International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.7 (2016), pp.383-390
http://dx.doi.org/10.14257/ijsip.2016.9.7.34

Classification of Verbal and Quantitative Mental Tasks Using Phase Locking Values between EEG Signals

Huseyin Atasoy[1] and Esen Yildirim[2]

[1]Department of Computer Engineering, Iskenderun Technical University, Hatay, Turkey
[2]Electrical and Electronic Engineering, Adana Science and Technology University, Adana, Turkey
[1]huseyin.atasoy@iste.edu.tr, [2]eyildirim@adanabtu.edu.tr

Abstract

In this study, electroencephalography signals recorded while participants were doing verbal and quantitative tasks, are classified. A dataset containing 1044 records obtained from 18 participants are used for subject-dependent classifications. Features are derived from phase locking values calculated between all channel pairs. Features are reduced before the classification process by using both analysis of variance and correlation based feature selection methods. Instances in the dataset are classified by using the nearest neighbor algorithm. An average classification accuracy of 92.35% is achieved over 18 participants. It is shown that phase locking value is distinctive especially when it is calculated on delta and gamma frequency bands measured between frontal and occipital regions.

***Keywords**: ANOVA, electroencephalography, mental task classification, phase locking, phase synchrony*

1. Introduction

Electroencephalography (EEG) is a method of measuring electrical current resulting from neurons in the brain, with electrodes placed on the scalp. Non-invasive EEG signals are widely used for brain-computer interface (BCI) applications [1-2]. Portable and affordable EEG devices or signal acquisition systems has led to more attention for EEG and its applications [3-4].

Mental activity or task classification is one of the challenging studies in this area. There are several studies that aim to classify or recognize mental tasks. Mohanchandra *et al*. have compared some EEG feature extraction and classification methods that are used for the mental task classification purposes [5]. Gupta *et al*. have proposed an EEG feature extraction method based on statistical, spectral, complexity and entropy parameters [6]. They have reported that their method increases mental task classification performance. In another study, Wang *et al*. have proposed a novel EEG feature extraction method that uses discriminative common spatial patterns to recognize mental tasks [7]. They achieved a recognition accuracy of 89.4% in their experiments. Shirazi *et al.* have recognized reading and relaxing activities with an accuracy of 97% using EEG signals [8]. Forney *et al*. have achieved accuracies of 95% and 65% using echo state networks for two-class and four-class mental task classification experiments, respectively [9]. Wang *et al*. have proposed a method that can classify mental arithmetic tasks in real-time [10]. In their subject-dependent experiments, classification accuracy of their algorithm was as high as 97.87%. Upadhyay *et al*. have reported successful classification of resting, mental calculation, letter composition and rotation tasks by using wavelet transform and neural networks [11].

ISSN: 2005-4254 IJSIP

In this study, EEG signals, collected during verbal and quantitative mental tasks, are classified by using functional connectivity concept. Previous studies on this dataset have focused on time-frequency resolutions of single channel (recorded as the difference between two electrodes) EEG recordings. Wavelet transform for feature extraction and BayesNet algorithm for classification yielded in 89.1% true positive rate on the average for a subject-based classification [12]. Same scheme resulted in higher positive rate for effective channels. These channels were determined based on correlation based feature selection method and mostly selected 10 channels resulted in a 90% true positive rate [13]. Arithmetic operations are classified as addition/subtraction vs. multiplication/ division by using k-NN classifier and these operations were separable from each other with 79.3% true positive rate [14].

Recently functional connections between channels have gained attention in analyzing and classifying EEG data [15-17]. EEG-based functional connectivity is basically used to investigate the integration of the functional areas widely distributed over the brain during a particular task. Similarities between the time series or activation maps are mostly used to define the functional connections. Phase locking Value [18] is one of the popular methods to explore the functional connectivity [19-20]. In this study, collected EEG signals are classified using phase locking values.

This paper is organized as follows: EEG data acquisition, feature extraction and selection procedures are given in Section 2. Results and conclusion are given in Section 3 and Section 4, respectively.

2. Material and Method

2.1. EEG Dataset

An EEG dataset, collected from 18 healthy college students, is used in this study. The students are aged between 19 and 24 (average: 20.39, standard deviation: 2.06). EEG signals were recorded at a sampling rate of 1 KHz from 26 channels using 22 electrodes. The electrodes were placed according to the international 10-20 system (Figure 1).

