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Automatic detection of non-convulsive seizures: A reduced complexity approach

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Abstract Detection of non-convulsive seizures (NCSz) is a challenging task because they lack convulsions, meaning no physical visible symptoms are there to detect the presence of a seizure activity. Hence their diagnosis is not easy, also continuous observation of full length EEG for the detection of non-convulsive seizures (NCSz) by an expert or a technician is a very exhaustive, time consuming job. A technique for the automatic detection of NCSz is proposed in this paper. The database used in this research was recorded at the All India Institute of Medical Sciences (AIIMS), New Delhi. 13 EEG recordings of 9 subjects consisting of a total 23 seizures of 29.42 min duration were used for analysis. Normalized modified Wilson amplitude is used as a key feature to classify between normal and seizure activity. The main advantage of this study lies in the fact that no classifier is used here and hence algorithm is very simple and computationally fast. With the use of only one feature, all of the seizures under test were detected correctly, and hence the median sensitivity and specificity of 100% and 99.21% were achieved respectively.

1. Introduction

Electroencephalograph (EEG) has been a useful and cost effective tool for monitoring electrical activity generated by collection of neurons within the brain. Different spatially placed electrodes collect the signal and reflect the activity within different brain regions (Kaplan, 2007; Murthy, 2003).

Seizures may be defined as the symptoms of abnormal brain function or are the results of sudden, usually brief, excessive electric discharges in a group of neurons. Different parts of the brain can be the site of such electric discharges which may affect any part of the body. Symptoms experienced by a person during a seizure therefore vary and depend on where in the brain discharges first start and how far they spread. Seizures can be categorized into two main types on the basis of outward effects as convulsive and non-convulsive. General symptoms of convulsive seizures are wild thrashing movement (tonic–clonic), loss of consciousness, change in mental state or

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various other psychic symptoms. Identification of a non-convulsive seizure is much more challenging than that of a convulsive seizure because the signs are much less obvious (Kaplan, 2007; Kaplan and Drislane, 2009).

In early 19th century, non-convulsive seizures (NCSz) were termed as "petit mal" by physicians and attendants in hospitals of the Paris city and also the term "absence" was introduced by Calmeil in 1824. NCSz are a few to several seconds long, hence they are easily missed out or cannot be noticed easily. Patient with NCSz may experience hundreds of seizures daily resulting in low quality of life and poor performance on work done. NCSz are mainly found in critically ill patients or comatose and neonatal (Xanthopoulos et al., 2010). Hence a reliable detection of NCSz is needed to diagnose them at early stage.

NCSz can be seen in scalp-recorded EEG as a large amplitude having spike-wave patterns generally occurring in bursts. It can produce lethargy, unresponsiveness, confusion, interfere with information processing or alter mental status. These changes are very subtle and mistakenly understood as occurred by some other causes. It is not rare, but clinically under diagnosed and if left undetected and untreated, they can cause severe brain and behavioral dysfunctions. Hence, non-convulsive seizures cannot be defined by clinical criteria instead EEG must show the electrographic seizure activity to confirm NCSz (Shorvon, 2007). NCSz are a range of conditions in which electrographic seizure activity is prolonged and results in non-convulsive clinical symptoms (Shorvon, 2007). NCSz have subtle and pleomorphic clinical manifestations including impairment of consciousness (mild confusion to coma), automatisms, eye deviation or jerking, and subtle limb or facial twitching and therefore may be difficult to distinguish from other disorders, hence to confirm NCSz, an electroencephalogram (EEG) must show electrographic seizure activity (Kaplan and Drislane, 2009).

A number of algorithms and techniques have been proposed in the field of convulsive seizures (Bedeeuzzaman et al., 2010; Daou and Labeau, 2014; Khan and Gotman, 2003; Naghsh and Aghashahi, 2010; Niknazar et al., 2013; Santaniello et al., 2012; Shoeb et al., 2004; Yadav et al., 2007; Meier et al., 2008) but there are very limited efforts in detection techniques of non-convulsive seizures (Jacquin et al., 2007; Khan et al., 2012a,b; Liang et al., 2010; Minasyan et al., 2009; Petersen et al., 2011; Xanthopoulos et al., 2010).

In the study of NCSz conducted by Jacquin et al. (2007), a reduced set of EEG channels were used i.e. 8 channels were used instead of 19. The algorithm was based on detection of spike-wave events using wavelet analysis of the EEG signal and combined with the fractal dimension (non-linear) methods. Fractal dimension is a measure of the irregularity or complexity of a signal hence used as a key feature for the removal of false positives detected in spike wave events which are caused by involuntary or voluntary artifacts such as fast eye blink. Data sets were obtained from two clinical sites: 93 recordings were from the New York University Epilepsy Center and 79 were from a private epilepsy practice in Virginia. Each data set was approximately 30 min long and was sampled at a rate of 100 Hz. Only five frontal leads F7, Fp1, Fz, Fp2, and F8 were used for the development and testing of seizure detection algorithm. Overall sensitivity and specificity recorded were 83% and 96% respectively.

