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Classifying Various EMG and EOG Artifacts in EEG Signals

***Abstract**. EEG is the most popular potential non-invasive interface, mainly due to its fine temporal resolution, ease of use, portability and low set-up cost. However, it has some limitations. The main limitation is that EEG is frequently contaminated by various artifacts. In this paper, a novel approach to classify various electromyography and electrooculography artifacts in EEG signals is presented. EEG signals were acquired at the Department of Electrical and Electronics Engineering Karadeniz Technical University from three healthy human subjects in age groups between 28 and 30 years old and on two different days. Extracted feature vectors based on root mean square, polynomial fitting and Hjorth descriptors were classified by k-nearest neighbor algorithm. The proposed method was successfully applied to the data sets and achieved an average classification rate of 94% on the test data.*

***Streszczenie.** W artykule przedstawiono nową metodę analizy sygnałów w technice EEG pod względem klasyfikacji błędów zakłóceniowych w wynikach badań elektromiografii i elektrookulografii. Badanie przeprowadzone zostało na podstawie rzeczywistych wyników EEG. (**Klasyfikacja zakłóceń sygnałów w technice EEG w badaniach EMG i EOG**)*

Keywords: Artifact, Classification, EEG, Feature extraction.
Słowa kluczowe: Artefakt, klasyfikacja, EEG, wybór cech obrazu.

Introduction

Electroencephalography (EEG) is a noninvasive technique that measures electrical brain waves with electrodes which are placed on the scalp. It is characterized by irregular frequency and low amplitude. The amplitude of the EEG signal is about 10-100 µV and its frequency changes between 0.5-100 Hz [1]. Measuring brain activity has many applications ranging from clinical use to biomedical engineering research and even games. Clinically, EEG is used to diagnose brain-related states and diseases such as epilepsy, sleep disorders, coma and brain death. In the field of biomedical engineering research, EEG is often used in brain computer interface (BCI) applications which allow paralyzed subjects to interact an external device without using their muscles [2].

Although EEG is the most popular potential non-invasive interface, mainly due to its fine temporal resolution, ease of use, portability and low set-up cost, it has some limitations. The main limitation is that EEG is frequently contaminated by various artifacts. These artifacts are divided into two types as external and internal. The external artifacts are generated from environment equipment such as power line or light fluorescent. The internal artifacts are arisen from body activities like eye movement, eye blinks or muscular activity [3]. The internal artifacts can be broken down as follows: 1) Eye blink; It is represented by a low frequency signal (< 4 Hz) that can be significant in amplitude. It is a symmetrical activity mainly located on front electrodes (Fp1, Fp2) with a low propagation. 2) Eye movement; it is also represented by a low frequency signal (< 4 Hz) but with a higher propagation. It is caused by the fact that eyes represent dipole and their movement leads to an alteration of the electrical field. It is characterized by a dissymmetry between the two hemispheres. 3) Forehead movement; it is mainly a high frequency activity (> 13 Hz) due to its muscular origin. However, slight electrodes displacement can be observed on low frequency (< 4 Hz). 4) Jaw clenching; it is also a high frequency (> 13 Hz) and muscular activity and may also cause some low frequencies [4]. These artifacts cause a significant miscalculation of the measurement of diagnosis and then reduce the clinical usefulness of the EEG recordings. On the other hand, they decrease the performance of BCI applications.

In literature, many methods have been proposed to remove artifacts from the EEG that can be controlled, as mentioned before artifacts due to electrooculography (EOG) and electromyography (EMG) signals. Boudet et al. removed artifacts using independent component analysis (ICA) on signals cut in frequency bands. They presented a global method based on a training step during which artifactual sources are identified from cerebral ones, artifacts such as eye blinks, eye movements, jaw clenching, forehead and head movements [4]. In another artifact removing based study, Babu et al. proposed an adaptive filtering method that used RLS (recursive least square) algorithm and fast recursive least square (FRLS) to remove ocular artifacts from the EEG through wavelet transform. They concluded that FRLS algorithm is more efficient in comparison to RLS algorithm [5]. Park et al. suggested ICA and oriented principle component analysis (PCA) methods for artifact-robust (ocular and muscle artifacts) feature extraction. They compared with the PCA-based method and reported that their proposed method gives an average performance around 95%, whereas the PCA-based method is around 84% [6]. In another approach, Gao et al. presented a novel and robust technique to eliminate ocular artifacts from EEG signals automatically. They used ICA method to decompose EEG signals. The features of topography and power spectral density were extracted. Then, a classifier was used to identify ocular artifacts components. They used different schemes for classification and among them the manifold learning plus *k*-nearest neighbor (*k*-NN) classification was the best with an accuracy of 99.79% [7].

