Migraine Analysis Through EEG Signals with Classification Approach

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ABSTRACT

Migraine is a common type of headache with neurovascular origin. In this paper, a quantitative analysis of spontaneous EEG patterns is used to examine the migraine patients with maximum and minimum pain levels. The analysis is based on alpha band phase synchronization algorithm. The efficiency of extracted features are examined through one-way ANOVA test. we reached the P-value of 0.0001, proving that the EEG patterns are statistically discriminant in maximum and minimum pain levels. We also used a Neural Network based approach in order to classify the EEG patterns, distinguishing between minimum and maximum pain levels. We achieved the total accuracy of 90.9 %.

Index Terms— Migraine, EEG, Phase Synchronization, Neural Network

1. INTRODUCTION

MIGRAINE is a common type of headache with neurovascular origin. This incapacitating disorder is characterized by symptoms such as nausea, vomiting, photophobia (hypersensitivity to light) and phono-phobia (hypersensitivity to sound) [1]. The diagnosis of migraine at present time is based on the guidelines offered by the International Headache Society (IHS) [2]. Although it is believed that migraine is caused by abnormal brain activity, the exact cause of migraine headache is unclear. Hyper-excitability of the cerebral cortex and/or abnormal control of pain neurons in the trigeminal nucleus of the brainstem are mostly believed to be related to migraine headache [3].

Since migraine is related to the abnormal brain activities, it is probable that a multichannel electroencephalogram (EEG) helps us detecting individuals suffering from migraine headaches. Identifying a set of discriminant features based on EEG signals is the main problem that should be overcome.

The migraine pathology through EEG analysis has been investigated in a number of studies. Different methods of feature extraction are developed in order to distinguish between migraine patients and control subjects. A time-frequency based approach is discussed in [4]. Since EEG signals are non-stationary, the Fourier analysis is not applicable. Therefore, the short-term Fourier transform (STFT) is applied to the EEG signals. Using the spectrogram, which is defined as $|STFT|^2$, they discussed the EEG patterns through visual examination of the spectrograms for the normal subjects and migraine patients.

Multi-resolution wavelet analysis is another method used in [5]. They also used a supervised neural network to carry out the classification in order to detect migraine patients among the control subjects. They evaluate their efficiency through the Receiver Operating Characteristic (ROC) analysis and the Wilcoxon-Mann-Whitney (WMW) test.

Visually evoked phase synchronization based on Hilbert transform is also studied in [6]. In this study, the patients were visually evoked with flash stimuli at frequencies of 3, 6, 9, 12, 15, 18, 21, 24, and 27 Hz. Based on the phase differences between each two channels of EEG signals,they evaluated the entropy S according to equation 1.

$$S = -\sum_{k=1}^{K} n_k \log(n_k) \tag{1}$$

where n_k is the relative frequency of phase differences in Kth bin in the interval $[0, 2\pi]$. They applied paired t-test in order to select discriminant channels for separating the patients from controls.

The aim of this paper is to conduct a migraine analysis through mathematical modeling of EEG signals with a classification approach, distinguishing migraine patients with the minimum and maximum pain levels without any stimulation. This study is based on phase synchronization of alpha band of EEG signals which has been introduced previously in epileptic EEG signal processing [7].

The rest of the paper is organized as follows. In section 2, we describe our feature extraction method which is based on phase synchronization. Furthermore, we explain our Neural

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Network based classification approach in this section. The information about subjects and our results including feature analysis and final classification accuracy are stated in section 3. Finally, concluding remarks and future works are given in section 4.

2. METHOD

In this paper, we deal with a classification problem based on the EEG signals, examining the migraine patients while suffering the minimum and maximum pain levels. Features are extracted based on alpha band phase synchronization approach and variance of multichannel EEG signals in the time domain. Feature analysis is then performed to select efficient and discriminant features. One-way ANOVA test is also used to examine whether the selected features are statistically discriminant or not.

2.1. Feature Extraction

In order to extract discriminant and efficient features, two different approaches are examined in this study: alpha phase synchronization between two channels, and variance of the multichannel EEG signals. First we describe our phase synchronization method, and then we describe our second approach which is based on the variance of the EEG multichannel signals.

