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Effect of artifact removal on EEG based motor imagery BCI applications

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ABSTRACT

Brain computer interface (BCI) is an emerging technology where the user can establish direct communication between the electrical device and himself without any physical exertion. The EEG signal is a noninvasive and low-cost method to extract brain signal from subject. The EEG signal contains different types of information including motor sensory information originating from the motor cortex region of the brain. Research and study have shown that motor cortex generates signals similar to the signals generated during deliberate limb movements. Therefore, motor imagery (MI) signals if extracted can be utilized to operate any electrical device establishing a BCI system. However, the EEG data can contain lots of artifacts. This degrades the signal quality and also cause false positive command to the connected device. Therefore, it is crucial to remove the artifacts from the EEG signal before classification. In this project, EEG data has been collected from 12 subjects who are instructed to perform MI activity. The EEG signal is then processed and an efficient artifact removal technique has been applied. The artifact removal method applies wavelet transform theorem and artifactual probability mapping method to detect artifactual epochs and eliminate it from the signal. Useful features are then extracted from the signal and artificial neural network (ANN) classifier is applied to it. The classification accuracy has been enhanced by 15-16% on average after removal of artifacts from the EEG recordings for MI-BCI experiments. Afterwards, performance evaluation such as finding signal to noise ratio has been done to evaluate the improvement in the signal after noise removal.

Keywords: EEG, BCI, Motor Imagery, Artifact, ANN, Wavelet Transform.

1. INTRODUCTION

1.1 Overview

A BCI- Brain Computer Interface is a promising field of great potential in controlling devices. Here, the brain activity of a human being is detected by various available means and then converted into control signals of an electrical device like prosthetics, computer, robots etc. [1]. The potential differences created by the cortical neurons of the cerebral cortex region of brain are converted into control signals of machineries. The cortical neurons produce decision making signals of the brain interpreting the surroundings through senses, consciousness and movement of the body. Therefore, valuable features are drawn out of the brain activity signal and converted into commands understood by electrical devices. Such feature extraction and its analyzation can be used for disease diagnosis, device control, as well as a rehabilitation tool for a patient or a training tool of an athlete [1],[2].

There are different techniques available for recording brain activities. Among these techniques the use of EEG signal is gradually gaining popularity for BCI applications because it is non-invasive, of low cost, has high temporal resolution, very flexible and processing can be done in real time [3].

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EEG signals are formed from potential differences due brain activity in the cortical region. Noise introduced in the signal will increase the potential difference. Artifacts or noises present in the EEG signal are detrimental to performance of the system. Noises in EEG for MI BCI are generated from the non-cognitive region of the brain or from an electrical source not related to the system [3], [4].

1.2 Background and Motivation

A multimodal cognitive simulation due to imagination of any kind of limb movement without an actual sensory input is known as motor imagery (MI) or mental imagery. MI is the mental state when an actual movement is rehearsed in mind. The motor cortex region of the brain along with nearby areas such as the supplementary motor area (SMA), premotor cortex (PMC), primary motor cortex (M1), posterior parietal regions etc. are active during actual movements of the limbs. Research have shown similar activity occurs during MI too. Furthermore, studies have proven that plastic change in motor networks can be induced due to MI which in turn influences synaptic activity in spine [5] [6]. Therefore, regular practice of MI can change physical structure of brain much like done during physical rehabilitation.

Artifact present in EEG creates difficulties in MI EEG classification. Wrong MI EEG classification can generate false positive output. This decreases the robustness of the BCI system. It is vital to apply an efficient and robust artifact removal method to process the EEG signal to increase the productivity of the output and form a competent BCI system.

Artifacts or noise present in the raw EEG signals provide hindrance in the accurate and efficient analysis of the signal as well as in BCI training [7]. The shape of the actual bioelectric signal occurring due to motor imagery is changed. Artifacts cause fluctuations of electrical activity in the signal. These fluctuations are not caused due to brain signals but rather for electrical sources not related to the brain activity [8]. Therefore, it is important to identify the main causes and investigate the effects of artifacts and the solutions for removing them. The artifacts can occur due to external causes such as muscle movement, eye movement, nearby electrical devices etc. and bioelectrical signals such as surface electromyogram (sEMG), electro-oculography (EOG), electrocardiogram (ECG) etc. In both spectral and temporal domains artefacts overlay the actual EEG signal occurring due to brain activity. The neural activity is misinterpreted and this causes the BCI system performance to decrease [8]. Therefore, it is important to identify the main causes and investigate the effects of artifacts and the solutions for removing them. This project intends to study the methods of removing artifacts present in EEG signals and study their outcomes to increase the accuracy of analyzing the EEG signals after artifact removal and translating the signals into command receptive by electrical devices for MI BCI.