In some studies, researchers have classified EEG artifacts to control an electronic equipment instead of removing artifacts. In one of artifact based research, Barea et al. presented an eye-control method based on EOG to develop a system for assisted mobility. Their study was focused mainly on guiding and controlling a wheelchair for disable people. The wheelchair was handled by eye movements within a socket [8]. In another study, Chadwick et al. proposed interference of artifacts in the EEG generated by eye and head movement. They presented the use of machine learning techniques to classify artifacts in the EEG [9]. They classified 21 different facial and head movement artifacts. According to their results they achieved an average classification rate of 54% on the test data.

In this paper, a novel approach to classify various EMG and EOG artifacts in EEG signals is presented. For a biomedical engineering application an electronic device (such as an electronic wheelchair, a robotic arm, etc.) can be controlled, or clinically, physicians become aware of subject’s movement by using those detected artifacts. We extracted features by using three different methods, including root mean square, polynomial fitting and Hjorth descriptors. Based on extracted features, EEG trials were classified applying *k*-NN algorithm.

The organization of the paper is as follows: after the introduction section, the experimental setup is provided. Then, preprocessing, feature extraction and classification stages are described respectively. After those descriptions, the results are provided. Finally, the conclusion and discussion are given in the last section.

Experimental Setup

In this study the Brain Quick EEG System (Micromed, Italy) was used to acquire EEG signals. The EEG signals were sampled with 2048 Hz and filtered between 0.1 and 120 Hz. Additionally, a 50 Hz notch filter was used to eliminate line noise. Six EEG electrodes from frontal lobe are located according to the International 10–20 System as shown in Fig. 1, and are referenced to the electrode Fz as follows: Channel 1: Fp1; Channel2: Fp2; Channel 3: F3; Channel 4: F4; Channel 5: F7 and Channel 6: F8. The International 10-20 System is the most widely used method to describe the placement of electrodes at specific intervals along the head. Each electrode site has a letter to identify the lobe, along with a number or another letter to identify the hemispheric location. Because the EOG and the EMG artifacts are strong on the frontal lobe (F) electrodes, Fp1, Fp2, F3, F4, F7 and F8 electrodes are selected to be analyzed.

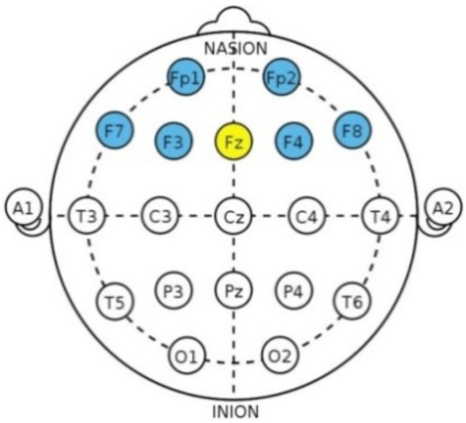

Fig. 1. Electrode placement as international 10-20 system

EEG signals were obtained from three healthy human subjects (male) in the age groups of between 28 and 30 years old and on two different sessions with about one week of delay. Before beginning to record, subjects were asked to calm down and relax in a chair for five minutes. The chair is placed in 1 meter in front of the wall and two signs on the wall in 3.5 meter distances from central point to guide subjects for two directions left and right as shown in Fig. 2. Then, the subjects were instructed how to perform these movements as seen in Table1. During the recording, the subject receives a beep sound in a 2-second period and in this interval the subject has to perform the movement task. There is a 5-second gap between each trial in order to omit the effects of physical weariness. Afterward, the subjects were asked to perform another task according Table 1. For the first movement task, subject moves his eyes from the center (C point) to the right direction (R point) with 74.05 degree as shown in Fig. 2. For the second movement task, subject moves his eyes from the center (C point) to the left direction (L point) with 74.05 degree. For the third movement task, subject starts to blink his eyes three times. For the fourth movement task, subject does not do any movement (no movement artifact). For the fifth task, subject grates left side of his teeth one time.

