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EEG SIGNAL DE-NOISING BASED ON THE FEJER-KOROVKIN WAVELET FILTER

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ABSTRACT

The procedure used to measure electrical activity in the brain is an electroencephalogram (EEG). Via electrical impulses, brain cells interact with each other. The EEG can be used to help identify possible issues associated with this operation. Processing of the EEG signals in a noisy environment is a major problem in biomedical signal processing. Especially, Electroencephalography (EEG) acquisition and processing is crucial and difficult concept to step forward. Many neurogenic sounds and non-neurogenic interferences follow the actual EEG signal. The calculated brain response is an event-related potential (ERP) that is the direct product of a sensory, cognitive, or engine event which is low. The challenging task is that rebuilding of ERP signal from contaminated EEG signal. In this article, we propose an efficient approach that combines the decomposition of the empirical mode of the ensemble (EEMD) and fejer- korovkin filtering. The proposed algorithm began with the decomposition of noisy signals Using EEMD Using the comparison between the decomposed IMFs and the original signal several intrinsic mode function (IMF) components are obtained. Then by using fejer-korovkin filtering IMF components are de- noised. From these de-noised IMFs required ERP signal is reassembled. The suggested algorithm is tested using real EEG signals and compared with existing methods of Hybrid Mother Wavelet Using DWT and EMD-IIT with the Performance parameters of Standard deviation, Peak signal to noise ratio (PSNR), Pearson correlation coefficient (PCC) and Root mean square error (RMSE).

Keywords: *Electroencephalography, Event-Related Potential, Ensemble Empirical Mode Decomposition, Intrinsic Mode Functions, Fejer-Korovkin.*

1. INTRODUCTION

Electroencephalography (EEG) is one of the main instruments for brain activity monitoring. While it cannot match the accuracy and resolution of the brain activity location in many other brain imaging techniques, its major benefits are cheap prices, relative simplicity of use and good time resolution. This is why EEG is extensively utilized in many fields of clinical practice and research. The extremely tiny signal-to-noise ratio of the brain signal we are attempting to detect is one of the major difficulties when utilizing EEG, combined with a broad range of noise sources. Artifacts understand all the signals that do not originate from the brain in the EEG record. The most frequent artifacts in the EEG data occur owing to many reasons, such as poor locations for electrodes, no clean hairy leather, impedance of electrodes, etc. Foundation of physiological artifacts, i.e. bioelectric signals from other areas of the body (heart and muscular activity, blinding of the eye and eye) which are recorded in the EEG Biological records, particularly EEG data, frequently get infected with the interference of the frequency line 50 or 60 Hz by cables, light fluorescents and other electrodes and acquisition system equipment. Fluorescent light ignition typically produces artificial spikes in the EEG. They are spread over multiple EEG channels and may be wrong in analyzing the data.
Poor electrodes contact and patient transpiration

beneath the electrodes may influence electrode impedance causing low-frequency anomalies. Baseline drift may

occasionally be induced by temperature and instrumental bias changes as well as amplification. This kind of noise is unwanted and must be eliminated for effective analysis and presentation of the EEG data before further signal processing. Surface electrodes which are not in close touch with the scalp are recorded. It results in a baseline walk of low frequency. EEG signals are frequently polluted by interference of the 50 or 60 Hz line resulting in interference with the power line.The EEG signals are very low in amplitude. These typically vary in amplitude from 0.5 µV to 100 µV when peak to peak recorded. The EEG signal spans from 0,1 Hz to 100 Hz with interest data ranging from 0,4 Hz to 30 Hz. EEG may be classified in four major frequency bands, based on frequency level: delta (0.4-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). EEG is a powerful random non-stationary signal and is very complicated in nature. These are prone to noise contamination because of this. Noise may be characterized by overlaying the activity from other sources not of interest to the observer as a change of the original signal. The noise in the brain signal may be an electrode noise added or produced by the body itself during recording. The EEG signal noise is termed artifacts. These artifacts must be eliminated, since they make it difficult to analyze and interpret the EEG data and may cause misdiagnosis. Various kinds of artifacts that may contaminate EEG data include electrode noise, baseline motion, EMG disorder, power line artifacts (eye moving and blinks) and even ECG disruption

