EEG Motion Artefact Classification and Removal Using SVM and Optimum Reduce Order Filter (OROF) Design

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KEYWORDS

Machine Learning, EEG signal, Artefact Classification, Motion artifacts removal, Unsupervised Min-MAX Optimization, Reduced Order Filter

ABSTRACT:

Electroencephalography (EEG) data often contain motion artefacts during acquisition, making it essential to remove them early in the analysis of neurological disorders. This paper presents a machine learning (ML)-based approach for detecting and classifying motion artefacts in EEG data. Two distinct databases, including original and synthetically generated artefact data, are utilized for evaluation. The classification process employs statistical features extracted from the EEG motion artefact database, which are then tested using ML classifiers to determine accuracy. Among the tested classifiers, cubic support vector machine (SVM) demonstrates the highest classification accuracy and computational efficiency.Once artefacts are identified, an optimal reduced-order filter (OROF) is proposed for artefact removal. The filter design is initially validated using an infinite impulse response (IIR) filter, followed by min-max optimization to ensure the integrity of the true EEG signals. The effectiveness of the proposed filter is assessed using a multichannel EEG artefact dataset. Finally, the peak signal-to-noise ratio (PSNR) is evaluated to verify the filter's performance in preserving EEG signal quality.The proposed approach successfully enhances EEG signal processing by accurately classifying motion artefacts and efficiently filtering them while maintaining signal integrity.

I. Introduction

Electroencephalography (EEG) signals play a crucial role in capturing brain activity, offering superior performance compared to other physiological signals. However, EEG recordings are often affected by artefacts, which can interfere with the accuracy of neurological assessments. These artefacts may arise due to electrode disturbances, muscular movements, nodding, and eye motions, all of which compromise data integrity and analytical reliability. The presence of artefacts in EEG signals can distort actual brain activity, making it challenging for researchers to interpret the data accurately. Therefore, developing an effective EEG artefact removal system is essential. Such a system must be capable of identifying artefacts and selectively filtering only those portions of the signal containing artefacts.EEG data may or may not contain motion artefacts.

If artefacts are absent, applying a filter indiscriminately may alter the true characteristics of the EEG signal. Thus, it is critical to detect and classify artefacts before applying filtering techniques [1]. This study focuses on first classifying EEG artefacts using Support Vector Machine (SVM)-based classifiers, evaluating their accuracy, and subsequently designing an Optimum Reduced Order Filter (OROF**)** for artefact removal. The objective is to develop a simple, low-cost, and effective filtering solution for removing artefacts while preserving the integrity of EEG signals.EEG signal analysis is particularly challenging due to its time-varying nature and susceptibility to measurement errors caused by electromagnetic noise. Among various artefacts, eye-related artefacts require special attention as they exhibit high peak amplitudes, making them difficult to remove effectively. The mathematical complexity associated with artefact removal has been a major focus of ongoing research. Although Ibrahim et al.'s Infinite Impulse Response (IIR) filtering techniques offer simplicity, they are highly sensitive to delay and may distort the true EEG signal structure. Therefore, it is necessary to design a method that not only removes artefacts efficiently but also preserves the original EEG waveform, especially in cases involving high-peak eye blink artefacts.EEG signals are recorded using electrodes placed on the human scalp, typically with 16 or 24 channels. The methodology proposed in this study, as illustrated in Figure 1**,** follows a systematic approach. Initially, feature set vectors are extracted from the input EEG dataset. Various SVM-based classifiers are then applied to categorize the EEG data as either artefact-free or artefact-contaminated. The artefact-containing data includes electrooculography (EOG) artefacts [2] from eye movements and electromyography (EMG) artefacts [3] caused by muscle activity. Although various filtering methods have been developed to remove motion-induced distortions from EEG signals, different artefact types do not always respond uniformly to existing techniques. This necessitates further research into optimizing artefact removal methods while maintaining EEG signal fidelity.

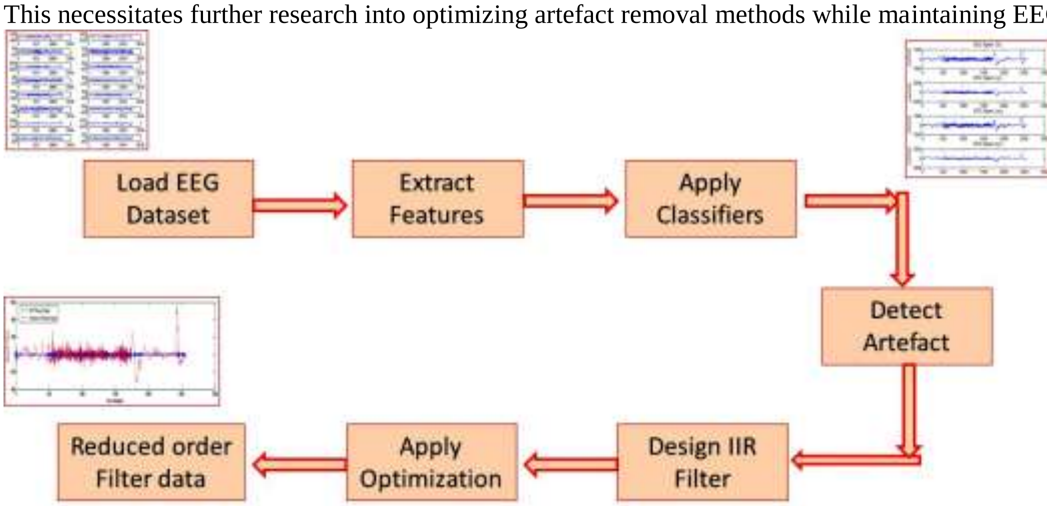
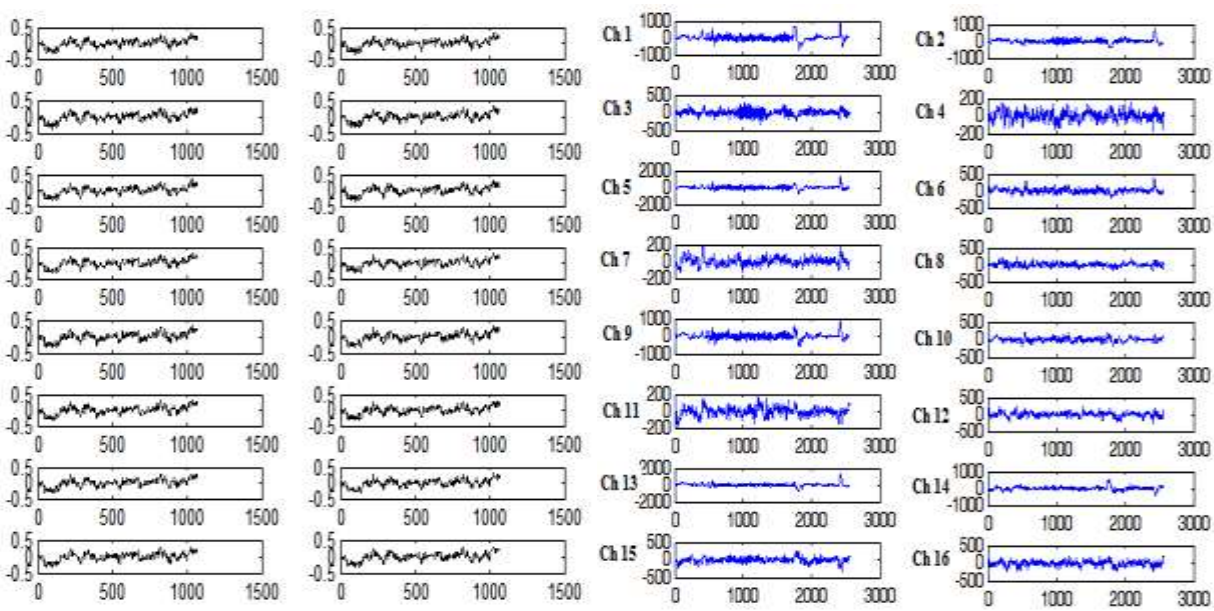
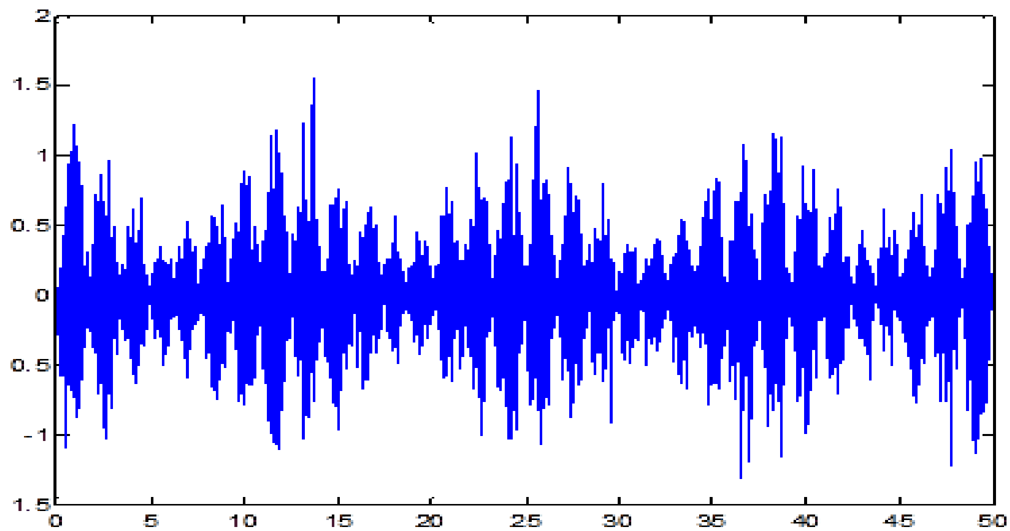