A bandpass FIR filter is utilized in order to extract the alpha band (8-13 Hz) in EEG signals. Then, the phase of analytical signal is derived for each channel based on the filtered EEG signals. If $s_x(t)$ and $s_y(t)$ are two passband signals with the Hilbert transforms $\tilde{s}_x(t)$ and $\tilde{s}_y(t)$ which are derived according to equation 2, then the corresponding phases are defined as $\phi_x(t)$ and $\phi_y(t)$ as stated in equation 3 based on the analytic signal $\xi(t)$ [8] :

$$\tilde{s}_i(t) = \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} \frac{s_i(\tau)}{t-\tau} d\tau \qquad i = x, y \tag{2}$$

$$\xi_i(t) = s_i(t) + j\tilde{s}_i(t) = A_i(t) e^{j\phi_i(t)} \qquad i = x, y \tag{3}$$

The phase difference $\Delta\phi_{xy}(t)$ between $\phi_x(t)$ and $\phi_y(t)$ is defined as:

$$\Delta\phi_{xy}(t) = \phi_x(t) - \phi_y(t) \tag{4}$$

Based on the phase difference $\Delta\phi_{xy}(t)$, the alpha band phase synchronization feature is defined as the Phase Lock Value (PLV) proposed in [9]:

$$PLV = \frac{1}{N} |\sum_{t=1}^{N} e^{(j\Delta\phi_{xy}(t))}| \tag{5}$$

Therefore, for each subject we derive PLV for each pairs of the channels, making a feature vector with 21 elements based on 7 EEG signal channels.

Next, the time variance of the filtered signals (8-13 Hz) are evaluated for each channel, deriving a variance feature vector with 7 elements for each subject.

2.2. Classification

A Neural Network with 2 hidden layers is used to do the classification task. Due to the limitation of the subjects, we use Multi-Layer Feed-forward Back-Propagation training algorithm [10]. The number of nodes in the hidden layers are respectively 6 and 2. All activation functions are log-sigmoidal with the total number of 500 epochs.

Due to the limitation of our dataset, a leave One Out cross validation approach is used; each time one subject is eliminated, and the NN is trained with the remainders. Finally the NN is tested with the eliminated subject.

3. RESULTS AND DISCUSSION

3.1. Subjects and Dataset

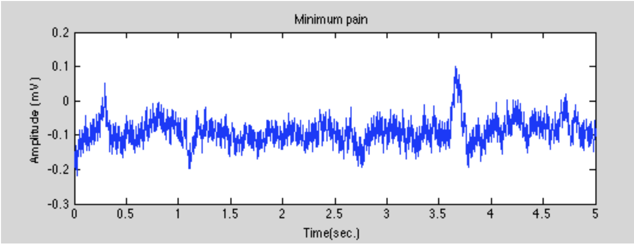
The patient's group consisted of 11 women who suffered from migraine for more than 2 years, aged between 18 to 40 years. The EEGs have been recorded through 7 channels positioned at C3, C4, T3, T4, P3, P4, F4 according to 10/20 standard at resting state with eyes closed. The signals are 240 seconds long, sampled at a frequency $f = 200Hz$. Hence, we have 48000 point for each channel. The EEGs are recorded in the maximum and minimum pain levels. The patients are requested to stop taking their medicine and to meet us while they feel their maximum pain in order to record EEG signals. During the treatment, patients are asked to rate their pain in a range of zero to ten while ten corresponds to maximum pain and one corresponds to minimum pain respectively.

Fig. 1 shows two sample EEG signals for a migraine patient recorded in this study.

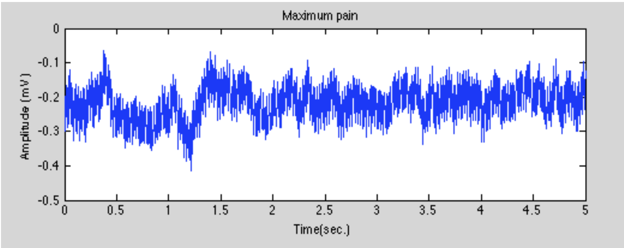
3.2. Feature Analysis

In order to analyze the efficiency of the extracted features, scattering plots and one-way ANOVA test are employed in this study. Fig. 2a and Fig. 2b respectively show the most and the least discriminant PLVs out of 21 evaluated PLVs. The most discriminant case is between channels P4 and P3 and the worst case is between channels C4 and C3. In Fig. 2, the central mark is the median, and the edges of the box are the 25^{th} and 75^{th} percentiles. The same analysis is performed on variance features. The variance of channels T3 and T4 are respectively the most and the least discriminant features among 7 extracted features based on variance. Fig. 3a and Fig. 3b show respectively the box plots for variance of the channels T3 and T4.

