Automated Ocular Artifacts Identification and Removal from EEG Data Using Hybrid Machine Learning Methods

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Abstract— **Brain Computer Interface (BCI) is an emerging field of research, which helps neuromuscular disabled people to communicate and control external devices with the brain. Electroencephalogram (EEG) signals have been used by doctors to diagnose brain activities. EEG signals are very sensitive to the physical movement of most of the body parts. Electrooculogram (EOG) are the signals which are directly related to eye movements. In the field of BCI, artifacts refer to those signals which are not required but will be present in data because of the involuntary actions of human muscles. In the proposed research, BCI Competition III Dataset IV A is used, which consists of two classes of signals right hand and right foot, so ocular artifacts were a prime hindrance for this type of data. The research involves the use of the following feature detection methods: ICA, ICA-RLS, ICA-LMS, ICA-DWT, EMD-ICA. The first common step is using ICA to obtain independent components(ICs). Using ICA, ICs that contain ocular artifacts can be identified and then further exposed to another round of ICA or adaptive filtering that uses LMS, RLS. The adaptive filtering technique reduces the need for parallel EOG recordings by removing the ocular ICs using reference signals. Hybrid` methods have gained much advantage over the traditional ICA process, which leads to better detection and removal of ocular artifacts with these techniques. Further, the research proposes a system involving the use of SVM-PSO for the classification of motor imagery signals obtained after the removal of artifacts. ICA-RLS and CSP as pre-processing and feature extraction techniques provided the best classification accuracy of 92.94%.**

Keywords—Motor imagery, ocular artifacts, Electroencephalogram (EEG), Independent Component Analysis(ICA).

I. INTRODUCTION

The Brain-Computer Interface (BCI) is a new technology adopted by people with neuromuscular disabilities to communicate with the world. These brain signals are translated as commands to control the external devices via a computer. The BCI design involves the following parts: the user, Electroencephalogram(EEG) acquisition, signal processing(preprocessing, feature extraction, classification) and the controlled device. Electroencephalogram(EEG) signals have the capability of capturing the brain information in a fast dynamic way and has a high temporal resolution but it has a low spatial resolution along with a high noise level. EEG recording involves collecting data over the scalp through electrodes in an extended 10-20 system [1]. The EEG signals are distorted by the electrical activity of levator muscles(that cause eye blink) called artifacts. Artifacts can be avoided or minimized by guiding the subject to be still, to avoid unnecessary eye blink and also proper grounding of EEG recorder. But avoidance is not the perfect solution for the removal of artifacts as the eye blink or other body movements can't be avoided for a long time by the subject, thus, EEG signal processing is done to remove these artifacts.

Electrooculogram(EOG), is one of the most important ocular artifacts. EEG signals get highly contaminated by them. Eyeblink occurs when a signal amplitude crosses a certain threshold and they are suppressed by removing the segment containing ocular activity. Then all the EEG epochs with signals higher than the threshold are rejected, but this causes a lot of portion to be lost. To overcome this a new Blind Source Separation(BSS) technique called Principal Component Analysis(PCA) was introduced, still, this wasn't able to remove the ocular artifacts completely, especially when the amplitude is comparable [2]. To overcome the limitations in PCA, more effective methods for the removal of artifacts are introduced which include Independent Component Analysis(ICA) [3], Independent Component Analysis Recursive Least Squares (ICA-RLS) [4], Independent Component Analysis Discrete Wave Transform(ICA-DWT) [5], and Independent Component Analysis Least Mean Square (ICA - LMS) [6]. This work will describe the detection and removal of artifacts using the above-mentioned methods as feature extraction and followed by classification using SVM (Support Vector Machine) and Particle Swarm Optimization(PSO).

II. RELATED WORKS

Many methods are proposed for the removal of artifacts from EEG signals. Li's work on the ICA method says that this method gives robust results and solves the problems of denoising [3]. This method involves the decomposition of the signal into independent components (ICs). ICA method is convenient to use, requires less memory space and high convergence speed [3].