Figure 1 Proposed ML based EEG Artefact Classification and removal methodology

This research is implemented in two phases. In **Phase 1**, EEG artefacts are detected using machine learning classifiers. In **Phase 2**, an effective **optimum IIR filter** is designed to eliminate these artefacts while preserving the true nature of the EEG signal. The EEG motion artefacts, as depicted in **Figure 2**, have numerous practical applications in neurological and biomedical research.The 16 MIT scalp multichannel artefact-free data refers to EEG signals recorded from 16 electrode channels placed on the scalp, ensuring no external disturbances such as motion, muscle activity, or eye movements. These artefacts, also displayed in black, result from factors like head movement, muscle contractions, or electrode displacement, leading to signal distortions that must be detected and filtered for accurate EEG analysis.



(a)16 MIT scalp multichannel artifacts-free data (in black) (b) 16 MIT scalp multichannel motion artifacts data (in blue)



c) Synthetic artifacts data with 10 dB SNR Ref. Shukla, Shailja & Roy [5]

Figure 2 The EEG signals data base that was utilised for validation in this research

II. Contribution of Work

This study focuses on detecting and classifying various EEG artefacts using machine learning (ML)-based Support Vector Machine (SVM) classifiers. The goal is to determine the precise presence of artefacts before designing an Optimum Reduced Order Filter (OROF) for effective artefact removal. Additionally, a novel adaptive optimum reduced order filter is proposed, employing an optimization technique to enhance artefact removal efficiency. This filter represents an advancement over the conventional two-stage Infinite Impulse Response (IIR) filter design. The OROF is specifically tailored to eliminate muscular and eye-blink artefacts while preserving the integrity of the original EEG signal. The study also evaluates the classification efficiency of various linear and non-linear classifiers, comparing their performance in detecting EEG artefacts. The evaluation metrics include accuracy and confusion matrix analysis for three different classifiers. Finally, the effectiveness of the OROF filtering process is quantitatively assessed by comparing it against traditional filtering methods, demonstrating its superior ability to remove artefacts while maintaining signal quality.

a. Dataset for Consideration

This research utilizes two distinct EEG artefact datasets, as illustrated in Figure 2(a) and Figure 2(b). The first dataset originates from the MIT scalp EEG database, consisting of 23 EEG channels capturing true EEG signals without artefacts. The second dataset comprises 16 EEG channels containing motion-induced artefacts, primarily electrooculography (EOG) and electromyography (EMG) artefacts. Additionally, synthetic artefacts are generated by averaging sinusoidal signals of varying amplitudes, following the standard method referenced in [5], as shown in Figure 2(c). To preprocess the original EEG data before creating synthetic artefacts, the baseline wandering method by Roy Vandana et al. [5] is employed. The EEG data is then decomposed into multi-channel signals using the Empirical Ensemble Mode Decomposition (EEMD) technique before undergoing filtering through the IIR algorithm. To ensure accurate artefact removal, it is highly recommended to apply OROF filtering on real-time EEG data that has been preprocessed to exclude artificial artefacts. Figure 1 highlights that not all EEG data contain motion artefacts, reinforcing the necessity of accurate artefact detection before applying filtering techniques. Furthermore, Algorithm 1 details the synthetic artefact generation process, ensuring the effectiveness of the proposed filtering method.

Algorithm 1: Synthetic Artefact Generation

1. Load artifacts mat files data
2. Initialize the SNR for artifacts signal
3. Set the sampling frequency ← f_s
4. Declare the artifacts free segment variable ← $xfree$
5. Loop over to add the selected SNR based artifacts data

```
if snr==N dB

load ('xart_N.mat'(uses N dB AWGN noise aided data)

end
```

6. Xart is saved as synthetic artifacts data
7. End algorithm

III. Related Work

Infinite Impulse Response (IIR) filters [16,17] are commonly used in EEG signal processing due to their ability to achieve the lowest possible order. However, their sensitivity to delay in filter response can alter the true nature of the EEG signal, making accurate artefact removal a significant challenge. One of the most critical aspects of designing an effective IIR filter is selecting the optimal cut-off frequency, which remains a major issue [3,4]. To address this, this study initially designs a low-order hybrid stop-band and band-pass filter, ensuring effective artefact suppression while minimizing distortion in the EEG signal. Sahabani M. et al. [1] conducted an in-depth review of EEG signal classification methods, focusing on k-nearest neighbors (kNN) and Support Vector Machine (SVM) algorithms. The study evaluates the applications of these classifiers in various EEG-related tasks, analyzing their advantages, disadvantages, and overall performance in distinguishing between artefact-contaminated and clean EEG data. Similarly, M. R. Calvache et al. [2] explored the effectiveness of a Perceptron Multilayer Neural Network vs. Fuzzy C-Means classification for analyzing graph-based functional neural networks. Their study involved stimulating scalp electrodes and using EEG data to distinguish between former soldiers and civilian control subjects while performing a modified Dual Term Valence Task, a widely used cognitive research tool.

In their research, Ibrahim K. et al. [3] discussed the limitations of EEG analysis due to the presence of artefacts, which are one of the most significant challenges in EEG-based studies. While some artefacts can be avoided, others are unavoidable due to the inherent nature of EEG techniques. EEG artefacts are typically categorized as internal (biological) or external (non-physiological). Proper artefact management is crucial for both event-related potential (ERP) and passive EEG studies to preserve the maximum signal integrity while minimizing unwanted noise.
Antti S. et al. [4] systematically categorized the most common EEG artefacts and their sources. Artefacts are defined as disturbances in brain signals that do not originate from actual neural activity. The study identified both internal and external artefact sources and used recorded signals to illustrate the characteristics of various artefacts. This classification is essential in designing effective artefact removal techniques, as different types of artefacts require distinct filtering approaches.

Vandana Roy et al. [5] introduced a novel EEG artefact removal method utilizing wavelet transform and Independent Component Analysis (ICA)-based decomposition techniques. Their method was evaluated on both synthetic and real EEG motion artefacts, demonstrating its effectiveness in reducing unwanted disturbances in neurological signals. Electroencephalograms (EEG), as described by Anand P. and Vandana R. in their publication [6], play a crucial role in studying various neurological disorders. However, EEG signals are frequently contaminated by artefacts, making brain signal analysis difficult. The most common artefacts affecting EEG recordings include motion artefacts, electrooculography (EOG), electrocardiography (ECG), and electromyography (EMG) artefacts. The study reviewed various artefact removal techniques, highlighting their properties and effectiveness in preserving the original EEG signal while eliminating unwanted noise.In previous research has extensively explored different methods for EEG artefact classification and removal, with a strong emphasis on machine learning-based classifiers, filtering techniques, and decomposition methods. While each approach has demonstrated success in specific scenarios, there remains a need for an optimized, low-cost, and efficient filtering method that effectively removes EEG artefacts while maintaining the integrity of the original signal. This study aims to build upon these findings by developing an Optimum Reduced Order Filter (OROF) that enhances EEG artefact detection and removal with improved efficiency and accuracy.Sing R. et al [7]. Presented an overview of electroencephalography (EEG) provided in their report, with a focus on pattern identification methods.

