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Efficient de-noising technique for electroencephalogram signal processing

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ABSTRACT

An electroencephalogram (EEG) is a recording of various frequencies of electrical activity in the brain. EEG signal is very useful for diagnosis of various brain related diseases at early stage to prevent severe issues which may lead to loss of life. The raw EEG signal captured through the leads contain different type of noises which is not susceptible for diagnosis. In this paper, an efficient algorithm is proposed to process the raw EEG signal to combat the noise. To obtain noiseless EEG data, the likelihood test ratio is applied to interference computation block. The likelihood ratio test converts EEG data signal into segmented data with nearly constant noise characteristics. This will aid in detecting the noise present in a tiny segment which ensures proper signal denoising. The processed signal is compared with the database of noiseless EEG of the same person using principal component analysis (PCA) classifier. The proposed algorithm is 99.01% efficient to identify and combat noise in the EEG signal.

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1. INTRODUCTION

Recently after stroke, epilepsy is the second most severe neurological disorder viewed in human. Nearly 50 million people, or around 1% of the global population, are affected. One out of every ten people will experience a seizure at some point in their life, but the majority of them will not have epilepsy because the root cause of the convulsions is not related to the brain. At any point in their life span, one in every 50 people will develop epilepsy. Everyday, about 75 new cases of epilepsy are discovered. Flashing lights can affect just around 3-5% of epilepsy sufferers (photosensitive epilepsy). It’s a common myth that all epileptics are affected by rapid visual stimuli; however, this is not the case. This disease affects just about two out of every 10,000 people in the general population [1]. It is estimated that 1.5 to 2 million people in the United States alone suffer from active epilepsy at this time [2]. Many people with epilepsy today have lives that have been significantly changed by medical science. Indeed, many people with epilepsy have gone on to have good careers or become very well-known. Alfred Nobel, the inventor of dynamite and the founder of the Nobel Prize, suffered from epilepsy. Hans Berger, a German psychiatrist, invented the electroencephalogram (EEG) test in 1924 and demonstrated its functional and diagnostic utility. Sheng Li and Hanxin Feng had proposed EEG signal classification method based on feature priority analysis and convolutional neural network (CNN). The importance of detection electrodes is sorted by random forest algorithm, and the higher priority electrodes are screened out. Hence, they concluded that proposed method is effectively realizes feature extraction and classification of EEG signals [3]. Special sensors are strategically positioned [4] around the head and linked to a computer that tracks electrical impulses on a screen or on paper. Trained neurologists have examined the various frequencies in the EEG and identify patterns that provide details about the epileptic condition [5]. Alpha (7.5-13) Hz, beta (13-30) Hz, delta (0-3.5) Hz, and theta (3.5-7.5) Hz are the four basic brain waves commonly used to characterize raw EEG signals. These bands reflect the brain's most active operation [6].

In this paper, effective noise minimization technique for real time EEG signal is proposed which is based on detecting the interferences using novel mathematical models. The interference calculation is used with likelihood test ratio detector to obtain the noise data small segmented EEG signal where noise variations remain constant. This helps in proper filtering supported by our obtained results through principal component analysis (PCA) classifier.

2. LITERATURE SURVEY

All Ictal states apply to the various stages of an epileptic seizure. In the broadest context, these states reflect the various phases of an epileptic seizure [7]. The following are the various stages of epilepsy. i) Interictal: a natural resting state without seizure disorder. ii) Preictal: a period of time preceding a seizure that does not refer to the brain's normal state [8]. ii) Ictal state of seizure termination: The duration of the seizure's activation phase [9]. iii) Postictal condition: The early strategies in the field were aimed at compressing data and, more importantly, PA-1-highlighting occurrences for subsequent evaluation by a neurologist. These semiautomated detection methods can expedite the review process, but also postpone intervention. Several papers [10]–[13] describe commonly used compression methods as compressed spectral array, density spectral array, spectrogram, and non-linear energy operator. The most extensively used strategy in the past was to evaluate the signal's frequency content using a variation of the fourier transform. There is a significant trade-off between time and frequency resolutions when employing this strategy. The time resolution is good when evaluating the spectrum in short windows, but the frequency resolution is inadequate. The frequency resolution improves with a longer window, but the information becomes less concentrated in time. The wavelet transform is a more contemporary method. Wavelet decomposition allows you to depict the qualities of a signal on different scales. This way, both the time and the money are saved. Expert systems, decision trees, clustering algorithms, self-organizing maps, and a variety of artificial neural network topologies are examples of machine-learning methods that have been used in this subject. While advanced machine learning approaches can improve the algorithm's performance, they can also be difficult to interpret for the end-user. The easier it is for specialists to learn to trust and understand a system, the simpler it is. Here are some of the most extensively utilised systems. Since the 1970s, Gotman has worked in the field of EEG monitoring and seizure detection. Stellate is the company that distributes his algorithms. The first algorithms examined the properties of EEG waves after decomposing them into constituent waves [14], [15]. A new module [16] was introduced to rule out typical reasons of false positive detections. Seizure detection software is also available from persyst development corporation. Reveal Rosetta, the algorithm, is also expected to have ICU applications. The algorithm's structure has mostly remained unknown. In [17] causal network elicitation technique (CNET) is a non-commercially distributed seizure detection programme. It describes cepstral characteristics [18].