ICA-RLS uses adaptive filters. The ICA-RLS method is ICA followed by RLS which involves the use of adaptive filters. Banghua Yang's work in this method shows that the ocular artifacts are removed from the corrupted EEG signals by subtracting the ocular activities from the given corrupted EEG signal where the ocular activity is the sum of the product of reference signals served by ICs and finite impulse response filter's kth coefficient [4]. The Discrete wavelet transform(DWT) method for the removal of artifacts is a common denoising tool and is a continuous transformation with discrete data. But DWT cannot completely remove the artifacts this is the reason ICA method is performed prior to applying DWT [5]. ICA-LMS was proposed by Saeid et. al [6] is an adaptive algorithm that has been recently used for ocular artifacts detection and removal. Md. kafuil Islam in his work [7] with empirical mode decomposition stated that EMD is ideal for EEG signals as it is developed to work on non-linear, non-stationary and stochastic processes. EMD involves decomposition of the EEG signal into band-limited components.

Recently, Machine Learning techniques have shown appreciable results for binary class EEG classification [8]. These approaches do not, however, meet the needs of real-time, brain-controlled, and neuro-gaming applications, which require multiclass classification. Nicolas et al. [9] proposed a generalized method for the classification of MultiClass Motor Imagery(MI)-based EEG signals. They have used MIBIF(Mutual-Information Best Individual Features) which in turn extracted optimal CSP features. Young et al [10] proposed a new approach in which they used the Filter Bank Common Spatial Approach (FBSCP) and CSP for the extraction of functions to preprocess the raw data accessible through a filter bandpass. SVM (Support Vector Machine) which is a well-known classifier in Machine Learning was also used to train system based on selected features extracted from EEG signals.

J.Pylkkonen introduced LDA(Linear Discriminant Analysis) which was used for classification tasks on the basis of features extracted [8]. In 2016, Gao et al. worked with Adaboost (Adaboost ELM) classification capabilities. They extracted features using Kolmogorov complexity (Kc). Meister et al. [9] proposed an improvement in the preprocessing method by applying Joint Approximate Diagonalization (JAD) which resulted in better CSP features and hence, efficient feature extraction. (SBCSP-SBFS) Novi [8] suggested the multi-classification results of the motor imaging brain signals enhance specific subband spatial patterns with the sequential rear-floating parts. Later researchers [11] also applied KNN, and NMPW classifiers but their accuracy was much less than that of LDA and SVM. Yuliang Ma et al. [12] has proposed Support Vector Machine with Particle Swarm Optimization.

Since the dataset is of motor imagery EEG signals many researchers have applied different techniques for classification of data. We, on the other hand, removed ocular artifacts and then classify the EEG signal, so on doing this we have seen different classification accuracy on the data obtained after artifacts removal from all the five methods.

III. MATERIALS AND METHODS

A. Dataset Description

The dataset used is BCI competition III dataset IV A [13]. The dataset consisted of a recording of the human EEG of 5 healthy subjects collected using 118 channels which had a frequency between 0.05 Hz to 200Hz. Each subject was subjected to 280 trails. Event-Related Potentials(ERP) are electro-cortical potentials which are measured in the EEGs before and after cued motor imagery events. The EEG had an ERP recording of the 5 subjects. For cued motor imagery the subjects were asked to move their right hand and right foot, i.e.; we had 2 classes. Out of the 5 subjects, responses from 2 subjects gave good training data (subject 1: 80 %; subject 2: 60%). The responses from the remaining 3 subjects gave less training data (subject 3: 30%; subject 4: 20 %; subject 5:10%). Using a sampling rate of 1000Hz the challenge is to detect and remove ocular artifacts followed by classification using the little training data.

B. Background Knowledge

The application of ICA on the datasets is done with the help of a very effective toolbox EEGLAB v. 2019.0 on MATLAB R2019a. The dataset is imported individually along with event makers and channel locations to the EEGLAB. This dataset is re-referenced or downsampled using average reference property. Kurtosis measure of identification is used for bad channel analysis, and removal using the channel plot with a z threshold of 5. Each IC consists of data from 118 channels that are present in the Dataset IV A of BCI Competition III. The final step in the ICA is the identification of bad components using the component activations and component spectra maps that consists of the power spectral density (DB) v/s frequency (Hz) and ERP (Event-Related Potential) Images. The identification of bad ICs using these is completely subjective. Once the bad components are identified, they are recorded and without removing these bad components, the data is further processed using one of the feature detection methods.