The initial steps cover the fundamentals of the human brain and several significant uses for electroencephalography. Introduced together with descriptions of the pertinent signals and artefacts.Santosh R. et al. [8] presented method for analysing and identifying Electroencephalography (EEG) is described in this work. As a result, significant features can be retrieved utilising sophisticated signal processing techniques for the diagnosis of various disorders. Time-frequency, non-linear, linear, and frequency domain A typical normal EEG signal is used to describe in depth techniques like correlation dimension (CD), greatest Lyapunov exponent (LLE), Hurst exponent (H), distinct entropies, and fractal dimension (FD), Higher Order Spectra (HOS), phase space plots, and recurrence plots. Mehmat A. et al. [9] in their paper used electrodes positioned on the scalp, electroencephalography (EEG), a non-invasive procedure, records the electrical activity of cortical neurons. Beyond the most advanced EEG research that is carried out in static settings, it has emerged as a viable study direction. EEG Artefacts and other physiological signs always taint signals. The amount of movement increases the amount of artefact contamination.P V Praveen et al [10] have preseted the FIR filter application and implementation but need more memory. Shukla, Shailja et al [11] have presented the use of wavelet based empirical approach to reduce the impact of EEG motion artefacts. They have used true and synthetic artifacts

Jorden j brid et al [12] detected mental states that are helpful for interactions between people and machines, this work attempts to identify prejudiced EEG-based characteristics and suitable methodologies for classification that can classify neural waves based on the frequency or degree of activity. Mathe, M et al [13] have studied two methods for classifying and removing artefacts are presented. First, clean EEG data and signals with artefacts are classified using a customized deep network. Shared area pattern elements are obtained using convolutional layers and then defined using a type of support vector machine decoder. The classification is done at the feature level.
The broad classification of the EEG artifacts classification methods are given in the Figure 3. Broadly there are supervisedor unsupervised classifiers. The ICA based classification belongs to unsupervised category [14]. The SVM based classifiers are widely used in literature and are further divided to simple SVM and weighted SVM. This section of paper describes the various classifiers available and used in this study.

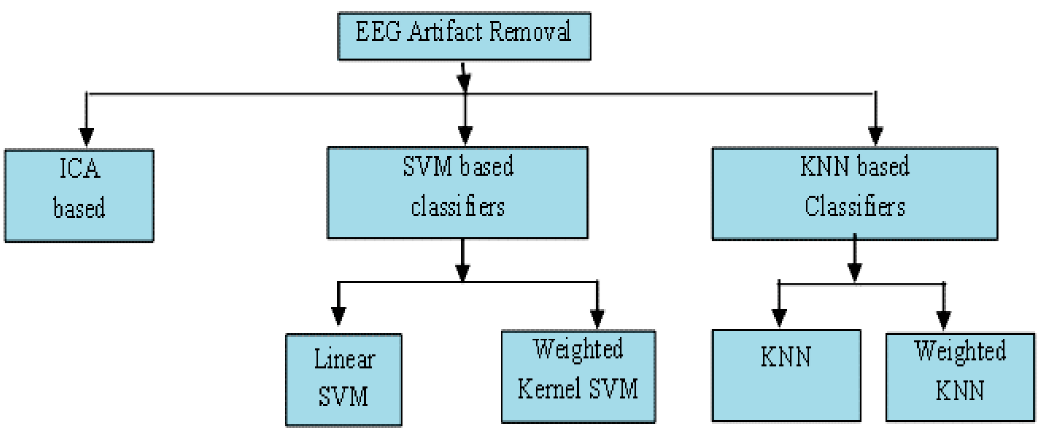


Figure 3: EEG Artefact Classification methodologies using ML

SVMs are a type of supervised learning technique [15 and 16] that can be applied to applications requiring classification or prediction. Finding a hyper plane that as substantially as feasible separates different categories in the training data is the main idea of SVMs. Finding the hyper plane with the largest marginmeasured as the separation between the hyper plane and the closest data points from each class enables this. Fresh data can be categorised by identifying which side of the hyper-plane it falls on after the plane has been located.Linear SVMs divide the data points into different classes using a linear decision boundary. Linear SVMs are ideal when the data can be accurately linearly segregated. This indicates that the data points can be completely divided into their respective classes by a single straight line (in 2D) or hyper-plane (in higher dimensions). The decision boundary is a hyper-plane that maximises the margin between the classes. But is not fitted best for the non-liberally featured EEG dataset and has low efficiency.

There are many non-linear SVM methods for classifications. When data cannot be divided into two groups by an uninterrupted path (as in 2D), non-linear SVM is able to be used to categorise the data. Nonlinear SVMs may manage nonlinearly separable data by utilising kernel functions. These kernel functions change the initial input data into a feature space with more dimensions that allows the linear separation of the data points. In this modified space, a nonlinear determination boundary is located using a linear SVM.

When data cannot be divided into two groups by a straight line (as in 2D), non-linear SVM can be used to categorise the data. Nonlinear SVMs may manage nonlinearly separable data by utilising kernel functions Stalin, Shalini et al [16] study artefacts suppression before the core motion artefact is identified from an a single-channel electroencephalogram (EEG) signal using a support vector machine (SVM). The group decomposition of empirical modes (EEMD) approach is used to separate the signal characteristics and perform further identification. In addition, motion artefact elimination is accomplished by the use of the canonical correlation analyses (CCA) filter technique. Finally, the wavelet transformation (WT) technique is used to eliminate the unpredictable nature of any remaining motion artefacts. These kernel functions convert the initial input data into a higher-dimensional space for features. In the domain of machine learning, SVM [15] and k-nearest neighbours (kNN) [17], are two extremely popular supervised techniques. Kubacki, A. et al [18] identify aberrations during an electroencephalogram (EEG) investigation is presented in this paper. The emphases are on identifying the one and only object that blinks, the eyes. Six synthetic neural systems having 1, 2, 5, 10, 100, and 1000 concealed layers have been used for identification. Xun Chen et al [19] proposes a unique method, called EEMD-CCA, for removing muscular artefacts from EEG data through the integration of the technique of ensemble empirical mode decomposition (the EEMD technique) and canon correlational analysis (CCA). The method fared better than cutting-edge methods like EEMD-ICA, CCA, and autonomous component analysis. SVM can only recognise a small number of data patterns, however it found computationally inexpensive than kNN and easier to explain. While on the other hand, kNN can uncover extremely complex patterns but its results are more difficult to decipher. As more training data is collected, kNN can adapt more closely to nonlinear borders because it avoids making a priori assumptions about the nature of the class boundary. Although, kNN exhibits greater variance than linear SVM, it has the advantage of generating classification fits that are flexible about any boundary

An EEMD-CCA oriented method for EEG artefacts reduction was once-again proposed by Xun Chen et al. [20]. EEG processing was used by Hanshu [21] to diagnose depression. For EEG signal demising, Vandana Roy et al. [22] employed wavelet filter in addition to newly suggested Gaussian elevation dependent GECCA algorithm. The method was superior to EEMD-CCA. Ibrahim et al.'[23] use of Genetic Algorithms (GA) for the generation of error signals and evaluation of FIR filters' performance. Min-Max optimisation based IIR filters have been proposed by Hemant et al [24] for ECG signal categorization and peak detections Monica R. et al. [25] presents an automatic method to classify between artefactual and neural components in EEG signals using an Independent Component Analysis (ICA) and a Support Vector Machine. With the resultant model, we obtained a classification accuracy of 95.6% validating the model over real data. Siyuan Wang et al. [26] have impulses in the temporal and spectrum domains may be impacted by this imprecise de-noising, which might lower the BCI the system's accuracy. In recent times Goldberger, A et al [27] have presented the EEG artifacts removal using the aut0 encoder deep method seams complex in hardware implementation. Jain, Nitin et al. offered a method that uses a hybrid consecutive system that includes band pass filters and a group stop filters. Thus, overall it is still a challenging field to design accurate and low-cost optimal filter for EEG artifacts removal.