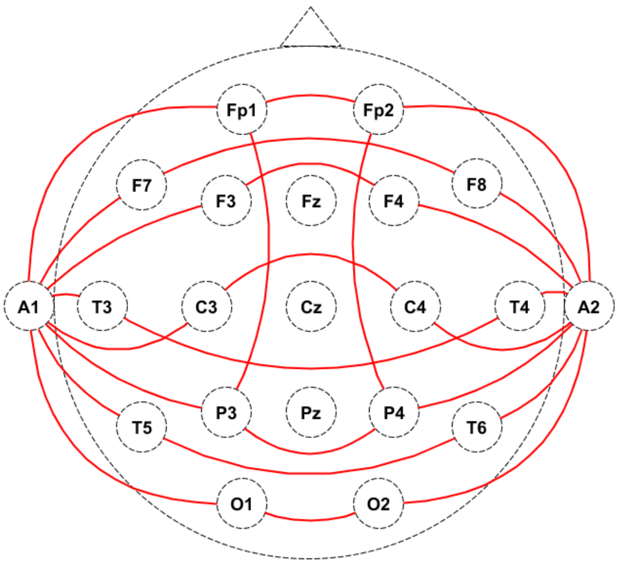

Figure 1. Placements of the Electrodes and Recorded Channels

EEG signals were collected while participants were reading texts and making mental arithmetic calculations written on images. 60 images, 30 images of paragraphs and 30 images of arithmetic calculations, were shown to the participants in a random order as a slide show for 13.25 seconds per slide. Sample slides are shown in Figure 2.

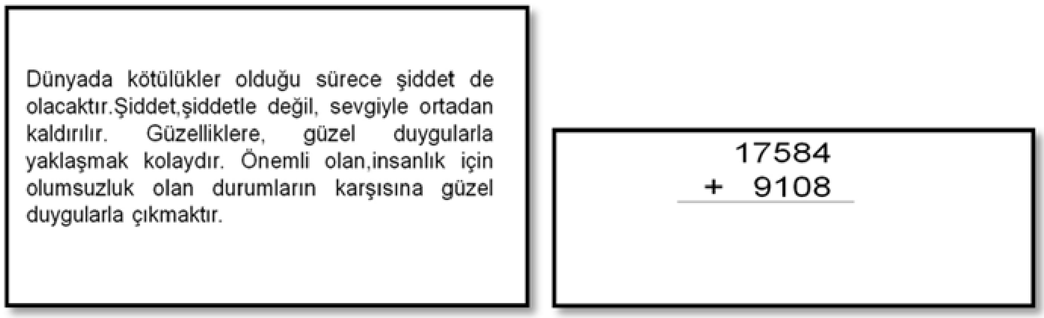

Figure. 2 Two Examples of the Images that are Shown to the Participants

EEG signals were filtered with 120 Hz low-pass filter to remove the high frequency artifacts. Besides, first and last slides are removed from the analysis due to possible artifacts, remaining recordings during 29 slides of text reading and 29 slides of mathematical operations.

2.2. Phase Locking Value

Phase locking value (PLV) is a statistical value that is obtained to detect phase synchrony between two signals. PLV ranges between 0 and 1, where value of 0 corresponds to no synchrony case while value of 1 corresponds to perfect synchrony. Significant interactions between brain regions can be investigated using this concept.

PLV is calculated in three steps [18]. First, signals are filtered with a band-pass filter to obtain the signals in a desired frequency band. Then, instantaneous phases are extracted by calculating phase angle of the signal obtained by using Hilbert transform of the filtered signal. Analytical signals of two signals s_x and s_y are calculated as in (1):

$$
\begin{aligned}
z_x(t) &= s_x(t) + j\tilde{s}_x(t) = A_x(t)e^{j\phi_x(t)} \\
z_y(t) &= s_y(t) + j\tilde{s}_y(t) = A_y(t)e^{j\phi_y(t)}
\end{aligned}
\tag{1}
$$

A_x and A_y are instantaneous amplitudes, $\phi_x(t)$ and $\phi_y(t)$ are instantaneous phases and $\tilde{s}_x$ and $\tilde{s}_y$ are Hilbert transforms of s_x and s_y respectively:

$$
\begin{aligned}
\tilde{s}_x(t) &= \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} \frac{s_x(\tau)}{t-\tau} d\tau \\
\tilde{s}_y(t) &= \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} \frac{s_y(\tau)}{t-\tau} d\tau
\end{aligned}
\tag{2}
$$

where P.V. is the Cauchy principal value. $A_x(t)$ and $A_y(t)$ are defined as:

$$A_x(t) = \sqrt{s_x(t)^2 + \tilde{s}_x(t)^2}$$
$$A_y(t) = \sqrt{s_y(t)^2 + \tilde{s}_y(t)^2} \quad (3)$$