C. Feature Detection Techniques

1) Independent Component Analysis(ICA):

ICA is an effective BSS identification and removal technique [3]. In ICA the multichannel EEG data are linearly broken down to generate a maximum of individual elements, temporarily independent and spatially defined. The ICs subject to artifacts are set to zero and the majority of the ICs are projected back onto the scalp to collect the true EEG information. These IC components are subjected to artifacts. Here, one component cannot infer with the data of another component. So statistically the joint probability is given as the product of the probability of each of the independent components. If there are n independent source signals $x_i(t)$, i =1,2,3,.....n and $1 \leq t \leq T$.

$$p(x(t)) = \prod_{i=1}^{n} p(x_i(t)) \tag{1}$$

$$y(t) = Ax(t) \tag{2}$$

Where A is an $n \text{ x } d$ scalar matrix where d is dimensional data vector and $d \geq c$.

A is determined by maximum likelihood techniques. Let the source of density be estimated by the parameter $\hat{p}(y; a)$ where a reduces the difference between the estimate and the source distribution.

Thus $\hat{p}(y; a)$ is an estimate of $p(y)$ and a is basis vector of A.

2) Independent Component Analysis-Recursive Least Square(ICA-RLS):

This algorithm is a combination of both ICA and RLS [4]. RLS technique uses adaptive filters, where the adaptive filter is given by

$$v_j(n) = \sum_{k=1}^{h} h_j(k)\, r_j(n-k+1) \tag{3}$$

Where $v_j(n)$ represents the ocular activities of EEG signal y(n). Each EEG signal $y_l(n)$ also contains nuclear activity $x_j(n)$ along with ocular activity $v_j(n)$. $r_1(n), r_2(n).....r_m(n)$ are the reference signals served by ocular ICs for the adaptive filter.

The EEG signals are hindered by the artifacts and it is given by e(n), e(n) is corrected by subtracting ocular activities $v_j(n)$ from EEG signal $y_l(n)$.

$$e(n) = y_l(n) - \sum_{j=1}^{m} v_j(n) \tag{4}$$

RLS technique is used for adjusting $h_j(n)$ for canceling as many ocular activities as possible and this is done by reducing the sum e(n) of the weighted square errors as less as possible and is given by-

$$\varepsilon_n = e^2(n) + \lambda\ \ e^2(n-1) + ... + \lambda^{n-L} e^2(L) \tag{5}$$

The 'forgetting factor' $0 < \lambda < 1$ is responsible for gradually reducing the effects of previous errors.

So, the ICA-RLS technique is the first ICA followed by RLS.

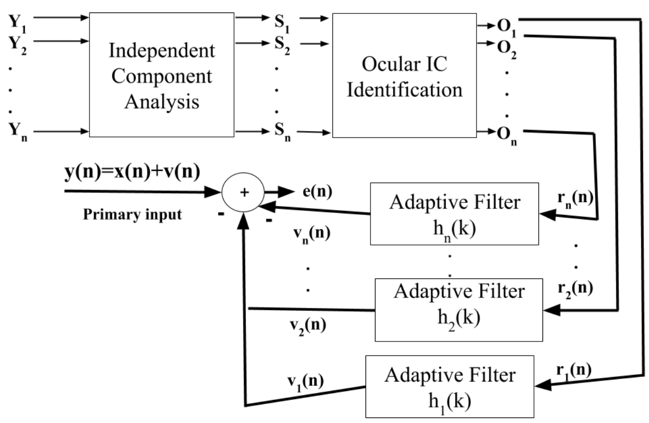

Fig1. Block diagram of ICA-RLS.

3)Independent Component Analysis- Discrete Wavelet Transform: Wavelet transform(WT):

It can be defined as the product of wavelet function's Ψ (t) shifted and time-scaled version and the signal f(t). The WT splits the signal into a series of coefficients on various scales which then reveal the wavelet-like signal. A standard DWT is a grid of dyadic amplitude and time scales of 2j and time-shift b = k2j, with both j and k integers.