It is suggested in this paper to design a lower order Min-Max optimized IIR filtering (OROF) to filter out noise signals and eye blinking (EOG) and muscular movements (EMG). IIR filters are created using a blend of pass bans when stop band filters. The goal of the unsupervised transfer function (TF) optimisation technique is to lessen the complexity of the hardware and order filter design. The effectiveness of the filter is assessed using multichannel actual EEG signal data. The peak signal to noise ratio (PSNR) and root means square error (RMSE) are two examples of metrics that are used to assess the filter's performance.SVM can only recognise a small number of data patterns, however it found computationally inexpensive than kNN and easier to explain. While on the other hand, kNN can uncover extremely complex patterns but its results are more difficult to decipher. As more training data is collected, kNN can adapt more closely to nonlinear borders because it avoids making a priori assumptions about the nature of the class boundary. Although, kNN exhibits greater variance than linear SVM, it has the advantage of generating classification fits that are flexible about any boundary An EEMD-CCA oriented method for EEG artefacts reduction was once-again proposed by Xun Chen et al. [20]. EEG processing was used by Hanshu [21] to diagnose depression. For EEG signal demising, Vandana Roy et al. [22] employed wavelet filter in addition to newly suggested Gaussian elevation dependent GECCA algorithm. The method was superior to EEMD-CCA. Ibrahim et al.'[23] use of Genetic Algorithms (GA) for the generation of error signals and evaluation of FIR filters' performance

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Table 1 The summary of the review work on Filter designing's

Authors	Filter Algorithm	Description	Parameters
Sha'abani, et al [1]	EOG signal classification using KNN and SVM.	SVM outperformed KNN and Decision Tree in classification accuracy	Kernel function used in SVM transformation for classification.
M.R.Calvache et al [2]	Reduced order IIR with SVM	SVM used to classify art factual and neural EEG component	C and g parameters tuned for SVM classifier model selection
Ibrahim k et al. [3]	EEG artifacts generic method	EEG artifacts pose challenges in monitoring diseases and brain-computer interfaces	Techniques developed for better detection and mitigation of artifacts.
Antti S et al [4]	EEG with ICA and CCA	The IIR filter design for the de noising of the Electro Cardio Graphic signal (ECG).	EEG artifacts can be challenging to distinguish from genuine information
Roy, Vandana et al [5]	Double Density Wavelet Transform and ICA	ICA and Double Density wavelet transform is used to reduces the artifacts	ICA and Double Density Wavelet Transform parameters for artifacts removal
Anand P et al [6]	ICA, BSS, CCA, EEMD	Review focuses on different artifact removal techniques for EEG signals	SNR, MSE, correlation coefficients
Sing R. et al [7]	IIR and wavelet transform	Designed IIR filter using wavelet transform to reduce the artifacts	SNR and MSE
G Santhosh R et al [8]	ICA and Infomax algorithm	ICA is one of the widely used methods and also having high accuracy for artifact detection and removal	SNR, MMSE
Mehmet A al [9]	BiLSTM and WSST-Net	BiLSTM-based WSST-Net model improves artifact removal significantly.	BiLSTM-based WSST-Net model with best average MSE value 0.3066
P. V. Praveen Sundar et al [10]	LMS adaptive filter algorithm	This adaptive filter shows 20% less area delay product and 40% less power delay product when compared with the existing architecture.	NA
Shukla et al [11]	EMS, CCA with DWT	EEMD and CCA technique with DWT outperform existing removal techniques	RMSE, DSNR
Bogaarts et al [17]	SVM algorithm with Neo and Adults data set	This paper evaluates the performance of classifiers trained on different datasets in order to determine the optimal dataset for use in classifier training for automated, age-independent, seizure detection	EEG from neonatal patients and adult patients

IV. EEG Artefact Classification

Paper proposed to classify the EEG artifacts data based on the statistical features sets. The six statistical features are calculated for each category of the EEG data for 35 EEG data including 16 true EEG, 16 EEG artifacts and 3 synthetic artifacts data with [10,15 and 20] dB SNR AWGN noise respectively. The mean, median, deviation, minima, maxima and the entropy of the EEG data are considered as the statistical features.

The Table 2 represented the features calculated for the EEG database. The statistical features are used for classification to reduce the computation load. The mathematical representation of features calculation is given in equations below

$$Mean = \frac{1}{L}\sum_{i=1}^{L} EEG_s \tag{1}$$

$$Med = \frac{EEG\left(\frac{L}{2}\right) + EEG\left(\frac{L}{2}+1\right)}{2} \quad since\ L\ is\ even \tag{2}$$

$$SD = \sigma = \sqrt{\frac{\sum_{i=1}^{L}(EEG_i - Meani^{\ 2}}{L}} \tag{3}$$

$$E = \text{entropy} = \frac{1}{p_j}\sum_{j=1}^{L} p_j \log(p_j) \tag{4}$$

The features are calculated separately for motion artifact EEG, Gaussian noise EEG and the synthetic artifacts EEG data. No pre-processing is applied on the EEG signal for feature calculation. For EEG signal classification the SVM models are trained using the no cross validation model with full feature data is used for training the EEG data. The features are passed to the classification functions to fit SVM and type of model is varied. The deflate kernel values are used for the Gaussian classification keeping box constrain unity.

Table 2 Feature set calculated for the EEG artifacts data.

Mean	Median	STD	Max	Min	Entropy
3.9175	-2	172.0907	840	-711	0.9992
6.4839	2	114.3495	748	-412	0.9998
2.4910	1	71.8080	267	-321	0.9999
1.7210	1	47.7057	148	-173	0.9999
8.0039	3	175.4709	1269	-700	0.9997
5.4730	3	65.9038	387	-284	0.9993
-0.2281	-1	43.6490	176	-129	0.9974
1.5535	0	52.4170	204	-174	0.9990
4.0796	1	138.1289	845	-563	0.9999
-1.2132	-1	56.4214	202	-190	0.9990
-2.9121	-1	50.3951	183	-187	0.9986
-0.5457	2	64.4945	232	-274	0.9995
12.8085	6	170.4668	1216	-714	0.9992
-5.7789	-4	102.1348	513	-488	0.9961
-4.8449	-3	65.3069	233	-314	0.9965
-2.6734	1.5000	68.5475	246	-247	0.9998

Table 3 Feature set calculated for the true EEG data with Gaussian noise.

Mean	Median	STD	Max	Min	Entropy
-0.0043	0	0.1143	0.2954	-0.3223	3.4504
-0.0051	0.0067	0.1143	0.3156	-0.3424	3.4779
-0.0051	0.0067	0.1187	0.2820	-0.3625	3.5375
-0.0049	0	0.1152	0.3290	-0.3491	3.4355
-0.0040	0.0067	0.1148	0.3625	-0.3290	3.4869
-0.0051	0.0067	0.1172	0.3156	-0.3491	3.5045
-0.0047	0	0.1169	0.3021	-0.3290	3.4430
-0.0038	0.00670	0.1096	0.3080	-0.3156	3.4681
-0.0049	0	0.1203	0.3021	-0.3220	3.4745
-0.0049	0	0.1198	0.3223	-0.3424	3.4619
-0.0034	0.0067	0.1185	0.3088	-0.3156	3.5056
-0.0043	0	0.1177	0.2820	-0.3223	3.4805
-0.0040	0.0067	0.1189	0.2820	-0.3357	3.5387
-0.0050	0	0.1167	0.2954	-0.3156	3.4533
-0.0050	0	0.1135	0.2954	-0.3156	3.4332
-0.0057	0	0.1139	0.2954	-0.3156	3.4211

Table 4 Synthetic artefact Features

Mean	Median	STD	Max	Min	Entropy
9.774	-0.0001	0.2789	1.5503	-1.3143	4.4446
0.0003	-0.0002	0.2770	1.4588	-1.1800	4.4512
-0.0004	-8.4629	0.3120	1.6573	-1.3299	4.5334

