the proposed methodology in an online BCI test with many subjects.



(a) The re-calculated local PLV of one subject during two kinds of tasks in recorded dataset. Different portions of the recorded EEG dataset are illustrated in different panels.



(b) A result obtained with the univariate EMD method applied to the single trial EEG of the same data as the upper panel of Fig. 6(a), which did not result with satisfactory movement imagery discrimination as compared with the proposed method using BEMD for preprocessing as shown in Fig. 6(a).

Fig. 6. Comparison of re-calculated local PLV between BEMD and classical UEMD methods.

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