Classification of Ocular Artifacts in EEG Signals Using Hierarchical Clustering and Case-based Reasoning

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Abstract. Analysis of Electroencephalograms (EEG) recordings is becoming an important research area. However, if the signal is contaminated with noises or artifacts then it could mislead the diagnosis result. Therefore, it is important to remove artifacts from the EEG signal. This paper presents a classification approach to detect ocular artifact in the EEG signal. The proposed approach combines several methods i.e., case-based reasoning (CBR), Hierarchical clustering and Independent component analysis. The results show that the proposed system can classify EEG signal and ocular artifacts 95% accurately.

Keywords. Electroencephalogram (EEG), Electrooculogram (EOG), Case-based Reasoning (CBR), Ocular Artifacts (OA)

1 Introduction

The Electroencephalogram (EEG) is a biological signal that measures the brain activity and is a diagnosis method of the central nervous system. Various research areas where EEG signal is widely used are, but not limited to, sleep study, epilepsy, neuroscience, and cognitive science. Like other biological signals EEG is also non-stationary and non-linear in characteristics. Klonowski (2009) [1] defined it as '3N': *nonstationary*, *nonlinear*, and *noisy*. One of the crucial aspects of using EEG in medical applications is to deal with noises and artifacts presented in the signal. In addition, these artifacts can cause significant miscalculation of measurements that reduces the clinical usefulness of EEG signal. In last decade, a large amount of studies have been carried out on ocular artifacts removal from EEG signal.

Several methods and algorithms have been proposed in different studies to identify and remove ocular artifacts from EEG signal. The traditional ocular artifact correction methods are linear filters and regression-based methods. In linear filter approach certain frequency bands that belong to ocular artifact (OA) range are removed from the EEG signal. One of the problems of this technique is that it can also cause significant loss of neural activity in EEG data because of spectral overlaps between neurological and OA signals [4]. On the other hand, regression-based method computes propagation factors or transmission coefficients to determine correlation between one or more electrooculogram (EOG) channels and each EEG channel. In time or frequency domain it subtracts EOG portions that are contributing in EEG signal. The problem with regression analysis is that it not only reduces ocular artifacts but it may also remove interesting cerebral activity. It also requires EOG reference channel for artifact removal and requires a calibration trail to determine the transfer coefficients between EOG and EEG channels. Independent component analysis (ICA) that belongs to blind source separation algorithms has been proved as an effective method to identify and correct ocular artifacts from EEG signals. However, most of the techniques based on ICA require visual inspection to identify OA. In the articles [23-26][31] ICA and clustering algorithms have been used to classify ocular artifacts in EEG signals. In the article [26] a hybrid algorithm using iterative ICA and fuzzy clustering has been proposed for artifacts rejection in EEG signals. In [23] different eye movement activities are classified from EEG signals using ICA and k-nearest neighbor classification.

This paper presents a combination of Case-based reasoning (CBR) [27][28] and Hierarchical clustering approach to classify OAs from EEG signals. Here, in the EEG signals, ICA has been applied to separate mixing signals from EEG and then features are extracted from each independent component. In this paper, 19 channels EEG signals are time-synchronized with respect to three ocular activity tasks. After that, each EEG recording is segmented considering the six trials that have been conducted for each subject during the data collection. Hence, after ICA on each segmented EEG signals 3192 independent components are obtained from the EEG signals. Then, these independent components are categorized using Hierarchical-clustering. Here, the data were collected in a controlled environment and these categories by Hierarchical-clustering are then labeled as either EEG component or OAs component by visual inspection. Finally, CBR is applied to classify the components into EEG signal or ocular artifacts i.e., eye blink, eye movement or saccades.

The rest of the paper is organized as follows: Section 2 presents related work on OAs in EEG signals and its identification. Section 3, describes the proposed approach. Section 4, discusses the experimental work. Finally, Section 5 ends with summary and discussion.

2 Background

EEG is the electric potential from the exposed surface of scalp and measured by the current flows when synaptic excitation of dendrites of many pyramidal neurons in the cerebral cortex. EEG signal is recorded from the scalp surface by electrodes and characterized by amplitude and frequency. The amplitude of the EEG signal is between 10-100 μV [5][6]. Based on source, EEG artifacts can be divided into two categories a) Non-physiological and b) Physiological artifacts.