Instantaneous phases are presented as:

$$\phi_x(t) = \arg\left[z_x(t)\right] = \arctan\left(\frac{\tilde{s}_x(t)}{s_x(t)}\right)$$
$$\phi_y(t) = \arg\left[z_y(t)\right] = \arctan\left(\frac{\tilde{s}_y(t)}{s_y(t)}\right) \quad (4)$$

Finally, the phase locking value at time t is calculated as average phase differences in all the trials:

$$PLV_t = \frac{1}{N}\left|\sum_{n=1}^{N} j\theta(t,n)\right| \quad (5)$$

where $\theta(t,n)$ is the phase difference at time t, at the nth trial.

2.3. Feature Extraction

Features derived from phase locking values calculated between channel pairs [21] were used as a feature set in this study. Prior to PLV calculations, EEG recordings were segmented into 0.5 second epochs with 25% overlap resulting in 35 EEG segments for each slide. Maximum and average PLVs and sum of squares of PLVs were used as features. These features were calculated between all possible pairs of channels. Thus, a feature set consists of 6825 features was obtained to represent each trial in the dataset.

2.4. Feature Selection and Classification

6825 features were subjected to a feature selection process before the classifications to eliminate irrelevant features from the feature set. Since correlation-based feature selection method (CFS) [22] takes very long time on large feature sets, number of the features was reduced using a faster feature selection approach; one-way analysis of variance (ANOVA) [23] before applying CFS.

One-way ANOVA tests whether the group means are equal or not. In this study, it is used to eliminate features that have the same mean over the instances in different classes and proceeded by correlation-based feature selection (CFS) method. CFS selects features that have high correlations with classes and low correlations with each other [22]. Thus, features that are irrelevant with the classes or that can be represented with other features are eliminated.

The instances in the dataset were classified using nearest neighbor algorithm. This is a simple approach that assigns class of the sample to the class of the nearest instance in the training set.

Classification results were calculated in terms of accuracy (*ACC*) which is the ratio of sum of numbers of true positives and true negatives (*TP*, *TN*) to the total number of instances (*TP*+*FP*+*TN*+*FN*):

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

3. Results

EEG signals recorded during two mental tasks, namely reading and arithmetic problem solving tasks are classified. PLV, which is used to investigate the neural synchronization from EEG data, are used for feature extraction. Results were evaluated using 10-fold cross validation. Previous studies on this dataset were focused on frequency domain features from single EEG channels. The first study on this dataset used wavelet transform for feature extraction and BayesNet algorithm for a subject-based classification and resulted in 89.1% [12]. These features and classification scheme was repeated for 10 mostly selected channels based on CFS and true positive rate was enhanced to 90.0% in [13]. k-NN (k=1) and decision tree classification results are given as 89.6% and 90.6% respectively in [24]. Table 1 shows the average classification accuracy and classification accuracies for each subject obtained in this study using PLV based features and nearest neighbor classifier. Results show that, classification accuracy based on interactions between EEG channels are higher than the accuracy obtained employing wavelet transform based features extracted from single channels.

Table 1. Classification Results and Average Numbers of Selected Features After Using ANOVA and After Applying CFS on these Selected Features

Participant Number	Classification accuracies (%)	Avg. numbers of features	
		ANOVA ($p<0.001$)	ANOVA-CFS
1	96.55	1128	115
2	87.93	822	65
3	84.48	542	35
4	91.38	971	35
5	89.66	890	55
6	94.83	425	56
7	94.83	1221	62
8	98.28	1458	101
9	96.55	1268	112
10	100.00	1452	114
11	93.10	1599	62
12	91.38	1629	37
13	98.28	1710	146
14	96.55	1510	109
15	98.28	2827	107
16	98.28	748	47
17	98.28	1743	146
18	98.28	1878	65
Average	**92.35**	**1323**	**82**

Table 1 also contains the number of features selected using ANOVA and CFS after ANOVA. Approximately 80.62% of the features were eliminated by using ANOVA. Then, selected features were reduced from 1323 to 82 using CFS, on average.

The maximum and minimum accuracies are calculated as 100% (participant 10) and 84.48% (participant 3), using 114 and 35 features, respectively. Number of selected features is generally decreased when PLVs between EEG signals are not distinctive.

