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PHASE SYNCHRONIZATION BASED CHANNEL SELECTION FOR A MOTOR IMAGERY PARADIGM

BY

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Abstract. An offline analysis based on phase synchronization measures is proposed. Phase locking value, phase lag index, weighted phase lag index are applied in order to discriminate between motor imagery tasks in a brain computer interface paradigm based on Mu rhythm. The pairs of channels with relevant features for classification were selected applying statistical tests. The purpose was to evaluate the phase synchronization based channel selection. Discrimination between right hand motor imagery and left hand motor imagery was evaluated with linear discriminant analysis, quadratic discriminant analysis, Mahalanobis distance classifier, k nearest neighbor analysis and support vector machine. The results obtained indicate that phase synchronization indexes can be used as online methods for motor imagery paradigms.

Key words: motor imagery; brain computer interface; phase lag index; phase locking value; weighted phase lag index.

1. Introduction

Brain computer interface (BCI) is a system designed to translate brain activities into commands for an external device (computer, prosthesis). BCI provides a communication way for people with severe motor disabilities. The

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most popular sensory signal used for BCI is the scalp-recorded electroencephalogram (EEG), because is a non-invasive measurement, is simple to use and implies low costs. EEG based BCI detects changes that appear in the brain activity while a person is performing mental tasks. During a mental activity (e.g. planning, control, execution or imagination of movement), changes in the frequency band 8 -12 Hz (Mu rhythm) or 12 -30 Hz (Beta rhythm) appears on EEG recordings. Movement or even preparation and imagining a movement triggers an event that desynchronizes the electrical activity of the neurons in the motor areas resulting in a loss of amplitude of the waves detected by the EEG. When the state of the user is reversed to the idle state, the electrical activity of the neurons is again synchronized in the opposite hemisphere of the brain. These events are called Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) (Pfurtscheller & Neuper, 2001).

The EEG signals are characterized by amplitude and phase information.

Common spatial pattern (CSP), power spectral density (PSD) (Lazar, 2005) has been applied to extract amplitude distinctive features from EEG in different mental states (Wolpaw *et al.*, 2002).

The phase synchronization is a fundamental neural mechanism which can provide significant and discriminative features for BCI systems. Phase content can characterize the cognitive processes like memory or attention. Phase synchronization occurs in two brain regions when the oscillatory phases in these regions are correlated. It has been noticed that the phase synchronization of the relaxation period is different from the phase synchronization from activity period and therefore it can be used in BCI applications (Gonuguntla *et al.*, 2013).

Two types of synchronizations are distinguished in the brain activity: local scale synchronization (between signals acquired by electrodes placed in the same motor area) and large scale synchronization (between signals acquired by electrodes placed in the primary motor area and by electrodes placed in the additional motor area) (Wang *et al.*, 2006).

Methods that explore phase information instead of amplitude one have been applied in motor imagery paradigms: the phase locking value (PLV) (Lachaux *et al.*, 1999), that uses the relative phase between signals to measure the phase-synchronization, the phase lag index (PLI) (Stam *et al.*, 2007) as a potential improvement of the PLV and the weighted phase lag index (wPLI) (Vinck *et al.*, 2011) for increasing the capacity to detect true changes in phase synchronization.

An off-line analysis is performed in order to detect changes in the large-scale synchronization by means of PLV, PLI and wPLI which appear during motor imagery focussed on Mu rhythm and large scale synchronization.

Section II presents the methodology used in analysis. It consists in presenting the methods used in assessing the phase synchronization, features extraction and classification. The results obtained for the database used are presented in Section III and Section IV concluded the paper.

2. Methodology

A. Methods

The phase locking value (PLV), the phase lag index (PLI) and the weighted phase lag index (wPLI) are used for measuring the phase synchronization between two signals $x(t)$ and $y(t)$.

PLV measures the synchronization in the time domain and has been used for analysing EEG signals recorded during motor imagery tasks.