The wavelet function is given as-

$$\psi_{j,k}(t)\ = 2^{j/2}(2^{j/2}t - k) \tag{6}$$

Where j indicates the degree of resolution and k is the time translation. This is named dyadic scaling because it requires the scaling factor to be 2.

The following formula will express the wavelet decomposition:

$$f(t) = \sum_{k=-\infty}^{+\infty} [c_k \varphi(t-k)] + \sum_{k=-\infty}^{+\infty} \sum_{j=0}^{+\infty} d_{j,k} \psi(2jt - k) \tag{7}$$

In which φ (t) is the scaling function, and in which c_k and d_k, k are respectively the coarse and accurate expansion coefficients.

The input and output equations for DWT is given as-

$$x_{a,L}[n] = \sum_{k=1}^{n} x_{a-1,L}[2n-k]\ \mathrm{g[k]} \tag{8}$$

$$x_{a,H}[n] = \sum_{k=1}^{n} x_{a-1,L}[2n-k]\ \mathrm{h[k]} \tag{9}$$

Where g[n] is just like scaling function which is a low-pass filter while h[n] is just like wavelet function which is a high-pass filter. Generally, DWT is accompanied by threshold selecting criteria. ICA algorithm is also required with DWT because DWT is not capable of completely extracting artifacts interfering with an EMG signal from a spectral domain like ECG [5].

4)Independent Component Analysis - Least Mean Square(ICA-LMS):

Least Mean Square Method uses an adaptive filter which adjusts the filter coefficients in accordance with an adaptive algorithm [6]. This method simplifies calculations and speeds up the process by estimating gradient with the help of instantaneous values of the correlation matrix of tap inputs and also by calculating the cross-correlation vector between tap weights and the desired response. ICA-LMS is considered an efficient method to remove ocular artifacts while working on Motor-Imagery Data. For Motor Imagery Data (especially hand and foot movement), suffers from ocular artifacts much more than any other EEG signal.

5)Empirical Mode Decomposition - Independent Component Analysis (EMD-ICA):

The EMD is a method that has been developed to operate on non-stationary, non-linear, stochastic processes, making it ideal for EEG signals.EMD doesn't have many online applications as it as high computational complexity.

The EMD algorithm breaks down nonlinear data signals and non-stationary data into a band-limited component summary, c[n] called IMF functions [7]. The zero mean amplitude components are determined by these IMFs.

$$\mathrm{s(t)} = \sum_{i=1}^{N} c_i\,\mathrm{(t),\ i = 1} \tag{10}$$

$$s(t) = \sum_{i=1}^{N} c_i(t) + r_i(t) \quad (11)$$

N - IMFs extracted count, r_i(t) - residue

The main function of EMD is to deal with the extraction of IMFs which involves the removal of higher-level components. The calculation of envelopes is done through interpolation.

In order to detect the abnormal elements in the signal that can be recognized as IMFs and can also be rejected to clean the signal, decomposition achieved via EMD is used. The EEG signal is then subjected to ICA when the IMFs are broken down into separate components (ICs). Using ICA, weak components are detected and cleaned by removing ICs and obtaining a clean signal.

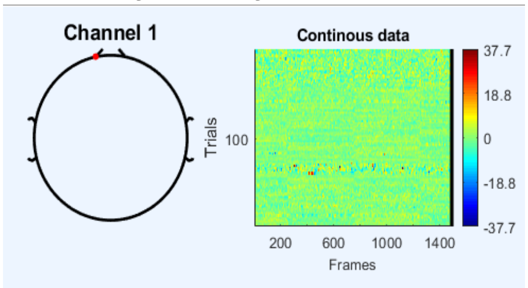

Fig2. The variation in ERP image of channel 1 after the EMD - ICA implementation

The EMD method decomposes the data into IMFs which are further identified by decomposition into ICs as bad IMFs based on a certain criterion which is subjective.

D. *Classification Method*

As mentioned, BCI Competition III Dataset IV A consists of EEG signals recorded from 5 subjects when they were told to move right hand and foot. Hence, this will be a case of binary classification.