Another technique based upon Artificial Neural Network (ANN) classifier for the detection of epileptiform in unresponsive patients was given by Minasyan et al. (2009). EEG database consisted of 21 records collected from the University of Virginia. Two ANNs and a rule based algorithm were used in this processing algorithm. ANN-1 and a set of algorithm were used for the detection and classification of 1-s EEG features. After which each 1 s epoch was assigned to one of the following groups: Delta, Theta, Alpha, Beta rhythms, PEA (paroxysmal epileptic activity), Sleep event and artifacts. In the next step, 1 s EEG features are accumulated over a period of 1 min and 10-element EEG State Vector (ESV) is computed. ESV vectors are passed to a multi-layer perceptron that classifies 1 min EEG epochs as NCSz, slow, fast, burst-suppression or artifact. One minute epochs from 9 training and 12 test records were expertly scored into one of the 5 EEG states listed above. Sensitivity and specificity achieved by this method are 71% and 99% respectively.

Xanthopoulos et al. (2010) proposed an algorithm based on the spectral characteristics of the seizures. The total recording of six subjects was 26 h long, among them 2 subjects were seizure free. All subjects were younger than 13 years. After applying continuous wavelet transform (CWT) to all the 16 channels data, variance of moving window of 1 s was calculated. Sensitivity was dependent on the length of the sliding window. The lesser the length, the more the sensitivity and more the chance of getting false positive detection. Hence an optimum value of window length was chosen. The algorithm detected 97% significant absence seizures of duration greater than or equal to 3 s and one false positive in two seizure free recording. The limitation of the algorithm is that it is not capable of detecting the seizures of less than 3 s duration.

Petersen et al. (2011) proposed a generic method for the single channel detection of absence seizures. Analysis was done on 18 channels EEG, taken from 19 subjects who were suffering from childhood absence epilepsy. A total of 24 recordings was used which consisted of 177 seizures. The duration of these records was 11 h and 48 min. All data were recorded using a Cadwell Easy II from Cadwell Laboratories at the Department of Clinical Neurophysiology, Rigs hospital at University Hospital. Sampling frequency of the data was 200 Hz, bandpass frequencies were ranging from 0.53 to 70 Hz and a notch filter was used to remove 50 Hz power-line noise. Wavelet transform and log-sum energy were used as the key features and linear SVM classifier was used for the classification purpose. Three consecutive 2 s epochs classified as seizure were declared as detected seizure. The best result was found for the electrodes in the frontal region and for the channel F7–FP1, having an overall sensitivity of 99.1% and false detection rate (FDR) of 0.5/h.

Khan et al. (2012a) proposed an algorithm for the automatic detection of non-convulsive seizures using 6th order AR model. A database of 5 subjects was collected at All India Institute of Medical Sciences (AIIMS), New Delhi, India. Simple linear classifier was used for the classification of seizure and non-seizure activity. Out of 13 seizures, 11 seizures were detected correctly and hence the sensitivity and specificity of the method were found to be 86.8% and 96.9% respectively. The drawback associated with this work was that the seizure should be present in at least 50% of the channels for the final detection.

Non-convulsive seizures (NCSz) are an under-diagnosed neurological disorder in which spike and slow wave discharges of brain activity on EEG can be seen. Since the performance of any algorithm is based on the selection of discriminatory features extracted from the data, in this paper a method for automatic detection of non-convulsive seizures using normalized modified Wilson amplitude which is simple and easy to compute was used. This feature is used to classify between normal and seizure activity. The main advantage of the proposed technique lies in the fact that no classifier is used here hence algorithm is very simple and computationally fast. Normalization from background data is done to provide robustness into features.

The rest of this paper is organized as follows. Section 2 gives the experimental procedure and the information about the database, its processing and identification of seizure and non seizure EEG data. The results obtained and the performance of the proposed algorithm are discussed in Section 3. Finally, Section 4 draws the conclusion based on the results obtained in Section 3.

2. Materials and methods

2.1. Database used

The database used was recorded at All India Institute of Medical Sciences (AIIMS), New Delhi, India. International 10–20 system was followed in the recording of EEG. Full description of the database is given in Table 3 in Section 3. All the 13 recordings were taken from 9 subjects (5 males and 4 females) and different numbers of channels were used for the recordings. Out of 13, 2 recordings had sampling frequency of 125 Hz and the remaining were sampled at 256 Hz.