Physiological (or internal) artifacts in EEG signal are the main concern of this paper. The common causes of physiological artifacts are eye and head movements [7-9]. Positive cornea and negative retina of human eye generates electrical dipole and EOG signal is produced because of the change of the dipole by eye movement and blinks [5][10]. Ocular artifacts (OAs) are often dominant over other physiological artifacts i.e. head movement, muscle artifacts and most of the research articles are about dealing with ocular artifacts. EOG waveform depends on the factors, for example, the direction of the eye movements. Eye blink artifacts are low frequency (<4 Hz) in nature and significant in amplitude. It can be located on front electrodes (FP1, FP2); which has symmetrical activity and low propagation. On the other hand, eye movement artifacts are represented by low frequency (<4 Hz) but with higher propagation [10][11]. Eye movements may occur in any direction and can be considered as combinations of rotations over two angles (a vertical angle and a horizontal angle). The vertical component can be estimated by using electrodes located above and below the eyes, and the horizontal component can be estimated by using electrodes located outside the outer canthus of each eye [5]. Different frequency ranges of EEG signal have been reported as neural information in several studies. Neural information can be obtained below 100 Hz from the EEG signal and in many applications information lies below 30 Hz [12]. In [7] the range of EEG signal is 0 to 64 Hz and they mention that ocular artifacts occur within 0 and 16 Hz. A fraction of EOG contaminates the EEG signal and stronger peaks are introduced in the EEG signal because of the ocular artifacts [7][11][13][14].

3 Classification approach for Ocular artifact identification

In order to identify ocular artifact i.e. eye movement, eye blink and saccades the proposed approach applies Hierarchical clustering and Case-Based Reasoning (CBR) methods [29][30]. Here, the Hierarchical clustering method is used to build the initial case-library and CBR is used for ocular artifact classification [32]. An overview of the proposed system to identify ocular artifact in EEG signal is presented in Fig. 1.

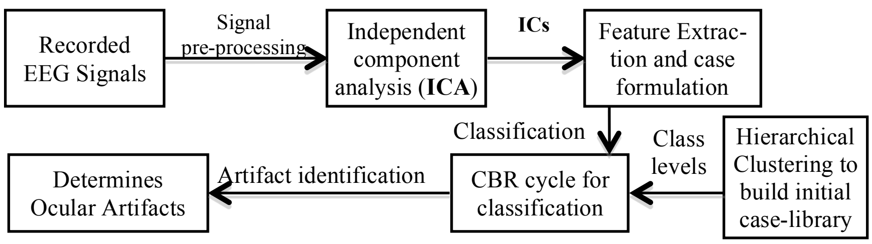

Fig. 1. Steps of the approach in order to classify ocular artifacts

Here, EEG signals are recorded at 2048 Hz. following the international 10-20 electrode placement system, where 19 channels locations are used and those are: Fp1, Fp2, F7, F3, Fz, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1 and O2. A controlled data collection scenario was used during the data collection and subjects were asked to perform three different ocular activity tasks, i.e. smooth pursuit eye movement, eye blink and saccades. For eye movement a cross symbol was moving on a computer screen, for eye blink the cross symbol was flashing on the screen, for saccades the cross symbol was jumping around the screen and subject was asked to follow the cross symbol. A time constrain was also applied, in saccades the cross symbol was jumping in 2 second interval as an example. Thus the data are recorded in a control environment and achieved three different types of ocular activities. An example of raw EEG signals of 16 seconds saccades movement is shown in Fig. 2.

