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ARTIFACTS CLASSIFICATION IN EEG SIGNALS BASED ON TEMPORAL AVERAGE STATISTICS

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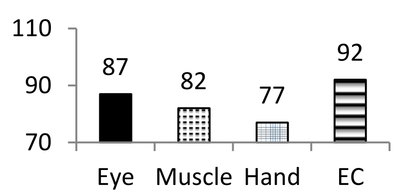
Graphical abstract



Abstract

EEG data contamination due to artifacts, such as eye blink, muscle activity, body movement and others pose as an issue in EEG analysis. This study aims to classify three different types of artifacts in EEG signal, namely; ocular, facial muscle and hand movement using statistical features coupled with neural networks as classifier. Temporal averages of five features are used as the feature vector for MLP classification. The experimental results for ocular, facial muscle and hand movement artifacts identification are ranging between 80% and 92%. The classification accuracy for the combination of these EEG artifacts and normal EEG of the subject for resting and eyes-close state are 86% and 96% respectively

Keywords: EEG classification, EEG artifacts, statistical features, temporal averages, multi layer perceptron.

Abstrak

Kewujudan artifak berpunca daripada kerdipan mata, regangan otot, pergerakan tubuh dan sebagainya boleh mempengaruhi proses menganalisasi data EEG. Kajian ini bertujuan untuk mengklasifikasikan tiga jenis artifak dalam isyarat EEG, termasuk pergerakan okular, regangan otot muka dan pergerakan tangan dengan menggunakan pembolehubah statistik dan artificial neural network sebagai classifier.Nilai digunakan sebagai input kepada mengelasan MLP. Keputusan eksperimen untuk mengenalpasti pergerakan okular, regangan otot muka dan pergerakan tangan dihasilkan dengan ketepatan di antara 80% hingga 92%. Ketepatan pengelasan artifak EEG dan isyarat EEG normal ketika subjek di dalam keadaan rehat dan mata tertutup ialah di antara 86% dan 96%.

Kata kunci: EEG classification, EEG artifak, statistical features, temporal averages, multi layer perceptron.

1.0 INTRODUCTION

Electroencephalography (EEG) is a technique to measure electrical activity caused by the firing of neurons in the brain. Such activity is also known as cerebral electrical activity. The generated flow of current is producing a small potential difference typically in millivolts (mV) magnitude. The EEG measurement is based on these potential differences recorded using electrodes attached to the scalp. The EEG measurement provides insight to the neuronal activity inside brain and has been widely used to study cognitive processes, the brain physiology as well as the different neurological disorders[1]. Its application penetrates even to the non-medical domain such as Brain Computer Interaction (BCI) -based applications, device control, training and education, gaming and entertainment[2]. In addition, EEG is one of the main tools used by neurologists and clinical experts in diagnosis of epilepsy, sleep disorders, schizophrenia, detection of spikes, seizures prediction, localizing the seizure focus, monitoring alertness, coma and brain death, locating damaged areas after head injury, stroke and tumor, testing afferent pathways and monitoring anesthesia depth[3].

While EEG is primarily designed to record cerebral activity but it also records electrical activities arising from locations other than the brain. In the context of EEG analysis, the recorded activity that is not origin from cerebral is labeled as artifact. The distinction between cerebral electrical activity and artifacts is crucial to understand various physiological, pathological, emotional and other aspects related to brain. A clean EEG measurement is crucial for actual interpretation and diagnosis. Hence, this paper proposes the usage of temporal averages of mean, skewness, variance, kurtosis and root mean square (RMS) statistical features coupled with Multi Layer Perceptron (MLP) classifier for ocular, facial muscle and hand movement artifacts classification.

2.0 MATERIALS AND METHODS

2.1 Data Acquisition

EEG signals are recorded with the 8-channel BIMEC amplifier system, digitized at 250Hz sampling rate. The electrodes are placed on the scalp of each participant according to International 10-20 system of Electrode Placement. The data is filtered using a band pass filter with settings 0.5~40Hz to capture and record the brain signals during resting condition, eye blinks, hand movements and facial muscle movement. Eight channels of C3, C4, F3, F4, P3, P4, T3, and T4 are used. The CZ channel is used as reference.

2.2 Methodology

The EEG data are collected by placing the electrodes on the 8 channels. The EEG data with artifacts consists of eye blinks, facial muscle activity and hand movements. For comparison purposes, normal EEG data are also collected for both eyes-open and eyes closed. Once the data has been collected, pre-processing is conducted to normalize the EEG signal as well as eliminating other noise except the three focused artifacts. The temporal averages of five statistical features, namely; kurtosis, skewness, mean, variance and root mean square are extracted to be the features vector. MLP will accept these inputs for artifacts classification. In order to ensure that MLP will not face over-fitting or memorization problem, k-fold validation is performed. 80% of the feature vectors are used for training while the remaining 20% are used for testing. The different training-testing pair is iteratively employed until all pairs are used. Performance is computed based on the accuracy of the correctly labeled artifact.

