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# EEG Fingerprints: Phase Synchronization of EEG Signals as Biomarker for Subject Identification

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**ABSTRACT** The goal of biometrics is to recognize humans based on their physical and behavioral characteristics. Preliminary studies have demonstrated that the electroencephalogram(EEG) is potentially more secure and private than traditional biometric identifiers. At present, the EEG identification method targets specific tasks and cannot be generalized. In this study, a novel EEG-based biometric identification method that extracts the phase synchronization (PS) features for subject identification is proposed under a variety of tasks. We quantified the PS features by the phase locking value (PLV) in different frequency bands. Subsequently, we employed the principal component analysis (PCA) to reduce the dimension. Then, we used the linear discriminant analysis (LDA) to construct a projection space and projected the features onto the projection space. Finally, a feature vector was assigned to the class label. The experimental results of the proposed method used on 3 datasets with different cognitive tasks showed high classification accuracies and relatively good stabilities. From the results, we found that particularly in the beta and gamma bands, the average accuracies are more than 97% with the standard deviation equal to or less than the magnitude 10e-2 for both Dataset 1 and Dataset 2. For Dataset 3, the PS feature vectors in all off the bands have high classification accuracies, which are more than 97% with the standard deviation of the same magnitude. Our work demonstrated that the phase synchronization of EEG signals has task-free biometric properties, which can be used for subject identification.

**INDEX TERMS** EEG biometric, Subject indentification, Phase synchronization, Linear discriminant analysis.

## I. INTRODUCTION

THe electroencephalogram (EEG) records the electrical activity of the human brain along the scalp and reflects the summation of the synchronous activity of thousands or millions of neurons that have a similar spatial orientation [1], [2]. The scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges and spatial distributions, which are associated with different states of brain functioning. In recent years, there is a growing interest in using EEG signals as biometric identifiers for subject recognition [3]. This is due to both an increase in the understanding of physiological mechanisms of brain activity and the growth of the research in the field of biometric recognition [1].

EEG signals have several advantages over traditional biometric identifiers such as fingerprints, palmprints, voice, iris and face features [4]. As a new type of biological features, EEG has unique advantages in non-stealing, unforgeability, inactivity and so on, which can provide a far more secure biometric identification approach. Unlike conventional biometric systems, EEG-based recognition systems are robust and secure against spoofing identification at the sensor by attackers because attackers cannot covertly acquire EEG signals in their physical form or synthetically generate them

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at a later time. Another advantage of EEG-based biometric systems is that they are also available for people with certain physical disabilities or injuries. In addition, EEG signals are capable of constantly and transparently monitoring spontaneous brain activity or responses to cognitive stimuli, which provide a safeguard against the substitution of another person [4].

Poulos et al. [5] applied autoregressive (AR) models to EEG signals acquired from subjects in a resting state with their eyes closed during the experiment. They employed the O2 channel, extracted the alpha rhythm activity of the EEG, and used Kohonenaŕs linear vector quantization to classify the signals. The correct classification scores ranged from 72% to 84%. Paranjape et al. [6] collected EEG data from 40 subjects who simply opened their eyes during the EEG recording. The researchers used AR models to estimate a model from the EEG signals and applied the discriminant function analysis to classify the subjects. The identification rates ranged from 49% to 85%. Marcel and MillÍćn [8] used the task of motor imagery for person identification. They employed imagined left- and right-hand movements as the stimuli to acquire EEG signals, and extracted the alpha and beta rhythms from the signals. Gaussian Mixture Models and the Maximum A Posteriori model were used to model the signals and classify their characteristics. Palaniappan and Mandic [9] analyzed the spectral power of the visual evoked potential (VEP) signals in the dominant frequency band (gamma band) with the multiple signal classification (MUSIC) algorithm. The authors used the Elman neural network as the classifier and achieved an average classification rate of 98.12% for 102 subjects. Brigham and Vijaya Kumar [10] classified imagined speech EEG signals from 6 volunteer subjects by using AR models and the support vector machine (SVM) classifier. The accuracy of the subject identification was 99.76% for their method. The same approach was tested on the VEP EEG data of 120 subjects who were stimulated by black and white pictures, and its identification accuracy was 98.96%. Das et al. [11] collected rapid visually evoked EEG activity from 20 subjects and extracted discriminative spatio-temporal features. They employed linear discriminant analysis (LDA) and SVM to classify these features separately, and the recognition accuracies of the two classifications were 75% and 94%, respectively, using 2-fold cross validation.