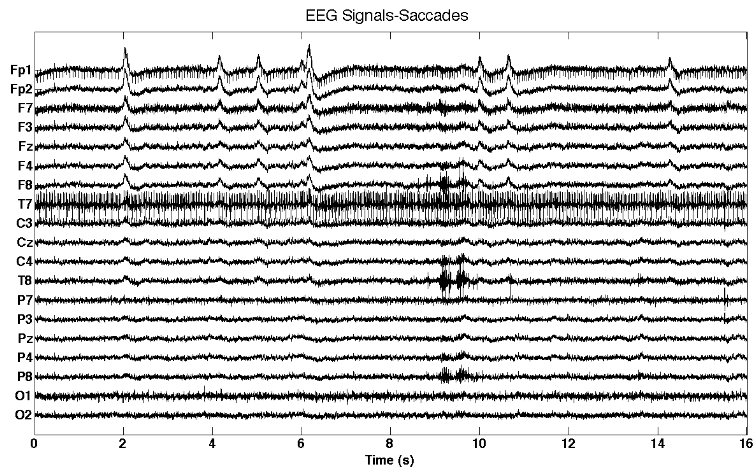

Fig. 2. EEG recording of Saccades movement

For the pre-processing the recorded EEG signals, are divided into 3 seconds epoch and the signals are pre-processed to remove 50 Hz channel noise using notch filter. After pre-processing, Independent component analysis (ICA) has been applied. ICA is a method that finds a linear representation of non-Gaussian where data are statistically independent [15]. ICA assumes a data model $X = AS$, where X is a queued column vectors, A is a weight matrix for mixing independent components back to original signals, S is queued column vector of statistically independent components. In the ICA model, number of sources N and the mixing matrix A are usually unknown. The task of ICA method is to recover unknown source signals $s(t)$ by introducing unmixing matrix W; $Y = WX$, Where W is the inverse matrix of the mixing matrix A. Y represents the independent components that are estimates of sources S. Since there is no knowledge of matrix A, it is not possible to determine W exactly.

A set of features are extracted and considered in order to abstract EEG signals based on each independent component (ICs) of ICA and they are: *sample entropy*, *hurst exponent*, *kurtosis, activity*, *mobility* and *complexity* from Hjorth's descriptors, and *mean* and *standard deviation* from mutual information. *Sample Entropy* is a non-linear feature, which helps to find a complexity of a time series signal and based on the complexity value the blinking in the EEG is identified. That is, the eye blink is related to sample entropy since they are more regular and predictable, and high entropy is for other activities [17]. *Sample Entropy* is calculated through the following equation [17]:

$$Sample\_Entropy\ (mT, r) = \log\left[\frac{C_r^{mT}}{C_r^{mT+1}}\right] \quad (1)$$

Here, the maximum length of epochs *mT* = 2 and tolerance r = 0.2 × SD (standard deviation of the data vectors) [18][19], and *C* is counter i.e. number of templates matches within the tolerance value r. *Kurtosis* is the fourth-order central moment of a distribution that characterizes the relative flatness or peakedness of a signal distribution. Kurtosis is defined by the following equation:

$$Kurtosis(s) = E(s^4) - 3E(s^2)^2 \tag{2}$$

Where *s* is the signal and *E* is the statistical expectation function of *s*. highly positive kurtosis indicates highly peaked distribution in the signal [20][21]. *Hjorth's descriptors* are defined by three descriptors as activity, mobility and complexity [22]. The activity and mobility are calculated follows:

$$Activity(X_N) = var(X_N) \tag{3}$$

$$Mobility(X_N) = \frac{\sigma X_N}{\sigma X_N} \tag{4}$$

$$Complexity(X_N) = \frac{(\sigma_4/\sigma_2)}{(\sigma_2/\sigma_0)^{1/2}} = [\sigma_4/\sigma_0]^{1/2} \tag{5}$$

Here, *Activity*(X_N) is the variance of the normalized signal, and σX_N is the standard deviation of the first derivative of X_N. *Hurst Exponent* usually used to evaluate the self-similarity and correlation properties of fractional Brownian noise. It is the measure of the smoothness of a fractal time series based on the asymptotic behavior of the rescaled range of the process.

$$H = \frac{\log(R/S)}{\log(T)} \tag{6}$$

Where *T* is the duration of the sample of data and *R/S* is the corresponding value of rescaled range. Long-range dependencies and its degree in time series can be evaluated using Hurst exponent. *Mutual information (MI)* measures the linear and non-linear dependencies between *M* random variables, $X = (X_1, \ldots\ldots, X_N)$. Mutual information is defined as:

$$MI(X) = \sum_i^N H(X_i) - H(X_1, \ldots\ldots, X_N) \tag{7}$$

Here, *H(X)* is the entropy,

$$H(X) = -\sum_{i=1}^{M_x} p(x_i) \log p(x_i) \tag{8}$$

Where, $H(X_1, \ldots, X_N)$ is the joint entropy of the random variable *X*, and *p(xi)* is the probability of *X* estimated at xi, *i=1,...,Mx*, and *Mx* is the number of samples of each realization of the random variable *X*.