Motor imagery based BCI (MI BCI) can be used for many important tasks like movement of prosthetics with brain signal commands, rehabilitation of patients who suffered from stroke or had a spinal injury, in sports for training the cognitive performance for active and determined movements and so on. The prospect of using the MI BCI has immense potential to bring significant change with ease of movement for people with disability. Not only in the medical sector but it can also be used to train robots with artificial intelligence.

1.3 Objectives

The objectives of this project are to study about different artifacts found in MI based EEG signals, identify an efficient artifact removal method and study the effects of artifact removal on motor imagery dataset by analyzing BCI classification performance.

2. LITERATURE REVIEW

Artifacts or noises present in the EEG signal are detrimental to performance of the system. Noises in EEG for MI BCI are generated from the non-cognitive region of the brain or from an electrical source not related to the system [3], [4].

There are mainly two types of artifacts: endogenous and exogenous. Endogenous artifacts are also known as biological artifacts which are generated from body movement and bioelectric signals such as eye blinking, muscular artifacts, cardiac artifacts etc. Exogenous artifacts are also known as non-biological artifacts. They occur due to technical issues like wrong electrode position, powerline frequency interference, thermal noise etc. Dry electrodes if used can introduce motion artifacts in the signal [2], [9], [10].

There have been many studies and research done to remove artifacts from EEG signals. Using independent component analysis (ICA) is one of the popular methods to find artifacts.

Multiple channel EEG signal is decomposed into independent components. The artifact components are then identified based on a statistical measure such as kurtosis value and removed. Artifacts can be removed by using ICA coupled with other methods such as ICA based MEMD technique, Hybrid ICA-ANC (Adaptive Noise Cancellation) algorithm, OD - ICA (Outlier Detection and Independent Component Analysis) which enhances the technique and improve the accuracy of removing artifacts such as ocular and muscle [19]. However, many times artifacts need to be found by manually investigating the ICs and does not allow online BCI application [4]. In [1], ocular artifacts have been removed using EMD-ICA-AF method and no EOG reference signal was used. The method is applicable for online BCI but ICA-AF has a longer computation time than ICA.

Butterworth and Chebyshev bandpass filters are used to allow the frequency of the EEG signal related to the motor imagery event to filter through. Spatial filters such as CAR filter which are computationally inexpensive, are also used to retain the information related to motor imagery represented in spatial domain [10].

Wavelet transformation is another technique used for identification and removal of artifacts from MI EEG signals. Among orthogonal Daubechies wavelet, bi-orthogonal Rbio wavelet and Coifman wavelets, Coifman wavelets shows preferable results because it is a compactly supported wavelet system which aids in smooth sampling approximation compared to other wavelets. Decomposition filters and reconstruction filters can then be used to gain the clean EEG signal [12]. Study have been made to remove ocular, muscle, blink artifacts using the stationary wavelet transform as well as combinations of wavelet transform and other methods [13], [14],[15]. The wavelet transform method shows favorable results of removing noise. The wavelet transform follows the theory of comparing the signal coefficients with an already determined threshold assuming the magnitudes of artifacts are subordinated by the magnitudes of the signal. If the coefficient is below the threshold, it is assumed as an artifact and the coefficient is set to zero. Another denoising method of using non-linear adaptive filters and linear adaptive filters uses a reference noise input and assumes the intended clean signal is not correlated with artifact [4], [9]. Wavelet transform method requires thresholding. In [15], non-negative garrote shrinkage function and Smooth Sigmoid-Based Shrinkage (SBSS) function has been investigated to avoid the disadvantages of soft and hard thresholding. Then the authors proposed an adaptive thresholding algorithm which would enable thresholding at a range of frequencies.