All off the above methods were focused on only one specific dataset with a specific cognitive task or stage. However, these methods could be difficult to apply in a real-world setting because all of them require the subjects' cooperation. Hence, we aim to establish an approach that is task-free for the subject and works well for identification. Phase synchronization (PS) analysis has been demonstrated to be an important and effective method to infer functional connectivity with multichannel EEG signals [12]. Synchronization phenomenon in the EEG, especially the oscillation in the high frequency bands, plays a key role in establishing the information exchange in different brain regions [13]. Varelaet and Engel et al. [14] had shown that the synchronization of neuronal assemblies played a major role in functional cognitive integration processes. Bao et al. [7] applied phase synchronization as one of the EEG features used to classify the motor imagery data from the BCI Competition 2003 dataset, and they used a neural network classifier and attained average recognition rates ranging from 81.2% to 90.6%. Gysels and Celka [15] investigated the performance of features for classifying mental tasks that were derived from the phase locking value and the spectral coherence. With the sole use of synchronization measures, the classification accuracy reached 62%.

In this paper, we proposed a novel method for person recognition using the phase synchronization features. The phase synchronization phenomena between two EEG signals were quantified by the phase locking value (PLV), since it examined the relationship of the phases without containing the influence of their amplitudes [16]. The proposed method calculated the time averages of the phase locking values in a certain stage with selected electrode pairs as the phase synchronization feature vectors for classification.

## II. METHOD AND MATERIAL

### A. THE ICA ALGORITHM

The ICA is a statistical method that can separate mixed signals, including EEG signals, to maximize the separation of components in a statistically independent measure [18]. Generally, the ICA problem can be described as: $Y = [y_1, y_2, \cdots, y_{N_s}]^T$ be a vector of random observation of $N_s$ dimensions, and $S = [s_1, s_2, \cdots, s_M]$ is the original unobserved sources of $M$. The ICA mode can be expressed as:

$$Y = AS \tag{1}$$

Where $A$ is a full-rank scalar matrix as $[N_s \times M]$ that mixes ICs back to observed signals, $N_s$ is the number of the channels to record EEG data, $M$ is the number of the original unobserved sources.Because we do not know the effective number of independent signals, we suppose that the number of source signals is equal to the number of observation signals, that is, $N = M$. Given the EEG data, the ICA algorithm can calculate the mixed matrix $A$ and the independent sources of $N_s$. The matrix $A$ is expressed as below:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1N_s} \\ a_{21} & a_{22} & \cdots & a_{2N_s} \\ \cdots & \cdots & & \cdots \\ a_{N1} & a_{N2} & \cdots & a_{N_sN_s} \end{pmatrix} \tag{2}$$

where $a_{ij} (i \leq i, j \leq N_s)$ is the transfer coefficient from the $j-th$ source to the $i-th$ observed channel signal. And the aim of ICA is to find out the linear unmixing matrix $W$ and acquire the ICs under the conditions of independent criterions which is an inverse problem of Equation (1), so that:

$$S = WY \tag{3}$$

Therefore, the ICA algorithm can effectively separate the eye-movement artifacts from weaker EEG signals.

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### B. PHASE FEATURE EXTRACTION

There are many different methods to measure synchronization between two time-series signals. The most commonly method used for analyzing EEG signals is the phase locking value (PLV) [19]–[21]. Phase synchronization of EEG signals is a reflection of the difference of physiological structure of white matter in the brain [22]. Phase difference is often used to estimate nerve conduction velocity and synaptic integration time. we can use the relationship between phase synchronization of EEG signals and physiological characteristics of brain individuals to analyze the phase synchronization characteristics of each channel of EEG signals to obtain phase synchronization matrix, and then extract the EEG features of individuals for identity recognition. Therefore, in this work, we employ PLV to quantify the interaction of EEG signals recorded from different channels. PLV examines the relationship of the instantaneous phase between two signals, which is defined as follows:

$$PLV = |\langle(j\{\Phi_x(t) - \Phi_y(t)\})\rangle| \tag{4}$$

where $\langle . \rangle$ means the operator of averaging over time, $\Phi_i(t)$ is the instantaneous phase of electrode $i = \{x, y\}$ at time instant $t$. Either the Hilbert transform or convolution with a complex Gabor wavelet can be used to calculate this phase value [16]. There is no obvious difference between those two methods when applied to the EEG data [23]. So, we used Hilbert transform in this paper, which is defined as