2.2. Data processing

The problem of seizure detection is a two class problem where relevant features are to be identified and extracted. For identification of these distinguishing features, it is essential to first visualize the two class data in time and/or frequency domain and to look into their statistical properties. A time domain plot of normal and non-convulsive seizure EEG for a single channel is shown in Fig. 1. Spike and wave events can be seen easily in waveform of a non-convulsive seizure. The range of amplitudes for non-convulsive seizure EEG varies from −800 μV to 700 μV, which is very high in comparison to normal EEG that is from −100 μV to 250 μV and this is a remarkable difference between the two cases.

A histogram is a graphical representation of the probability distribution of a signal in time domain. Probability distribution function is an important parameter by which significant information regarding the signal can be obtained. In Fig. 2 the histogram of normal and non-convulsive seizure activities using same single channel is shown. The difference between these two cases can be noticed easily as the variability or spreading of non-convulsive seizure data is higher but the frequency of occurrence is much lower in comparison to normal data.

Power spectral density (PSD) gives the amount of power at different frequencies. A plot of PSD of normal and non-convulsive seizures is also shown in Fig. 3. There is a noticeable difference among them as the power of non-convulsive seizure data is high at frequencies below 30 Hz.

The characteristic of the recorded EEG varies from subject to subject. Normalization of features by 25 s background is done to provide robustness into features and to remove subject dependent variations. A gap of 15 s is used as the guard time between normal and seizure activity (Khan and Gotman, 2003). A seizure is considered to be detected if at least in one of the channels, seizure is detected i.e. minimum one detection is required to confirm the presence of a seizure.

2.3. Detection process

Wilson amplitude (*WAMP*)*:* It can be defined as the absolute difference between the amplitude of two adjacent sample values that exceeds a predefined threshold. Mathematically it can be represented as follows:

$$\mathrm{WAMP} = \sum_{n=1}^{N-1} f(|x_n - x_{n+1}|) \qquad (1)$$

$$f(x) = \begin{cases} 1, & x \geqslant \mathit{threshold} \\ 0, & \mathit{otherwise} \end{cases}$$

Wilson amplitude has been used earlier in the processing of EMG signals (Shoeb and Guttag, 2010). In this work, normalized modified Wilson amplitude is used as the only feature to differentiate between normal and seizure epochs. The dynamic range of EEG signal is large for a non-convulsive seizure and has same frequency range as the normal EEG, therefore, a higher value is expected for seizure EEG as compared to normal. Thus, a suitable threshold can be selected to decide about seizure and normal EEG data. As expected, Fig. 4 shows a high difference in the adjacent amplitudes of NCSz EEG in comparison to the normal EEG. For NCSz the difference in amplitude is frequently higher than 200 μV, while for normal EEG this difference is never reached, except when artifacts are present such as eye blink or muscle activity. It can be concluded that EEG signal of a non-convulsive seizure has a high difference between the amplitudes of adjacent samples hence it can be used as an important discriminatory feature between normal and seizure activity. The use of threshold helps to use simple decision logic and eliminates the use of complex classifier; hence the algorithm is very simple and computationally fast. The accuracy of this algorithm hinges on evaluation of suitable WAMP threshold which will maximize accuracy. A general block diagram of the proposed method is given in Fig. 5.

The acquired EEG signal is first pre-processed before feature extraction. In general a pre-processing stage may include anyone or all of the following: signal cleansing (i.e. denoising), line frequency suppression (removal of 50/60 Hz using a notch filter), selecting desired frequency bands for feature extraction and data windowing. In this proposed work simple notch filtering was carried out and 1 s rectangular window was used to select 256 samples for onward feature extraction. The preprocessing is applied to all the N channels and then the signal is given to the feature extraction stage. The details of processing during feature extraction and decision making is shown in Fig. 6 for 16 channels EEG recorded data and explained in Tables 1 and 2.