PLV characterizes the stability of the phase difference between instantaneous phases $\varphi_x(t)$ and $\varphi_y(t)$ of signals $x(t)$ and $y(t)$, respectively, using the formula (Gysels & Celka, 2004):

$$\mathrm{PLV} = \left| \left\langle \mathrm{e}^{\mathrm{j}\Delta\varphi(t)} \right\rangle \right|, \tag{1}$$

$\Delta\varphi(t) = \varphi_y(t) - \varphi_x(t)$ and $\langle . \rangle$ is average operator.

When the averaging is performed on trials, the PLV is defined by the expression:

$$\mathrm{PLV} = \frac{1}{N} \left| \sum_{t}^{N} \exp\left[\mathrm{j}\left(\varphi_y(t) - \varphi_x(t) \right) \right] \right|, \tag{2}$$

where: N is the number of EEG samples of the trial.

When the phase difference is constant, PLV is equal to 1. If the phase difference is randomly distributed in the interval [0, 2π], the phase difference follows a normal distribution, so that PLV is equal to 0.

Instantaneous phases $\varphi_x(t)$ and $\varphi_y(t)$ are calculated in order to obtain PLV. Instantaneous phases are determined using Hilbert transform (Le Van Quyen *et al.*, 2001).

The Hilbert transform of a signal $s(t)$ is given by the equation (Gabor, 1946):

$$\tilde{s}(t) = \frac{1}{\pi} p.v. \int_{-\infty}^{+\infty} \frac{s(\tau)}{t - \tau} \mathrm{d}\tau, \tag{3}$$

where: *p.v.* is the Cauchy principal value. The analytical signal is characterized by:

$$S(t) = s(t) + \mathrm{j}\tilde{s}(t). \tag{4}$$

The instantaneous phase is calculated by the formula:

$$\varphi(t) = \arctan\left(\frac{\tilde{s}(t)}{s(t)} \right). \tag{5}$$

The phase lock index can be determined from the asymmetry of the instantaneous phase difference distribution $\Delta\varphi(t)$, $k = 1,\ldots,N$ between two signals:

$$\mathrm{PLI} = \left|\left\langle \mathrm{sign}\left[\Delta\varphi(t_k)\right]\right\rangle\right|, \tag{6}$$

where: sign is the signum function and $\langle . \rangle$ denotes the average over the time.

The PLI ranges between 0 and 1. A PLI of zero indicates either no coupling or coupling with a phase difference $\Delta\varphi$ centered around $[0,\pi]$. A PLI of 1 indicates perfect phase locking at a value of $\Delta\varphi$ different from $[0,\pi]$ (Stam *et al.*, 2007).

The weighted phase lag index is calculated using the formula:

$$w\mathrm{PLI} = \frac{\left|\left\langle I(X)\right\rangle\right|}{\left\langle\left|I(X)\right|\right\rangle} = \frac{\left|\left\langle I(X)\,\mathrm{sign}\,I(X)\right\rangle\right|}{\left\langle\left|I(X)\right|\right\rangle}, \tag{7}$$

where: $I(X)$ is the imaginary component of the cross spectrum between two signals $x(t)$ and $y(t)$.

The values of the wPLI are ranged between 0 and 1, where 1 means total synchronization. Synchronization is defined by $P\left\{\mathrm{sign}\left(I(X)\right)=1\right\}=1$ or $P\left\{\mathrm{sign}\left(I(X)\right)=-1\right\}=1$, where $P\{.\}$ denotes probability (Vinck *et al.*, 2011).

B. Dataset

The dataset used is provided by Dr. Allen Osman in BCI Competition 2002 (Osman, 2001). The recordings were acquired according to informed consent standards (Toader & Toader, 2012).

The EEGs are recorded from 59 electrodes placed on the scalp according to the International System 10-20 and referenced to the left mastoid. The signals are sampled at 100 Hz.