$$\tilde{x} = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{5}$$

where $\tilde{x}(t)$ is the Hilbert transform of the continuous time signal $x(t)$ and $P$ denotes the Cauchy principal value. Then we define the analytic signal as

$$Z_x(t) = x(t) + j\tilde{x}(t) = A_x(t)e^{j\Phi_x(t)} \tag{6}$$

where $A_x(t)$ and $\Phi_x(t)$ are the instantaneous amplitude and instantaneous phase of EEG signal $x(t)$ respectively. The instantaneous phase can be calculated as

$$\Phi_x(t) = \arctan \frac{\tilde{x}(t)}{x(t)} \tag{7}$$

In the same way, we can define the analytic signal $Z_y(t)$ and calculate the instantaneous phase $\Phi_y(t)$ for signal $y(t)$.

In this work, we study the phase synchronization of EEG as biomarker for subject identification in different frequency bands. The PLV values can be calculated with a one-second time window using the selected electrodes signals. In our experiments, there are $N$ non-overlap segmentations for each stage, the overall PLV during a certain stage is the mean of $N$ PLV corresponding to its segmentation. Therefore, the average PLV can be written as

$$PLV_{avg} = \frac{1}{N} \left| \sum_{N}^{n=1} \langle exp(j\Delta\Phi) \rangle \right| \tag{8}$$

where $\Delta\Phi$ denotes the phase difference between $\Phi_x(t)$ and $\Phi_y(t)$ i.e., $\Delta\Phi = \Phi_x(t) - \Phi_y(t)$, and $n = 1, 2, ..., N$ is the number of the segmentations.

Different electrode pairs can be constructed by pair-wise electrodes. To get an optimal feature vector set, we only consider the average PLV of the electrodes which satisfied $x \neq y$. For selected $M$ electrodes, we compute average PLV values in a certain stage of all electrode pairs as a $M \times M$ upper triangular matrix of $\mathbf{A}$, which contains both the phase synchronization relationship and the spatial information among all electrodes. The matrix $\mathbf{A}$ is expressed as

$$\mathbf{A} = \begin{bmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1(M-1)} & a_{1M} \\ 0 & 1 & a_{23} & \cdots & a_{2(M-1)} & a_{2M} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & a_{(M-1)M} \\ 0 & 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \tag{9}$$

We rearrange this upper triangular matrix into a column vector $\mathbf{B}$ as $\mathbf{B} = [a_{12}, \cdots, a_{1M}, a_{23}, \cdots, a_{(M-1)M}]$. Then we employ such kind of vector calculating from each stage of certain subject as the phase synchronization (PS) feature vectors for subject identification.

### C. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) is a well-known dimension reduction method for multivariate data [24], [25]. It is primarily used to transform the data space into a lower dimensional feature space when the size of the original dataset is unwieldy [26].

In this paper, PCA is applied to retain the most important components of the PS features. Let matrix $\mathbf{Z}$ represents the original dataset, and each column $\mathbf{z}_i$ represents a sample, i.e., a PS vector from some stage of some subject. In addition, we define deviation vector $\mathbf{z}_i^{'} = \mathbf{z}_i - \mathbf{m}$, where $\mathbf{m}$ is the mean vector of all columns of matrix $\mathbf{Z}$ and $\mathbf{Z}^{'}$ is the deviation matrix of $\mathbf{Z}$. Thus, $\mathbf{Z}$ can be calculated as

$$\mathbf{R} = \mathbf{E}(\mathbf{Z}^{'}\mathbf{Z}^{'T}) \tag{10}$$

Then the eigenvalue decomposition is performed on $\mathbf{R}$, and we obtain $\mathbf{V}$ and $\mathbf{D}$, where $\mathbf{V}$ is a orthogonal matrix consisting of eigenvectors and $\mathbf{D} = diag(d_1, d_2, \cdots, d_n)$ is the diagonal matrix consisting of eigenvalues. The projected vector $\mathbf{y}_i$ in eigen-space $\mathbf{V}$ can be calculated by

$$\mathbf{y}_i = \mathbf{V}^T \mathbf{z}_i^T \tag{11}$$

Actually, according to Bishop's research [27], the eigenspace is not consisting of all eigenvectors, and it can be established with a subset of eigenvectors which is corresponding to several largest eigenvalues. In such way, the main information of data could be retained and the noise could be eliminated.