3. PROPOSED MODEL

The flow diagram of proposed method is shown in the Figure 1 which consists of proposed de-noising method, PCA classifier and comparator blocks. The different types of noises are added by the noise generator algorithm present in matrix laboratory (MATLAB) tool. The interference calculation block is used to calculate the noise and interferences present in the signal using proposed mathematical modelling. The noise minimization block is used to detect noises and perform smoothing of the signal through proposed mathematical model. Now using the separate PCA signal classification [19]–[21] algorithms the actual EEG signal (noiseless) and smoothen EEG signal are classified into different state's which are compared using eucledean distance to check the effectiveness of the de-noising algorithm.

3.1. Read EEG signal

The EEG signals are read through the "Read EEG Signal" block which contains certain artifacts. Artifacts can originate from various sources such as the subject, equipment, or the environment and consist of ocular artifacts, such as eye blinks; movement of the EEG sensors; and electromyogenic artifacts, caused by muscle movement. The standard database [22] are used for the calculation.

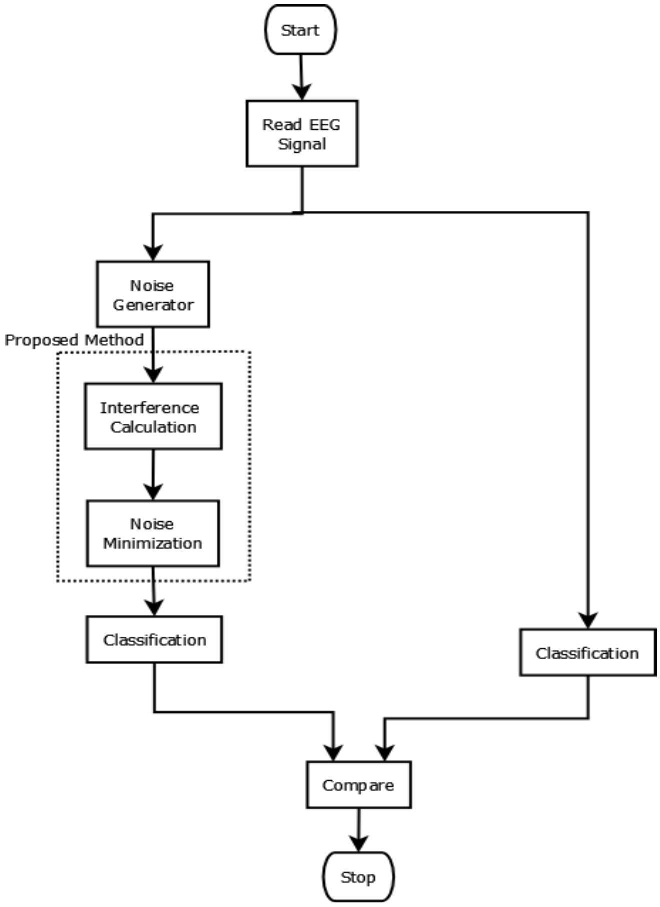

Figure 1. Proposed noise reduction method with performance analysis

3.2. Interference calculations

Dynamic interference calculation method is used to detect the artifacts. In this method, interferences are analysed in learned subspace followed by a novel technique generated from modified robust subspace detection [1] method. In this method, first the unknown interferences are calculated and then using those interferences the actual interferences are calculated. Let us consider the EEG signal consists of EEG data with some unknown noise which is expressed mathematically as

$$x = r_s + r_u + \eta \tag{1}$$

where, r_s is the actual EEG data, r_u is the unknown interference, and η is the noise. The (1) is for the space containing the entire EEG signal. To get accurate interference, subspace calculation method is used. Let us consider S is the subspace which is used to estimate the data. As a result, K vector and M-dimensional subspace is used to define the total subspace S which modifies the (1) as

$$x = S\theta + U\phi + \eta \tag{2}$$

where, θ is the unknown gain of the noise, U is noise amplitude, and ϕ is phase of the noise. Through likely-hood ratio test [1] of (2), the equation for log yields become

$$\lambda(x) = \left(\frac{1}{\omega_1}\|x - s\overline{\theta}\|_2\right)^2 + \left(\frac{1}{\omega_0}\|x - N\overline{\phi}\|_2\right)^2 \tag{3}$$