2.3 Experimental Protocol

The participants are asked to perform eye blinks, facial muscle movements and hand movements for 30 seconds. These three form the artifacts data. For comparison purposes, two resting state conditions of eyes close and eyes open are also captured for a period of 30 seconds.

3.0 FEATURES EXTRACTION

Many statistical feature parameters have been defined in the pattern recognition field [4]. It has been used in many signal processing analysis such as vibration analysis, fault detection as well as EEG analysis[5].The features selected in this paper are the combination of fundamental statistical features (mean and variance) with higher order statistical features (skewness, kurtosis and RMS). Each EEG segment with 7500 sample points is divided into a 0.4 sec segment with 100 sample points. For each of these segments, the moving averages of the selected features are calculated in temporal domain. Thus, for the whole EEG segment the features are based on time domain. Description of each features are briefly presented next.

3.1 Kurtosis

Kurtosis is a measure of degree of peak, for instance the flatness or the peakiness of the random variable data distribution. It describes the distribution of the observed data around its mean value.

$$Kurt = \frac{\sum_{i=1}^{N} (Xi-\mu)^4}{N\sigma^4}$$

where, μ and σ are the mean and the standard deviation of the signal series Xi (i=1-N), respectively.

3.2 Skewness

Skewness measures the symmetry of the data around the mean. The positive value of skewness implies that the data is spread to the right of the mean whereas the negative value means the data spread is inclined towards the left. Mathematically, defined as:

$$Skew = \frac{\sum_{i=1}^{N} (Xi-\mu)^3}{N\sigma^3}$$

3.3 Mean

Mean is mathematical representation of the typical value of a set of data, computed as the sum of all the numbers in the dataset and divided by the size of the dataset. Suppose we have sample space {x_1, x_2,

$x_3 \ldots x_n\}$ then the arithmetic mean μ is defined as mean of the raw signals:

$$\mu = \frac{\sum_{i=1}^{N} (Xi)}{N}$$

3.4 Root Mean Square (RMS)

The RMS value of a set of values is the square root of the arithmetic mean (average) of the squares of the original values (or the square of the function that defines the continuous waveform). In the case of a set of n values{x1, x2, x3….xn}, RMS is given as:

$$\text{RMS} = \sqrt{\frac{\sum_{i=1}^{N} (Xi)^2}{N}}$$

3.5 Variance

Variance is a statistical parameter which gives information about data distribution from its mean. It is the one type of probability distribution which measures how far a set of numbers get spread out.

$$Var = \frac{\sum_{i=1}^{N} (Xi-\mu)^2}{N}$$

4.0 CLASSIFICATION

MLP classification is performed to classify three different artifacts of ocular, facial muscle movement and hand movement. In addition, comparison between EEG with artifacts and normal EEG is also conducted. Similar MLP parameters are used based on our prior works in [[6][7][8]. Two-hidden layer MLP with 10 neurons each is employed for 2 neurons output layer.

5.0 RESULTS AND DISCUSSION

The experiments are divided into individual and collective results. Individual experiment focuses on the disparity between the EEG data of one participant to another. This is to show that there are unique parameters for each individual that can be used to classify artifacts and normal EEG. Moreover, collective experiment addresses the general parameters that aggregately similar from a group of participants' EEG data that make it possible to identify the target class of either artifacts or normal EEG. Different numbers of target class experiments are conducted to further analyze the ability of the proposed method to correctly classify.

The label Eye representing ocular artifacts, label Muscle representing facial muscle artifacts, label Hand representing hand movement artifacts, label EO representing eyes-open state and label EC representing eyes-close state normal EEG. These labels will be used interchangeably throughout the following of this paper.

Identification experiments are conducted to recognize the three different artifacts of ocular, facial muscle and hand movement for the four participants. The result is given in Fig. 1. The eye blink artifact is the highest artifact identified compared to the other two artifacts. It is observed that the accuracy pattern for Participant 1 and 4 is similar in such a way that the performance of the artifact identification can be sorted into the following arrangement: ocular > hand movement > facial muscle. However, Participant 2 and 3 share a similar accuracy pattern with the highest artifacts identification result recorded is facial muscle followed by eye blink and hand movement artifacts respectively. It is interesting to note that the proposed method manages to yield consistently high accuracy ranging from 81% to 92% for all the participants regardless of the artifacts identified.