### D. LINEAR DISCRIMINANT ANALYSIS

After the dimention of the PS vectors has been reduced by PCA, the next step is to project these vectors for all samples in the new feature space. Linear discriminant analysis

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(LDA) is a multivariate statistical method that can be used for classification. LDA is commonly used to construct a projection space. The model is constructed according to a set of observations called the training set, which has the class labels known in advance. The projection space can be built from the training set and used to project the training sample and the new test sample [24], [28], [29].

Here, we use LDA to derive the optimal projection space $\mathbf{W}_{opt}$ using the PS training sample set.

The purpose of the LDA is to calculate an optimal $\mathbf{W}_{opt}$. The parameters of $\mathbf{W}_{opt}$ are determined in such a way that the distance between the classes is maximized and the distance within the classes is minimized, which achieves the best discrimination between the classes. Each of the training and test PS feature vectors is projected on the $\mathbf{W}_{opt}$, and then the distances between each test PS feature vector and all training PS feature vectors are calculated by the nearest neighbor (NN) algorithm. Subsequently, the test PS feature vector is assigned to the class label with the shortest distance.

This method can be described as follows. Let $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$ be a dataset of the given D-dimensional feature vectors, where $N$ is the number of the feature vectors. Each data point belongs to one of the classes $\{\mathbf{x}_c^1, \mathbf{x}_c^2, \cdots, \mathbf{x}_c^{N_c}\}$ , where $c = \{1, 2, \cdots, C\}$. The between-class scatter matrix $\mathbf{S}_b$ and the within-class scatter matrix $\mathbf{S}_w$ are defined as

$$\mathbf{S}_b = \sum_{c=1}^{C} N_c(\mathbf{m}_c - \mathbf{m})(\mathbf{m}_c - \mathbf{m})^T \tag{12}$$

$$\mathbf{S}_w = \sum_{c=1}^{C} \sum_{x \in X_c} (\mathbf{x} - \mathbf{m}_c)(\mathbf{x} - \mathbf{m}_c)^T \tag{13}$$

where $N_c$ denotes the number of vectors in class $\mathbf{X}_c$, $\mathbf{m}_c$ is the class mean of class $\mathbf{X}_c$ and $\mathbf{m}$ is the global mean of the entire dataset.

To maximize the ratio of the determinant of the between-class scatter matrix to the determinant of the within-class scatter matrix, a matrix $\mathbf{W}$ is computed as

$$\mathbf{W}_{opt} = \arg\max_{\mathbf{W}} \frac{|\mathbf{W}^T \mathbf{S}_b \mathbf{W}|}{|\mathbf{W}^T \mathbf{S}_w \mathbf{W}|} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_k, \cdots, \mathbf{w}_K] \tag{14}$$

Where $\{\mathbf{w}_k | k = 1, 2, \cdots, K\}$ is the set of generalized eigenvectors of $\mathbf{S}_b$ and $\mathbf{S}_w$ corresponding to the $K$ lagrest generalized eigenvalues $\{\lambda_k | k = 1, 2, \cdots, K\}$, i.e.,

$$\mathbf{S}_b \mathbf{w}_k - \lambda_k \mathbf{S}_w \mathbf{w}_k = 0, k = 1, 2, \cdots, K \tag{15}$$

Note that there are $C-1$ nonzero generalized eigenvectors, so there is an upper bound on $K$ is $C - 1$, where $C$ is the number of classes. See [28].

### E. SUMMARY OF THE PROPOSED METHOD

In this paper, we propose a novel method for person recognition with phase synchronization features, which are quantified by the PLV. This method can be summarized as having two main algorithm stages. In addition, each algorithm stage includes several steps.

**Training Stage**

Input: Training EEG signals $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$ ;

Output: Eigen-space $\mathbf{V}$, and LDA projection space $\mathbf{W}_{opt}$.

(1) Calculate the PLV of $N$ non-overlapping segmentations in a certain stage using the training EEG signals, and produce $N$ upper triangular matrices corresponding to the segmentations;

(2) Average the PLV matrices of this stage as a matrix $\mathbf{A}$, and then rearrange the upper triangular matrix $\mathbf{A}$ into a column vector $\mathbf{B}_{train}$;

(3) Calculate the eigen-space $\mathbf{V}$ from the $\mathbf{B}_{train}$ by PCA;

(4) Project the training set $\mathbf{B}_{train}$ on the eigen-space $\mathbf{V}$ and produce $\mathbf{Y}_{train} = [\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_N]$;

(5) Use the $\mathbf{Y}_{train}$ to project on the $\mathbf{W}_{opt}$, and produce $\mathbf{T}_{train} = \mathbf{Y}_{train}^T \mathbf{W}_{opt} = [\mathbf{t}_1, \mathbf{t}_2, \cdots, \mathbf{t}_N]$ .