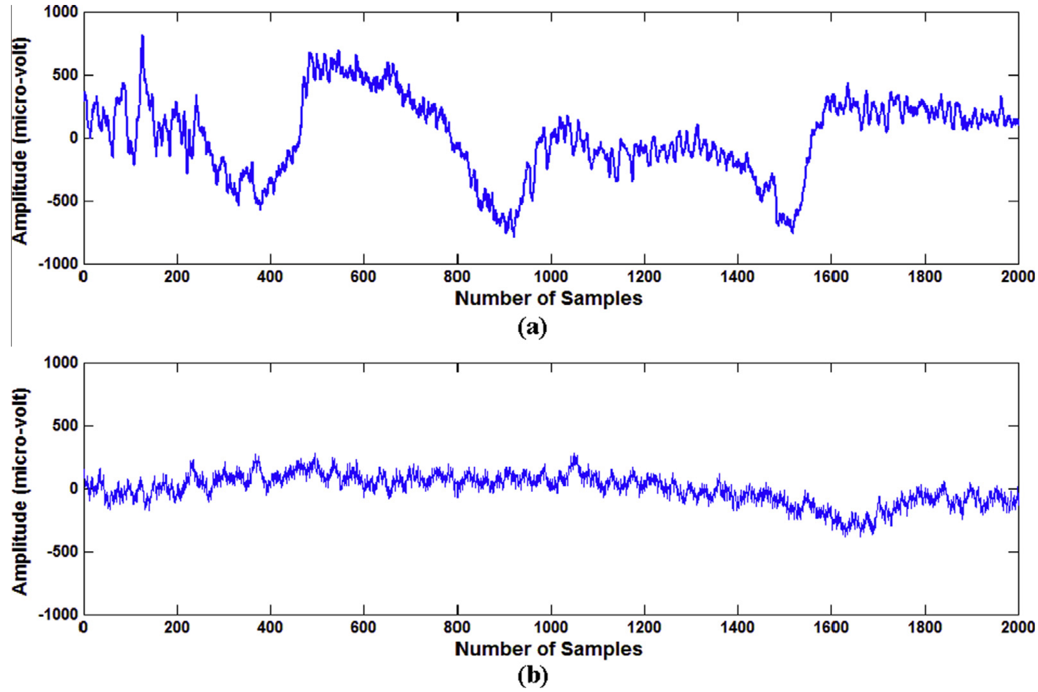

Figure 1 Time-domain plot of EEG signal corresponding to an exemplary channel for (a) non-convulsive seizure, (b) normal.

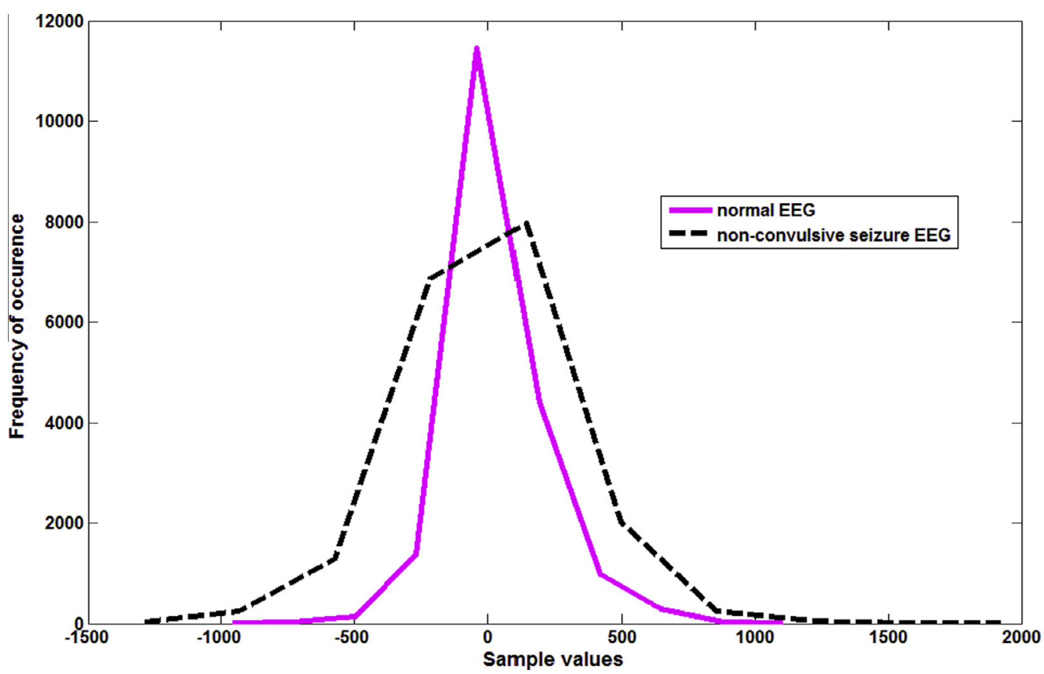

Figure 2 Histogram of normal and non-convulsive seizure EEG.

Absolute difference between successive samples over 256 samples for each channel is calculated and average value (Mean Absolute Difference i.e. MAD^{ch}, single value per channel) is calculated as shown in the first stage of feature extraction block (Fig. 6). To normalize this value (MAD^{ch}) a background of 25 s normal EEG is considered. 25 windows of 1 s duration each of normal EEG is formed and the median of these 25 MAD^{ch} values is selected per channel denoted as MAD^{ch}_{bkgnd}. Normalization of MAD^{ch} i.e. the EEG data under test is done by dividing it by MAD^{ch}_{bkgnd} during the second stage of feature extraction. The normalized modified Wilson amplitude (MAD^{ch}_{nor}) can thus be calculated a shown in Eq. (2) by using the median of the 25 s background window.