SVM-PSO method will overcome the problem of choosing a kernel function for SVM and the mandatory prior knowledge of the distribution characteristic of the signal. This algorithm selects the best kernel function with penalty parameters and hence the accuracy is improved as compared to the traditional SVMs.

Common Spatial Pattern (CSP) -

The principle component forms the base of the CSP method. Previously, CSP has been used in tasks associated with object recognition and face recognition, and anomaly detection. Recently, it was successfully applied to problems related to brain-computer interfaces. In order to extract features using CSP, firstly the EEG signals are passed through CSP filter, to make the data-set such that it will be divided into two classes, one with maximum variance and second with the minimum variance.

Before decomposition of features using Principal Component Analysis, the covariances for both the classes were measured. Also, the eigenvectors of the covariance matrix are the same. Hence, if one feature comes out to be maximal other will be automatically classified to minimal. That's why both the classes are easily separable when we apply CSP.

SVM(Support Vector Machine):-

SVM is a discriminative classifier and is normally defined by a hyperplane, which is a line dividing a plane into two parts, and this two-part will represent two classes. As mentioned by Chandaka [14], non-linear classification problems can be converted to linear classification problems just by raising a degree. Also in case of non-linear classification problems in SVM, instead of inner product computation, kernel function is used.

PSO (Particle Swarm Optimization):-

PSO is extensively used nowadays due to the independence of the target optimization of PSU and Parallelism.

1. Initialization:- All the input vectors must be initialized with setting the parameters and initial weight of parameters. At the end of this step, the largest number of iterations will be determined and the size of the population will also be reported.
2. Calculate Fitness:- After training the model with the help of training data-set, calculate the overall fitness using fitness function.

$$f_j = \left(\frac{var(Y_j)}{\sum_{k=1}^{2m} log\,(var(Y_k))} \right); j = 1,2,3,....2m \quad (12)$$

where Y is class, and j is class number.

3. Adjusting:- Global and personal best positions are adjusted in accordance with the fitness value of each particle.
4. Updating:- Velocity and Position are updated.
5. Determination:- Stop after a maximum number of iterations are over or error condition is fulfilled.
6. Classification:- This is the final step where we have obtained the most optimal kernel parameter and penalty factor, hence the SVM classifier will retain training samples. Then we will use class prediction for containing best classifiers.

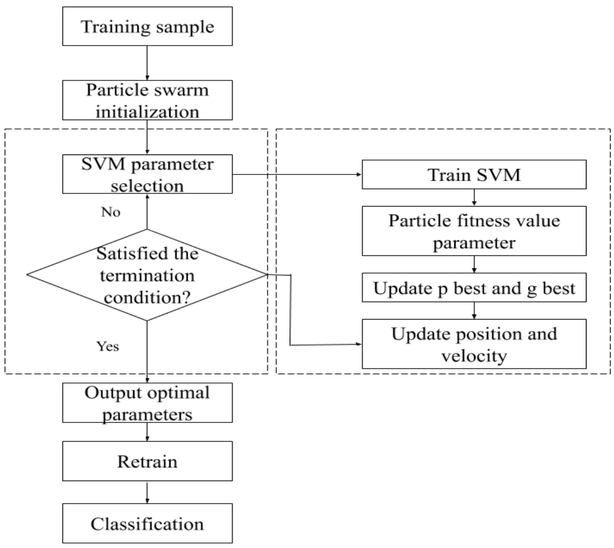

Fig3. Flowchart of PSO optimized SVM parameters

IV. RESULTS

The use of hybrid methods gives better accuracy and output than the normal and standardized method of ICA.The comparison of spectral component activations of the first 35 components for the ICA and the first 35 components after application of various methods along with ICA result in the observation of a significant improvement over the standard ICA method. The output from preprocessing is supplied as an input to the final classification through the SVM-PSO.

After performing the artifact removal task, binary classification using SVM-PSO was performed to classify the given two classes. We have applied classification on the output obtained after artifacts removal techniques. As, ICA-RLS gives the highest classification accuracy and hence we can conclude that it must have removed a large number of ocular artifacts and is the best method to remove ocular artifacts for the given dataset. The detailed analysis of the classification is mentioned in Table 1.