Well trained subjects were asked to imagine left or right hand movement and to relax (each subject executed 180 trials, 90 trials for imagery of the left hand movement and 90 trials for imagery of the right hand movement). Each trial epoch lasted 6 seconds.

The signals acquired from 9 electrodes (FC_3, FC_Z, FC_4, CP_3, CP_Z, CP_4, C_3, C_Z and C_4) over the sensorimotor area are considered for further processing.

C. EEG signal processing

EEG signals are loaded in Matlab and segments for each mental task are extracted. Four sets of data are formed: the right hand motor imagery, the relaxation succeeding the right hand motor imagery, the left hand motor imagery, the relaxation succeeding the left hand motor imagery. Signals are band pass filtered in 8,…,12 Hz frequency band (Mu rhythm) with a finite impulse response filter of 50th order, in order to avoid phase distortion.

In order to compute the phase synchronization, instantaneous phase of the signals is calculated using Hilbert transform. The Hilbert transform is performed for all EEG channels.

Three electrodes from the supplementary motor imagery area, FC_Z , CP_Z and C_Z, three electrodes from the left hemisphere, FC_3, C_3, CP_3 and three electrodes from the right hemisphere FC_4, C_4, CP_4 are used. Nine combinations for the right hemisphere (FC_Z-FC_4, FC_Z-C_4, FC_Z-CP_4, C_Z-FC_4, C_Z-C_4, C_Z-CP_4, CP_Z-FC_4, CP_Z-C_4, CP_Z-CP_4) and nine combinations for the left hemisphere (FC_Z-FC_3, FC_Z-C_3, FC_Z-CP_3, C_Z-FC_3, C_Z-C_3, C_Z-CP_3, CP_Z-FC_3, CP_Z-C_3, CP_Z-CP_3) are formed (18 pairs of channels) as listed in Fig. 1.

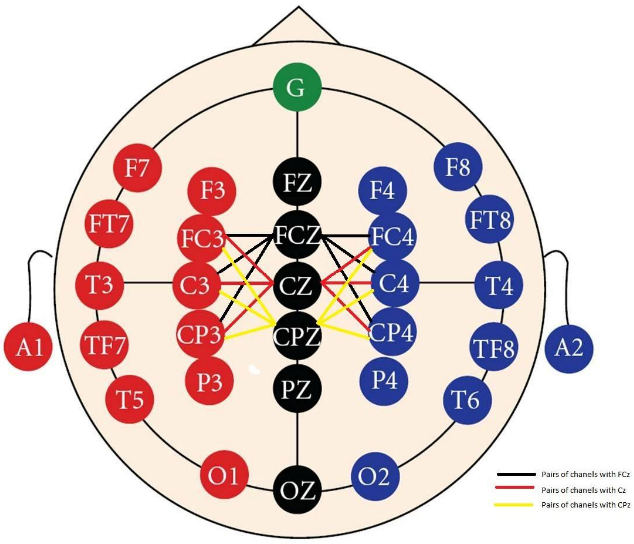

Fig. 1 – The pairs of channels formed with FC_Z, C_Z and CP_Z.

The difference between PLVs of the motor imagery period and the relaxation period is computed for all pairs of electrodes. Two new sets of data are formed: the difference between PLVs corresponding to the left motor imagery tasks and the difference between PLVs corresponding to the right motor imagery tasks. Statistical tests are applied on the sets of data.

The statistical difference between two states is evaluated. The *Shapiro-Wilk test* (King & Mody, 2012) is performed in order to evaluate if the new obtained signals follow a normal distribution.

The *paired t test* (King & Mody, 2012) is applied for those pairs of channels for which the normality conditions did meet in order to assess the statistical difference between left or right motor activity. The *Wilconox signed-tank* test is computed (King & Mody, 2012) for channels that did not meet the normality condition. The confidence interval is 95%.

The approach is firstly tested using the PLV and then the PLI and WPLI.

Two feature vectors were created in order to discriminate between left or right motor activity.