$$MAD^{ch}_{nor} = \frac{\frac{1}{M}\sum_{n=1}^{M}|x_n - x_{n-1}|}{median\left(\frac{1}{M}\sum_{n=1}^{M}|x_n - x_{n-1}|\right)_{bkwin}} \qquad (2)$$

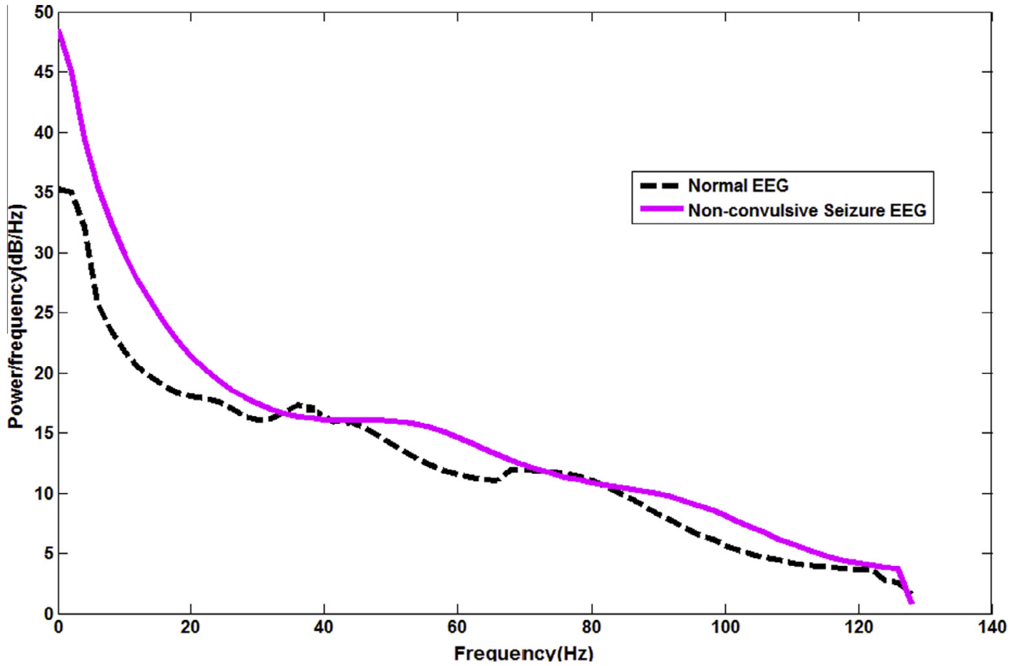

Figure 3 PSD of normal and non-convulsive EEG.

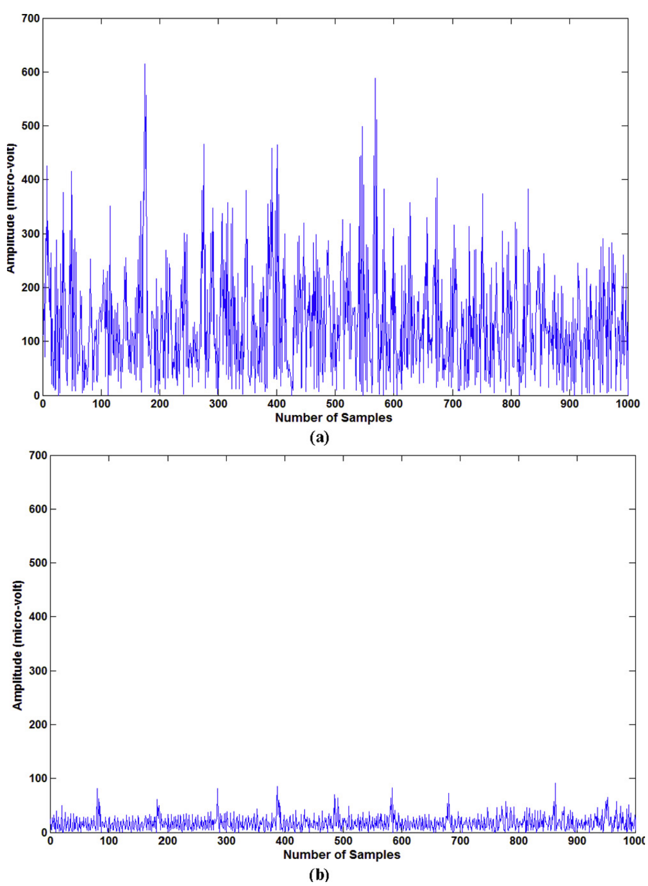

Figure 4 Plot of absolute difference between adjacent sample amplitudes of EEG signal for (a) non-convulsive seizure and (b) normal EEG.