The use of likely hood ratio test for the (2) results in segmentation of entire EEG data signal into very small segment where the noise characteristics are almost constant. This will helps to track the proper noises present in small segment which in turn helps to perform proper de noising of the signal. Since the feature vector x to be in a space with components in the direction of and orthogonal to the signal subspace S, the unknown gain of the signal is

$$P_S = \frac{s^t . s^t}{s^t . s} \tag{4}$$

By considering the ratio of the portion of x in the subspace of S, the interference equation is then

$$\lambda(x) = \frac{X^T(P_S - P_N)X}{2\omega^2} \tag{5}$$

$$\lambda(x) = \frac{X^T . P_S . X}{X^T . P_N . X} \tag{6}$$

where, P_N is projection matrix onto the part of the measurement space orthogonal to the signal.

3.3. Noise minimization of EEG signal

To minimize noises, it is essential to calculate the noises present in the input signal. In this case, the interference equation explained in the "Interference Calculation" block are used to learn the interference characteristics with respect to the calculated inferences. The "Adaptive Matched Subspace detector" [2] is then used to minimizes these noises which is written as

$$\lambda(x) = \frac{X^T . (P_S - P_B)X}{X^T(P_N - P_B)X} \tag{7}$$

3.4. Classification of noise

The general PCA [3] technique is used to classify the signals.

$$Z = \frac{(X - \mu)}{\sigma} \tag{8}$$

where, x symbols and μ mean value. The covariance matrix equation is then

$$COV(X,Y) = \frac{1}{(n-1)\sum_{i=1}^{n} \frac{1}{[(X_i - \overline{X})(Y_i - \overline{Y})]}} \tag{9}$$

The final data is then

$$final\ data = feature\ vector * transpose(scaled(data)) \tag{10}$$

3.5. Compare

The eucledian distance is used to compare the features. Now by using different threshold values, the ROC is calculated. The different threshold values are used to calculate the corresponding False acceptance ratio (FAR) and total success rate (TSR) values [23] using separately noisy and noiseless signals from the (10). Similarly the accuacy calculation equation is given as

$$Accuarcy = \left(\frac{Accurate - Denoised}{Accurate}\right) \times 100 \tag{11}$$

4. SIMULATION RESULT AND DISCUSSIONS

The proposed algorithm is implemented on MATLAB tool where the entire algorithm is coded using standard MATLAB programming techniques. The standard EEG database [22] are used to check the performance of the algorithm. To calculate the detection accuracy, the entire databases are used. But for simplicity, only the snapshots of three persons are shown.

4.1. Case I: person 1

The resulting receiver operating characteristic (ROC) graph is shown in the Figure 2, it can be seen that the both graph of our proposed method for smoothened version of noisy EEG data and the existing noiseless present in the EEG database for the person 1 is almost similar and is overlapped which proves the effectiveness of the algorithm. The analysis of the detection of interference with changing magnitude is plotted on fixed threshold at fixed noise level is shown in the Figure 3 for existing technique [24] mentioned in blue color and proposed method mentioned in red color. It can be seen that True positive rate is same for both technique with the proposed technique is nearly generating same curve almost similar to noiseless signal.