For PLV, PLI and *w*PLI, the first feature vector is formed by the data from the pairs of channels which meet the conditions imposed by the *paired t-test* and the *Wilcoxon signed-rank test.*

The second features is formed by the same data from the pairs of channels which fulfilled the conditions required by the statistical tests but the features for PLV, PLI and *w*PLI are combined.

Discrimination between the left or the right motor activity is evaluated with five classifiers: linear discriminant analysis (LDA) (Lotte *et al*., 2007), quadratic discriminant analysis (QDA) (Hastie *et al.*, 2009), Mahalanobis distance (MD) (Babiloni *et al.*, 2001), *k* nearest neighbor (kNN) (Chaovalitwongse *et al.*, 2007) and support vector machine (SVM) (Bennett & Campbel, 2000). A 10×10 fold cross validation estimated the classification rate for each subject. The results obtained in the frequency band 8,…,12 Hz are presented. We have also applied the methods for 12,…,30 Hz, but the classification rates are better for Mu rhythm.

3. Results and Discussions

The pairs of electrodes selected for each subject for PLV, PLI and *w*PLI are listed in Table 1. For S7 the highest number of pairs was selected and for subject S3 the smallest number of pairs of electrodes.

Table 1
Number of Selected Pairs of Electrodes for PLV, PLI and wPLI

Subject	PLV	PLI	wPLI
S1	10	10	13
S2	11	11	13
S3	8	8	7
S4	7	7	13
S5	14	14	13
S6	14	14	9
S7	17	17	10
S8	11	11	9
S9	10	10	10

Classification accuracy rates for PLV, PLI, wPLI using classifiers LDA, QDA and MD are displayed in Figs. 2,…,4, respectively. Subjects S1 and S7 achieved maximum classification rates with MD classifier for PLV and PLI. For *w*PLI, the discrimination rates are smaller than those obtained with PLV and PLI. The highest classification rates are obtained with MD classifier.

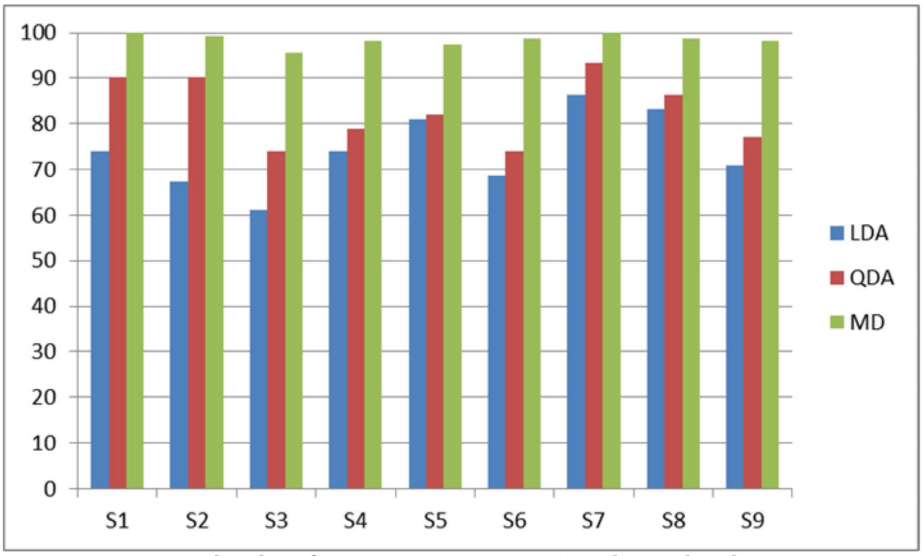

Fig. 1 – The classification accuracy rates (%) obtained with LDA, QDA and MD for PLV.

