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Artifact Removal using Back Propagation for Brain Computer Interface in EEG Signal

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ABSTRACT: An external device and the brain can communicate through a brain-computer interface (BCI). The electroencephalogram (EEG) is the most used method for obtaining BCI control signals from the brain. The suggested research simulates an artifact reduction technique for the electroencephalogram (EEG). Patients' EEG signals are recoded while some fake signals are recorded. These artificial signals can be created by non-biological sources (including power-line noise), muscle and heart noise, eye movements, and blinks. These fake signals can be eliminated with the use of appropriate filters. In order to eliminate spurious signals from EEG signals, this article calculates and compares metrics like mean and standard deviation with other approaches like LAMICA and FASTERs. Additionally, it is suggested in the paper

KEYWORDS: Electroencephalogram (EEG), Brain-Computer Interface (BCI), Artifacts, Independent Component Analysis (ICA), Blind signal separation (BSS)

I. INTRODUCTION

Brain computer interface (BCI), also called brain machine interface (BMI), is a system that uses control signals from electroencephalogram (EEG) activity to allow people to interact with their environment without the use of muscles or peripheral nerves. It is a direct line of communication between the human brain and an external device [1]. Through direct measurements of brain activity, these technologies enable communication without the need for movement [2]. Numerous research communities, including those in neuroscience, neuroimaging, rehabilitation medicine, pattern recognition, signal processing, machine learning, and other fields, have become more interested in BCI. Restoring normal capabilities for those with severe neuromuscular disorders or improving specific functions for healthy individuals with a new technology is one of the main objectives of BCI research.

II. RELATED WORK

The issue of adding artificial signals is covered in this section. BCI, in particular, is based on electroencephalograms (EEGs), which monitor brain activity directly by recording electric potentials from electrodes applied to the scalp. However, undesirable signals known as artifacts typically taint EEG recordings. Both endogenous (such as physiological sources like heart, muscle, and eye activity) and exogenous (such as non-physiological sources like power-line coupling, impedance mismatch, etc.) factors can contribute to artifacts, which are a source of noise in EEG acquisitions [4]. To guarantee that any control obtained may be accurately ascribed to the participant's brain activity, each of these artifact types must be eliminated before the EEG is analyzed and used in BCI control. But In Hadler method [12] is proposed for artifact removal based upon ICA and Support vector machines (SVMs) to classify artifactual components. However, the method is only designed to work with electrooculogram (EOG) and electromyogram (EMG) artifact types and is not highly accurate**.**

Fabien Lotte and Cuntai Guan [13] have described the Learning spatial filters that maximize the variance of band pass filtered EEG signals.

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Hyohyeong Kang, and Yunjun Nam [14] have proposed concepts of improve classification performance over the standard CSP, especially in the case fewer number of training samples. H. Nolan, R. Whelan, R.B. Reilly [7] introduced the Fully Automated Statistical Thresholding for EEG artifact Rejection (FASTER) which incorporates Independent Component Analysis (ICA) method. FASTER method is tested across different numbers of scalp electrodes (128, 64 and 32). The results of the analysis of the simulated data indicates that the FASTER had generally high sensitivity and specificity for detection of artifacts.

S. P. Fitzgibbon [20] used a blind signal separation (BSS) algorithms for separating common types of contamination from EEG. This BSS appears to be most effective at separating muscle and blink contamination. So BSS algorithm is more effective and powerful tool for separating and removing contamination from EEG. Its quality of the separation is highly dependent on the type, degree of contamination and the choice of BSS algorithm.

Xinyi Yong, Mehrdad Fatourechi [19] have proposed an artifact detection algorithm to detect different types of artifacts in a self-paced BCI system. This algorithm is mainly based on a simple the amplitude of EEG signals and thresholding method.Many different automated artifact removal methods have been proposed for EEG de-noising. Wavelet based de-noising are used for removal of artifacts while transmitting the EEG signals. The complete literature review are presented in the 2.1. and table 2.2.

The rest of the paper is organized as follows, Section I contain the Introduction about BCI and its applications, Section II related work, Section III contain the study area and the methodology proposed, Section IV contain Result Analysis. In section V describes the conclusion.

1. Proposed Methodology

Three fundamental steps make up the suggested methodology: input data, pre-processing, feature extraction, and artifact removal. In the input data step, patient data—that is, their EEG signals—is gathered online. Pre processing is necessary since this raw EEG data is typically not clean enough for additional processing. A high-pass filter is typically used as pre processing to eliminate the signals' DC components and drifts (a frequency cut-off of 1 Hz is typically sufficient). The high frequency components can also be eliminated by applying a low pass filter. Nowadays, it is uncommon to examine frequencies in EEG signals higher than 90 Hz, which belong to the Gamma range. Signals are frequently chopped in epochs of a few after they have been preprocessed.