In order to select the most significant channel pairs in classification task, number of features selected from channel pairs using ANOVA and CFS are investigated. 10 channel pairs, from which mostly selected features are derived, are marked as the most significant channels and listed in Table 2, with frequency bands of the signals measured on these channels.

Table 2. Channels and Frequency Bands of the Most-Selected Features

Channel Pairs		Frequency Bands
Fp1-Fp2	F7-F8	delta
Fp2-O2	Fp1-O1	delta
T5-A1	T5-T6	gamma
Fp1-Fp2	F7-F8	delta
Fp1-Fp2	F7-F8	gamma
P3-A1	Fp1-O1	theta
Fp1-Fp2	F7-F8	beta
Fp2-O2	Fp1-O1	gamma
T5-T6	O1-O2	gamma
C3-A1	O1-O2	gamma

The most significant features were obtained from delta and gamma bands in frontal lobes (Fp1-Fp2 and F7-F8) as it can be seen from Table 2. Besides, results also show that, phase locking values measured on gamma bands of occipital and temporal lobes are useful for classification of EEG signals during verbal and quantitative processes.

4. Conclusion

In this study, two types of mental tasks; verbal and quantitative tasks, are classified by using phase locking values between EEG channels and nearest neighbor classifier. Statistical values calculated on PLVs are considered as a feature set. Redundant and irrelevant features are eliminated using ANOVA and CFS, gradually. A subject dependent analysis is performed and results are presented using 10-fold cross validation. The average subject-dependent classification accuracy is 92.35% and subject based classifications are higher than 95% for 10 out of 18 subjects. Besides, delta and gamma bands of the signals measured over frontal and occipital lobes are found to be significant for verbal/quantitative task classification using EEG signals.

Results clearly indicate that verbal and quantitative mental tasks can be distinguished using PLV based statistical values. Synchronized brain regions and increase/decrease in PLVs during verbal or quantitative mental tasks will be investigated in future studies.

References

[1] J. S. Lin and W. C. Yang, "Wireless brain-computer interface for electric wheelchairs with EEG and eye-blinking signals", Int. J. Innov. Comput. Inf. Control, vol. 8, no. 9, **(2012)**, pp. 6011-6024.

[2] G. Onose, C. Grozea, A. Anghelescu, C. Daia, C. J. Sinescu, A. V. Ciurea and C. Popescu, "On the feasibility of using motor imagery EEG-based brain–computer interface in chronic tetraplegics for assistive robotic arm control: a clinical test and long-term post-trial follow-up", Spinal Cord, vol. 50, no. 8, **(2012)**, pp. 599-608.

[3] N. Robinson and A. P. Vinod, "Bi-Directional Imagined Hand Movement Classification Using Low Cost EEG-Based BCI", In Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on, , IEEE, **(2015)** October, pp. 3134-3139

[4] M. Ahamed, M. Ahad, M. Sohag, H. Ali and M. Ahmad, "Development of low cost wireless biosignal acquisition system for ECG EMG and EOG", In Electrical Information and Communication Technology (EICT), 2015 2nd International Conference on, IEEE, **(2015)** December, pp. 195-199.

[5] K. Mohanchandra, S. Saha, K. S. Murthy and G. M. Lingaraju, "Distinct adoption of k-nearest neighbour and support vector machine in classifying EEG signals of mental tasks", International Journal of Intelligent Engineering Informatics, vol. 3, no. 4, **(2015)**, pp. 313-329.