The IIR filter is implemented and validated using combination of the pass and stop band filters. The cut in and cut-off frequencies are carefully tuned for EEG signal sampling rates. The transfer function of the 16 order IIR filter is given in the Equation (5). Since higher order of filter thus it is offer more delay in the system and are sensitive to change in nature of EEG data thus it is required to design OFOR filter with reduced order.

$$H_{IIR}(s) = \frac{\begin{array}{c}0.06531s^{16} + 0.8693s^{15} + 5.585\,s^{14} + 22.93\,s^{13} + 67.23\,s^{12} + 149.1s^{11} + 258.5\,s^{10} + 357.2\,s^{9} \\ +397.4s^{8} + 357.2s^{7} + 258.5\,s^{6} + 149.1s^{5} + 67.23\,s^{4} + 22.93\,s^{3} + 5.585s^{2} + 0.8693s + 0.06531\end{array}}{\begin{array}{c}s^{16} + 9.039s^{15} + 39.16s^{14} + 108.5\,s^{13} + 215.7s^{12} + 327.2\,s^{11} + 392.2s^{10} + 378.7s^{9} \\ +297.8s^{8} + 191.2s^{7} + 99.83s^{6} + 41.96s^{5} + 13.91s^{4} + 3.518s^{3} + 0.6403s^{2} + 0.075s + 0.004266\end{array}} \quad (5)$$

V. Proposed OROF Filter Design

Compared to other filters, the Optimum Reduce Order Filter (OROF) has a lower computing cost and may have a shorter latency, allowing it to better maintain the true nature of the EEG signal. Using OROF may eliminate the need for sophisticated circuitry and make it easier to implement on a chip. The OROF approach is assumed to be used for artefacts that are stationary in nature. The OROF filter optimises the transfer function using the Min-Max algorithm.

As a result, learning the best filtering coefficients is advantageous. It is critical to compare the performance of OROF with other approaches for your specific data and artefacts.

Employing pass and stop bands, two cards stage combination IIR filter is initially built in this research. The fundamental strategy is to choose the best pass band as well as stop band frequencies. For the design of the IIR filter in this study, the Butterworth filter of form II is utilised. The second degree Butterworth filter is utilised for the pass band. The 8th order filter is chosen while at the stop band. Suppose the input EEG signal looks like

$$Art = EEG_i + A_i + \eta_i \tag{6}$$

Where, $Art(t)_i$is the recorded EEG data, which also contains additive noise and the artefact Ai. Therefore, the challenge is to recreate the real EEG data while removing distortions and noise.The transfer function architecture and its frequency characteristics affect the fundamental filtering performance. Let R(s) be the input response in the s domain, and let C(s) correspond to the filtered response. Then, the definition of the kth order filters TF is as follows:

$$H(s) = \frac{C)s)}{R(s)} = \sum_{k=0}^{M} b_k s^k \Big/ \left(1 + \sum_{K=1}^{N} a_k s^k\right) \tag{7}$$

The overall IIR filter response is the cascade of pass band and stop band TF as

$$H_{IIR}(s) = H_{Pass} * H_{stop} \tag{8}$$

The Filter frequency reposes of the proposed filter design is given in the Figure 4.

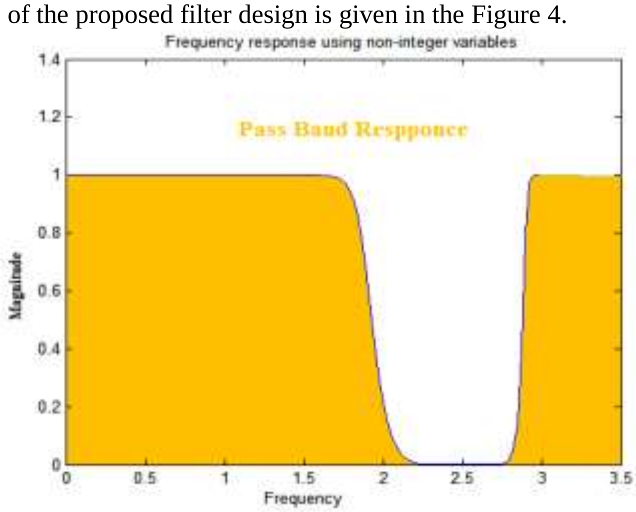


Figure 4: frequency responses in the pass band and stop band IIR filter

The overall complete IIR filter TF is given as the 16th order EQ as shown in EQ (4) The cut off frequencies of the fitter are tuned for the optimum performances.

Optimization Algorithm

Paper proposed to use the Minimax optimization for filter design. The optimization method takes the filter coefficient of IIR filter and eliminates the maximum and minimum range of coefficients to produce new filter designs. Paper proposed to optimally minimize the filter coefficients of the transfer function $H(s)_{IIR}$. In this paper it is proposed to use the unsupervised Min-Max optimization algorithm for transfer function coefficientsoptimization. The IIR filter coefficients are sequentially optimized as shown in the Flow chart in Figure 5.

$$H(s)_{opt} = \frac{0.09131\,s^4 - 0.1826\,s^2 + 0.09131}{s^4 - 0.2014s^3 + 0.993s^2 - 0.1133s + 0.3477} \tag{9}$$

The optimization based filter is optimal and better outcomes than IIR filters. The sequential algorithm for the proposed optimization based filter design is given as follows.

Algorithm 2 Classification and Filtering Algorithm

1: Load artifacts mat files data

2: Generate synthetic artifacts EEG by looping over SNR Loop over to add the selected SNR based artifacts data

3: **if** snr = NdB **then**

4: load(xartN .mat (uses N dB AWGN noise aided data)

5**: Feature Extraction** : Determine the statistical features

6: Feature set → (Mean, Medan, STD, and Entropy)

7: Apply classifiers to detect artifacts signals

8**: if** artifactsdetected **then**

9:Initialize filter

10: Begin Filter design

11: Initialize Parameters→ fs, S, time t, Noisy EEG xn

12**: IIR Filter Design**: Set the pass band and stop band frequencies

13: Pass band FL = 90/((Fs/2) ,FH = 150/((Fs/2)

14: Stop Band FL1 = 150/(Fs/2), FH1 = 230/(Fs/2)

15: Filter xn noisy EEG signal

16**: Initialize Min-Max Optimization**

17: Initialize the parameter for reduced order filter

18: Parameters→ nbits, order n, cutoff frequency wn, and w

19: Setting Filter coefficient bounds

20: Optimisation @ MinMax for x = [b1, a1];

21**: if** (any($x \leq 0$)) **then**

22: vlb = -[maxbin(ones(1, 2 ∗ n) − 1)]

23: vub =[maxbin(ones(1, 2 n))]

24: **else**

25: all positives

26: Scale Coefficients→ x =Scalefactorx

27: Optimization: Minimize the absolute MaxValues

28: Loop over to fit optimization for m = 1: iterations

29: Reduce filter order coefficients.

30: Compare frequency response and filtered outpost

End Algorithm

6. RESULTS AND EXPERIMENTAL ANLYSIS

This section presented the experimental results in two passes first the presence of EEG artifacts is classified and detected in raw data. The primary goal of this study is to first categorise the EEG artefacts data using SVM-based classifiers, assessing accuracy. Then second pass presented the results of EEG artifacts eradication by proposed OROF for artefact elimination method. MATLAB is used as simulation tool for performing experimentations. All simulations are carried out on true EEG MIT-SCALP database version v1.0.0 [28] available on Physio Net at https://physionet.org/content/chbmit/1.0.0/chb01/chb01_01.edf/ and also on synthetically generated data. Research has used the 16 channels out of 23 for classification problem with 2630 samples each. The data is considered to have muscular and eye blink artifacts with high peaks as shown in Figure 2. This study proposes designing a simple and optimal low-cost filter for artefact elimination. In order for the evaluation 15 true EEG and the synthetic EEG are considered. The MIT scalp data base of 16 artefact EEG channels is used as the input data base. Noise, eye blinking (EOG), and muscular movements (EMG) artefacts affected channels 1, 5, 9, and 13.