This An EEG is a test that detects abnormalities in your brain waves or in your brain's electrical activity. Electrodes made of tiny metal discs with thin wires are pasted onto your scalp during the operation. Tiny electric charges arising from the activation of your brain cells are identified by the electrodes. The payments are extended and show on a computer screen as a graph, or as a recording that can be printed out on paper. The reading is then interpreted by your healthcare provider. Over the last decades, EEG has become a significant diagnostic tool for controlling and treating the human brain's dysfunctions and different neurological conditions under growing medical demand. Two origins of objects mainly influence Signal to the EEG. These are extra-physiologic and physiological. Muscle, eye and heart functions are physiological sources, whereas line interference and electrode noise are included later. Many researchers have developed quantitative methods for the study of EEGs. Sometimes, spurious signals from other unwanted sources contaminate the registered EEG signal. This form of contamination is called an artefact in medical terminology. One of the most attractive problems in biomedical signal processing is high resolution EEG extraction from contaminated videos. In order to solve this problem, there have been plans for an increasing number of denoising techniques. A significant number of artifacts may be prevented by careful planning and preparation of experiments and recording sessions. Several techniques may also be used in rejecting noisy data, removing artifact signal and improving data SNR. Simple averaging of the signal is a very fundamental technique. The foundation of signal average is that the signal noise is random, while the signal of interest is steady and stationary. The drawback of the signal average is that it is not possible to utilize it when the signal of interest itself is changeable, for example the EEG signal. Another method is simply to discard polluted EEG epochs. However, this technique requires examining the data manually, detecting polluted parts and discarding such segments afterwards. This procedure is tedious and leads to an unacceptable loss of data when contamination is significant. The use of EEG in medicine has a significant effect on human brain research. As mentioned previously, the EEG signal is polluted by different artifact kinds. There are various ways to denote EEG with benefits and limits. These techniques are used in a specific domain and for artifacts. For example, for ocular artifacts, the regression technique works better than any other artifact. This becomes an important restriction if the signal is polluted with additional artifacts. In addition, techniques based on regression rely on one or more EOG channels. Because of this occasionally regression-based artifact, the neuronal potential in this EOG channel is eliminated.

The PCA technique exceeds the methods based on regression. When compared to regression-based techniques, PCA more successfully eliminates the artifact that contains components. But PCA techniques cannot eliminate artifacts entirely if they have similar amplitudes PCA retrieves unrelated signals using second-order statistics and is not able to function effectively with higher-order statistics. In order to address this, ICA may be employed on the basis of the blind source separation. The ICA approach operates on the premise that independent

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components are separated. This technique is usually used to isolate and remove a variety of EEG artifacts. ICA was referred to as the PCA technique extension. The ICA technique offers a broad variety of EEG artifact reduction applications. It is one of the best-known techniques. The drawbacks of this approach include computational complexity, the human selection of separate artifact components. Alternatively, certain techniques have to be used instead of rejection to rectify polluted signal epochs. The primary reason for all denoising is the reduction of the artifact level without compromising the signal information content The level of direct decontamination Impacts on the quality of the feature extracted from the EEG signal that They are used for neurological disease diagnosis.

Several approaches have been suggested for Neurological signal denoising. Among the wavelet-based ones Denoising outperforms compared with others. As For extra-physiological artefacts, spectral isolation, Approximate filtering techniques can eliminate them. You can remove line noise with a notch filter. Noise in white Spectral power density (PSD), overlap of pupils, muscle artefacts, With EEG signal PSD, clean cleaning can be difficult to distinguish EEG signal from polluted noise EEG signal with a normal EEG signal Filters for Band Pass

This paper is organized as follows. in the next section, we present literature survey. The related theoretical basis is presented in section 3. The proposed method is presented in section 4. The simulation results are presented in section 5 followed by conclusions in section 6.