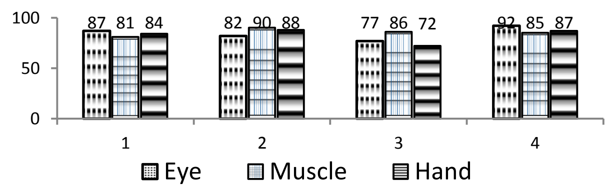


Figure 1 Artifacts Identification Results based on different

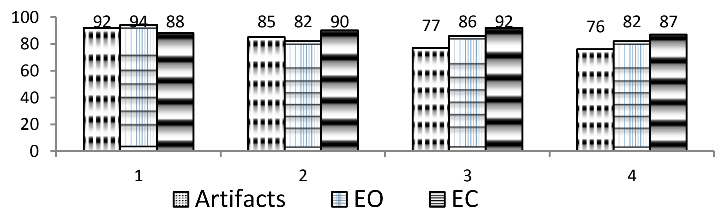


Figure 2 Classification of artifacts (eye + muscle + hand), eyes-open and eyes-close states for different participants

Then, a comparison of artifacts with normal EEG is conducted. The normal EEG condition of eyes-close and eyes-open are used as a threshold so that artifacts can be removed later. Typically eyes-close state signal is used as norm. However, in this paper we are trying to empirically measure if there are any disparity between eyes-close and eyes-open effects against artifacts. Fig. 2 illustrates the classification results of artifacts, eyes-open and eyes-close states. From the result, only Participant 3 and 4 has similar accuracy pattern that eyes-close result is the highest followed by eyes-open and artifacts. As discussed previously, individual result may not be consistent from one to another because of the unique characteristic of human EEG. Hence, it is not surprising that Participant 1 and 2 did not have similar accuracy pattern as Participant 3 and 4.

Further analysis is conducted by contrasting the artifacts with eyes-close and eyes-open states in verification experiment (2-class classification).

Hypothetically, both eyes-close and eyes-open state should provide almost similar results provided that both signals are occurred in the normal condition. Fig. 3 shows the difference between eyes-open and eyes-close state verification results against artifacts. It is observed that the accuracy for both experiments of the different normal EEG is almost identical with minimal variation accuracy.

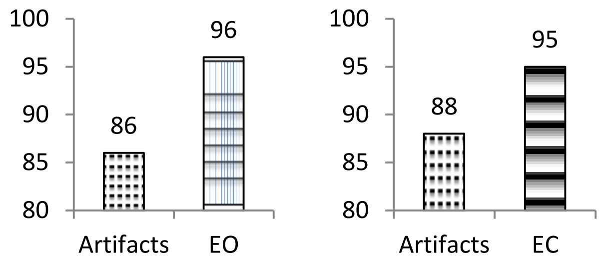


Figure 3 Verification result of artifacts (eye + muscle + hand) and eyes-open and eyes-close states

For further analysis, identification experiment to classify artifacts, eyes-open and eyes-close states are conducted. The result obtained is presented in Fig. 4. The eye-close state yielded the highest accuracy followed by the eyes-open state and artifacts respectively. Although artifacts accuracy is the lowest performance recorded, the result shows that recognizing the artifacts is feasible using the proposed approach with accuracy of 83%.

For more detailed result of the artifacts identification, Fig.5 is presented. From the result, it can be seen that hand movement artifact is the most difficult artifact to be recognized. On contrary, eye blink artifact scores the highest classification performance. It may be due to the location of the source of artifact itself. For instance, eye is located in the head which is nearer to the scalp as compared to the hand. Therefore, the eye blink artifact is easier to detect compared to hand movement artifacts. It is also interesting to note that artifacts classification performance yielded is between 77% and 87%. Such result gives indication that the proposed approach is feasible to be used for artifacts classification and detection.

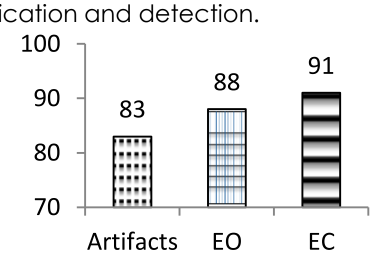


Figure 4 Identification result for artifacts, eyes-open and eyes-close states.

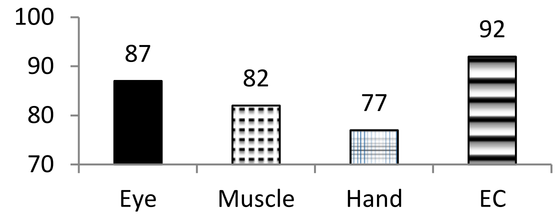


Figure 5 Classification of eye, facial muscle, hand movement artifacts and ec combined for all four subjects

6.0 CONCLUSION

In this study, three common artifacts of ocular, facial muscle movement and hand movement that contaminate EEG signals are studied in detail. Based on the morphology of the EEG signal in time domain, the temporal average of five statistical features, namely; mean, variance, skewness, kurtosis and RMS are used as feature vectors. Such relevant features are then fed to the Multi Layer Perceptron for classification purposes.

Experimental results show that the proposed approach manages to yield comparable accuracy ranges from 75% to 85%. Further analysis to compare the artifacts and normal EEG of both eyes-open and eyes-close states are also conducted. The results show promising insight that the recognition performance ranging from 83% to 96%are recorded. These results indicate that it is plausible for such experimental approach to be extended to be part of automated artifacts removal tool. Such tool can be used not only to clean EEG data but speech data as well. It is envisages with the development of automated artifacts removal, time needed to manually process the raw data can be minimized and expedited and yet manage to capture an acceptable clean data for further analysis.

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