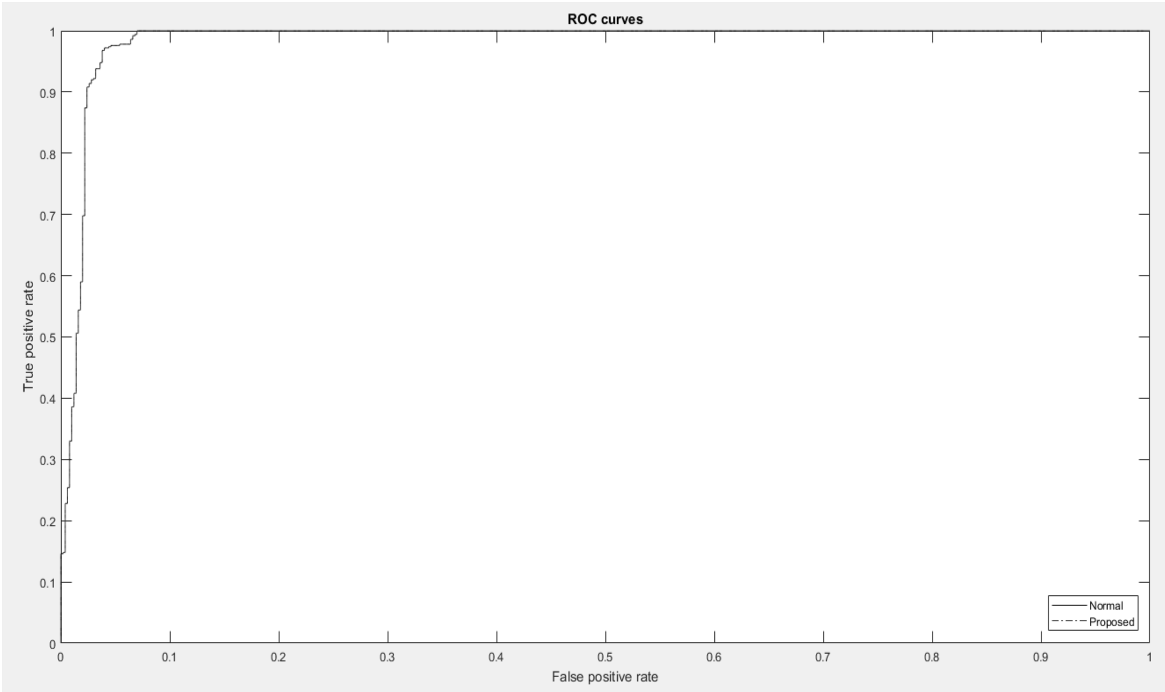

Figure 2. ROC curve of actual and detected interferences of database image 1

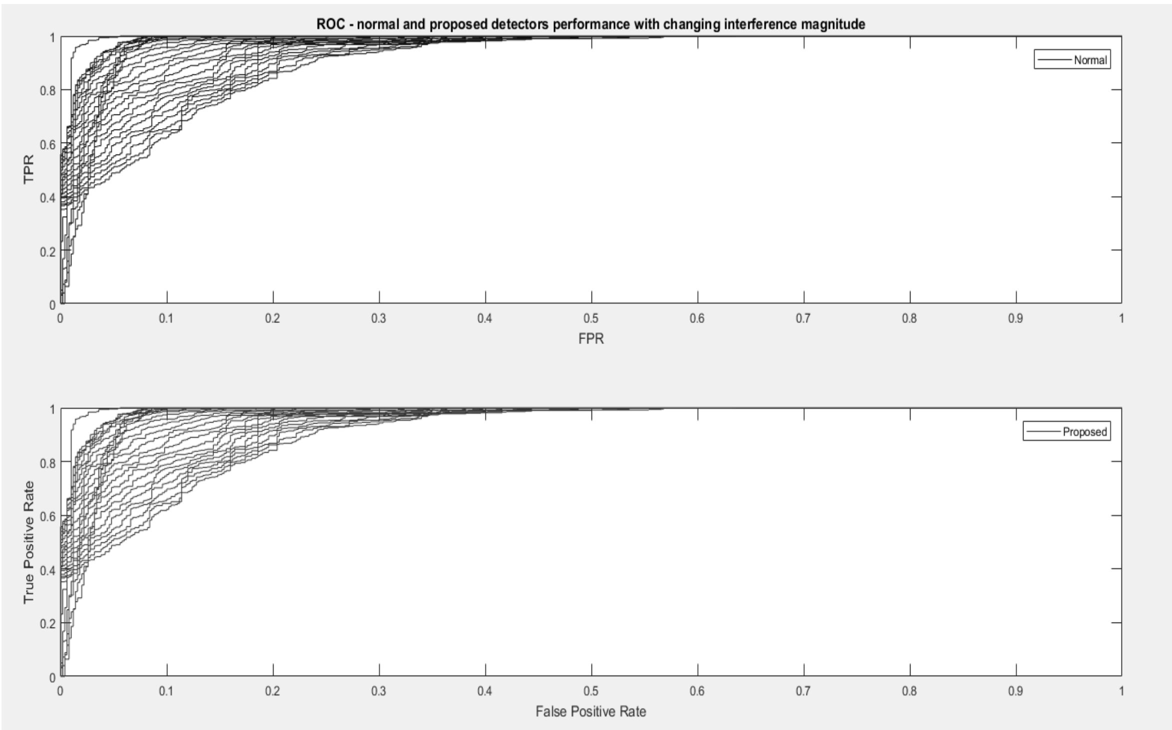

Figure 3. Interference magnitude of actual and detected interferences for database image 1

The analysis of the detection of interference with changing magnitude is plotted on fixed threshold at fixed noise level is shown in the Figure 3 for existing technique [24] mentioned in blue color and proposed method mentioned in red color. It can be seen that true positive rate is same for both technique with the proposed technique is nearly generating same curve almost similar to noiseless signal. The false positive rate with interference magnitude is plotted in Figure 4 and it is observed that the proposed method shown in red color is minimum compared to existing [24] technique shown in blue color which shows the effectiveness of the algorithm and it is visible that the dynamic tracking mechanism can track interference more efficient than existing. Since small duration characteristics are defined properly.