**Test Stage**

Input: Test EEG signal $\mathbf{X}_{test}$;

Output: The class label $k$ for $\mathbf{X}_{test}$.

(1) Calculate the PLV matrix for test EEG signal $\mathbf{X}_{test}$, and rearrange it into a column $\mathbf{B}_{test}$;

(2) Project the test sample $\mathbf{B}_{test}$ on the $\mathbf{V}$, and produce $\mathbf{Y}_{test}$;

(3) Use the $\mathbf{Y}_{test}$ to project on the $\mathbf{W}_{opt}$, and produce $\mathbf{T}_{test}$;

(4) Calculate the distance between each $\mathbf{T}_{test}$ and all $\mathbf{T}_{train}$ by NN;

(5) Assign the class label $k$ by the shortest-distance.

The processing flow of the proposed method is given in Fig. 1.

## III. EXPERIMENTAL RESULTS

### A. DATA ACQUISITION

There were three different kinds of datasets used in this paper. The first dataset was collected from 20 healthy volunteers, including 10 males and 10 females aged between 22 and 25 years. All subjects had no personal history of neurological or psychiatric disorder. During the neuromarketing experiment, subjects were asked to watch a video, which contained a neutral documentary of 8 minutes, and six TV commercials of approximately 30 s for each one. For the data acquisition, subjects were required to be seated on a chair in a quiet and isolated room and pay attention to what they watched without knowing the purpose of the experiment.

The second dataset was recorded from 12 right-dominant Chinese volunteers aged from 23 to 25 without a personal history of neurological or a psychiatric disorder. All of the subjects had a driving license and were prohibited to drink alcohol, coffee or tea for one day before the experiment. In the experiment, subjects were asked to drive using a simulator system with manual gear. This experiment included training and experimental sessions, and both of them were performed after dinner on different days. The experimental session consisted of eight conditions or stages, and the subjects had to drive under different conditions in which they