[6] A. Gupta and J. S. Kirar, “A novel approach for extracting feature from EEG signal for mental task classification”, In Computing and Network Communications (CoCoNet), 2015 International Conference on, IEEE, **(2015)** December, pp. 829-832.
[7] X. Wang, L. Ma, H. Li and M. Wu, “CSP Based Extraction and F-Score Based Optimization of Time-Frequency Power Features for EEG Mental Task Classification”, In 2015 Fifth International Conference on Instrumentation and Measurement, Computer, Communication and Control (IMCCC) , IEEE, **(2015)** September, pp. 820-824.
[8] A. S. Shirazi, M. Hassib, N. Henze, A. Schmidt and K. Kunze, “What's on your mind? Mental task awareness using single electrode brain computer interfaces”, In Proceedings of the 5th Augmented Human International Conference, ACM, **(2014)** March.
[9] E. Forney, C. Anderson, W. Gavin and P. Davies, “A stimulus-free braincomputer interface using mental tasks and echo state networks”, In Proceedings of the Fifth International Brain-Computer Interface Meeting: Defining the Future, **(2013).**
[10] Q. Wang and O. Sourina, “Real-time mental arithmetic task recognition from EEG signals”, Neural Systems and Rehabilitation Engineering, IEEE Transactions on, vol. 21, no. 2, **(2013)**, pp. 225-232.
[11] D. Upadhyay, “Classification of eeg signals under different mental tasks using wavelet transform and neural network with one step secant algorithm” International Journal of Scientific Engineering and Technology, vol. 2, no. 4, **(2013)**, pp. 256-259.
[12] S. G. Eraldemir and E. Yildirim, “Classification of simple text reading and mathematical tasks from EEG”, In Signal Processing and Communications Applications Conference (SIU), IEEE, **(2014)** April, pp. 180-183.
[13] S. G. Eraldemir, E. Yıldırım, Y. Kutlu and S. V. Yıldırım, “Kognitif EEG İşaretleri İçin Öznitelik Seçimi Tabanlı Kanal Seçimi ve Sınıflandırma”, Akıllı Sistemlerde Yenilikler ve Uygulamaları, **(2014)** October pp. 9-10.
[14] S. G. Eraldemir, E. Yildirim and Y. Kutlu, “Classification of Mathematical Tasks from EEG Signals Using k-NN Algorithm”, Elektrik - Elektronik - Bilgisayar ve Biyomedikal Mühendisliği Sempozyumu, **(2014)** November 27-29.
[15] Y. Y. Lee, and S. Hsieh, “Classifying different emotional states by means of EEG-based functional connectivity patterns”, PloS one, vol. 9, no. 4, **(2014)**, e95415.
[16] R. Yuvaraj, M. Murugappan, U. R. Acharya, H. Adeli, N. M. Ibrahim and E. Mesquita, “Brain functional connectivity patterns for emotional state classification in Parkinson’s disease patients without dementia”, Behavioural brain research, vol. 298, **(2016)**, pp. 248-260.
[17] Y. Sun, J. Lim, J. Meng, K. Kwok, N. Thakor and A. Bezerianos, “Discriminative analysis of brain functional connectivity patterns for mental fatigue classification”, Annals of biomedical engineering, vol. 42, no. 10, **(2014)**, pp. 2084-2094.
[18] J. P. Lachaux, E. Rodriguez, J. Martinerie and F. J. Varela, “Measuring phase synchrony in brain signals”, Human brain mapping, vol. 8, no. 4, **(1999)**, pp. 194-208.
[19] J. S. Kang, U. Park, V. Gonuguntla, K. C. Veluvolu and M. Lee, “Human implicit intent recognition based on the phase synchrony of EEG signals”, Pattern Recognition Letters, vol. 66, **(2015)**, pp. 144-152.
[20] M. Hassan and F. Wendling, “Tracking dynamics of functional brain networks using dense EEG”, IRBM, vol. 36, no. 6, **(2015)**, pp. 324-328.
[21] E. K. Yildirim, “Signal processing approaches to MEG data analysis: Comparison of* localization methods and neural synchrony detection”, University of Southern California, **(2006)**.
[22] M. A. Hall, “Correlation-based feature selection for machine learning”, Doctoral dissertation, The University of Waikato, **(1999)**.
[23] R. G. Miller Jr, “Beyond ANOVA: basics of applied statistics”, CRC Press, **(1997)**.
[24] S. Eraldemir, Göksel and E. Yıldırım, “Comparison of wavelets for classification of cognitive eeg signals”, 23nd Signal Processing and Communications Applications Conference (SIU), IEEE, **(2015)** May 16-19.

Authors

Huseyin Atasoy, received the B.S. degree in Computer Engineering from Mustafa Kemal University, Hatay, Turkey, in 2012. Currently, he is pursuing the M.S. degree in Electrical and Electronic Engineering and he is a Research Assistant in Computer Engineering Department, at Iskenderun Technical University, Hatay, Turkey. His general research interests include signal processing, artificial intelligence, classification algorithms, electronics, robotics and internet technologies.

Esen Yildirim, received the B.S. degree in Electrical and Electronics Engineering from Cukurova University, Adana, Turkey, in 1997, and the M.S. and Ph.D. degrees in Electrical Engineering from University of Southern California (USC), Los Angeles, in 2000 and 2006, respectively. She is currently an Assistant Professor of Electrical and Electronic Engineering, at Adana Science and Technology University, Adana, Turkey. Her general research interests include biomedical signal processing, epileptic seizure detection, learning methods, and emotion recognition from physiological signals.