In [8], a novel algorithm to calculate the probability based on the normalized entropy, kurtosis, skewness and periodic waveform index has been proposed. SWT method decomposes signal into wavelets. The thresholding is done using the nonnegative garrote shrinkage function (NN-GSF). The wavelet coefficients with probability less than the probability threshold set by the user are rejected. The algorithm can be applied for the MI BCI ((i.e. 0.05-128 Hz), Mu (7–13 Hz) and Beta (14–30 Hz)) applications by adjusting the universal threshold value as well as for ERP-based BCI and SSVEP. Other methods used in [9] and [16] are adaptive noise cancellation method (ANC) and multichannel Wiener filter (MWF) respectively.

Indeed, there have been studies made on artifact detection and artifact removal. However, the research made on noise removal methods particularly available for MI BCI is limited. In addition to that, the artifacts and processes used for artifact removal for all kinds of BCI is not the same. EEG signals for MI BCI has different artifacts from EEG signals used for other purposes such as emotion recognition or a disease diagnosis. Moreover, the accuracy of the available methods is quite low and needs further research for reaching an accuracy much higher so that the method can easily be opted for real-time BCI application. Therefore, it is crucial to concentrate on study of the artifact presence and artifact removal methods from EEG signals for MI BCI.

3. MATERIALS AND METHODS

At first, EEG data has been collected to work on this project. With due permission of IUB authority and written consent of volunteers, the MI data has been collected on university premises. By doing a thorough literature review a procedure has been designed to collect the data. About 12 volunteers participated for data collection. However, due to some uncontrollable errors in the EEG signal, data of only 10 volunteers have been considered for further processing. Next, EEG preprocessing has been done which requires segmenting the continuous signal into known MI classes and labelling has been done accordingly. Then, artifact removal method has been applied on the signals. Followed by feature extraction and feature selection. Different classifiers have been later used to confirm the best possible accuracy achieved by different classifiers. Fig. 1 summarizes the procedure that has been adapted to achieve the outcomes of the project.

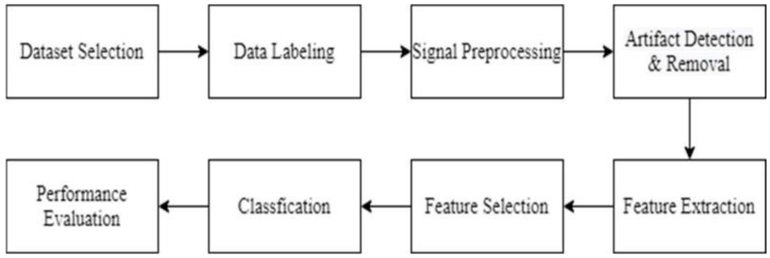

Figure 1. Overall Process Flow.

The following sections provide a detailed description of each of the above steps, along with any relevant information.

3.1 Experimental Design and Data Acquisition

Usually, the participants are told to carry out a particular movement (movement of limbs), such as deliberate movement of right hand only or left leg only. The movements create signals in the cerebral cortex region of the brain and the EEG signal is recorded using headsets like L64 Sagura EEG amplifier system, BioSemi ActiveTwo EEG system, etc.

For data acquisition for this project, a 14 channel Emotive pro EEG headset has been used following a 10/20 international electrode placement system. The sampling frequency of the data is 128Hz.

Figure 2. Experimental Procedure for EEG Data Recording

Before beginning the data acquisition, a one-minute training session including left hand and right-hand movements were practiced. In the training session the subjects performed real hand movements and, also tried to imagine the movements. After the training session, the subject takes a two-minute break to prepare for the data acquisition sessions. The first session starts with a 5 second cue. Each session includes 30 times imagination of left-hand movement and 30 times imagination of right-hand movement with a five seconds break in between the MI tasks respectively. Each MI time length is also of five seconds. The MI task is to imagine grabbing an object kept in front of the subject with left hand or right hand as per the instruction shown on a video screen in front of them. Each session consisted of 60 trials. The instructions for left- and right-hand movement were varied simultaneously to avoid adaptation. Later, simulated artifact has been added to the collected data. Data collection sequence is shown in Fig. 2.

10 healthy right-handed subjects participated in data acquisition. The age of the subjects ranged from 22 years to 31 years. The experiment has been conducted with the consent of the participants and IUB authority in university premises. All participants had no past experience of using BCI.

3.2 Data Labeling

Data labelling has been done since; the two types of MI instructions were randomly provided to the participants. By watching the instruction video, at first, an excel file which contains the class specific labels has been created. The right-hand MI is labelled as 1, the left-hand MI is labelled as 2 and the breaks in between the MI is labelled as 0. Considering that each of the instructions are of 5 seconds duration, the EEG segments corresponding the respective label have been extracted separately. The recorded data is extracted as ‘csv’ file which is converted in to ‘mat’ format readable in MATLAB environment. Using the codes in MATLAB software environment, the labeling has been done and finally, all the samples of right hand and left-hand MI have been stored as subject wise data file for further processing.