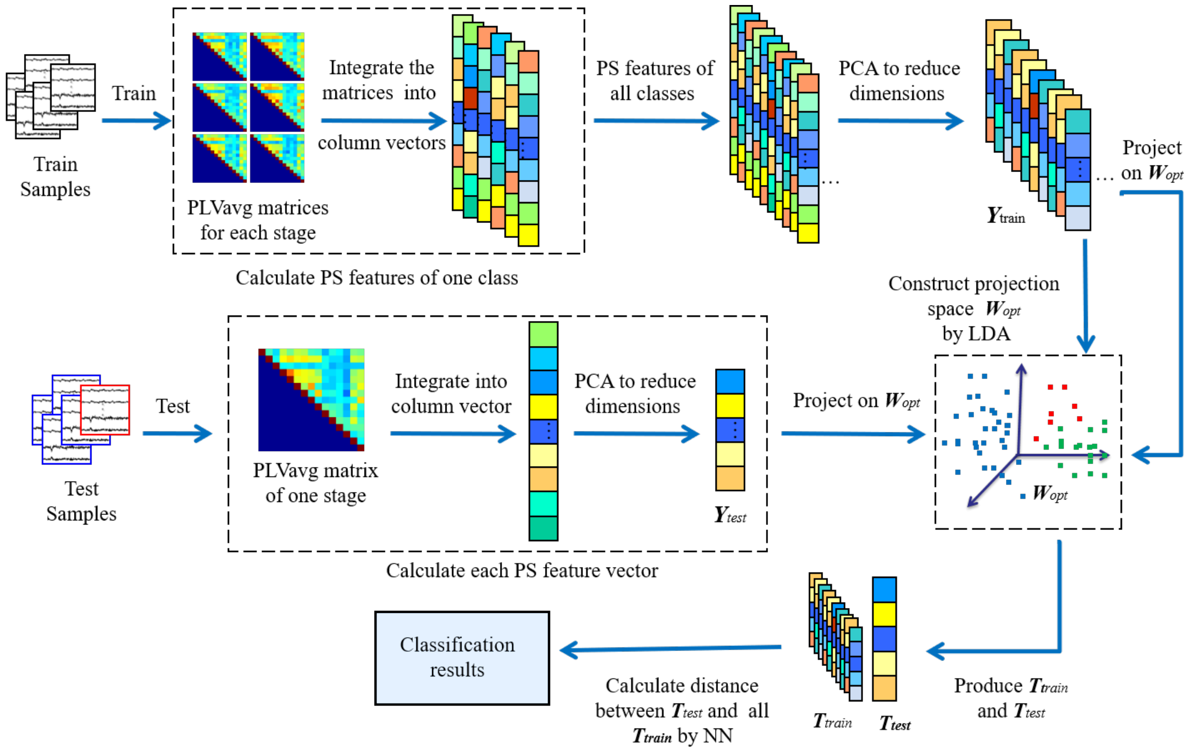


**FIGURE 1.** Principal process of the proposed method.

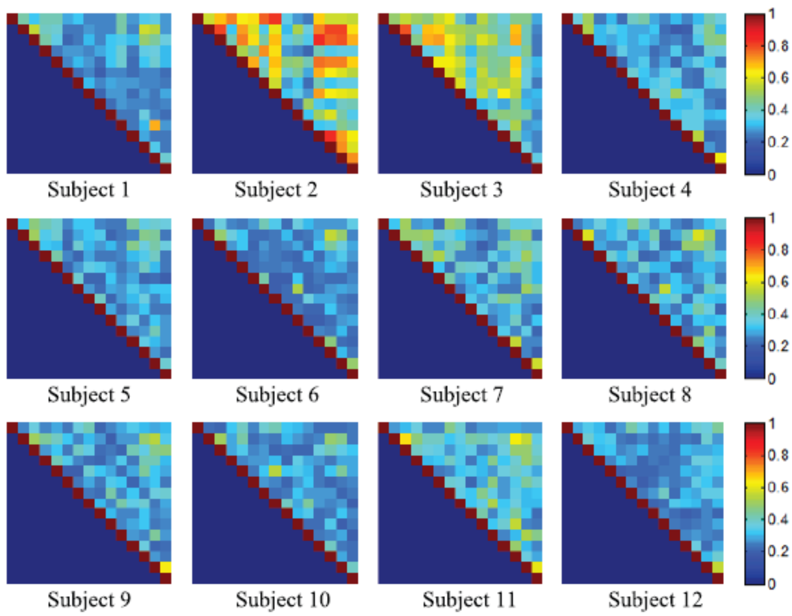


**FIGURE 2.** The overall PLV matrix in gamma band from the signals in the first stage of 12 subjects from the dataset 2.

had priority to control the driving. In five conditions, there were extra tasks of alert and vigilance(TAV) to enhance the workload for the driver. At the end of each condition, subjects were required to fill out a questionnaire for the subjective workload assessment.

Both of the first two datasets were recorded by a 16 channels system with the gUSBamp amplifier (g.Tec medical engineering GmbH) at a sampling rate of 256 Hz while the impedances were kept below 5 kΩ. The electrode cap that we used was built according to the 10-20 international system.

The 16 electrodes were FPz, Fz, Cz, Pz, POz, AF3, AF4, F3, F4, T7, C3, C4, T8, P3, P4 and EKG. The EKG electrode was placed in the pulse position on the left wrist to record the EKG data. The right ear was used as a reference.

We used motor imagery data from the BCI Competition 2008 as the third dataset to further validate our method. This dataset is comprised of recorded data from 22 channels with a sampling rate of 250 Hz. The electrode cap was built according to the 10-20 international system, and the 22 electrodes were Fz, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2, CP4, P1, Pz, P2, and POz. The reference electrode was placed on the left earlobe, and the right earlobe was the GND.

Furthermore, all 3 of these datasets contain the resting state session as the baseline. The datasets include descriptions of states such as resting, motor imagery, being alert, being fatigue and viewing five different videos. Additionally, they also have in common that no matter what cognitive task is experienced, a spontaneous EEG is produced. This is different from the evoked EEG such as P300, where the cognitive tasks require that the subjects cooperate with the experimental protocol. To reduce the effect of artifacts, the description data above are band-pass filtered with a cutoff frequency of 2-47 Hz, and eye-movement artifacts were removed with the recorded continuous horizontal and vertical electro-oculograms (EOGs) by means independent component analysis (ICA) method [17], [18], Further, EEG signal was re-referenced to a common average reference. Before calculating the PLV, a Butterworth band-pass filter is employed to filter the EEG signals of each electrode to get the phase synchronization in the desired frequency range. In this work, the phase synchronization features are computed in the theta, alpha, beta and gamma bands.