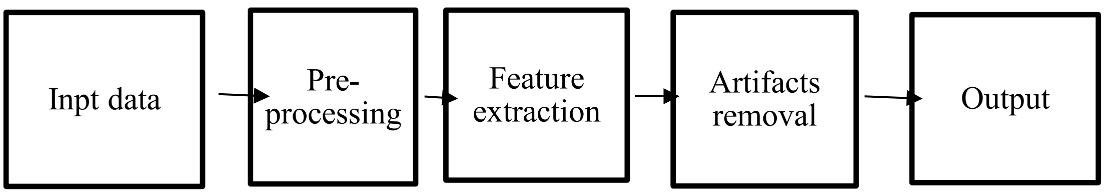

Figure 1 Proposed Methodology for BCI

III. SIMULATION RESULTS

The results of the proposed work are presented in the following sections. The results includes, the results of preprocessing, feature extraction and artifacts removal. Performance of the proposed work are compared with the state of art work.

3.1 Input data set

The input data is EEG signal which is collected from the online shown in Fig 2 X-axis having sample index and Y-axis having amplitude. Collected EEG signal are contaminated by noises called as artifacts.

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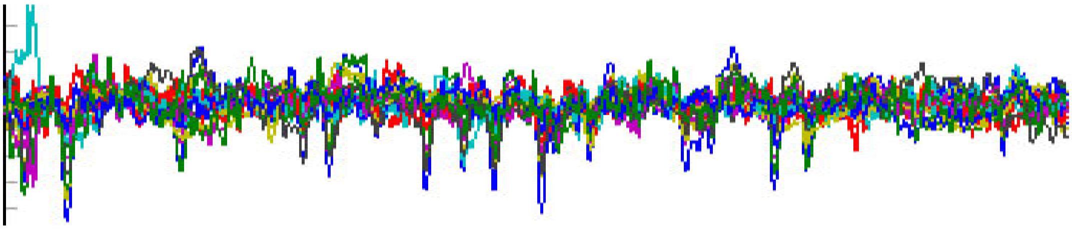

Fig 2 Input EEG signal of a patient

3.2 Artifacts Removal

Fig 3 shows the recorded EEG at 512 Hz and it consist of 16 channels. After the selection of input EEG signal desired method i.e., Discrete Wavelet Transform (DWT) is helps to separate the noises in an EEG signal. Decomposed using a Discrete Wavelet Transformation (DWT) and thresholding. In wavelet decomposition, wavelets attempt to decompose a signal. The daubechies 'db20' mother wavelet is used in this work to decompose the signals into approximation and detail coefficients down to 2 decomposition levels. The basic idea of wavelet technique is that noise mainly exists on the high frequency components and thus can be removed. DWT is a discrete version of continuous wavelet transform and its computation may consume significant amount of time and resources, depending on the resolution required. The DWT is based on sub-band coding, is found to yield a fast computation of wavelet transform. It is easy for implementation and reduces the computation time and resources required.

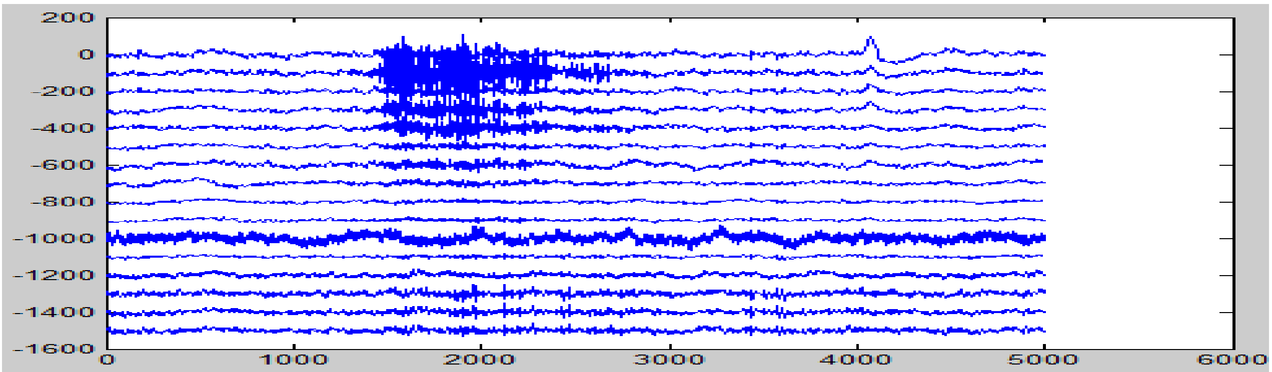

Fig 3 Recorded EEG

3.3 Cleaned EEG Signal Fig 4. shows the cleaned EEG signal x-axis represent a time in second and y-axis represent a channels. It mainly works based upon the combination of wavelet decomposition and thresholding.