The normalized feature MAD_{nor}^{ch} is compared with a threshold MAD_{Th} which gives an output '1' if it is greater than or equal to MAD_{Th}, and '0' otherwise. Seizure detection is declared for a channel if '1' is obtained else the windowed EEG channel is considered as normal. Thus if 4 channels have values greater than MAD_{Th} the output of the adder will be 4. If the output of the adder is greater than the predefined channel threshold ($Channel_{Th}$) a seizure is flagged. The details of the algorithm for the proposed feature extraction and seizure detection are also shown in Table 1, while Table 2 gives the features extracted from the background EEG for normalization.

Receiver operating characteristic (ROC) curve is a plot of the sensitivity against the false positive rate. It shows the achievable best performance of any algorithm as the highest left most value (showing the highest sensitivity) and lowest false positive rate achieved Kim and Rosen (2010). Different values for normalized mean threshold (MAD_{Th}) were tried and the optimum value where the highest sensitivity and specificity were achieved was selected. According to the ROC as shown in Fig. 7 an optimum accuracy of 94.01% was achieved for 1.8 value of MAD_{Th}. To detect the channel threshold $Channel_{Th}$ a balance between seizure detection and false positive is to be achieved. Reducing the number of channels improves the seizure detection but increases the false positive rate. For the given data, the optimum number of channels was found to be 3.

The most commonly used parameters for performance evaluation of seizure detection techniques are sensitivity, specificity and accuracy. Sensitivity is a ratio of actual seizure cases (true positive) detected out of the total seizure (true positive + false negative) cases. Specificity is a ratio of actual normal cases detected (true negative) to the total normal cases (true negative + false positive). The accuracy gives a measure of all the correctly classified cases. All these parameters are usually represented as percentage and are calculated as:

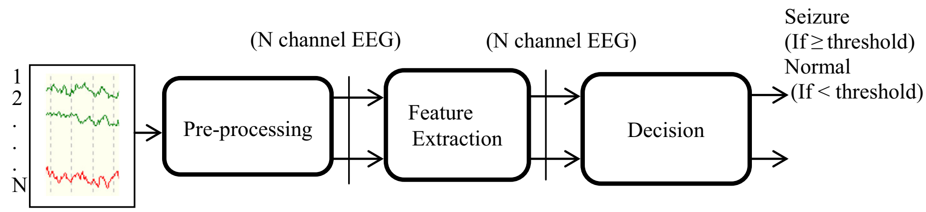

Figure 5 Block diagram of the proposed method.

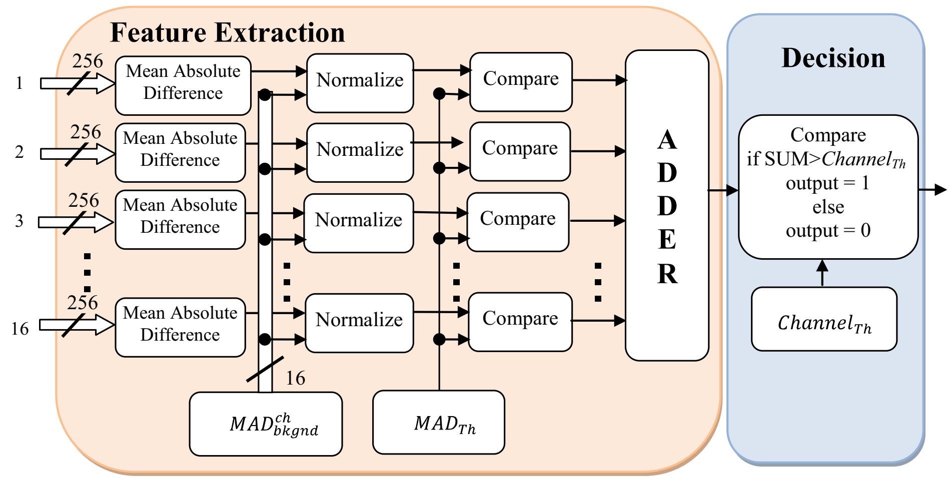

Figure 6 Details of the processing carried out during feature extraction and decision stage for identification of normal and seizure EEG data.

Table 1 Procedure to calculate the normalized modified Wilson amplitude based features for seizure detection.