2. LITERATURE SURVEY

Research is going on the elimination of artifacts from EEG data. In that an empirical mode decomposition (EMD) technique developed by B. S. Raghavendra, D. Narayana Dutt [1] may be used to rectify errors in EEG recordings by alleviating artifacts caused by eye blink. The blinks of the eye constitute a signal of some kind and EMD detrending is used. The duration of the period should be carefully considered, since it is required to deconstruct it into component waves. The research approach suggested by Arjon Turnip and Jasman Pardede[2] produces a signal matching the EEG signal with amplitude and frequency ranges. In this study, Wavelet uses Daubechies db1 signal denoising level 3 of SWT denoising 1-D to indicate the necessary examination, utilising various forms of Daubechies to determine the denoising signal results. It is useful in some circumstances, but it should be avoided in others.

For S.O. Regan, S. Faul, W. Marnane k[3] suggested categorising these artefacts of head- movement as a different class and utilising Help Vector Machines to identify their appearance automatically. The usage of gyroscope signals is discussed in the detection of objects of head-movement. EEG and gyroscope function fusion features are carried out and a Support Vector Classifier is added. This method need to focus on accuracy. Using an adaptive threshold algorithm, noise artefacts have been eliminated by V. Krishnaveni et [4]al. In order to preserve signal originality and high and low frequency values, the Adaptive Threshold on signal data shows the strongest performance. They used power spectral density plots and frequency correlation plots to get an estimate of the disturbance correlated with relative dominance. In order to locate the OA areas,calculate the edges, and find the item's rising and falling edges, this algorithm is long. Furthermore, performance indices dependent on the power density continuum were just checked to maintain a blind eye on them. This methodology has some drawback in that it causes the loss of the underlying brain signal, and more effort is required to keep the background EEG information intact.

From SNR, R used the de-noise translation-invariant EEG. From Coifman et al. [5]. The mechanism operates by extending the rotating principle of the loop to wavelets. Cycle Spinning's formal mathematics and wavelets allow it easier to identify and thereby eliminate objects. This approach may be integrated into a brain-computer interface in a manner that uses an appropriate control methodology They have attempted to identify and correctly describe ocular EEG objects in[6]. As the base function is decomposed, the method is based on the Symlet (sym3) Stationary Wavelet Transform and the authors suggested that the EEG filtered signal had no ocular artefacts. In addition, the soft threshold used in the process is not often recommended for a wide number of artefacts found in the EEG.Need more focus onaccuracy. K.P. Indiradevi, E. Elias, P.S. Sathidevi, S. Dinesh Nayak, K. Radhakrishnan [7] suggest a technique focused on a multi-resolution, multi-level analysis to automatically classify epileptiform behaviour in the 18-channel human electroencephalogram (EEG). Using differential wavelet transformation, the signal on each channel is decomposed into six sub-bands. An adaptive threshold is added on sub-bands 4 and 5. From the raw info, the spike component of the EEG signal is then obtained, and the signal energy is calculated to find the exact location of the epileptic focal point. The key points of this approach are the identification of the suitable wavelet for the decomposition of EEG signals, the identification of the required resolution stage and the measurement of the suitable dynamic threshold.