One-way ANOVA test is also applied to the extracted features in order to select the features which are statistically discriminant. Table. 1 and Table. 2 respectively show the P-

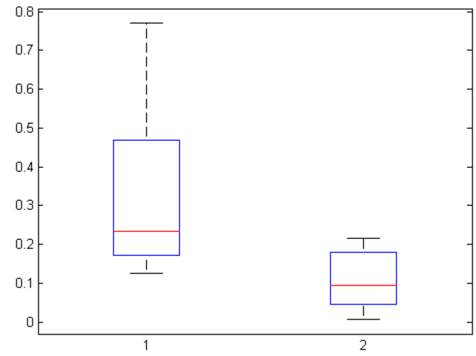


(a) Sample EEG signal in minimum pain (channel T3)

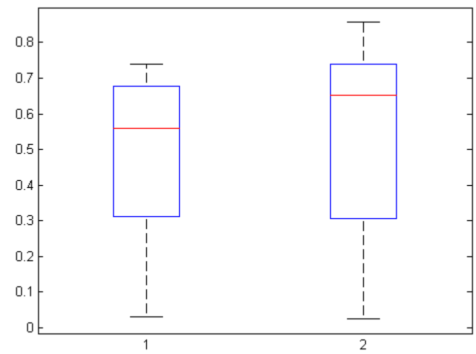


(b) Sample EEG signal in maximum pain (channel T3)

Fig. 1. Sample EEG signals used in this study



(a) PLV between channels P4 and P3



(b) PLV between channels C4 and C3

Fig. 2. Box plot for PLVs: class 1 and class 2 represent respectively Maximum and Minimum pain levels

value for PLVs and variance of the channels. According to Table. 1, by applying the threshold of 0.04 on the derived P-values, we select the PLVs for channel pairs (P3,P4), (P3,F4), (P4,F4), and (T4,P4) with corresponding P-values of 0.0038, 0.0062, 0.0385, 0.0388 as the most discriminant PLVs. By applying the same threshold value of 0.04 to Table. 2, we select the variance of channels T3, F4, and C3 with corresponding P-values of 0.0104, 0.0151, 0.0183 as the most discriminant variance features.

Due to the limitation of data for train and test sets, the 7 selected features are excessive. In order to classify the subjects using Neural Networks, we need to reduce the number of selected features in an efficient way. There are some complex feature reduction algorithms such as Fisher method [11]. However, heuristically we find out that the average of 7 selected features is a well discriminant feature. Hence, If we define the variable η as the average of the 7 selected features for each subject, an efficient feature is derived. In order to check the efficiency of the new feature, we performed the one-way ANOVA test again. The P-value of 0.0001 proves our assumption. Fig. 4 shows the box plot for the feature η.

3.3. Results

A classification task usually involves separating data into train and test sets. However, due to the limitation of the data acquired for this study, an LOO (Leave One Out) approach is used. Hence, for each sample of data, we eliminate it once, train the classifier based on the other samples and finally test the trained classifier with the one eliminated.

In order to assess the network capability in a statistically acceptable way, we do the classification problem 20 times. The proposed method has achieved the final average accuracy of 90.9%. True Positive Rate (sick people correctly diagnosed as sick) and True Negative Rate (healthy people correctly identified as healthy) are both 90.9% too.

4. CONCLUSION

In this paper, we examined the EEG signals recorded for 11 migraine patients. The EEGs are recorded through 7 channels. In order to analyze the EEG signals, first we extract 28 features: 21 features based on alpha band phase synchronization between channels, and 7 features for the variance of each channel. Then, we select 7 features based on the P-values derived from the one-way ANOVA test. Next, we introduce the new feature η as the average of the selected features. P-value of 0.0001 is derived through one-way ANOVA test for this feature. Finally, a neural network is trained based on the feature, achieving the final accuracy of 90.9%.

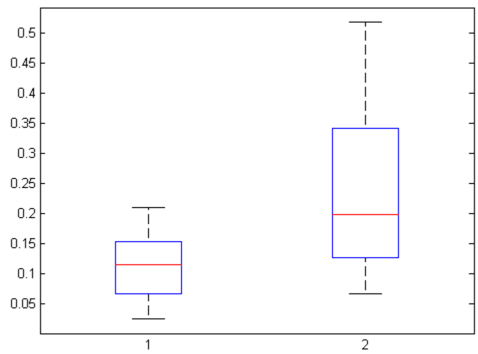
Classification between different levels of pain has been not carried out previously in migraine context. In addition,

Table 1. The P-value for the PLVs of 21 channel pairs. This table has 49 cells but it has a diagonal symmetry and just lower (upper) triangular elements are sufficient. It is obvious that the diagonal elements are meaningless.