Table 1. Subject movement tasks

Class	Movement Task	Number of Train Trials	Number of Test Trials
class1	Move eyes to the right	20	20
class2	Move eyes to the left	20	20
class3	Eye blink	20	20
class4	No movement artifact	20	20
class5	Grate left teeth	20	20

In each session, 100 trials (20 trials for each task) were recorded from per subject and all the trials were divided into two groups. The first group is called training set which contains the first session's trials and the second group is called test set which contains the second session's trials. We labeled movement tasks as *class1*, *class2*, *class3*, *class4* and *class5* as given in Table 1. The typical recorded EEG signals are shown in Fig. 3.

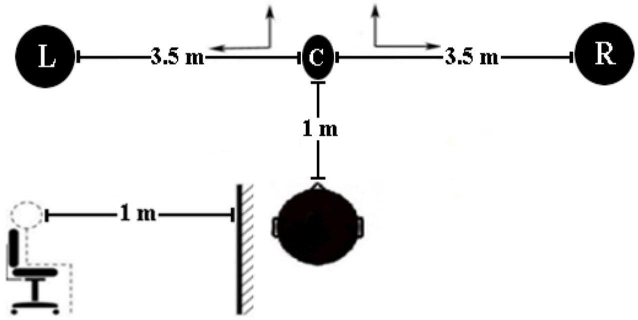

Fig. 2. Signs configuration place on wall

Preprocessing

As mentioned before, EEG signals are obtained in different sessions. This session to session variation can directly influenced the amplitude of signals and naturally classification performance of the test set. Therefore, a normalization process should be implemented to the training set and test set in order to alleviated the impact of the magnitude change. In this study a mean normalization process was implemented to the all trials as Equation 1 [10].

$$X_N = \frac{x-\bar{x}}{\max|x-\bar{x}|} \tag{1}$$

Here, $x, \bar{x}$ and X_N denote the original signal, mean of the original signal and the normalized signal, respectively.

Feature Extraction

In this study, only the Channel 5 was used for extracting features. The features were extracted by using three different methods. These methods can be summarized in the following subsections.

A. Root Mean Square (RMS) Method

After the normalization process, EEG trial was passed through fast Fourier transform filter bank and α subband ([8 - 13] Hz) of the signal was extracted, which was denoted as X_N^α [11], [12]. Then, the rest of the signal was calculated by subtracting X_N^α from normalized signal, as given in Equation 2. The diagram of this algorithm is shown in Fig. 4.

Afterward, RMS values, which were used as features, were calculated for each part, X_N^α and X'_N, as given in Equation 3a and 3b, respectively [13],[14].