Gao, C. Zheng, P. Wang[8] suggest a novel and stable strategy to remove EMG objects inreal-time from EEG signals. Second, for the isolation of EMG objects from EEG signals, the canonical correlation analysis (CCA) approach is used on simulated EEG data polluted by EMG and electrooculography (EOG) artefacts. Based on relative low autocorrelation, the components responsible for EMG objects are distinct from thoseresponsible for brain function. We show that the CCA approach is more appropriate than independent component analysis (ICA) methods for the reconstruction of EMG-free EEG results. Furthermore, a connection threshold is calculated using an impartial method by applying CCA to evaluate a number of EEG data polluted by EMG objects. CCA should, however, be used to automatically delete EMG objects. Finally, an illustration is provided to verify that not only the underlying brain function patterns, but the EOG artefacts are retained with no distortion after EMG artefacts have been effectively eliminated from the EEG data polluted by EMG and EOG simultaneously.P.A. A. Bizopoulos, T.Al-Ani, D.G. Tsalikakis, A.T. Tzallas, D.I. Fotiadis, D.D. Koutsouris[9] suggest a system of identification and elimination from EEG of EOG Flickering Objects (BAs). Centered on a preset BA prototype library, the Normalized Correlation Coefficient (NCC) was used for the recognition of BA. Ensemble Empirical Mode Decomposition (EEMD) was implemented in the contaminated region, and a statistical algorithm was calculated which corresponded to the BA intrinsic mode functions (IMFs). For model EEG signals that were tainted with artificially generated EOG BAs, the suggested technique was used, improving the EEG Contaminated Region (CR) Signal-to-Error Ratio(SER) by an average of 35dB.

D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, A. Biraben, F. Wendling, L. Senhadji, I. Merlet [10] concentrate on the basic context of the muscle artifact's epileptic contamination signs (interictal spikes), as EEG is a crucial diagnostic instrument for this disease. Comparison of the ability to derive muscle artefacts from EEG signals by means of two blind root separation stochastic techniques, namely autonomous component analysis (ICA) [11-15] and canonical interaction analysis (CCA), and two deterministic approaches, namely decomposition of the empirical mode (EMD) and wavelet transformation (WT). To quantitatively compare the performance of these four algorithms, the epileptic spike-like EEG signals were simulated from two distinct source configurations and artificially contaminated with different quantities ofreal EEG-recorded myogenic activity. The effectiveness of CCA, ICA, EMD, and WT[16-25] was calculated in order to repair the muscular artefact, both by calculating the uniform mean-squared error between denoted and original signals and by comparing the results of source localization obtained before and after correction of the artefact from artifact-free and noisy signals. From the literature it is observed that need more concentration on noise removal on EEG signals. For this we propose an efficient approach method for noise removal. The main objective the proposed method is that combines the decomposition of the empirical mode of the ensemble (EEMD) and fejer- korovkin filtering for decomposition of noisy signals Using EEMD. Using the comparison between the decomposed IMFs and the original signal several intrinsic mode function (IMF) components are obtained. Then by using fejer-korovkin filtering IMF components are de-noised. From these de-noised IMFs required ERP signal is reassembled. By this process we successfully remove the noises from the EEG signals.

3.RELATED THEORETICAL BASIS

3.1 Hybrid Mother Wavelet Using DWT

In DWT, data is mapped to the wavelet domain from the time or frequency domain, resulting in a vector of identical dimensions. The signal is divided into low-frequency components named as the Approximation Coefficients (CA) and

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high- frequency components named as the Detailed Coefficients (CD) at every stage. In this technique for DWT decomposition Biorthogonal, Daubechies and Symlets Mother Wavelets are used. Peak Signal to Noise Ratio (PSNR), Root mean square error parameters are used here for performance comparison purpose.

3.2 EMD-IIT

Iterative EMD Interval Thresholding (EMD-IIT) is opted to correct the artifacts in acquired EEG signal. In this method first step is the decompose the raw EEG signal into IMFs by EMD and next Exclude the first IMF and construct a signal using the last K -1IMF s, Alter the first IMF sample locations arbitrarily, create a new version of the raw EEG signal, Apply EMD. Peak Signal to Noise Ratio (PSNR), Root mean square error parameters are used here for performance comparison purpose.

3.3 DT-CWT with KNN

Dual tree complex wavelet transform (DTCWT) is a recent enhancement to the discrete wavelet transform (DWT) that has additional properties in two and higher dimensions, including almost invariant and directionally selective shift. After decomposition, a KNN is applied for classification purpose. The K-Nearest Neighbors algorithm (KNN) is a method of classification used by non- parametric learning algorithms. The Nearest neighbor rule achieves consistently high performance among the various methods of supervised statistical pattern recognition, without a priori assumptions on the distributions from which the training examples are derived. Standard deviation for different bands is calculated from mean of calibrated signals for performance evaluation purpose.

