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Extraction of useful ICA component features using image processing algorithms applied to EEG

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***Abstract*—Electroencephalogram (EEG) which is the recording of brains spontaneous electrical activity. EEG signals are low voltage signals that can be easily contaminated by different types of noises. This noise is also called as artifacts. Even though independent component analysis (ICA) decomposes data in linearly independent components(IC), its classification as artifacts or EEG signal require inspection by experts. In this paper we uses automated artifact elimination using Linear Discreminantanalysis (LDA) in the Brain Computer Interface Lab (BCILAB). The EEG signals are used for the diagnosis of various brain related diseases like narcolepsy, insomnia and parasomnia. It is necessary to make these signals free from artifacts for proper detection of these diseases.**

***Keywords*—Linear Discriminant Analysis (LDA) Electroencephalogram (EEG), Independent component Analysis (ICA), Independent Components(IC), Brain Computer Interface Lab (BCILAB)**

INTRODUCTION

Electroencephalography (EEG) is a method to record electrical activity of the brain within a period of time. It is usually non-invasive, with the electrodes placed along the scalp, sometimes invasive electrodes are used for particular applications [1]. EEG measures the voltage fluctuations originating from ionic current within the neurons of the brain. In clinical view, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as it is recorded from multiple electrodes placed on the scalp.

Due to EEG's temporal resolution, it is a widely used technique forfinding human brain activities. A major problem is the pollution of the EEGsignal by various physiological and non-biological artifactsfor exampleeye movements, eye blinks, muscle movements, heart beating, high electrodeimpedance, line noise, and the interference from electric devices nearby etc.The discarding of entire EEG segments due to contamination is a common methodand this results in the loss of experimental data which is recorded. This becomes a problem if there are only a fewepochs available and artifacts such as blinks or movementsoccur frequently as the person while recording blinks his eyes frequently. Other used methods for artifactelimination are basedon regression in the time or frequency domain [13]. On removing ocular artifacts,can introduce new artifacts into the EEGrecording which are not suitable for real-time instances [12]. A review of BCI-system artifact reduction techniques is givenby Fatourechi et al.[6]. Anefficient method which has established as an important part of EEG analysis is the application of independentcomponent analysis (ICA) for data decomposition [12] and separation of neuronal brain activity from artifacts[7]. The main idea to this method is that the EEG signal is a mixture of linearly independent source components (IC) which can be separated by ICA, and can be visuallyinspected, and classified as artifact or EEG signal components. Oncethe artifact components are identified, they can be removed. The examination and classification of the ICs is time consuming.

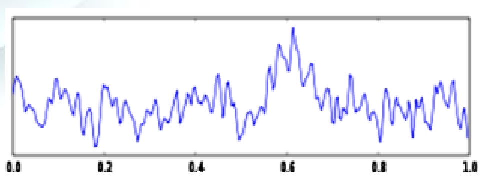

Fig 1: One second EEG signal

METHODOLOGY

Thus a MATLAB toolbox consisting of three main modules of pre-processing, feature extraction, and classification is used here. The module then automatically classifies the ICs, based on the new generated topoplot features.. Artifact components are discarded from subsequent processing. Components classified as EEG components are

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taken back, and in this way reconstruct an artifact-free EEG signal.

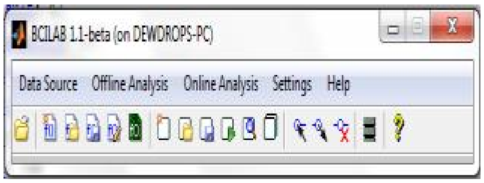

Fig 2: GUI of BCILAB

First the EEG signal is loaded into MATLAB by using the BCILAB toolbox. We can also take the EEG signals already available in the toolbox.

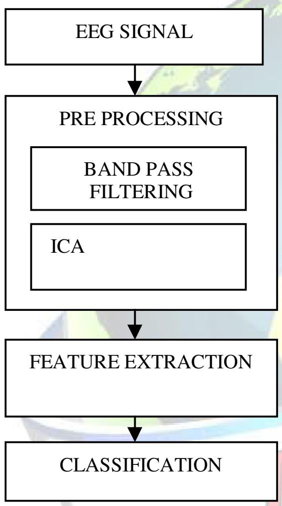

Fig 3: Flow of Denoising EEG signal

I. PRE-PROCESSING

All recorded EEG signal data or sample EEG datais imported into MATLAB (Math-Works, R2010b) by using BCILAB. The signals were filtered by a band pass filter between 0.5 and 40 Hz and independent component analysis was applied to the EEG signal:

$$W \cdot x = u \qquad (1)$$

Where 'x' is the signal of scalp EEG channels, 'W' (1) the unmixing matrix and 'u' the sources (ICs). This forms two-dimensional scalp projection maps, which is referred to as topoplots.