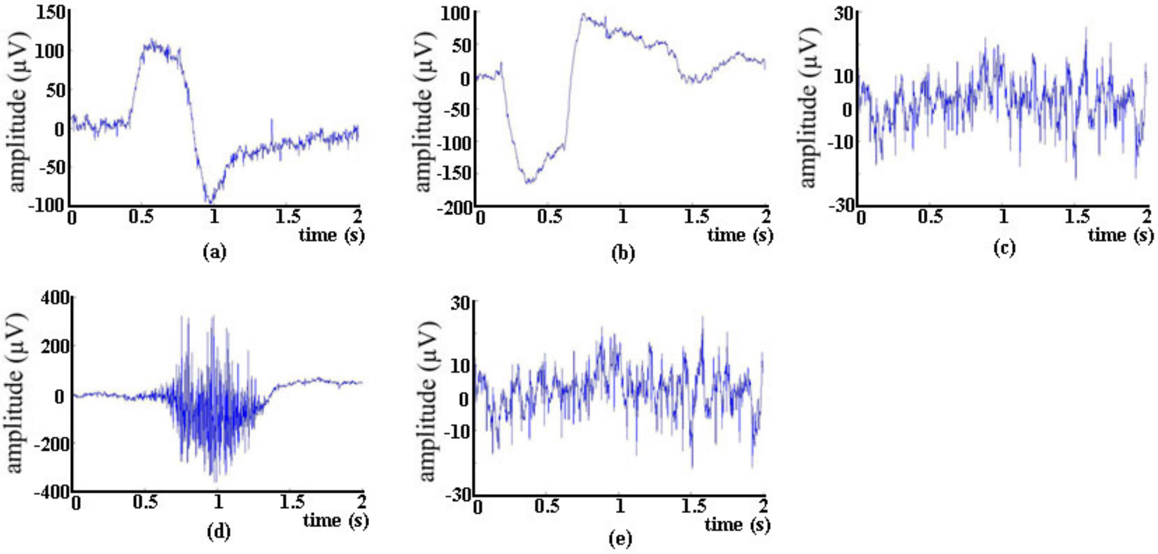

Fig.3. Typical recorded EEG signals, (a) Move eyes to the right, (b) Move eyes to the left, (c) Eye blink (d), Grate left teeth (e), No movement artifact

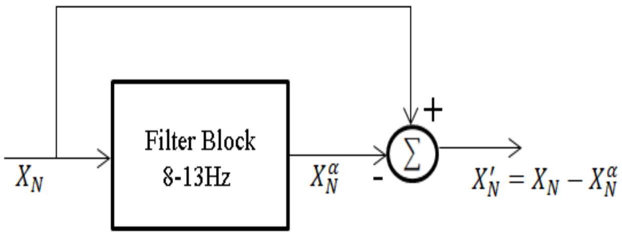

Fig. 4. Diagram of the filter bank algorithm

(2) $$X_N' = X_N - X_N^\alpha$$

(3a) $$RMS(X_N^\alpha) = \sqrt{\frac{1}{k}\sum_{n=1}^{k} X_N^\alpha(n)}$$

(3b) $$RMS(X_N') = \sqrt{\frac{1}{k}\sum_{n=1}^{k} X_N'(n)}$$

Here, *n=1, 2, 3,..., k* and *k* denotes length of X_N respectively.

B. Polynomial Fitting Method

After close examination, it was observed that the signals of *class1* and *class2* reveal as a third order polynomial. A third order polynomial is defined as a cubic curve function, which includes one local maximum and one local minimum However, one of the general differences for aforementioned classes is that, for the *class1* trials the local maximum comes before the local minimum as can be seen from Fig. 5a, but for the *class2* trials the local minimum comes before the local maximum as seen from Fig. 5b. Based on this observation, we seek to develop a feature extraction algorithm in order to distinguish *class1* and *class2* trials. For each of the trial signals of Channel 5, a third order polynomial is fitted to the normalized signal of the trial. We denote the third order polynomial fitted to the signal by $f(t) = at^3 + bt^2 + ct + d$, where *a*, *b*, *c*, *d* are coefficients of the third order polynomial.

Table 2. Sign of *a* and *b* coefficient

Class	Coefficient *a*	Coefficient *b*
class1	+	-
class2	-	+

After estimating the coefficients *a*, *b*, *c* and *d*, we concluded that the order of the local maximum and local minimum influences the signs of the coefficients of *a* and *b*. The signs of *a* and *b* coefficients for *class1* and *class2* are given in Table 2. Based on these strong clues, we considered *a* and *b* values can be selected as features to classify *class1* and *class2* trials.