3.4 Neural Networks

Using the different features from different rhythms in time and frequency domain, four neural networks are developed for the classification approach. Neural nets are a means of doing machine learning, in which a computer learns to perform some tasks by analyzing training examples. Quantitative EEG analysis demonstrates high reliability in studying the effects of drugs on the brain. Earlier preclinical pharma co-EEG studies showed that different types of drugs can be classified according to their mechanism of action on neural activity. Here, we propose a convolutional neural network for EEG- mediated DTI prediction. This new approach can explain the mechanisms underlying complicated drug actions, as it allows the identification of similarities in the mechanisms of action and effects of psychotropic drugs. Standard deviation for different EEG signals is calculated from mean of calibrated signals for performance evaluation purpose.

4. PROPOSED EEMD WITH FEJER-KOROVKIN FILTER ARCHITECTURE

The proposed architecture block diagram is as shown in above figure1. First block involves real time data acquisition of Centre for Research and Technology Hellas using MATLAB signal processing tool. Further, all channels combined by sequentially selecting among themselves based on sensors positions in channel selection block. Here, pre-processing block is designed to represent frequency domain EEG into time domain representation. Succeeding blocks involve EEG decomposition, noise removing using EEMD and FEJER-KOROVKIN respectively.

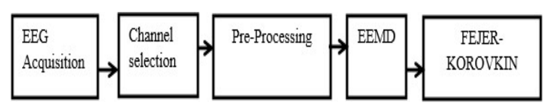

Figure 1: Proposed Architecture

4.1 EEMD (Ensemble Empirical ModeDecomposition):

In order to solve the mode mixing phenomenon in EMD, the new model called the Ensemble Empirical Mode Decomposition (EEMD) applied white noise to the original signal according to the white noise power spectral density uniform distribution function so that the signal was continuous on different scales. In the processing of non-stationary signals, EEMD reserves EMD advantage; moreover, it can effectively overcome the mode mixing issue of EMD. EMD (Empirical Mode Decomposition) is an adaptive method of time-space analysis suitable for non-stationary and non-linear processing series. For analyzing natural signals, which are most often non-linear and non-stationary, the approach is useful.

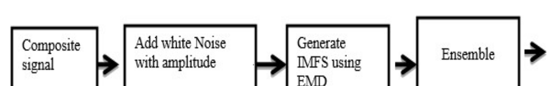

Figure 2: EEMD block diagram

Above shown figure2 represents EEMD architecture. It involves addition of white noise

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to original EEG signal, Generation of intrinsic mode functions using EMD algorithm, combining them using simple threshold-based process.

The sifting algorithm is called the process of extracting IMFs through EMD, which is an iterativemethod defined in detail as follows:

$$S(x) = rn(x) + ci + ci(x) \quad (1)$$

Where the residual of the n IMFs After extraction isrn (x), IMF is ci(x). The word IMF is the mono component feature or one instantaneous frequency oscillatory mode, which must meet tworequirements:

(1) They have the zero-crossings & identical number of extremes

(2) The average value is equal to zero for the envelopes of upper and lower.

iii. By relating the upper and lower envelopes calculate the average values (blue).

iv. For creation of the first IMF1component intrinsic mode feature subtract the mean from the original signal.

v. Calculate the first residual portion by deducting IMF1 from the original signal. It should be viewed as new data to find out the next IMFF mentioned above.

vi. Do the same process until a monotonic function becomes the final residual component and no more IMFs can be removed.

Rebuilt the two superimposed sinus waves in the initial signal by using EMD is shown in Figure 4. The original data vector is fragmented into high& low frequency components. All these are summed together to get the perfect original signal.