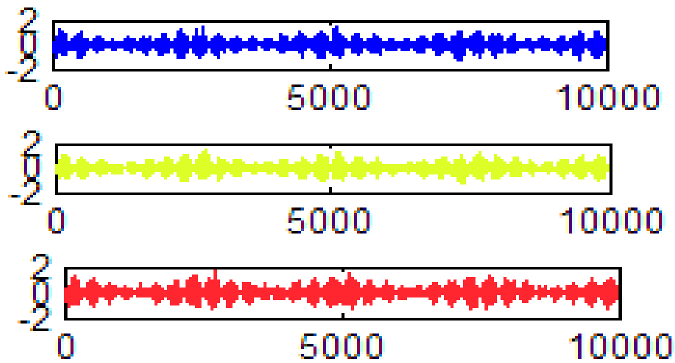


Figure 5 Synthetic artefacts data generated with [10,15 and 20 DB SNR respectively.

In Figure 6, the designed IIR filter is compared to the proposed lowest-order optimum IIR filter for channels 1 and 5. The average number of samples collected is 1500. It has been discovered that low order optimal filters produce smoother and better outcomes than IIR filters The synthetic EEG signals are generated using accumulating amplitude modulated frequencies and three synthetic channel for [[10, 15 and 20] dB SNR are shown in Figure 5. The three synthetic artifacts signals are generated with different amount of Gaussian noise aided to system as shown in Figure 5. he parameters used for the experimental setup and simulations are illustrated in the Table 5. It is clear from the Table that for the experimentation thenumber of bits to realize OROF filter is kept to 8 for optimal results.

Table 5: input simulation parameters

S. No	Parameter	Description
1	EEG database	MIT scalp of 16 EEG channels.
2	Fs	sampling frequency 500 Hz
3	S = 499	No. Of samples
4	N_{bits}	bits to realize filter = 8
5	Max_{bins}	$maxbin = 2^{nbits} - 1$
6	N8	Number of coefficients = 4
7	Wn	Cut off frequency
8	Rp	Ripple decibel = 1.5
9.	W	Window of frequency points =128

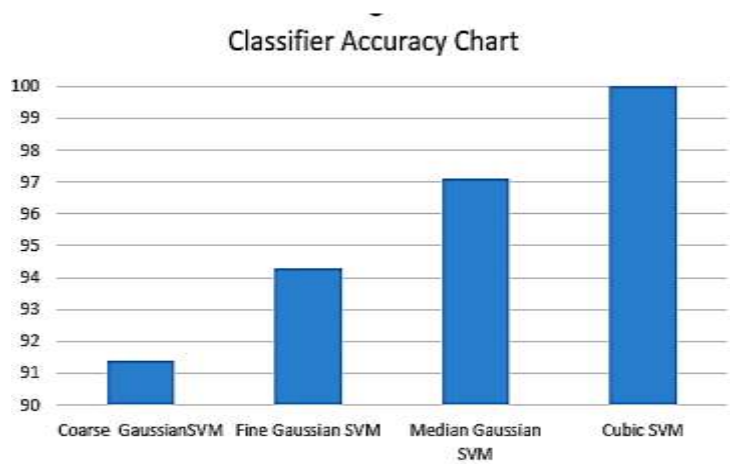


Figure: 6 Accuracy of different Classifier

Figure 6 depicts that Coarse SVM classifier has accuracy of 91.4% which is least among all the classifiers. Fine Gaussian SVM classifiers have 94.3% accuracy which is better than Coarse SVM. Median Gaussian SVM has accuracy of 97.1%. Cubic SVM has 100% accuracy. Cubic SVM and Linear SVM has 100% accuracy but cubic SVM has more prediction speed with 790 obs/sec and less Training Time 0.8015 as compare to linear SVM.

The comparison of performance with referred state of art methods is given in the Table 6. The accuracy improvement is clearly observed.

Table 6 State of art performance comparisons

Authors	Methods	Artifacts types	Accuracy
Monica Rodriguez; et al [25]	ICA-CSVM	Eye Blink, ECG, EMG	95.60%
Maliha Rashida et al. [26]	ANN	Eye Blink,	97%
Proposed	SVM	Eye Blink, and MOG	97.12
Proposed	Cubic SVM	Eye Blink, and MGO	99.99998

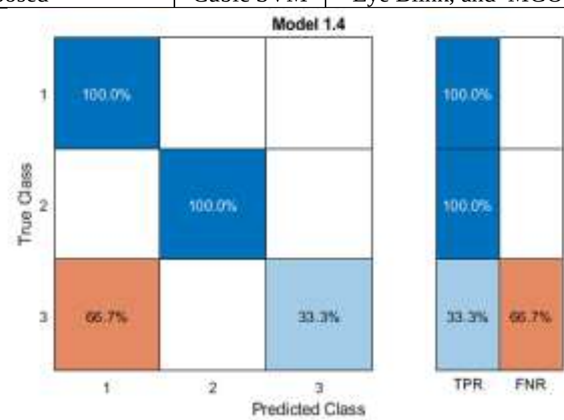


Figure: 7Confusion Matrix for evaluation of Fine Gaussian classification

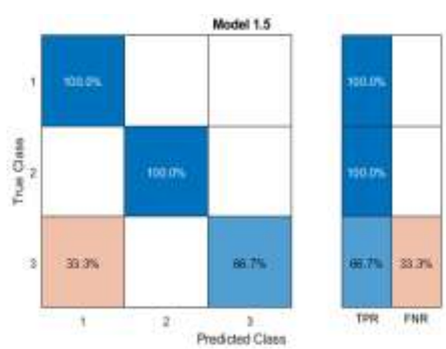


Figure: 8Confusion Matrix for evaluation ofMedian SVM classifer

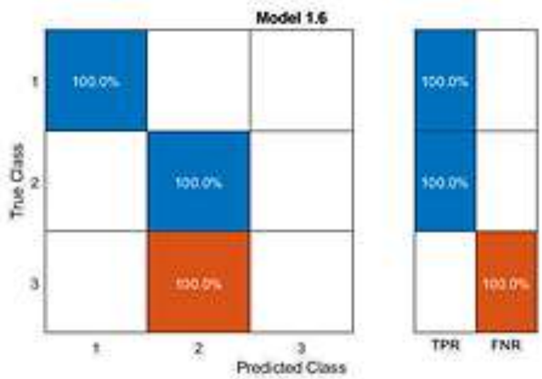


Figure: 9 Confusion Matrix for evaluation of Coarse SVM classifier

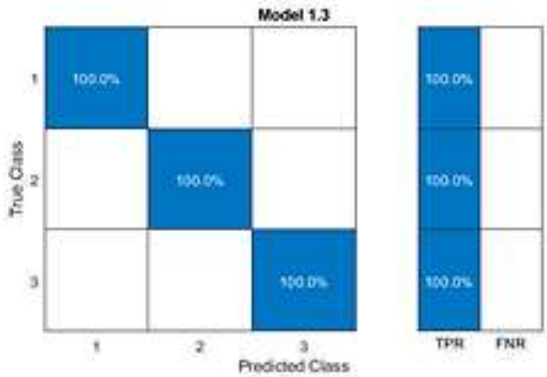


Figure 10: Confusion Matrix for evaluation ofCubic SVM classifier

Figure 7-10 represetingEEGFeature_extrection

The results of Confusion matrix for the different Classifers applied for EEG artifct dtection and classife are shown for the Fine Gaussian model in Figure 7, Median SVM in Figure 8, Course SVMin Figure 9, and the proposed Cubic SVM model in Figure 10 respectivlly. It can be observed from the Figures that the the less faulse possitive raates are achieved fro the medio=um SMV with 97.1% accuracy and the no faulse negative is achieved with 100% accuracy for usd data case with Cubic SVM models.

Data Pre-Processing

The input EEG data is aided with random Gaussian noise of zero mean for pre-processing stage.The simulation parameters are required to tune as per the desired sampling frequency of the data. For the experimentations the sampling frequency is defined as 500 Hz and corresponding to the fs the cut in and cut off frequencies of stop and pass bands are tuned as follows.