The following steps followed to remove the artifact

Step1: Decompose the EEG on each channel into a set of approximation and detail coefficients via a wavelet decomposition.

Step2: Identify spikes zones in both approximation and detail coefficients sets

Step3: Then apply the soft thresholding.

Step4: Remove the artifacts.

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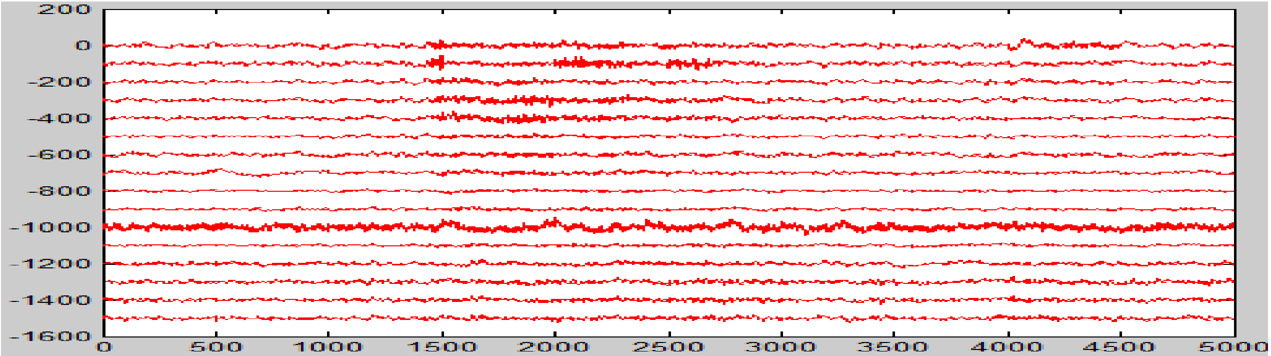

Fig 4 Cleaned EEG signal

Artifacts are known to differ from clean EEG in the following properties
1. The amount of temporal dependency within the signal.
2. The amount of spiking activity.
3. Measuring the peaked ness of the signal amplitudes over times.
4. The power spectral density in the gamma frequency band and above (>30Hz)
5. The peak amplitudes of the EEG time series.

3.4 Simulation results and Analysis of Classification of EEG signal

In this section, the simulated results of each stage are presented and discussed

In this stage classifying the collected EEG signal either normal or abnormal. In abnormal stage classifying the two diseases Epilepsy and tumor.

Step1: After data collection, before parameter extraction is being done, a set of measurements is to be performed. The signals are acquired using the electrode placement or EEG signal can be collected from PhysioBank in www.physionet.org website. The fig5 shows the original input signal.

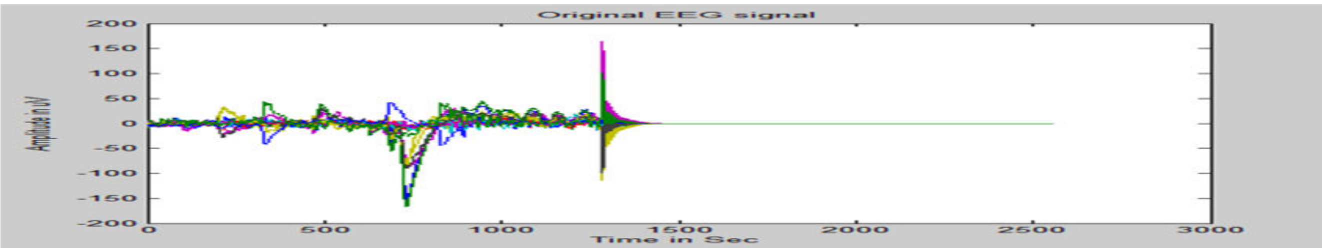

Fig 5: Input of EEG signal

Step2: . Pre-processing techniques help to remove unwanted artifacts from the EEG signal and hence improve the signal to noise ratio. A pre-processing block aids in improving the performance of the system by separating the noise from the actual signal. In proposed method using recursive least squares (RLS) is an adaptive filter that recursively finds the coefficients that minimize a weighted linear least squares cost function relating to the input signals. Normalizing the all the co-efficient and finding the mean to minimizing the error. The preprocessed signal which is free from noise signal is shown in fig 2