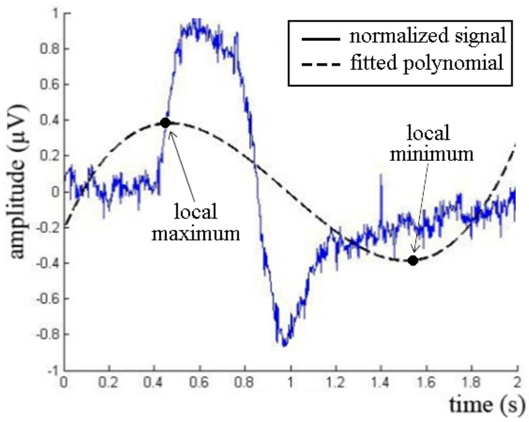

Fig. 5a. Typical normalized *class1* trial data and fitted polynomial

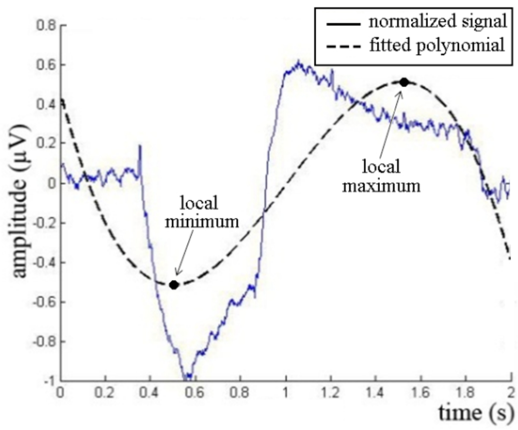

Fig. 5b. Typical normalized *class2* trial data and fitted polynomial

C. Hjorth Descriptors Method

Hjorth method is defined by three descriptors as activity, mobility and complexity [16]. Activity and mobility are calculated follows:

$$\text{(4)} \qquad \text{Activity} = A(X_N) = \sigma_{X_N}{}^2 = \frac{\sum(X_N-\overline{X_N})^2}{k-1}$$

$$\text{(5)} \qquad \text{Mobility} = M(X_N) = \frac{\sigma_{\dot{X}_N}}{\sigma_{X_N}} = \frac{\sqrt{\frac{\sum(\dot{X}_N-\overline{\dot{X}_N})^2}{k-1}}}{\sqrt{A(X_N)}}$$

where $\overline{X_N}$, $\dot{X}_N$ and $\overline{\dot{X}_N}$ denote the mean of the X_N, the first derivative of X_N and the mean of the first derivative of X_N, respectively.

In this study, activity and mobility are used as features to distinguish *class3* and *class4* trials.

Classification Procedure

A classifier is an algorithm which has to be trained with labeled training examples to be able to distinguish new unlabeled examples between a fixed set of classes. In this study, *k*-NN algorithm is used to classify facial movement artifacts in EEG signals. In this section, the training and the testing stages are explained

A. Training Stage

k-NN algorithm was trained for each classifier as can be seen in Fig. 6. For *classifier1*, all training trials; for *classifier2*, *class1* and *class2* training trials; for *classifier3*, *class3* and *class4* training trials were used to train classifiers. In order to determine optimum *k* value leave-one-out cross validation (LOOCV) technique was used. Because of the number of each movement task trials in training set was chosen 20, the optimum *k* value was searched in interval between 1 and 20, with the step size of 1.

In this approach, LOOCV technique was applied, since it makes the best use of the available data and avoid the problems of random selections.

B. Testing Stage

In this study, total procedure to classify EEG artifact signal was performed in three steps as seen in Fig. 6.

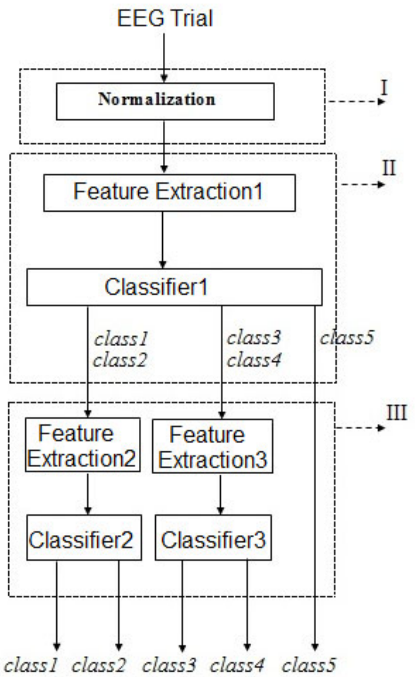

Fig. 6. Block diagram of proposed method

The three steps are described as follows:
Step1. Initially, the EEG signal was normalized.
Step2. Features were extracted by RMS method (*Feature Extraction1*) and classified by trained *classifier1* algorithm, then the EEG trial was recognized temporarily as *class1, class2, class3, class4* and *class5*.
Step3. If the EEG trial was recognized as;
i) class1 or class2 the *Feature Extraction2* method was used and features were extracted by polynomial fitting method. Then the trained *classifier2* algorithm was determined as exactly the trial *class1* or *class2*,
ii) *class3* or *class4* the *Feature Extraction3* method was used and features were extracted by using Hjorth descriptors method. Then the trained *classifier3* algorithm was determind exactly the trial *class3* or *class4*,
iii) class5 then the trial was determined directly as *class5*

Results

For each subject we trained three *k*-NN classifier and tested 100 trials. The training classification accuracies (TCAs) for each classifier and subject are given in the Table 3. Also, at the bottom of the TCAs the calculated *k* parameters are provided. The TCA was defined as the percentage of the number of trials classified correctly over the size of the validation set. For *classifier1*, *classifier2* and *classifier3* the average rates of *TCA1*, *TCA2* and *TCA3* were obtained as 99.33%, 99.16 % and 93.33%, respectively.