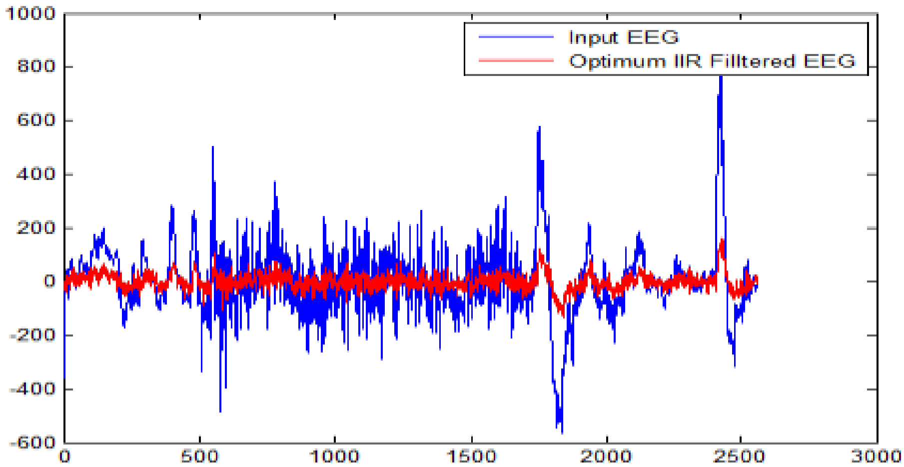
$$F_L = 90/((F_s/2));\ F_H = 190/((F\ \ /2)) \quad \text{for pass band} \tag{10}$$

$$F_{L1} = 130/((F_s/2));\ F_{H1} = 230/((F\ \ /2)) \quad \text{for stop band} \tag{11}$$

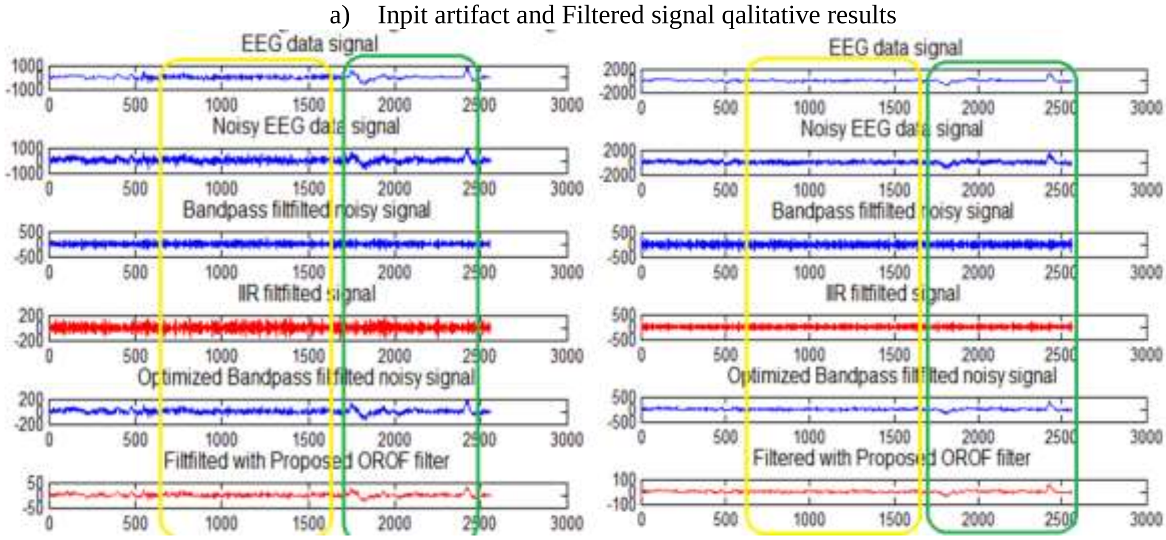
And the IIR filter is a combination of stop and pass band filter.

Qualitative Results

For the results qualitative evaluation the aditional random gaussian noise is added at the pre processing stage using AWGN function. The noisy artifacts data is sequentially filterd using bandpass, IIR filter, optimum IIR filter and the reduced order OROF filter. The comparative results are shown in the Figure 11. It can be clearly observed that, proposed method significantly maintain the nature of true EEG data and efficiently filters the higher peaks of eye blinks too. It can be claerlly observed from the Figure 11 a) and Figure 11 b) and Figure c) that the qualittativlly proposed OROF filter preserves the true nature of EEG and also capable oef elimiating the artifacts too speciallyy the high peak eye blinks. This is illustrated using the rectagular box in Figure.



a) Inpit artifact and Filtered signal qalitative results



b) Comparative resuts for Ch9 , c) Comparative resuts for Ch13

Figure 11 Qualitative comparison of the sequentual Filtering stages for with Proposed OFOF Filter

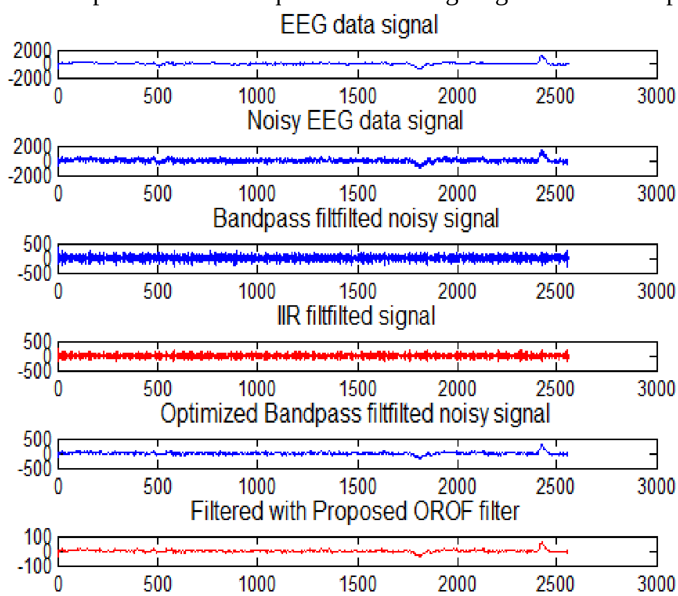


Figure 11 Qualitative comparison of the sequentual Filtering stages for with Proposed OFOF Filter

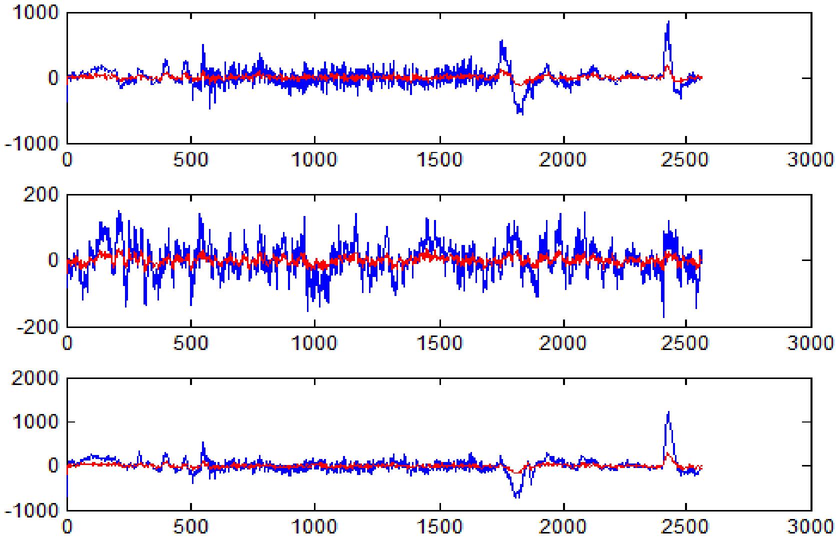


Figure 12: Results of qualitative comparison of the designed IIR filter and the lower order Optimum IIR filter for the EEG input channels CH 9 and Ch4 and Ch 13 respectively

The further study of the qualitative results comparison of the designed OROF filter with the EEG input channels CH 9 and Ch4 and Ch 13 respectively illustrated in Figure 12. It can be observed from Figure 12 tht for channel 4 which is true EEG without arttifacts the propsed method is capable of elimiating the noise significantly and for Ch9 and Ch13 considered as motion artifact channels with hugh eye blinks the proposed OROF method signig=ficantly filters the signal also maintian the natrue of signal

Quantitative Results

The Quantitativee results of the OROF based filter are illustrated in the Table 7. The mean square error (MSE and the signal to noise ration SNR are evaluated fro the state of art comparsion of EEG artfact removla methods. The comparison of parametessr for EEG signal 9 with the motion artifact and significant magnitude is presented in the Table 7. It can be concluded that OROF filter oput perfrom intems of SNR and tus preserve the features better then IIR filter with 16 order filter. It can be clearly observed from the Tablle 7 that the proposed OROF method offers significant reduction in MSE=0.093, and SNR improvement. The significance of DC gain is to simplify the requred onchip implimentation cost. If the DC gain of filter is low that means it may take less area and cost of imlimentation . Thus proosed OROF based filter ofers the optimized and reduced DC gain of the 0.3488 which has significant improvement ofer IIR Filter.