Finally, a new problem case was formulated considering the extracted features, which were fed into the case-based retrieval classification scheme. The initial case-library has been built by applying hierarchical clustering and manual inspection presented in chapter 3.1. The cases are labeled as *EEG*, *Eye Movement*, *Eye Blink* and *Saccades* and considered as a classification solution. The similarity of a feature value between two cases (i.e. a target case and one case from library) was measured using the normalized Manhattan distance between the feature values of two cases. The top most similar case and its classification were used to classify the ocular artifacts. Finally, artifacts were identified from the recorded EEG signals.

3.1 Hierarchical clustering in order to build initial case-library

The Hierarchical algorithm clusters data over a variety of scales by creating a hierarchical structure (tree) or 'dendrogram'. The tree is not a single set of clusters, but rather a multilevel hierarchy, where clusters at one level are joined as clusters at the next level [16]. Hierarchical clustering applied on each epoch data to categorize each ICs in to two clusters. For eye movement and saccades EEG recording clusters were labelled as EEG and eye movements ICs. And, for eye blink recording data clusters were labelled into EEG and eye blink ICs. The steps of the approach to build initial case-library are presented in Fig. 3.

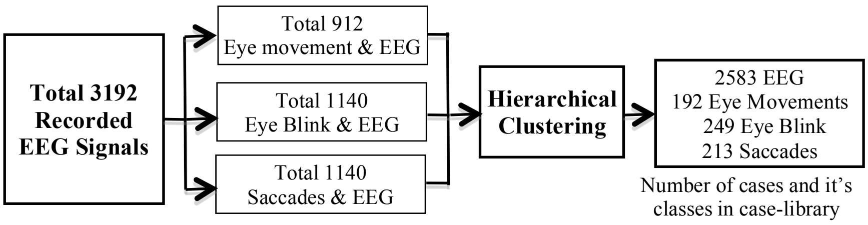

Fig. 3. Steps of the approach to build initial case-library

In Hierarchical, the distance between pairs of objects is calculated using Euclidean distance as a 'correlation' parameter of the MATLAB function 'pdist'. The linkage function applies 'complete' (i.e. Furthest distance) as parameter, which determines the objects in the data set that should be grouped into clusters. Finally, a cluster function is applied to group the sample data set into clusters by specifying the cluster's number.

Case Classes	**Total cases**
EEG	2538
Eye Movement	192
Eye Blink	249
Saccades	213
Total	3192

Table 1. Number of cases and class distributions identified by Hierarchical clustering algorithm and used to initiate the case-library.

Here, a visual inspection has been applied to label the ICs for the clusters since the data were recorded in a controlled environment and each epoch is time synchronized with the task performed by the subject. Thereafter, a case library has been created using these clusters data [32]. Number of cases and class distributions from 1st order categorization using Hierarchical clustering algorithm are presented in Table 1.

4 Experimental work

The classification accuracy of the CBR retrieval classification scheme has been evaluated by developing a prototypical system where the main goal of the experiment is to see how accurate the CBR approach can classify with the extracted features from the signals. The evaluation has been conducted by considering both the control and test data sets. The control data set is used to develop and fine tune of the CBR retrieval classification scheme. The case-library has been built with 3192 cases with 4 classes (i.e. *EEG, Eye Movement, Eye Blink* and *Saccades*) in total, and each case contains 8 features extracted from the signals. For the retrieval, a “leave-one-out” retrieval technique is used i.e. one case is taken from the case library as a query case and then the system retrieves the most similar cases. The confusion matrix of the correctly classification on the 4 classes are presented in Table 2.

	EEG	**Eye Movement**	**Eye Blink**	**Saccades**	**Total**
EEG	2365 (91.6%)	33 (1.3%)	63 (2.4%)	77 (2.9%)	2538
Eye Movement	39 (20.3%)	96 (50%)	37 (19.3%)	20 (10.4%)	192
Eye Blink	68 (27.3%)	38 (15.3%)	75 (30.1%)	68 (27.3%)	249
Saccades	53 (24.9%)	28 (13.1%)	60 (28.2%)	72 (33.8%)	213
Total	2538	192	249	213	3192

Table 2. Confusion matrix based on CBR classification.