Table 3. Training classification accuracy

Subject	TCA1 (%)	TCA2 (%)	TCA3 (%)
A	99 (*k*=3)	97.5 (*k*=3)	97.5 (*k*=5)
B	99 (*k*=3)	100 (*k*=1)	100 (*k*=1)
C	100 (*k*=1)	100 (*k*=1)	82.5 (*k*=15)
Average	99.33	99.16	93.33

The classification results of test data are provided as confusion matrix in the Table 4, 5 and 6. Confusion matrix gives detailed information about breakdown of misclassifications. In the tables the observed class is displayed at the top of matrix, and the predicted class down the side; each cell contains a number, showing how many trials of the actual given observed class were assigned by the model to the given predicted class. In a perfectly performing confusion matrix, all the trials are counted in the leading diagonal. For subject A, while *class1*, *class2* and *class5* were classified perfectly, *class3* had one misclassification and *class4* had five misclassifications, which were classified as *class3*. For subject B, all classes were classified perfectly, except one misclassification. Similarly to subject A, *class1*, *class2* and *class5* were classified perfectly for Subject C. However, *class3* had ten misclassifications which were classified as *class4*, and *class4* had one misclassification.

Table 4. Confusion matrix for the Subject A

		Predicted Class				
		1	2	3	4	5
True Class	1	20	0	0	0	0
	2	0	20	0	0	0
	3	0	0	19	1	0
	4	0	0	5	15	0
	5	0	0	0	0	20

Table5. Confusion matrix for the subject B

		Predicted Class				
		1	2	3	4	5
True Class	1	20	0	0	0	0
	2	0	20	0	0	0
	3	0	0	20	0	0
	4	0	0	1	19	0
	5	0	0	0	0	20

The overall test classification accuracies were also computed which are provided in the Table 7. . As can be seen in the table for subject A, B and C, 94%, 99% and 89% classification accuracies on the test data were achieved. The average test classification accuracy (CA) was calculated as 94%.

Table 6. Confusion matrix for the subject C

		Predicted Class				
		1	2	3	4	5
True Class	1	20	0	0	0	0
	2	0	20	0	0	0
	3	0	0	10	10	0
	4	0	0	1	19	0
	5	0	0	0	0	20

Table 7. Test Classification Accuracy

Subject	CA (%)
A	94
B	99
C	89
Average	94

Conclusion and Discussion

In this paper, a successful approach to classifying facial movement artifacts in EEG signals, which are recorded in different sessions, is presented. The means of artifacts are the combination of EMG and EOC signals that influence on EEG signals. The movement tasks are easy and simple for users to accomplish basic tasks the first time.

The dataset was based on a six-channel scalp. Only signals of Channel F7 yielded discriminative features. Extracting features from the signals of the remaining five channels resulted in slightly poorer performance than that of Channel F7. It is worth mentioning that using only one channel in many EEG based applications provides much more practicality in use.

Another good attribute of the proposed method is its simplicity in the feature extraction procedure. The feature vectors are two-dimensional. Their entities are extracted from only one channel and they are fast and simple. As a feature extraction method, the third order polynomial fitting method is one of the novelty of this approach. It is worth to mention that in order to avoid overfitting problem higher order polynomial fitting was not used.

The results also showed that the *k*-NN algorithm achieved good performance to classify five tasks. Furthermore, *k*-NN algorithm is easy to use, fast and requires only one parameter, *k*.

This work is the first study that applied a combination of given five facial movement artifacts in EEG signals. So, this is another novelty of this approach.

One of the disadvantages of this research is lack of international standard data base. So, comparison of these results with other studies applying the same data set was not possible.

These proposed tasks and method can be used with a high accuracy and performance to control an electronic device, a wheelchair or a robotic arm.

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