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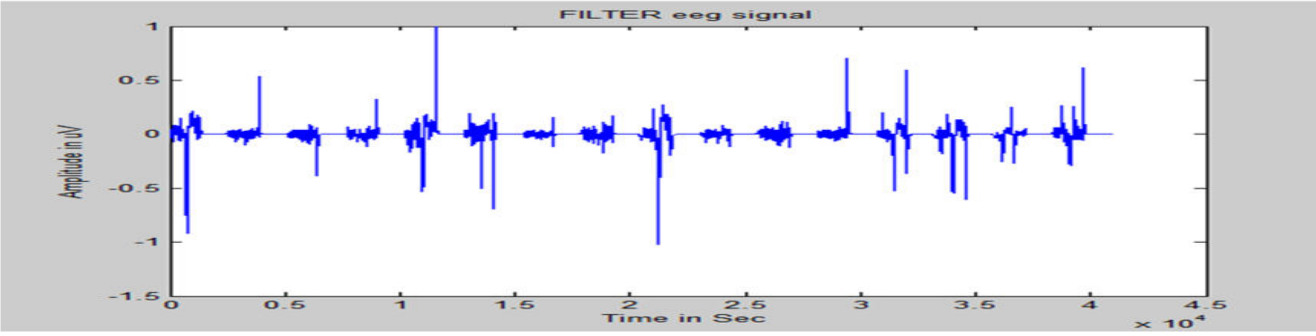

Fig 6: Filtered of EEG signal

Step 3: In the feature extraction phase, the information that is most relevant for classification is extracted from the raw data. The EEG signal is a complex function of the brain characteristics such as mental stress, emotional state, neurological disorders, e.g., epilepsy, early diagnosis and localization of brain tumours. In the proposed paper Discrete Wavelet Transform is used. Wavelets are useful because as they remove the highest frequencies, local information is retained and the image looks like a low resolution version of the full pictures. The feature extracted signal is shown in fig 7.

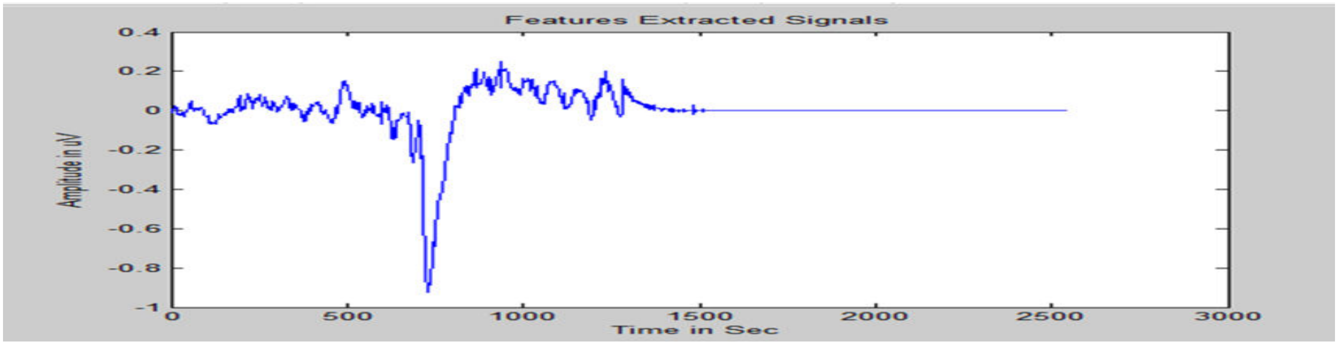

Fig 7 Feature extracted of EEG signal

Table 1: Performance comparison

Diseases case	SNR (db)	PRD	Sensitivity(%)	Specificity(%)	Accuracy	MSE
NORMAL	27.7172	4.1128	75.7	98	90.9	1.8249
EPILIPSY	20.59	9.33	75.5	98	90.5	1.8
TUMOR	19.8294	10.1984	64.9	97	91.1	1.7

IV. CONCLUSION

Three fundamental steps make up the suggested methodology: input data, pre-processing, feature extraction, and artifact removal. In the input data step, patient data—that is, their EEG signals—is gathered online. Preprocessing is necessary since this raw EEG data is typically not clean enough for additional processing. A high-pass filter is typically used as preprocessing to eliminate the signals' DC components and drifts (a frequency cut-off of 1 Hz is typically sufficient). The

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high frequency components can also be eliminated by applying a low pass filter. Nowadays, it is uncommon to examine frequencies in EEG signals higher than 90 Hz, which belong to the Gamma range. Signals are frequently chopped in epochs of a few after they have been preprocessed.

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