The EEG signal has been acquired in a controlled environment due to which the number of artifacts present in raw data is lower than real life situations. The subjects were instructed to make as much less body movement as possible, less eye movement as possible. Eye blinking, EOG signal, could not be controlled and it has been eventually included in the raw data. However, the room in which the experiment was conducted was kept as much noise free as possible. To increase the artifacts in the raw data, publicly available simulated artifact templates have been added to it.

3.3 Channel Selection

During MI, the characteristic ERD and ERS is present in the electrical activity generated from the frontal lobe. The motor cortex and sensorimotor cortex lies in the frontal lobe. Therefore, the dominant activity for MI lies within the medial region of the head. Alpha and beta rhythm are the dominant from this region during MI. Characteristic activity of other bands are also evident but the alpha and beta rhythm are the dominating ones and can be mostly deduced by the electrodes after passing through the dura and skull. Therefore, electrodes around the regions other than the frontal lobe can also be used for less dominant but also important activity and for reference.

From the literature review out of the 14 available channels of Emotive Pro headset, 4 of the frontal channels F3, F4, FC5 and FC6 are selected to be analyzed (Fig. 3). The selected channels are the nearest to the motor cortex region and have been previously used to acquiring MI data in various references [15, 17, 18].

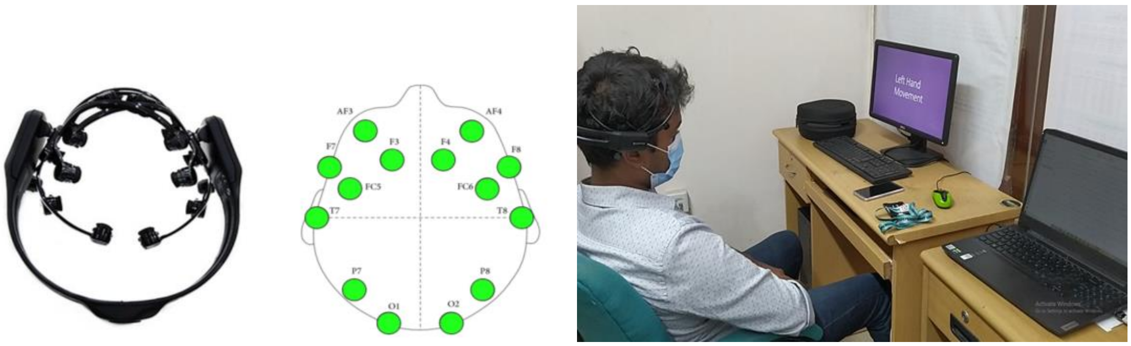

Figure 3. 14-channel Emotive headset and channel locations (left). Subject performing MI experiment by imagining left or right movement (right)

3.4 Artifact Detection and Removal

Previously, literature review generalized that only EMD and wavelet transform can be applied on non-stationary waves for signal analysis at present. Wavelet transform, as well as, EMD can express the signal in both time and frequency domain corresponding to each other. EMD breaks down a signal into characteristic intrinsic mode functions (IMFs). However, the computational complexity of EMD is high. Therefore, wavelet transform is the better option. There are different types of wavelet transform – discrete wavelet transform (DWT), continuous wavelet transform (CWT), and stationary wavelet transform (SWT). Traditional DWT and CWT is time variant. Since SWT is a time- invariant transform, SWT satisfies the requirement [19]. SWT acquires better resolution in lower frequency region than in the higher frequency region. Since the EEG signal and mostly other biomedical signals are of low frequency region (0.5 Hz to 200Hz), SWT is a suitable method for signal analysis which can be opted for applying artifact removal method.

For this project, the artifact removal method presented in [8] has been adopted for application in raw EEG data to study the effect of artifact removal from MI BCI. This is a distinct approach to study the effect of the proposed method in MI BCI. The proposed method used SWT for signal decomposition and a novel approach of probability mapping to set a threshold for artifact removal from contaminated epoch.