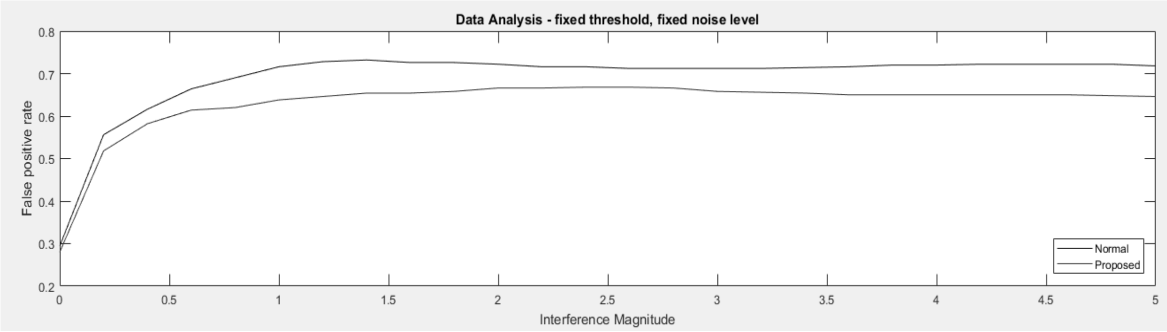

Figure 4. Detection of actual and detected interferences at fixed threshold and fixed noise database image 1

4.2. Case II: person 2

Similar to Figure 2, the ROC curve of different for different random person (person 2) present in standard database [22] is considered to prove the efficiency as shown in the Figure 5 which shows that the both graph of proposed technique for our smoothened version of noisy EEG and existing noiseless in database is almost similar and overlapped which proves the effectiveness of the algorithm. The analysis of the detection of interference with changing magnitude is plotted on fixed threshold at fixed noise level is shown in the Figure 6 for existing technique [24] mentioned in blue color and proposed method mentioned in red color. It can be seen that true positive rate is same for both technique with the proposed technique is nearly generating same curve almost similar to noiseless signal. The false positive rate with interference magnitude is plotted in Figure 7 and it is observed that the proposed method shown in Red color is minimum compared to existing [24] technique shown in blue color which shows the effectiveness of the algorithm and it is visible that the dynamic tracking mechanism can track interference more efficient than existing. Since small duration characteristics are defined properly.