II. FEATURE EXTRACTION

Feature extraction components starts whensignal processing ends, they accept epoched or continuous signals and output sequences of feature vectors, after that transforming the segments ofEEG data into some abstract domain also called as feature space. Feature extraction mostly simplifies the data and can reduce its dimensionality. The processing can be static or adaptive If it is adaptive, it uses information about the value of the variables which have to be predicted frequently. Feature extraction functions are most frequently available in the BCI Paradigm.

III. CLASSIFICATION

Linear Discriminant analysis (LDA) an easily comprehensible and reproducible method should be used for classification.LDA should be applied to all computed features. LDA minimizes the within-class variance S_W(2)while maximizing the between-class variance S_B(3)by computation of the projection matrix W_{LDA}(4)

$$S_{W}=\sum_{i=1}^{C}\sum_{n=1}^{l_i}(x_{in}-m_i).(x_{in}-m_i)^T \qquad (2)$$

$$S_{B}=\sum_{i=1}^{C} l_i.(m_i-m).(m_i-m)^T \qquad (3)$$

with C as the number of classes, and is m_i the mean of the class i and l_i the number of samples in class i. Hence the ratio of $S_B$to $S_W$have to be maximized for maximal separability of the classes:

$$W_{LDA}=argmax_W \frac{|W^T.S_B.W|}{|W^T.S_W.W|} \qquad (4)$$

Opposite to principal components analysis (PCA), LDA aims to maximize the class-separabilityinformation. Thus it provides class separability and a decision boundary between the classes by maximizing the separation between the classes. Euclidean distance is used to classify the given data.

IV.SIMULATION RESULTS AND DISCUSSION

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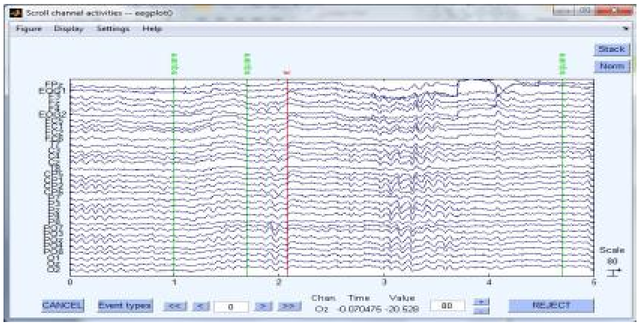

Fig 4: Input Sample EEG Signal

This is the sample EEG signal which is imported into MATLAB for pre-processing.

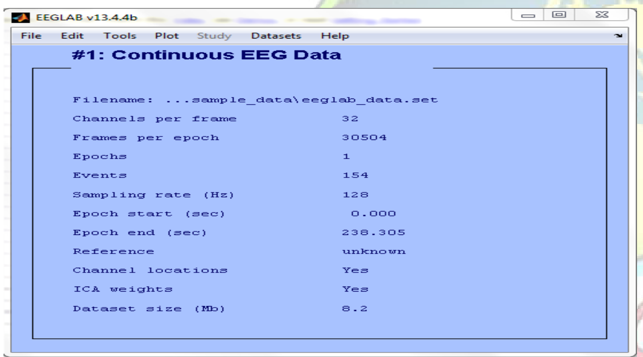

Fig 5: Specification of EEG signal

1. PRE PROCESSING

1a) Band Pass Filtering

This is a processing technique that deals with the preparation of EEG signal for further analysis.The EEG signal is filtered with a band pass filter between 0.5 and 40 Hz. This frequency range is taken because the brains activity lies within this range. After this range of frequency the signal will be noisy.