Select a test window of EEG data $\{x_1, x_2, x_3, \ldots, x_{256}\}$ to be analyzed for seizure detection
Set count $= 0$
for ch $= 1$ *to number of channels*
$AD^{ch}_n = |x_n - x_{n-1}| \quad n = 1, 2, 3, \ldots, 256$
$MAD^{ch} = \frac{1}{M}\sum_{n=1}^{M} AD^{ch}_n$ where $M = 256$
$MAD^{ch}_{nor} = \frac{MAD^{ch}}{MAD^{ch}_{bkgnd}}$
if $MAD^{ch}_{nor} > MAD_{Th}$ (MAD_{Th} = 1.8, obtained from ROC plot as shown in Fig. 7)
count = *count* + 1
else
end
ifcount > $Channel_{Th}$ ($Channel_{Th} = 3$, obtained from ROC plot)
output = *Declare Seizure EEG*
else
output = *Declare Normal EEG*
end
end

$$\text{Sensitivity}(\%) = \text{Number of true positive decisions} \times 100/\text{Number of actually positive cases} \quad (3)$$

$$\text{Specificity}(\%) = \text{Number of true negative decisions} \times 100/\text{Number of actually negative cases} \quad (4)$$

$$\text{Accuracy}(\%) = \text{Number of correct decisions} \times 100/\text{Total number of cases} \quad (5)$$

Table 2 Feature extraction procedure of 25 s window of background EEG data for feature normalization to be used in Table 1.

for ch $= 1$ *to number of channels*
for bkwin $= 1$ *to 25 number of background windows*
$AD^{ch}_n = |x_n - x_{n-1}| \quad n = 1, 2, 3, \ldots, 256$
$MAD^{ch}_{bkwin} = \frac{1}{M}\sum_{n=1}^{M} AD^{ch}_n$ where $M = 256$
end
$MAD^{ch}_{bkgnd} = median(MAD^{ch}_{bkwin})$
end

Table 3 Detection Results using normalized modified Wilson amplitude.

Data no.	No. of seizures	No. of channels	Duration (s)	Sensitivity (%)	Specificity (%)
1*	3	16	27	100	100
		16	17	100	100
		16	25	100	100
2#1	3	22	42	100	100
		22	15	100	100
		22	92	100	100
3#1	1	22	32	100	62.5**
4	1	21	56	100	94.643
5*		16	16	100	100
	2	16	22	100	100
6	1	21	27	100	100
7	2	22	163	100	100
		22	140	100	100
8#2	1	22	78	100	98.72
9#2	1	22	88	100	38.64**
10#2	1	22	156	100	67.31
11#3	1	22	109	100	94.60
12#3	4	22	125	100	54.40**
		22	127	100	99.21
		22	91	100	89.01
		22	215	100	59.07**
13	2	22	49	100	79.59
		22	53	100	86.79

#: #1 are the data of the same subject and so as the #2 and #3.
* Only these data have sampling frequency of 125 Hz otherwise all data have sampling frequency as 256 Hz.
** Specificity is poor in these cases.

3. Results and discussion

In the proposed detection algorithm only two stage thresholding is used after single feature per channel is extracted as shown in Fig. 6. First, 1 s epoch from the test data is isolated and mean absolute difference is evaluated per channel (MAD^{ch}). In order to make this feature subject independent, it is normalized by the background feature to get normalized modified Wilson amplitude (MAD^{ch}_{nor}) after which the channel thresholding is performed. To declare the presence of seizure in a given epoch, a minimum of 4 channels must affirm detection. The results achieved using this detection algorithm is given in Table 3 for all the 13 recordings of 9 subjects having 23 seizures.

The algorithm detected all of the seizures present in the database of 9 subjects. The median sensitivity and specificity were found to be 100% and 99.21% respectively. It can be observed that a generic method for automatic detection of a non-convulsive seizure is proposed. Without having any previous record of EEG of the subject, non-convulsive seizures were detected easily using the proposed algorithm.

In a total of 23 recordings, the specificity of 4 recordings was found to be poor as shown in Table 3. It was observed that these normal EEG recordings had rhythmic and seizure like patterns as shown in Figs. 8 and 9. Hence a few false positives were detected in these EEG sections. Recording of the EEG is done continuously in an on-line system, thus possibility of having only clean EEG for analysis is small. Therefore, EEG recording may consist of some paroxysmal activity and some bad or disconnected EEG sections. Due to this reason, a few false positives were detected in these EEG sections, which could be reduced to a lower value if these EEG sections were removed in the pre-processing stage.

A comparison between different existing methods (Jacquin et al., 2007; Khan et al., 2012a; Minasyan et al., 2009) and the proposed method is given in Table 4. It can be observed that the proposed method is better in terms of accuracy as well as simplicity since normalized modified Wilson amplitude is the only time domain feature used. For discrimination between normal and seizure EEG, instead of using any classifier, a two stage thresholding i.e. MAD_{Th} and $Channel_{Th}$ is used. Due to the use of time domain feature no transformation is needed, hence it requires lesser computation as well. The results reported by Khan et al. (2012a) are on the same database but only for 5 subjects. Comparing their results to results