TABLE-I
CLASSIFICATION ACCURACY OF PROPOSED METHODS

Methods used to Remove Artifacts	Classification Accuracy
ICA-RLS	92.94%
ICA-DWT	91.23%
EMD-ICA	90.67%
ICA-LMS	90.46%
ICA	87.04%

TABLE-II
CLASSIFICATION ACCURACY OF ALREADY EXISTING METHODS

Authors	Year	Feature Extraction	Classification Method	Accuracy
Proposed	2019	ICA-RLS + CSP	SVM-PSO	92.94%
Kervin & Subasi [15]	2018	Empirical Mode Decomposition, DWT	k-NN	91.5%
Zhou et al. [16]	2017	DWT & Hilbert Transform	RNN LSTM Classifier	91.43%
Baig et al [17].	2017	CSP	SVM-PSO	90.4%
Yu et al. [10]	2014	CSP	SVM	76.34%
Bermudez &Garcia [18]	2012	AAR Modelling, PSD	LDA	69.4%

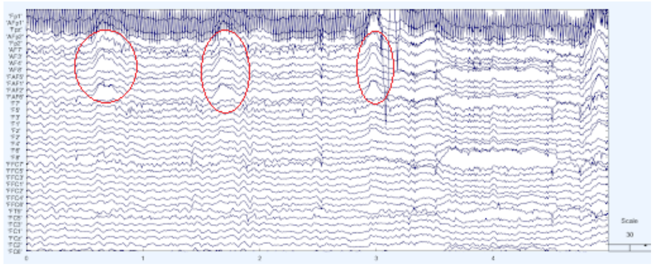

Fig4. Representation of channels before running ICA

Figure 4 shows the channel activations and the channels that remain after filtering through the kurtosis measure. These channels are now made to be passed through ICA in order to obtain independent components.

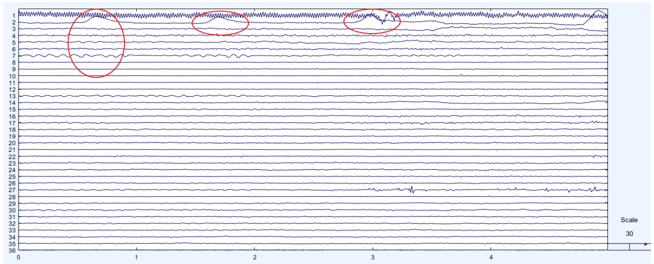

Fig5. Representation of components using Independent Component Analysis (ICA)

Figure 5 shows the first 35 independent components after the decomposition through ICA. These ICs contain data from all of the channels of the initial data. These ICs are used to obtain blind source-separated components from the initial data.

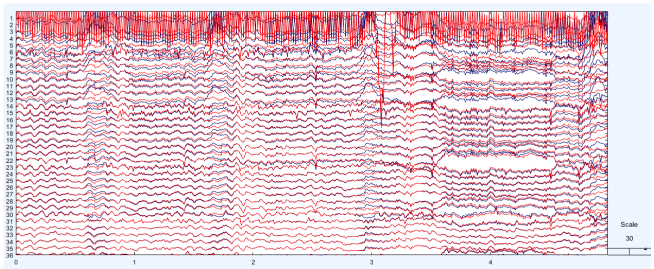

Fig5.1. Output and Input comparison of ICA

Figure 5.1 shows the comparison of different methods with the component activations obtained after applying ICA. These comparatives are a result of the selection of components that is done using various methods. As a result components are decomposed differently from each method. The components with the most noise levels are selected and marked for rejection. The graph that shows red curves are obtained after the removal of these components.