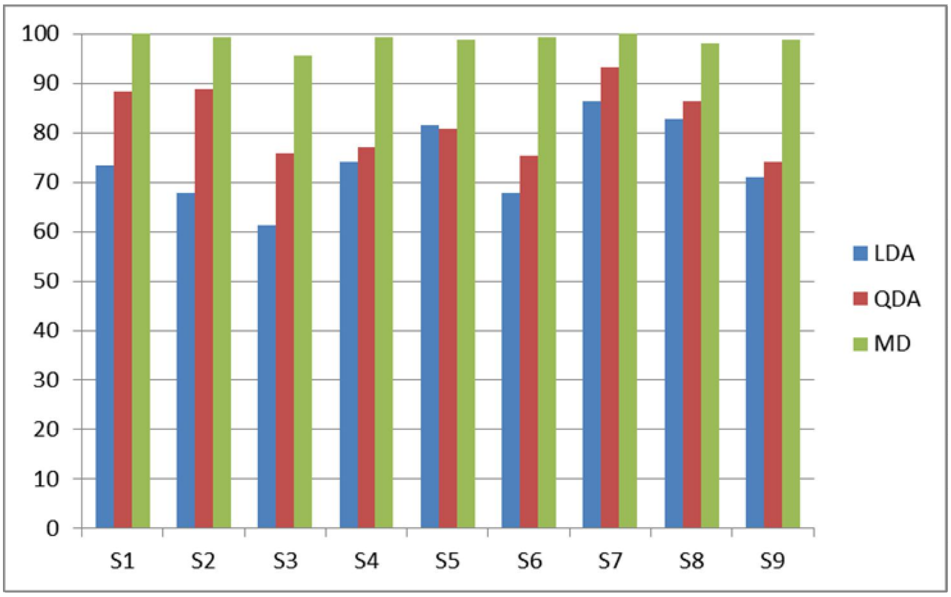

Fig. 2 – The classification accuracy rates (%) obtained with LDA, QDA and MD for PLI.

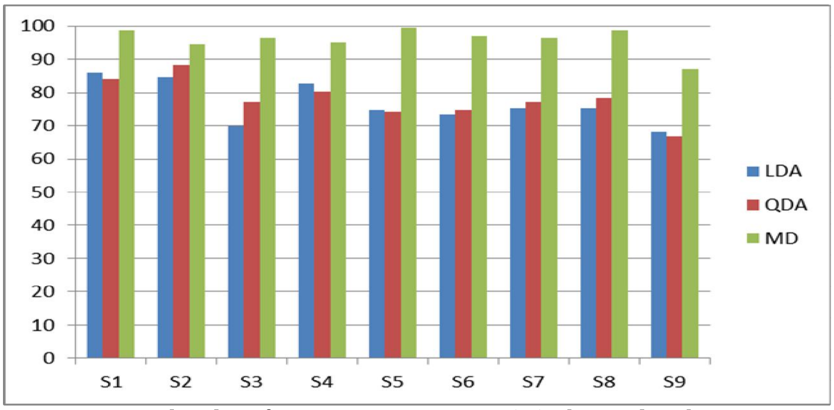

Fig. 3 – The classification accuracy rates (%) obtained with LDA, QDA and MD for wPLI.

In Tables. 2,…,4 the classification accuracy rates (%) obtained with kNN (k=1:5) are presented for PLV, PLI and wPLI. The discriminations rates are above 94%. There are no major differences between neighbors.

Table 2

The Classification Rates (%) Obtained with kNN (k=1:5) for PLV

Subject	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
S1	99.89	99.89	99.89	99.90	99.90
S2	99.78	99.78	99.79	99.79	99.79
S3	98.23	98.26	98.29	98.32	98.35
S4	99.56	99.57	99.57	99.58	99.59
S5	98.24	98.27	98.30	98.33	98.25
S6	99.67	99.68	99.68	99.69	99.59
S7	99.78	99.78	99.79	99.79	99.79
S8	97.69	97.73	97.77	97.80	97.84
S9	98.24	98.27	98.30	98.33	98.25