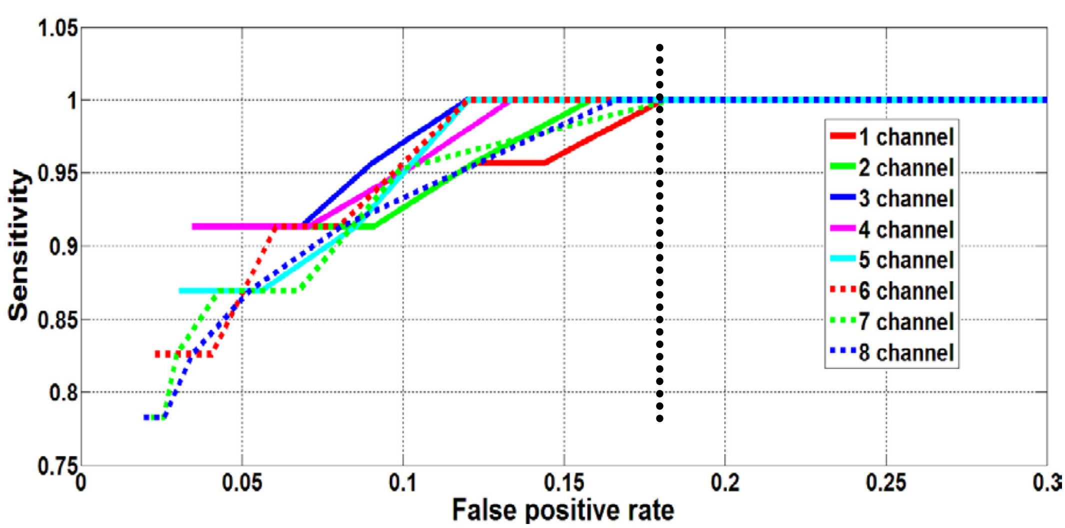

Figure 7 ROC curve of different channels plotted at different values of WAMP threshold.

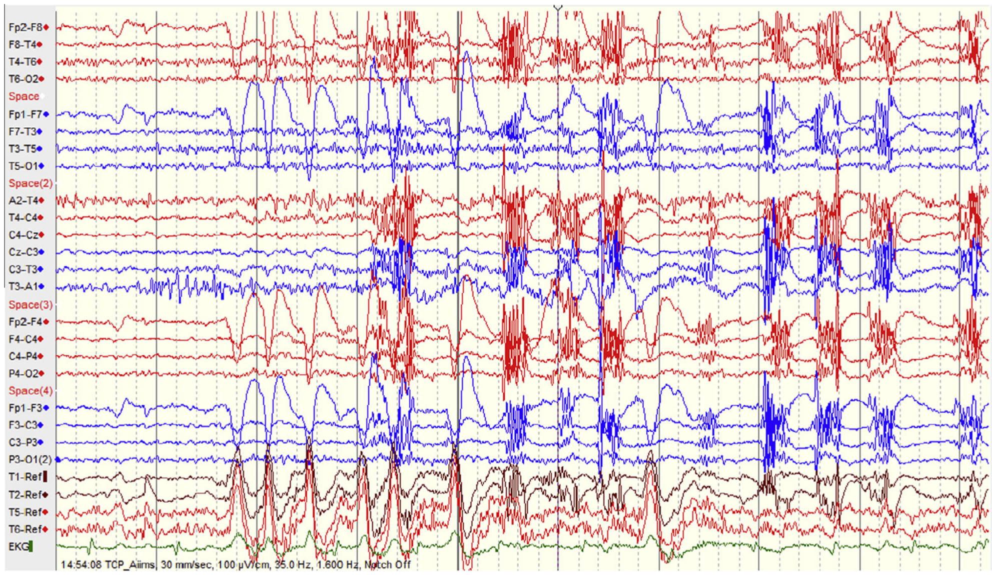

Figure 8 Normal EEG of subject number 9.

Figure 9 Non-convulsive seizure EEG of subject number 9.

Table 4 Comparison with other methods.

Methods	Avg. sensitivity (%)	Avg. specificity (%)	Accuracy (%)
Jacquin et al. (2007)	83	96	89.5
Minasyan et al. (2009)	71	99	85
Khan et al. (2012a)	86.8	96.9	91.85
Proposed method	100	88.02	94.01

obtained by the proposed method, it is clear that better sensitivity and accuracy are achieved by the new method. However, there is a reduction in specificity.

4. Conclusions

The proposed method detected all the non convulsive seizures present in the database. Since there is no classifier used in the algorithm it is very simple to implement and detection is done at a fast rate. If a few artifacts were present in the normal EEG, false detection rate would have been lowered and thereby giving higher specificity. A total of 23 recordings of 9 subjects' data from a large database have been tested in this initial work and the research is in progress to extend this technique on a continuous EEG database and for more number of subjects. The method depends on the threshold selection which was based on the data used in this paper. It is possible that this threshold may be different for pediatric EEG or in the case of elderly persons.

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