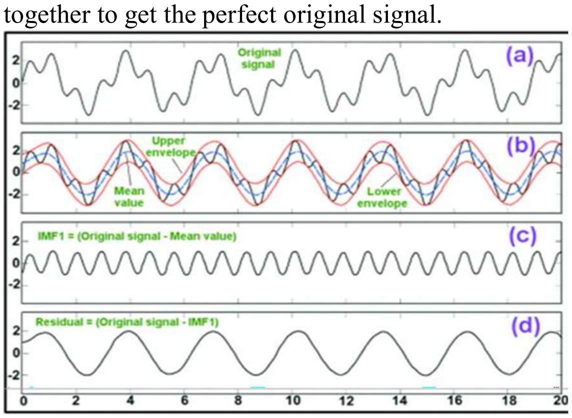

Figure 4: EMD Two-wave signal decomposition, (a) two-wave sum, (b) the lower and upper envelopes (red) and their mean (blue), (c) the first IMF, and (d) the first residual envelopes (Red)

To obtain a portion that satisfies the conditions mentioned above, a sifting method iteratively extracts IMFs from the signal.

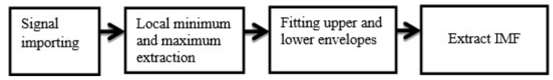

Figure 3: EMD Architecture

Figure4 illustrated the EMD technique. The procedure for converting to IMF of the signal is given below:

i. Recognize the maximum and minimum peaks of the initial signal.

ii. Construction of the lower and the upper envelopes is cubic spline form method.

4.2 De-Noising of EEG Signal using FEJER-KOROVKIN

In this phase, the stationary wavelet transforms (SWT) based on Fejer- Korovkin wavelet (FK) filter is used to extract a high frequency (HF) component of intra-annual periodicity and a low frequency (LF) component of inter-annual periodicity is shown in below figure 5.

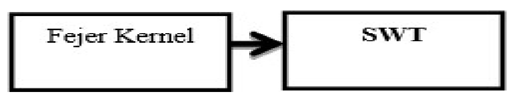

Figure 5: FEJER-KOROVKIN

We use those convolution kernels to create explicit examples of quadrature filter families with optimal frequency resolution (optimal in the sense of order).The lower bound applies to all 2N length filters to get the perfect upper bound EEG. The theorem of Fejer-Riesz thus decreases the issue of finding non- negative trigonometric polynomials. However, a

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different definition of level is applied to Fejer-Korovkin wavelet. The level in this type of family wavelet denotes the number of filter coefficients. All levels are designated as positive integers. The minimum level is 1, whereas the maximum number of decompositions of each wavelet is floor (log_2(N)). N is the number of samples in a data.

Unlike Fourier transformation in signal processing, Wavelet transformation provides high frequency resolution at low frequencies and high time resolution at high frequencies, as opposed to STFT providing similarly spaced time-frequency localization. This concept chooses Fejer-Korovkin transformation to filter acquired EEG signal for improved amplitude and frequency envelopes. Compared to Fourier transform (FT), Wavelet transform (WT) is very effective since it can describe any sort of signals simultaneously in both the time and frequency domain when describing a signal from the time domain to the frequency domain for FT. The Fejer kernel Fn is defined by

$$F_n(\xi) = \sum_{j=-n}^{n} \left(1 - \frac{|j|}{n+1}\right) e^{ij\xi} = \frac{1}{n+1} \left\{ \frac{\sin \frac{n+1}{2} \xi}{\sin \xi/2} \right\}^2 \quad (2)$$

5. SIMULATION RESULTS AND COMPARATIVE ANALYSIS

axis represents time period and y axis represents amplitude of the EEG waves.

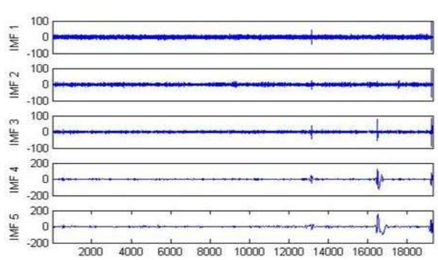

Figure 7: IMFs of EEMD

Above Figure7 is the snap wave form and this snap wave forms are the outputs of the EEMD procedure. Total five intrinsic mode functions are in frequency decreasing order, yields from Raw EEG data. Labels in above figure are frequencies, amplitudes in both x-axis and y-axis respectively.