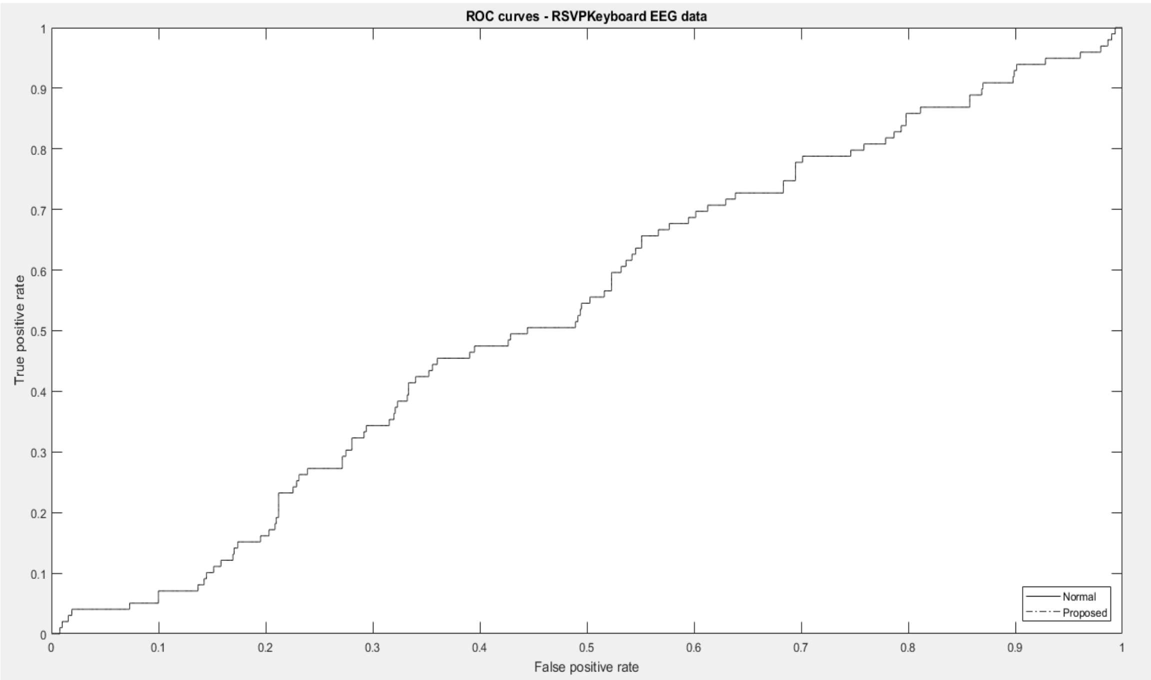

Figure 5. ROC curve of actual and detected interferences of database image 2

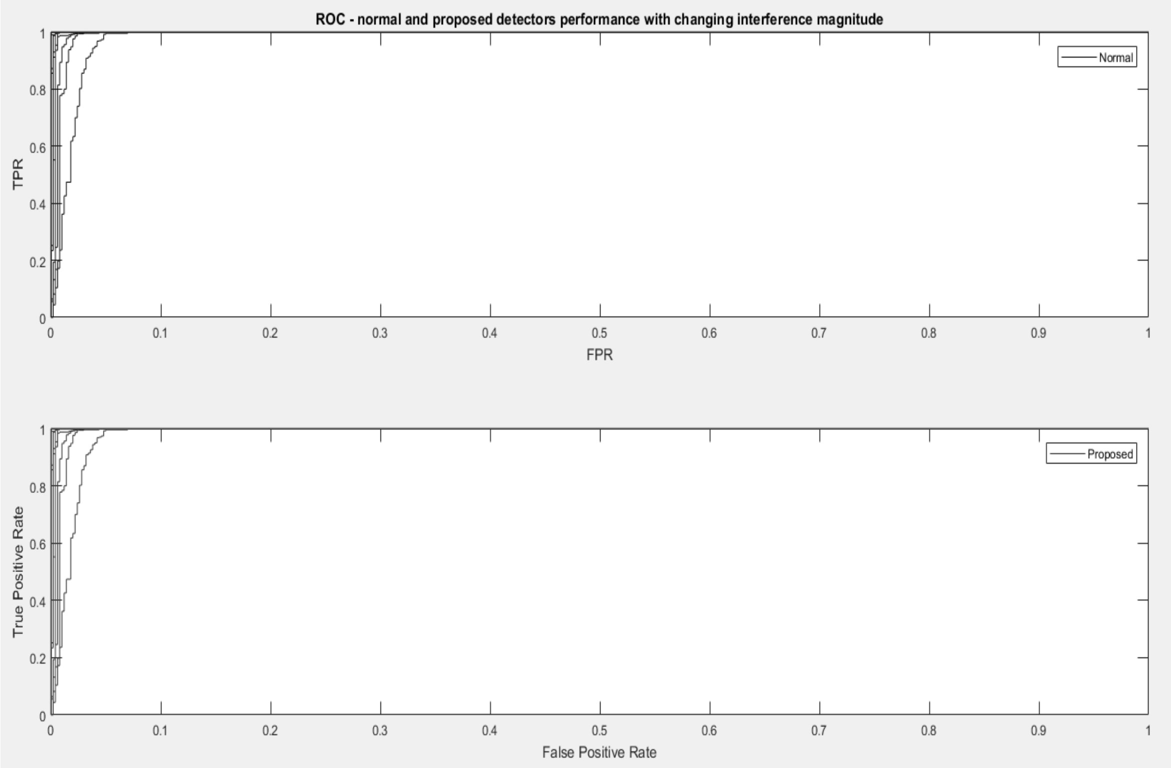

Figure 6. Interference magnitude of actual and detected interferences for database image 2