Table 3

The Classification Rates (%) Obtained with kNN (k=1:5) for PLI

Subject	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
S1	99.89	99.89	99.89	99.90	99.90
S2	99.56	99.57	99.57	99.58	99.59
S3	98.57	98.59	98.62	98.64	98.66
S4	99.56	99.57	99.57	99.58	99.59
S5	98.68	98.70	98.72	98.74	98.77
S6	99.34	99.35	99.36	99.37	99.38
S7	99.67	99.68	99.68	99.69	99.69
S8	97.03	97.08	97.13	97.18	97.22
S9	99.23	99.13	98.93	98.85	98.66

Table 4
The Classification (%) Rates Obtained with kNN (k=1:5) for wPLI

Subject	*k* = 1	*k* = 2	*k* = 3	*k* = 4	*k* = 5
S1	98.46	98.48	98.30	98.12	97.94
S2	97.47	97.40	97.34	97.28	97.22
S3	97.68	97.61	97.44	97.38	97.12
S4	96.68	96.74	96.80	96.86	96.91
S5	98.13	98.16	98.19	98.22	98.15
S6	98.46	98.48	98.40	98.33	98.15
S7	96.26	96.32	96.38	96.44	96.50
S8	98.46	98.48	98.51	98.54	98.56
S9	94.49	94.48	94.47	94.46	94.34

The classification rates for PLV, PLI and WPLI using SVM classifier are shown in Fig. 5. The discrimination rate for subjects S4 and S7 is 100% using the PLI and PLV methods.

In (Ince *et al.*, 2007) a space time–frequency approach using six subjects (S1, S2, S5, S6, S7, S9) and the pair C_3-C_4 is investigated. For subject 5 the classification rates are reported in the range 67.20%,…,76.40%. With PLV, PLI, wPLI, distinct features and combined features, the classification rates were in range 62.55%,…,100%.

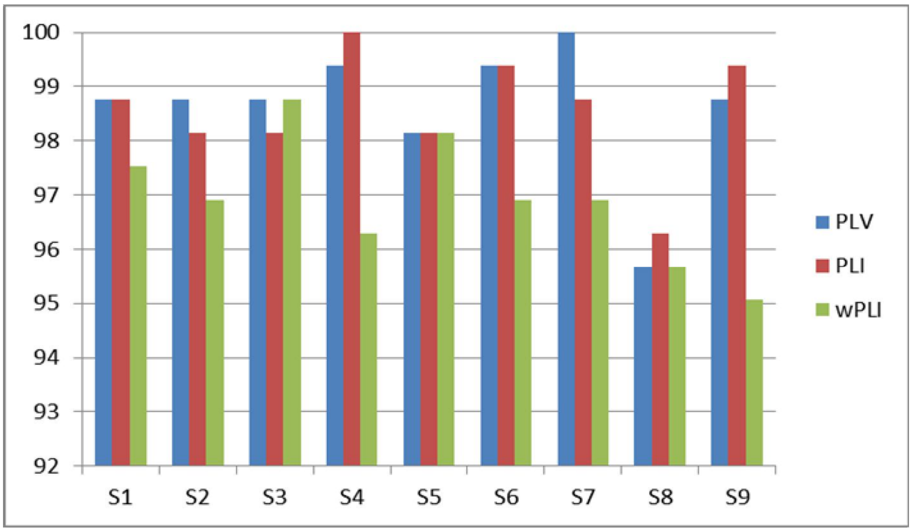

Fig. 5 – The classification accuracy rates (%) obtained with SVM for PLV, PLI and wPLI.

The research evaluated three phase synchronization based methods with three indexes: phase locking value, phase lag index and weighted phase lag index. The synchronization measures were applied on a dataset with nine well trained subjects.