5.1 Data Set taken

EEG signals from 11 subjects performing an experimental protocol based on SSVEP with 14 channels recorded. For visual stimulation, five separate frequencies (6.66, 7.50, 8.57, 10.00 and
12.00 Hz) were used and the Emotive EPOC was used to capture the signals using 14 wireless channels. Eleven volunteers participated in this study. They all were present employees of Centre for Research and Technology Hellas (CERTH).

5.2 Simulation Results

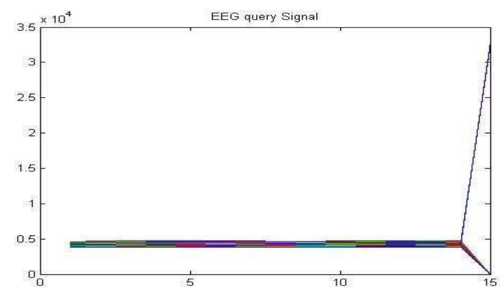

Figure 6: Input EEG signal

Above figure 6 represents original mixed EEG signal in frequency domain, taken from Centre for Research and Technology Hellas database-III.X

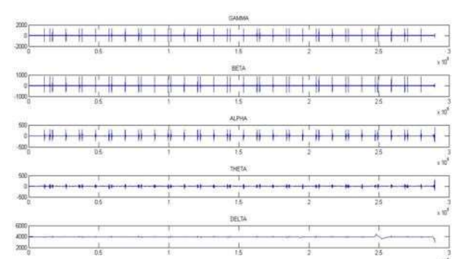

Figure 8: De-noise signals

Above snaps represents final classified EEG de-noised signals using FEJER-KOROVKIN filter technique. Above plot shows time at x direction, amplitude at y-direction.

5.3 Comparative analysis

The Proposed EEMD with FEJER-KOROVKIN filter is compared to existed methods of Hybrid Mother Wavelet Using DWT [7] and EMD-IIT [9] with the Performance parameters of Standard deviation, Peak signal to noise ratio (PSNR) and Root mean square error (RMSE).

5.3.1 Standard deviation

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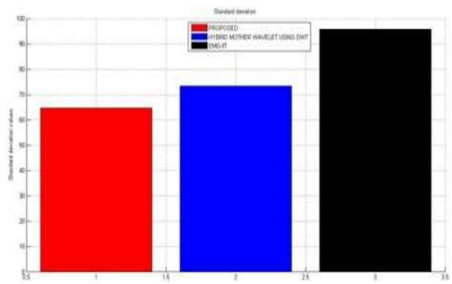
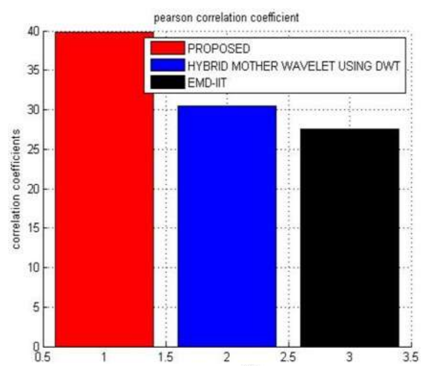


Figure 9: Proposed method Comparison in Standarddeviation

From the above graph the standard deviation value of the proposed EEMD with FEJER-KOROVKIN filter is 64.7113, Hybrid Mother Wavelet Using DWT standard deviation value is 73.21and EMD- IIT standard deviation value is 95.74. The proposed method deviates only 64.7113 percentages with original input EEG compared with existed methods