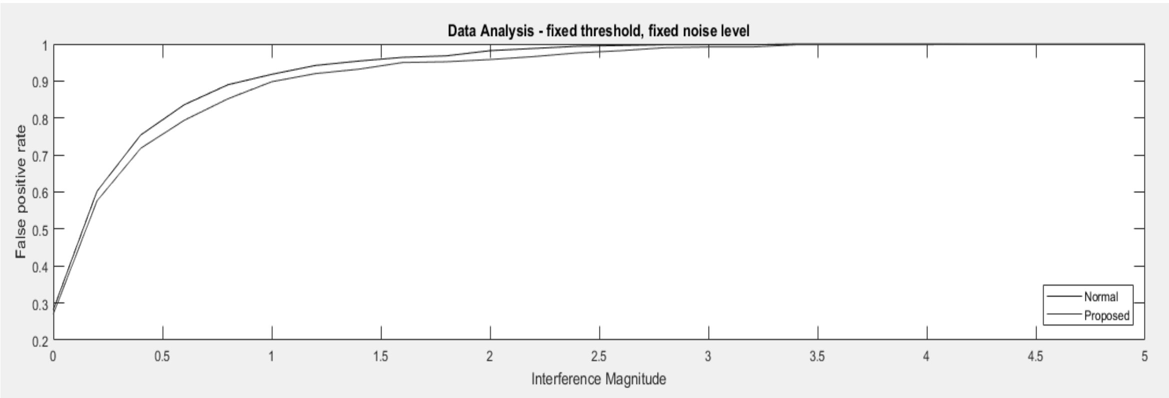

Figure 7. Detection of actual and detected interferences at fixed threshold and fixed noise database image 2

4.3. Case III: person 3

Similar to Figure 2, the ROC curve of different for different random person present in standard database [22] is considered to prove the efficiency as shown in the Figure 8 which shows that the both graph of proposed technique for our smoothened version of noisy EEG and existing noiseless in database image 3 is almost similar and overlapped which proves the effectiveness of the algorithm. The analysis of the detection of interference with changing magnitude is plotted on fixed threshold at fixed noise level is shown in the Figure 9 for technique [24] mentioned in blue color and proposed method mentioned in red color. It can be seen the true positive rate is same for both technique with the proposed technique is nearly generating same curve almost similar to noiseless signal. The false positive rate with interference magnitude is plotted in Figure 10 and it is observed that the proposed method shown in red color is minimum compared to existing [24] technique shown in blue color which shows the effectiveness of the algorithm and it is visible that the dynamic tracking mechanism can track interference more efficient than existing. Since small duration characteristics are defined properly.