Table 5
The Classification Accuracy Rates (%) Obtained with LDA, QDA, MD, KNN and SVM Using Combined Features of PLV, PLI and wPLI

Subject	LDA	QDA	MD	KNN					SVM
				k = 1	k = 2	k = 3	k = 4	k = 5	
S1	81.48	85.60	85.39	96.48	96.54	96.56	96.58	96.54	98.35
S2	83.95	86.83	93.83	97.50	97.51	97.52	97.52	97.50	96.30
S3	72.84	78.19	85.60	93.93	93.93	93.90	93.86	93.83	91.56
S4	78.81	93.00	90.33	96.99	97.04	97.09	97.14	97.19	99.18
S5	76.95	90.74	91.15	97.06	97.11	97.13	97.18	97.22	98.35
S6	79.01	81.48	80.04	94.71	94.77	94.79	94.84	94.68	97.12
S7	67.90	84.16	84.98	94.71	94.77	94.79	94.80	94.72	97.53
S8	80.45	94.44	90.95	95.99	96.06	96.13	96.20	96.26	96.30
S9	62.55	79.22	79.63	93.90	94.01	94.04	94.11	94.14	95.06

Pair channels selection using statistical test was applied in order to extract only the important features contained in signals.

Combining synchronization measures (PLV, PLI and *w*PLI) can lead to improved results compared to classifications using the synchronization measures separately. Subjects S5 and S8 obtained better discrimination rates for combined features of PLV, PLI and *w*PLI – Table 5.

The smaller classification rates (range 61.11%,…,85.80%) are obtained using LDA classifier. LDA offers satisfactory results because the boundary between the classes is not linearly separable.

QDA classifier provides better results than LDA. Comparing the results obtained with LDA, QDA and MD classifiers, the higher classification rates are obtained with MD one. Subjects S1 and S7 achieved maximum classification rates for PLI and PLV with MD classifier. kNN classifier (k = 1:5) provides classification rates in the range 94.34%,…,99.90% and between neighbors no major differences are identified. Using SVM classifier two subjects also obtained the maximum classification rate.

Comparing these methods, no significant differences are distinguished between PLV and PLI. Although wPLI is a more complex method by introducing weighted normalized phase difference, the classification rates obtained are above 95% for SVM and 94% for kNN.

4. Conclusions and Future Work

Offline analysis based on synchronization measures are tested for a motor imagery paradigm.

Algorithms are simple to implement, few EEG channels are used, the important information contained in selected pair of channels are taken into consideration for further processing and so the classification rates are improved.

The classification rates obtained reveal that the proposed methods can detect changes that appear during mental tasks. Discrimination between right hand motor imagery and left hand motor imagery can be made by means of phase synchronization.

Further work implies developing an ensemble classifier (a combination of classification methods) for improving the classification rates.

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SELECȚIA CANALELOR ÎN SINCRONIZAREA DE FAZĂ PENTRU O INTERFAȚĂ CREIER CALCULATOR

(Rezumat)

Se propune o metodă de analiză offline pentru extragerea şi clasificarea trăsăturilor conținute de semnalelor electroencefalografice folosind indici ce caracterizează sincronizarea de fază pentru o paradigmă creier calculator bazată pe ritmul Mu. Indicii utilizați care măsoară sincronizarea de fază dintre două semnale au fost: indicele de blocare al fazei (Phase Locking Value – PLV), indicele de decalaj al fazei (Phase Lag Index – PLI), indicele ponderat de decalaj al fazei (Weighted Phase Lag Index – WPLI). Teste statistice sunt aplicate pentru extragerea perechilor de canalele care conțin trăsături relevante pentru clasificare. Analiza discriminantă liniară, analiza discriminantă pătratică, clasificatorul bazat pe calculul distanței Mahalanobis, clasificatorul "celor mai apropiați *k* vecini" clasificatorul vector suport au fost applicate pentru discriminarea sarcinilor motorii . Rezultatele obținute după selecția perechilor de canale sugerează faptul că indicii care măsoară sincronizarea de fază pot fi folosiți ca metode online pentru paradigmele creier calculator.