- Stage 1:

The base line and power line noise is removed from raw EEG if not removed previously. The EEG is then segmented into separate epochs (around 1 second time window) of N samples. The epoch, x_i duration is crucial for the proposed design for later stages [12].

$$x_i = [s(i_N - 1), s(i_N - 2) \dots \dots, s(i_N - N)] \quad (1)$$

- Stage 2:

The artifact removal method uses the concept of taking decision of whether or not to remove the artifactual epoch based on probability mapping. To select the threshold for denoising, the probability of the artifact presence in any particular region (an epoch) is calculated first by using the quantitative measures of entropy, kurtosis, skewness and Periodic Waveform Index (PWI). Artifacts tend to be mainly non-rhythmic and superpose the EEG signal randomly. The amplitude increases due to superposition of the artifact. Therefore, there will be higher peaks of the signal, if noise is present. Asymmetrical distribution is often evident due to artifacts. The data histogram will have longer tail on either side. Clean EEG is less skewed than the noisy EEG due to asymmetrical distribution. The randomness of the artifact can be quantified by entropy. Normal EEG will have lower entropy than contaminated epoch. The periodicity of the epoch can be quantified with PWI and the peakedness with kurtosis value. Contaminated epoch will have lower PWI and higher kurtosis value than the clean one [8].

The equation used for calculating entropy Hi, kurtosis Ki, PWI Pi, skewness Si

$$\hat{H} = -\sum_{t=1}^{N} \quad p_t log p_t \tag{2}$$

$$\hat{S_i} = \frac{\frac{1}{N}\sum_{t=1}^{N} \quad (x_t - \underline{x})^3}{\left(\frac{1}{N}\sum_{t=1}^{N-1} \quad (x_t - \underline{x})^2\right)^{3/2}} \tag{3}$$

$$\hat{K_i} = \frac{\frac{1}{N}\sum_{t=1}^{N} \quad (x_t - \underline{x})^4}{\left(\frac{1}{N}\sum_{t=1}^{N} \quad (x_t - \underline{x})^2\right)^{2}} - 3 \tag{4}$$

$$P_i = \frac{\frac{1}{N}|FFT\ (x_i)|^2}{\frac{1}{N_t}|FFT\ (s)|^2} \tag{5}$$

The contamination probability ($Pr\ Pr\ (x_i)$) of the epoch is then given by:

$$Pr\ (x_i) \ = \frac{h_H H_i + h_k K_i + h_S |S_i| + h_p (1 - P_i)}{4} \tag{6}$$

Alpha and beta band is dominant during MI BCI. Hence artifact removal method is to be applied on the band of 7Hz-30Hz. The probability $Pr(x_i)$ of the artifact presence in any particular region (an epoch) is calculated by using the quantitative measures of entropy, kurtosis, skewness and Periodic Waveform Index (PWI). The user is to carefully manually set a probability Pr_{user} threshold to compare with $Pr(x_i)$. If Pr_{user} is less than $Pr(x_i)$, then the epoch is contaminated and thresholding is applied.

- Stage 3:

SWT is applied to the epochs. The wavelet transform decomposes the bandwidth of the given signal into approximate levels (Ai) and detailed levels (Di) generating detailed coefficients and approximate coefficients. The detailed coefficients include the higher frequency bands of the signal and the approximate coefficient includes the lower frequency band of the signal. The maximum and minimum frequency bands equal to the power of 2. In this project a data of bandwidth from 0.5Hz to 50 Hz is used. So, the detailed and approximate levels produced (D1, D2, D3, D4 and A1) are as depicted in the following block diagram in Fig. 4.

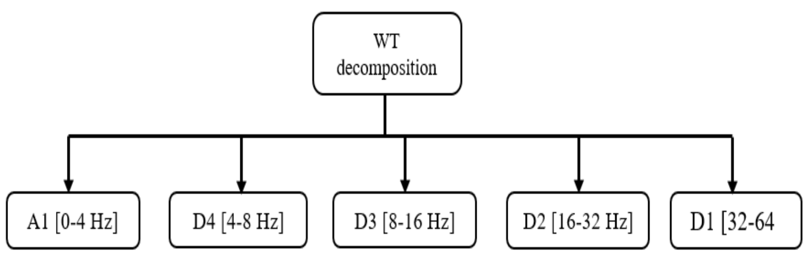

Figure 4. Approximate and detailed coefficients after WT decomposition

3.5 Feature Extraction

Feature extraction will reduce the dimensionality of raw data and arrange the data into more manageable sets of numerical features. The raw data is a combination of large number of variables. These variables are combined using mathematical relation and formed as groups resulting in distinguishable features. Feature extraction speed up the training duration of a classifier and compliments data visualization. However, not all kind of features are relevant for a particular dataset. For this project, 27 types of features were generated for the dataset after artifact removal stage using a publicly available feature extraction toolbox.