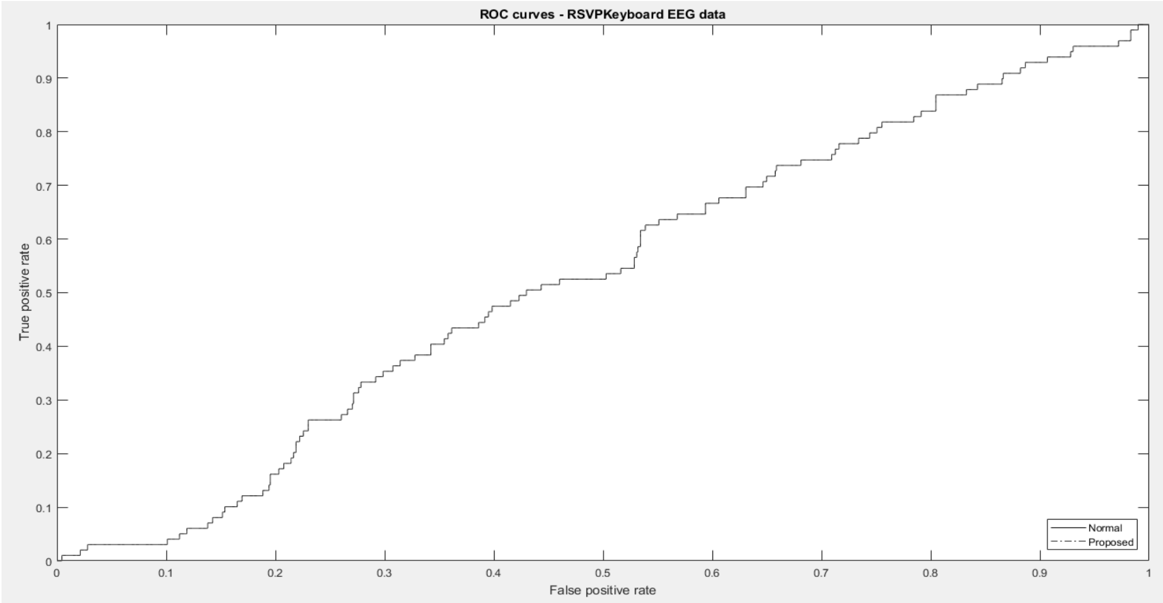

Figure 8. ROC curve of actual and detected interferences of database image 3

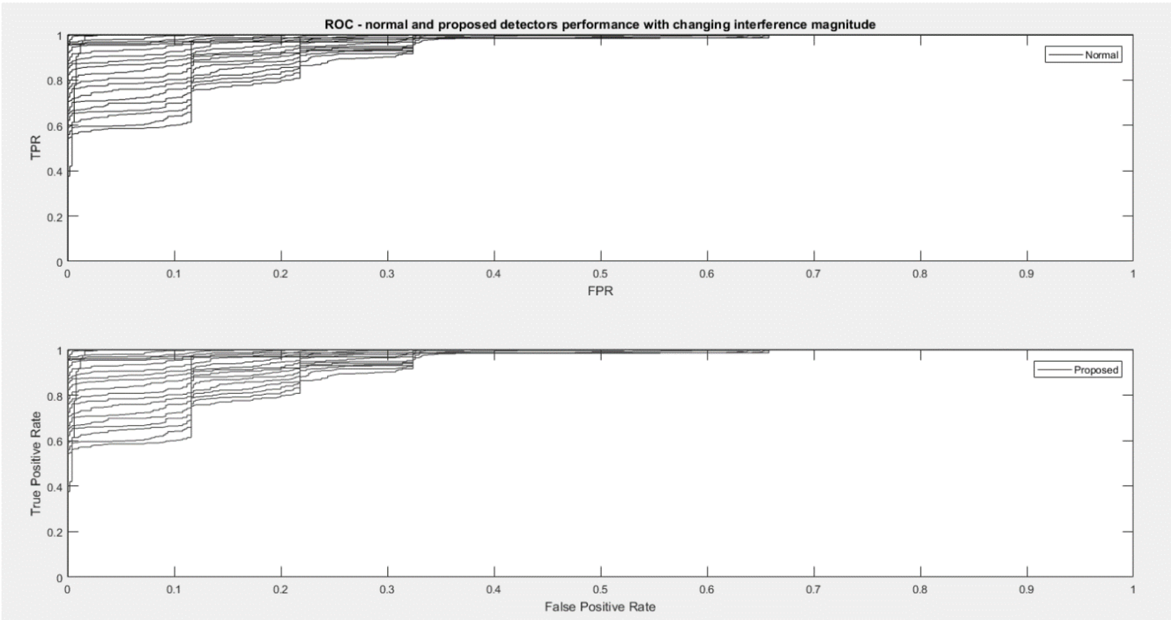

Figure 9. Interference magnitude of actual and detected interferences for database image 3

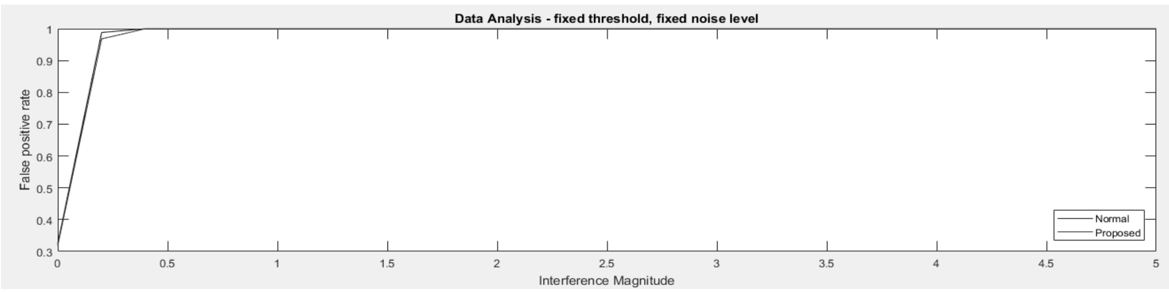

Figure 10. Detection of actual and detected interferences at fixed threshold and fixed noise database image 3

5. COMPARISONS WITH EXISTING TECHNIQUES

The accuracy is compared in the below Table 1, which shows that the proposed technique is better in terms of accuracy with respect to existing technique presented by Balamareeswaran and Ebenezer [25]. The discrete wavelet transform (DWT) is used to denoise input EEG signal and the weighted support vector machine (SVM) technique is used for classification. On other hand the use of likekihood ratio test in our proposed method converts EEG data signal into segmented data of constant noise charactristics for proper denoising . Further, the denoised signal is used to characterize the disease depending upon variable threshold using PCA classifier to achieve higher accuracy rate.

Table 1. Comparison of existing technique with proposed technique

Authors	Technique	Accuracy
Balamareeswaran and Ebenezer [25]	DWT	97.66%
Proposed	Statistical Mathematical Model	99.01%

6. CONCLUSION

An efficient de-noising algorithm for EEG signal is proposed in this paper where the noise present in the raw EEG signal is detected through novel mathematical modelling and depending upon the noise characteristics the de-noising has been performed. The only limitation is if the noise is fully random then the tracking may not be effective. Since the algorithm segments the entire EEG signal in to smaller segments depending on similar or same kind of noise characteristics. The de-noised signal is then used to characterize the disease depending upon variable threshold using general PCA classifier. The above graph is compared with the graph generated by corresponding noise free EEG signal using same technique. This shows that the proposed algorithm can pre-process the signal effectively due to effective novel mathematical tracking of noises.

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