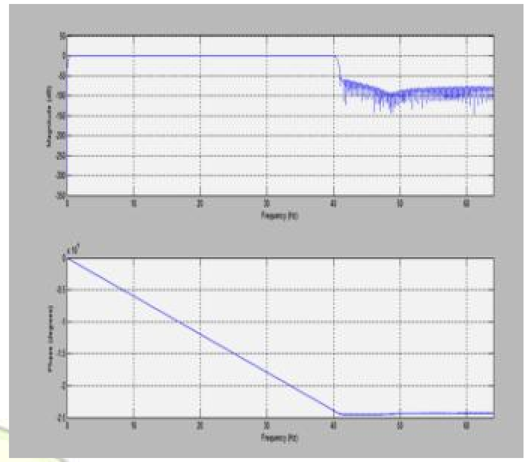

Fig 6: Band Pass Filtering for EEG signal

1b)Independent Component Analysis

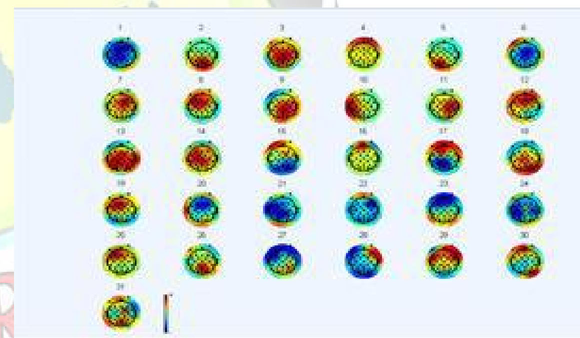

Fig 7: Independent Components

Independent Component Analysis is used for extracting individual EEG signal from a mixture of signals coming from each electrode.ICA identifies individual signal components of the mixture that are unrelated and statistically independent. This method relay upon the idea that the artifact and EEG can be regarded as arising from different sources that is they are statistically independent.

1c)Feature Extraction and Classification

The technique used in BCILAB for feature extraction is Common Spatial Pattern (CSP). It has been used on EEG data for BCI systems. CSP is used in signal processing for separating features that have maximum differences in variance with respect to the normal signal. This is a technique for selecting the subset that retains a specific

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fraction of total information content

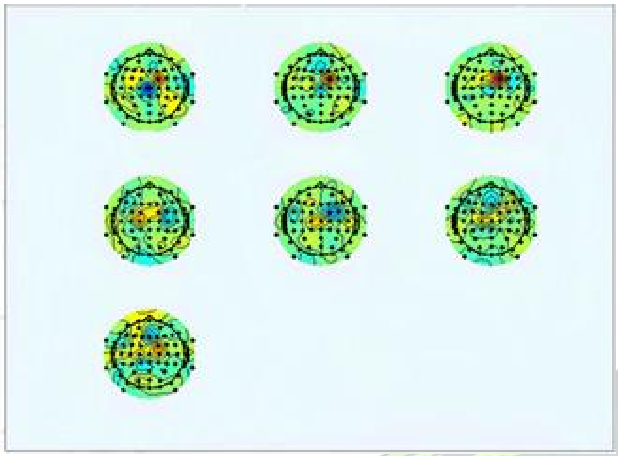

Fig 8:Artifact free EEG topoplot

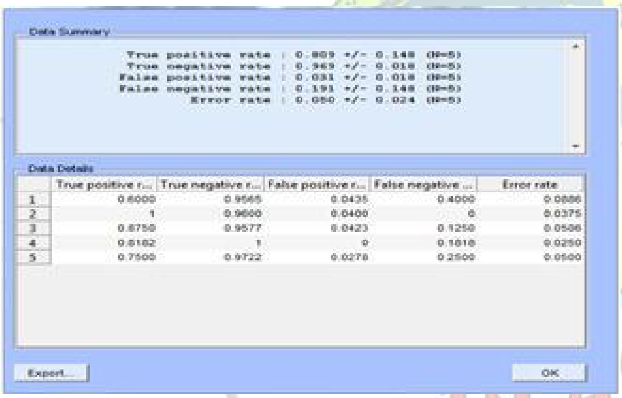

Fig 9: Classification Output

In BCILAB, classifier outcomes are labelled either as positive (*p*) or negative (*n*). There are four possible outcomes from a classifier in BCILAB. If the outcome from a prediction is p and the actual value is also p, then it is called a true positive (TP);

If the actual value is n then it is said to be a false positive (FP).A true negative (TN) has occurred when both the prediction outcome and the actual value are n

False negative (FN) is when the prediction outcome is n while the actual value is p.

CALCULATION OF SENSITIVITY AND ACCURACY FOR THE CLASSIFIER

TABLE 1
TP, FP, TN,FN VALUES

True Positive	0.80864
False Positive	0.0372
True Negative	0.96925
False Negative	0.19136

TABLE 2
SENSITIVITY AND ACCURACY OF THE CLASSIFIER.

SENSITIVITY=TP/(TP+FN)*100%	**80.864%**
ACCURACY =(TP+TN)/(TP+FP+FN+TN)*100%	**88.60%**

CONCLUSION

In this paper we implemented an approach for EEG artifact elimination by extraction of useful ICA component features. The method uses a tool box which can be integrated with MATLAB. The classification technique used is Linear Discriminant Analysis (LDA). High value of sensitivity shows that artifactual EEG and non artifactual EEG are correctly classified.Accuracy of the classifier is 88.60%. Thus we can say that the input EEG signal which contained artifacts are eliminated and we get an original EEG signal free of artifacts which can be used for diagnosis of various brain related diseases.

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