MI based BCI causes the power fluctuation in particular frequency bands of EEG signals. This is due to the fluctuations in temporal domain of the signal caused by ERD and ERS generated from neurons. The fluctuation varies between users and different tasks. The frequency bands alpha (8-12Hz), beta (13-30Hz), mu (9-13Hz) and gamma (>30Hz) are dominated by fluctuations caused by MI. Different categories of methods for feature extraction are time domain method, spectral methods, time-frequency methods, spatio-spectral, spatio-temporal methods and many more are available. Common spatial pattern (CSP), statistical feature determination (like mean, median, variance, kurtosis, entropy), BSS, wavelet packet decomposition (WPD), are examples of feature extraction methods [3], [10], [18].

3.6 Feature Selection

For feature selection the 27 of the features were extracted and tabulated. The features of the two MI class are plotted against each other. The most distinguishable features, previously seen to be used in literature review, among the plotted ones were selected for final features to be extracted. These features have been discussed in the following sections.

- Band power of Alpha, Beta, Theta and Delta

The Alpha, beta, theta and delta band consists of the range of 7-13 Hz, 13- 30 Hz, 4- 7 Hz and 0.5- 4 Hz respectively. The band power is calculated using the MATLAB built in function to calculate the band power. The sample frequency and the signal used as the input for the function as well as the frequency range for which the power is required to be calculated had to be specified. The result is the alpha band power is returned in the form of two-element vector.

3.7 Classification

ANN classification toolbox available in MATLAB was used for classifying MI-BCI EEG events before and after artifact removal and classification performances including confusion matrix, accuracy, sensitivity, specificity, etc. were recorded for result analysis.

4. RESULTS AND DISCUSSION

A synthetic artifact template has been added to the raw EEG data since the data was collected in a controlled environment. The amount of noise included in the artifact is very low. Therefor an artifact template has been added with all the data for each subject's EEG. Then the artifact removal technique has been applied to measure the accuracy percentage before and after noise removal.

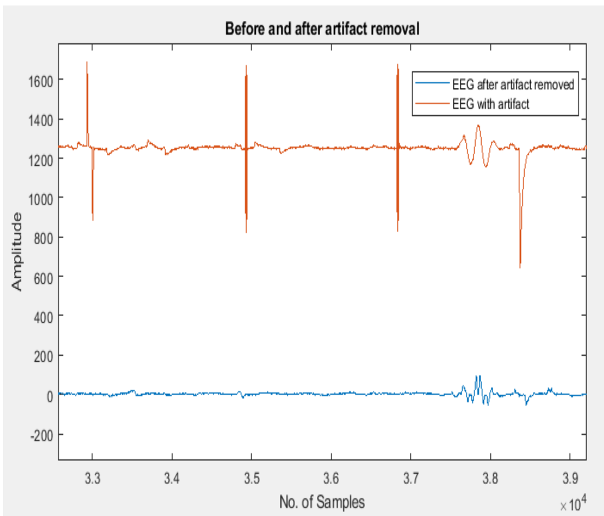

Figure 5. EEG data before (top) and after (bottom) removing artifacts

Data from all 14 channels of the headset have been added with the artifact for each subject. Figure 5 shows the EEG of channel F3 data of a subject before and after applying artifact removal. It can be seen that sudden spikes of amplitude of the signal (noise) which were added have been removed considerably after applying artifact removal method. However, not all of the artifacts were removed.

Figure 6 shows the power spikes representing the artifacts which have been removed. Figure 7 shows the power spikes in the beta band representing the artifacts which have also been removed.