### B. PHASE SYNCHRONIZATION FEATURES

For the first dataset, we intercept 480 second signals from each subject, including 2 minutes of baseline data, 3 minutes of neutral material data and 3 minutes of advertising data. Signals of all the subjects are filtered separately to theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-40 Hz) bands by Butterworth band-pass filters. The same length of data interception from the second dataset is selected, including 2 minutes of baseline data and 6 minutes of driving data. All of the signals are filtered to the same four bands to calculate the PLV.

To analyze the phase synchronization on the whole brain region of each subject, the phase locking values are calculated with a one-second time window using the signals from the selected 15 channels (excluding the EKG).

For the third dataset, we select the same length of data interception from each subject to further validate the classification results. Signals of all the subjects are filtered separately to the above four bands by Butterworth band-pass filters. The phase locking values are calculated with a one-second time window using the signals from the selected 22 channels.

**TABLE 1.** CLASSIFICATION RESULTS OF DATASET 1 (ADDATA)

| bands | theta | alpha | beta | gamma |
|---|---|---|---|---|
| Average | 0.883 | 0.957 | 0.981 | 0.974 |
| standard deviation | 0.0193 | 0.0064 | 0.0087 | 0.0110 |

**TABLE 2.** CLASSIFICATION RESULTS OF DATASET 2 (DRIDATA)

| bands | theta | alpha | beta | gamma |
|---|---|---|---|---|
| Average | 0.951 | 0.940 | 0.974 | 0.989 |
| standard deviation | 0.0190 | 0.0195 | 0.0198 | 0.0159 |

For 15 electrodes, 105 different electrode pairs can be constructed. In our experiments, there are 30 non-overlapping segmentations of each stage, and the PLV values of each segmentation are computed as a $15 \times 15$ upper triangular matrix. Additionally, for 22 electrodes, the PLV values of each segmentation are computed as a $22 \times 22$ upper triangular matrix. The matrix contains both the phase synchronization relationship and the spatial information between electrodes. Then, the mean of the 30 PLV matrices corresponding to different segmentations is calculated as the overall PLV during a certain stage. There are 16 different stages for each subject in the experiments, and the overall PLV matrix for the first stage of 12 subjects from Dataset 2 is shown in Fig. 2.

To get the optimal feature vectors, we rearrange the overall PLV matrix into a column vector. The column vectors that are computed from the different stages of each subject provided the phase synchronization feature vectors for classification.

### C. CLASSIFICATION RESULTS

In this work, the PS feature vectors, which are obtained after dimension reduction using PCA, are projected by LDA and then classified by NN. Each subject has 16 PS features calculated from 480 s EEG signals for classification. During the classification processing, 8 trials are selected randomly as the training samples, and the remaining trials are treated as the test samples. To enhance the accuracy of the classification and analyze the effects of the different frequency bands on the classification results, the PS feature vectors are computed in four frequency bands.

A total of 320 PS feature vectors (16 PS features$\times$20 subjects) and 192 PS feature vectors (16 PS features $\times$12 subjects) are used respectively from Dataset 1 and Dataset 2. In addition, a total of 144 PS feature vectors (16 PS features$\times$9 subjects) are used from Dataset 3. The PS feature vector is assigned to the class with the shortest-distance and then is compared with the actual class to determine the classification accuracy. The training and test are repeated 10 times to get the average accuracies for each dataset, and the standard deviation of the accuracies are calculated to study the robust stabilities of the results. The classification results of the three datasets using the proposed method are given in Tables I-III.

As shown in Table I and Table II, the classification accuracies in the beta and gamma bands are generally higher than