5.3.2 Peak Signal to Noise Ratio (PSNR)



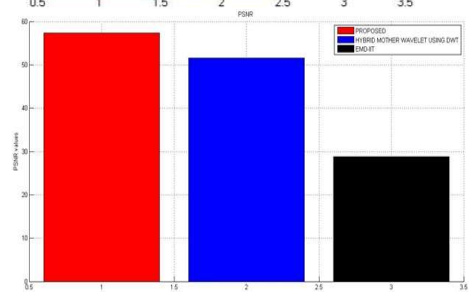


Figure 10: Proposed method Comparison in PSNR

From the above graph the Peak Signal to Noise Ratio value of the proposed EEMD with FEJER- KOROVKIN filter is 57.3802, Hybrid Mother Wavelet Using DWT Peak Signal to Noise Ratio value is 51.59 and EMD-IIT Peak Signal to Noise Ratio value is 28.8. The proposed method Peak Signal to Noise Ratio value is maximum of 57.3802 with original input EEG compared with existed methods

5.3.3 Root Mean Square Error (RMSE)

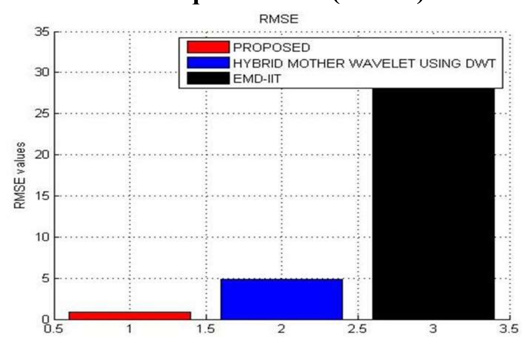


Figure 11: Proposed method Comparison in RMSE

From the above graph the Root Mean Square Error value of the proposed EEMD with FEJER- KOROVKIN filter is 0.9140, Hybrid Mother Wavelet Using Root Mean Square Error value is
4.90 and EMD-IIT Root Mean Square Error value is 30.88. The proposed method Root Mean Square
Error value is minimum of0.9140 with original input EEG compared with existed methods.

5.3.4 Pearson Correlation Coefficient

Figure 12: Proposed method Comparison in PCC

As shown in above plot, proposed method PCC is 40; which represents more accurate yields when compare with existing methods. Hybrid Mother Wavelet using DWT produces 31 and EMD-IIT gives 27.

5.4 Comparison Table

Below table distinguish standard deviation values between existing and proposed methods. Our proposed method deviates only 35.288 percentages with original input EEG. Also compares the Peak signal to noise ratio and Root mean square error values of existing and proposed methods. Proposed method shows efficient results in Performance matrices in regards with among all PSNR, RMSE, PCC and standard deviation.

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Table1: Comparison of Standard deviation, PSNR and RMSE

Methods	STD	PSNR	RMSE	PCC
Proposed EEMD with FEJER-KOROVKIN filter	64.71	57.38	0.91	40
Hybrid Mother Wavelet Using DWT	73.21	51.59	4.90	31
EMD-IIT	95.74	28.8	30.88	27

6.CONCLUSION

In this article, we propose an effective method toavoid the noises in the EEG signals. In that process we combine the decomposition of the ensemble empirical mode (EEMD) and the filtering of fejer-korovkin. The proposed algorithm started with noisy signal decomposition using EEMD.in the decomposition of noisy signals using EEMD we compare the decomposed IMFs and the original signals to obtain the several intrinsic mode function (IMF) components. Denoising is using fejer- korovkin filtering. Finally, from these de-noised IMFs, the desired ERP signal is reconstructed. The proposed method is successfully removed the artefacts in EEG raw signal. Analysis of real EEG data from the data collection iii in centre for research and technology HELLAS (CERTH). The experiment shows that the proposed method of de- noising has greater accuracy compared to the existing hybrid mother wavelet using dwt and END-IIT de-noising techniques. From the results it shows that proposed method generates minimum standard deviation value of 64.7113, maximum peak signal to noise ratio value of 57.3802 Pearson correlation coefficient is 40 and minimum root mean square error value is of 0. 9140. These findings shows the proposed EEG signal de-noisingprocess will work with quantitatively, the efficacy and practicability. The positive results obtained in this work demonstrate that this hybrid approach results in a major increase in the removal of objects.

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