As can be seen from Table 2, the percentage of classification accuracy of the CBR system considering *EEG*, *Eye Movement, Eye Blink* and *Saccades* classes are 92%, 50%, 30% and 33%. Here, the classification accuracy shows poor result and the cases are classified by other classes. Since *Eye Movement, Eye Blink* and *Saccades* classes are related to the *Ocular Artifacts* by definition the CBR system classifies them as 80%, 77% and 75% respectively. A sensitivity, specificity and overall accuracy are also calculated and presented in Table 3, here, all the cases belong to *Eye Movement, Eye Blink* and *Saccades* are treated as *Ocular Artifacts* group and rest of them are *normal* group.

Criteria/Indices	**Values**
Total cases	3192
Cases belong to *Ocular Artifacts* group (P)	654
Cases belong to *Normal* group (N)	2538
True positive (TP):	494
False positive (FP):	173
True negative (TN):	2365
False negative (FN):	160

Sensitivity = TP / (TP + FN)	≈ 0.76
Specificity = TN / (FP + TN)	≈ 0.93
Accuracy = (TP+TN)/(P+N)	≈ 0.95

Table 3. Statistical Analysis of the system's classification

It can be seen from Table 3, 2538 cases belong to the *normal* class and 654 cases belong to *Ocular Artifacts* group. The sensitivity, specificity and overall accuracy are 76%, 93% and 95% respectively.

The test dataset contain 12 cases from 2 subjects where each case is 42 seconds long and it contains the artifacts between 11 and 33 times. However, the case library still used the controlled 3192 cases and 4 classes discussed earlier. Here, CBR retrieval approach considers only one top similar case to calculate the classification accuracy and the results are presented in Table 4.

No.	**Test_Case_id**	**Number of *Ocular Artifacts***	**Correctly Classification**	**Missed Classification**
1	Subject_1_Test_1	87	74 (85.1%)	13 (14.9%)
2	Subject_1_Test_2	57	43 (75.4%)	14 (24.6%)
3	Subject_1_Test_3	62	57 (91.9 %)	5 (8.1%)
4	Subject_1_Test_4	67	59 (88.1%)	8 (11.9%)
5	Subject_1_Test_5	64	51 (79.7%)	13 (20.3%)
6	Subject_1_Test_6	64	53 (82.8%)	11 (17.2%)
7	Subject_2_Test_1	54	31 (57.4%)	23 (42.6%)
8	Subject_2_Test_2	44	26 (59.1%)	18 (40.9%)
9	Subject_2_Test_3	42	29 (69%)	13 (31%)
10	Subject_2_Test_4	35	25 (71.4%)	10 (28.6%)
11	Subject_2_Test_5	46	22 (47.8%)	24 (52.2%)
12	Subject_2_Test_6	32	24 (75%)	8 (25%)
Total ***Ocular Artifacts*** in 12 test cases		654	494 (75.5%)	160 (24.5%)

Table 4. Ocular Artifacts identification on 12 test data sets, where each case is 42 seconds long and it contains the artifacts between 11 and 33 times.

As can be seen from Table 4, around 76% that is 494 out of 654 ocular artifacts are correctly classified and around 24% is misclassified by the CBR system.

5 Summary

Brain waves or neural signals obtained by the EEG recordings is an important research area and plays vital role in medical and health applications and in Brain Computer Interface (BCI). In this study eye movement and eye blink artifacts are identified and classified from EEG signals. The proposed approach is a combination of

ICA, Hierarchical clustering and CBR. Here ICA is mainly used to separate the eye movement and eye blink components from the EEG signal. Since, the representation of components i.e., components represent EEG and eye movement is unknown in the independent components of ICA, Hierarchical clustering is used to cluster the data. Later, these clusters are classified as EEG, eye movement, eye blink and saccades based on the visual inspection and time synchronized information. After that CBR classification has been performed to evaluate each component. In this study only 2 subjects data have been used and the total number of cases in the case library was 3192. We are collecting more data in the project so in future the case library will also increase in size therefore clustering will help to mine the cases to build the case library. However, with the increased number of cases it will become difficult to perform visual inspection of components. Therefore, in future the system can be updated for instance, hierarchical clustering can group known components into cluster and later spectral analysis or statistical measures can be used to automatically classify the data.

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