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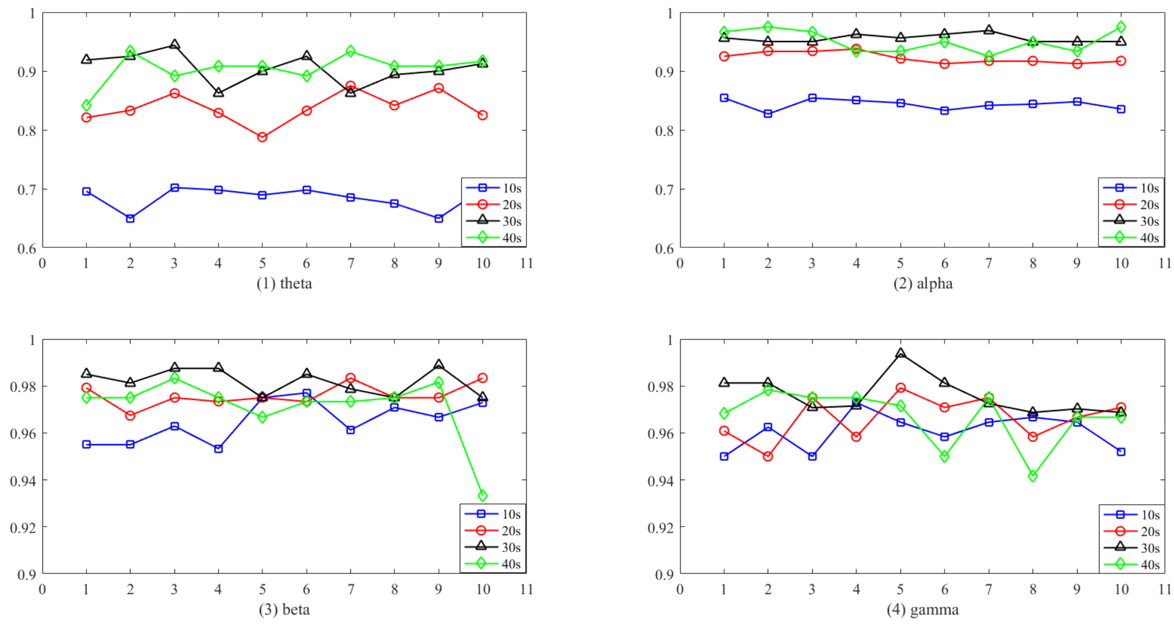


**FIGURE 3.** Classification results of different time lengths in theta, alpha, beta and gamma band from Dataset 1.

**TABLE 3.** CLASSIFICATION RESULTS OF DATASET 3 (BCIDATA)

| bands | theta | alpha | beta | gamma |
|---|---|---|---|---|
| Average | 0.974 | 0.983 | 0.996 | 0.990 |
| standard deviation | 0.0168 | 0.0129 | 0.0068 | 0.0115 |

those in the theta and alpha bands. When the EEG signals are filtered in the theta band, the PS features of Dataset 2 have better classification results than those of Dataset 1. The difference in average accuracies between Dataset 1 and Dataset 2 is not significant in the alpha band, but the classification accuracies of Dataset 1 have a smaller standard deviation, which means that these results are more stable. For both of these two datasets, the classification accuracies in the beta and gamma bands are not significantly different. The average classification accuracies are more than 97% when the frequency is greater than 13 Hz. This results from the fact that the beta band involves conscious thinking and logical thinking and gamma band involves higher processing tasks and cognitive tasks. Then, there are very important in learning, memory, and information processing. In the case of excitement or cognitive tasks, such as simulated driving and watching advertising videos, the beta band and gamma band activities will increase. Therefore, the beta and gamma bands have higher classification accuracies. In Table III, for Dataset 3, all of the four frequency bands have high classification accuracies, with the average greater than 97%.

To further analyze the effects of different time lengths on the classification results, we calculated the average PLV matrices of Dataset 1 in the theta, alpha, beta and gamma band with four different time lengths: 10 seconds, 20 seconds, 30 seconds and 40 seconds. The results of the classification are shown in Fig. 3. The PS feature vectors calculated from 30 s EEG signals obviously have better classification results than those calculated from 10 s and 20 s EEG signals. Since the accuracies from 40 s EEG signals are not better than the 30 s EEG signals, we choose 30 s as the time length for calculating the PS feature vectors.

## IV. CONCLUSION

In this paper, a novel classification method using PS features is proposed, which can be used to identify task-free EEG signals. We research phase synchronization of the whole brain region in four bands for person recognition. The phase locking values in the proposed method are computed from the EEG signals with a one-second time window. To get more effective PS features, we compare the classification results in the alpha band with four different time lengths, and the average PLV matrices that are calculated from 30 s EEG signals produce better results. For all three datasets, the experimental results using the PS features show high classification accuracies and relatively good stabilities. Especially in the beta and gamma bands, the average accuracies are more than 97% with the standard deviation equal to or less than the magnitude of 10e-2 for both Dataset 1 and Dataset 2. For Dataset 3, the PS feature vectors in all bands have high classification accuracies that are greater than 97% with the standard deviation of the same magnitude. Our experiments demonstrate that phase synchronization features calculated from the PLV can be an efficient biometric identifier to recognize different subjects. Exploring the spatial position of electrode pairs and determining the length of segmentation to compute the PLV is our future work.

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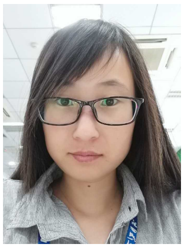

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