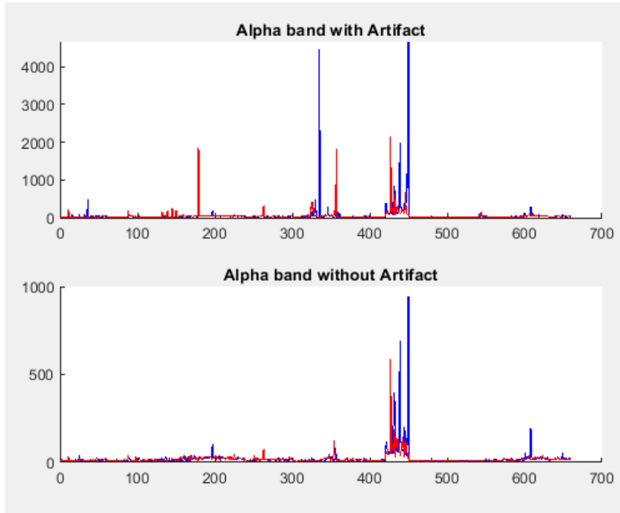

Figure 6. Alpha band power with and without artifact.

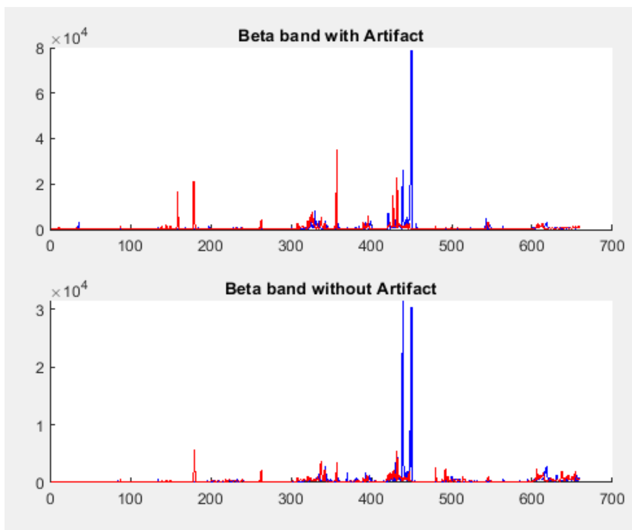

Figure 7. Beta band power with and without artifact.

Table I shows the improvement in MI BCI classification accuracy after artifacts are removed from the artifactual EEG in comparison with the improvement in EEG signal SNR for each of the ten subjects data considered for analysis.

There were few limitations identified in this project. The absolute accuracy is low due to number of channels available were the nearest to the motor cortex but did not directly lie on the middle region of the head where the motor cortex is located. Also, due to varying hair thickness of the volunteers, the quality of the EEG data varied from subject to subject. All the subjects were introduced to the MI BCI for the first time through the data collection procedure. Therefore, BCI illiteracy is also a factor of the varying quality of the raw EEG data, which resulted in lower accuracy performance than expected. In addition, the number of subjects participating during data collection was low. Since, the sampling frequency of the headset is only 128 Hz, the gamma band feature could not be used for classification. Also, many other features like skewness, kurtosis etc. could be explored for classification. Other machine learning classification methods like support vector machine (SVM), k-nearest neighbors algorithm (KNN), etc. were not explored. Finally, Artifact removal method could not remove all types of artifacts. Hence, the average accuracy has not met the expected accuracy percentage.

Table 1. Improvement in EEE SNR and MI BCI classification accuracy due to artifact removal from raw EEG.

Subject No.	**Improvement in Classification Accuracy (%)**	**Average Improvement in SNR (dB)**
1	15.63%	9.46
2	11.42%	10.26
3	17.28%	10.37
4	12.45%	5.22
5	15.20%	5.98
6	13.83%	2.07
7	11.29%	1.17
8	18.61%	-1.06
9	21.84%	7.21
10	20.00%	4.24
Average	**15.68%**	**5.49**

5. CONCLUSION

This article presents a study on the effect of artifact removal from EEG signal for MI BCI. An artifact removal technique based on probability mapping and wavelet theorem is applied on the EEG signal to denoise the signal. Afterwards, the performance of the signal has been evaluated. The average accuracy increases around 15-16% proves the efficiency of the denoising method.

In future, work on the performance evaluation criteria and applying different types of classifiers such as- support vector machine (SVM), k-nearest neighbors' algorithm (KNN) etc. is planned. By using the different ML techniques, a performance evaluation could be done to figure out the best classification method for the project. More performance evaluation criteria like coherence, sensitivity, correlation etc. can be explored for performance evaluation. The artifact removal method could be used for other types of BCI- such as steady-state visual evoked potentials (SSVEP). Therefore, the project could be continued to explore more classification methods and performance evaluation and check the improvement in average accuracy in the future.

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