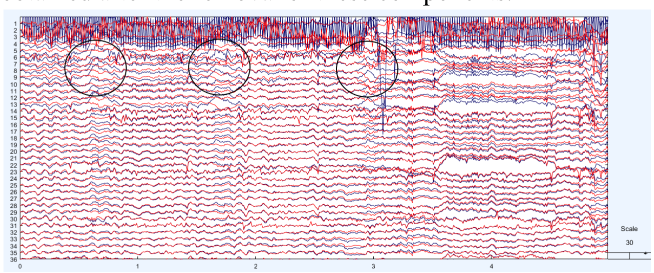

Fig5.2. Output and Input comparison of ICA-LMS

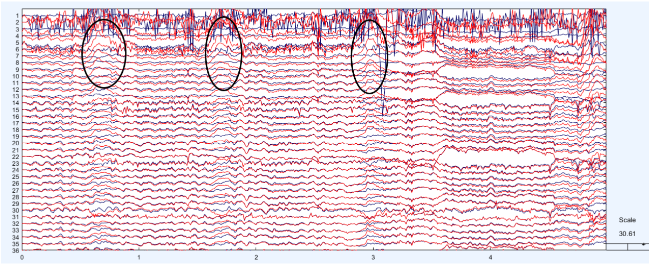

Fig5.3. Output and Input comparison of ICA-RLS

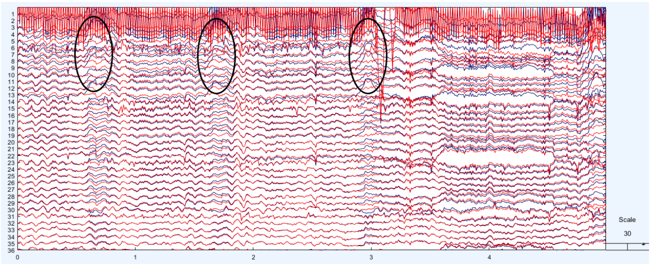

Fig5.4. Output and Input comparison of ICA-DWT

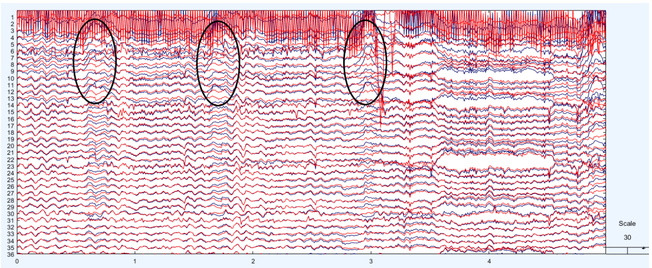

Fig5..5. Output and Input comparison of EMD-ICA

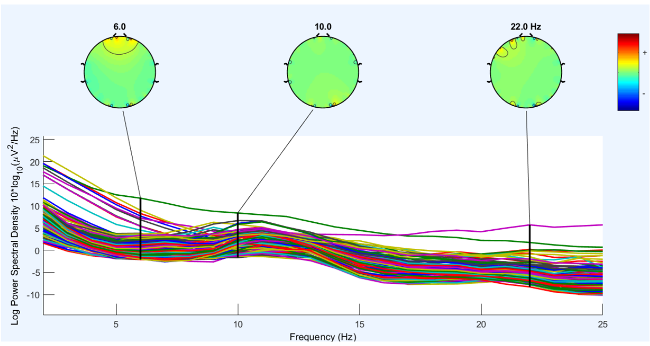

Fig6. Variation of log PSD v/s Frequency curve along with components.

In Figure 6 Components with frequency 6 Hz, 10 Hz, 22 Hz are kept as reference components and based on these reference components the log PSD v/s frequency curve is further evaluated to look for the components that are 'bad' or 'erroneous' and should be rejected.

V. CONCLUSIONS

This work is a conclusive study of 5 different methods that have been used to analyze the EEG data. These methods have shown a significant improvement over the standard ICA procedures. From the classification results, we can conclude that ocular artifacts have been removed by hybrid methods with greater accuracy than the standard ICA method. Thus, hybrid methods in this work perform better than standard ICA. For classification, we have used SVM-PSO and we have performed feature detection using CSP and various hybrid methods.

This work can be extended by performing classification of multi-class motor imagery EEG signals. In this work, we have removed ocular artifacts only, since motor imagery signals are produced by muscular signals, hence muscular artifacts are very difficult to remove as we have to distinguish between voluntary and involuntary muscular movements. We would extend this research on multi-class data and also incorporate muscle artifacts removal techniques.

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