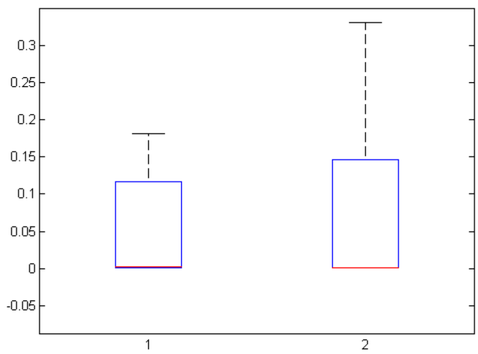
	C3	C4	P3	P4	T3	T4	F4
C3		0.7993	0.7098	0.0 461	0.6956	0.2728	0.0592
C4	0.7993		0.5917	0.0594	0.7144	0.6537	0.0982
P3	0.7098	0.5917		0.0038	0.3416	0.4653	0.0062
P4	0.0461	0.0594	0.0038		0.052	0.0388	0.0385
T3	0.6956	0.7144	0.3416	0.0520		0.3567	0.2420
T4	0.2728	0.6537	0.4653	0.0388	0.3567		0.3127
F4	0.0592	0.0982	0.0062	0.0385	0.2420	0.3127	

Table 2. The P-value for the variance of the channels

C3	C4	T3	T4	P3	P4	F4
0.0183	0.1546	0.0104	0.4748	0.0913	0.0415	0.0151



(a) Variance for channel T3



(b) Variance for channel T4

Fig. 3. Box plot for variance values: class 1 and class 2 represent respectively Maximum and Minimum pain levels

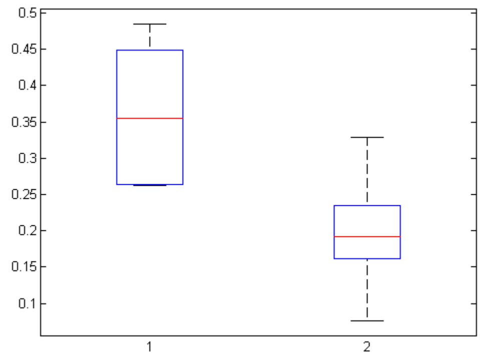


Fig. 4. Box plot for η:class 1 and class 2 represent respectively maximum and minimum pain levels

applying phase synchronization based on PLVs to non-evoked migraine EEG is a novelty in our study. The main limitation of the work presented here is the relatively small size of the dataset. We plan to examine our proposed method on a larger dataset by recording more EEG signals. In this study, we just tried to classify the migraine patients with maximum and minimum pain levels. However, classification between migraine patients and control subjects would lead to helpful results too. The Neural Network could be replaced by other classifiers too.

5. REFERENCES

[1] P.J. Goadsby, R.B. Lipton, and M.D. Ferrari, *Migraine Current Understanding and Treatment*, New England J. Med. 346, 257, 2002.

[2] "Headache classication committee of the international headache society," *Cephalalgia*, vol. 24, 2004.

[3] D. Dodick, *Why Migraines Strike*, Nature America, Inc., Jun 2011.

[4] A.MD Zulkarnain, "Detection of migraine in eeg by joint time-frequency representation," *Student Conference on Rcscarch and Development Proceedings, Shah Alam, Malaysia*, 2002.

[5] R. Bellott, F De Carlo, M de Tommaso, and M Lucente, "Migraine detection through spontaneous eeg analysis," *Proceedings of the 29th Annual Internationa Conference of the IEEE EMBS, Cit Internationale, Lyon, France*, AUG 2007.

[6] M. Tommasoa, D. Marinazzoa, M. Guidoa, G. Librob, S. Stramaglia, L. Nitt, G. Lattanzi, L. Angelini, and M. Pellicoroa, "Visually evoked phase synchronization changes of alpha rhythm in migraine: Correlations with clinical features," *International Journal of Psychophysiology*, vol. 57, pp. 203–210, 2005.

[7] F. Mormanna, K. Lehnertza, P. Davidb, and C.E. Elgera, "Mean phase coherence as a measure for phasesynchronization and its application to the eeg of epilepsy patients," *Physica D*, vol. 144, pp. 358–369, OCT 2000.

[8] A.V. Oppenheim and R.W. Schafer, *Discrete-Time Signal Processing*, Perntice Hall, Upper Saddle River, New Jersey 07458, third edition, 2010.

[9] E. Gysels and P. Celka, "Phase synchronization for the recognition of mental tasks in a braincomputer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 4, DEC 2004.

[10] S. Theodoridis and K. Koutroumbas, *Pattern Recognition*, Academic Press, 4 edition, 2009.

[11] R.A. Fisher, *Statistical Methods for Research Workers*, Oliver and Boyd, London, 4 edition, 1932.