Table 7 paramertic comparsion of different flter used for the EEG artifact removal for Ch 9 of data.

Parameter	IIR Filter N=16 Jain, Nitin [30]	Notch Filter N=8 Jain, Nitin [30]	OROF Filter N=3 proposed
MSE	0.131	0.097	0.093
SNR	0.903	1.803	1.8190
DC Gain	15.3094	1.0549	0.3488

Table 8 Comparison of the ROC curve parameters for state of art methods

Parameter	EEMD-CCA-DWT Vandana Roy et al [22]	EEMD-GECCA-SWT Vandana Roy et al [22]	Proposed EEMD-CCA-DWT	With Proposed OROF
Specificity:	0.74062	0.82656	0.76133	0.96094
AROC:	0.52613	0.5132	0.52413	0.49173
Accuracy:	57.0117%	63.227%	59.5117%	71.9141%
PPV:	60.6402%	71.629%	64.2481%	92.4357%
NPV:	55.2287%	59.5218%	57.1387%	64.7709%

An quantitative evaluation the parameters of the ROC curves are compared with the method of Vandana Roy et al [22] the EEMD-GECCA-SWT. The comparison of state of art method is preseted in the Table 8. It can be clearly observed from the Table 8 that the significant accuracy improvement of 8.6871 % is offered by the proposed OROF method. This is also observed as AROC reduction in Figure 13. The ROC curve of proposed EEMD-CCA-DWT and the final Proposed OROF filter methods are compared in the Figure 13.

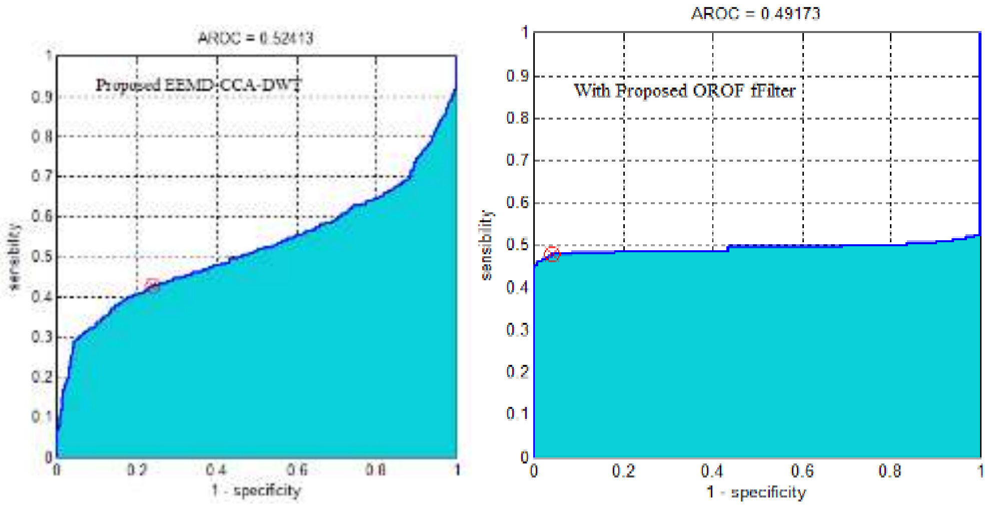


Figure 13 Results of the ROC curves for proposed OROF method

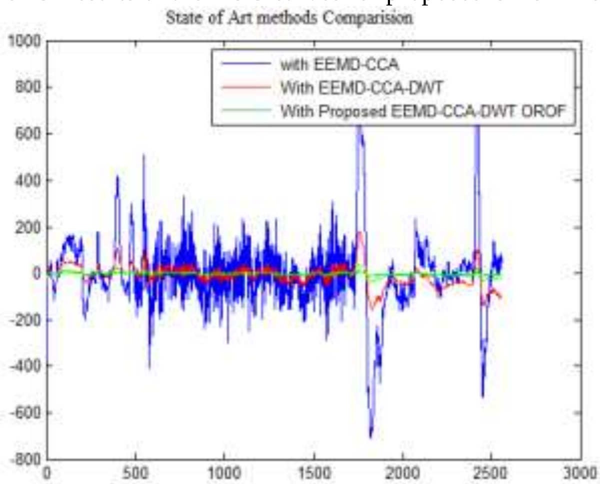


Figure 14 State of art method performance comparison for EEG ch-9 for three methods.

As another results the state of art comparison of EEMD-CCA, EEMD-CCA-DWT and proposed method with OROF filter are presented in the Figure 14. The filtered signal maintained the true nature of signal but may require additional amplifier. Over all with the qualitative and quantitative comparison of state of art methods it is clear the proposed OROF method out performs for EEG artifacts removal.

Strengths and Limitations: the major strength of proposed method is that it detect (classify) the presence of artifacts first using ML and then only apply filter on desired signals. The paper proposed using the extension of the IIR filter for EEG artifacts removal. The major limitation of the IIR filter is its higher order design the order of IIR filter in this paper is 16 thus it is sensitive to lager delay in the signal as also clearly visible in Figure 11. Thus due to higher delay the IIR filter may significantly change the nature of the EEG data. Thus this paper proposed to design OROF filter. The major advantage of proposed OROF filter is that it offers lowered order thus is less sensitive to the delay. The nature of EEG data is truly preserved. Although the impact of high amplitude Eye blinks are minimized significantly but not completely eliminate. Although, the proposed method is limited to the stationary nature of motion and it is required to study under dynamic motion artifacts.

VII. CONCLUSIONS

The purpose of this work is to use machine learning (ML) to detect and classify the presence of motion artefacts in an EEG data base. This study discusses machine learning algorithms that are commonly employed in the treatment of EEG artefacts. This article gives an overview of how various machine learning approaches have been used to handle various EEG artefacts. Two different synthetic and original data bases are used in this paper to evaluate. For the removal of artifacts proposed filter validated the IIR filter design first then min- max optimization is applied for the maintaining the true nature of the EEG signals.Based on the experimentation of EEG artifacts classification it is concluded that out of all the classifiers, the Coarse SVM classifier has the lowest accuracy at 91.4%. The accuracy of Fine Gaussian SVM classifiers is 94.3%, higher than that of Coarse SVM. The accuracy of the median Gaussian SVM is 97.1%. Cubic SVM accuracy is 100%. Both cubic

SVM and linear SVM are 100% accurate, but cubic SVM predicts more quickly than linear SVM 790 obs/sec and requires less training time 0.8015, to be exact.

The major practical implications of using OROF based filter for EEG artifacts eradication are its reduced delay and filter order which makes them suitable to design for real-time applications. The practical performance of IIR filter is compared with the proposed OROF Filter. Proposed OROF offers better de noising since maintain the nature of EEG post filtering. And that to with fewer arithmetic operations this makes it easy to implement on chip.Additionally, it is concluded that the Minmax optimization is best fit for the reduced order filter design.

Future Scopes

In future large EEG artifacts data set can be used for testing the deep learning CNN problem for EEG artifacts classification. The dynamic motions artifacts may be considered for the study in the near future. As it is observed that still slight impact of eye blink remain after filtering which can be eliminated using the neural network based learning in near future.The performance of the other optimization methods can be tested in future and compared with performance of min max optimization for EEG filter design.

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