Indian Journal of Science and Technology, *Vol 11(10), DOI: 10.17485/ijst/2018/v11i10/99176,* March 2018
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Early Seizure Detection Techniques: A Review

Manpreet Kaur[1*], Neelam Rup Prakash[2] and Parveen Kalra[1]

[1]Department of Centre of Excellence (Industrial & Product Design), PEC University of Technology, Sector-12, Chandigarh - 160012, India; manpreetkaur173@gmail.com, parveenkalra@pec.ac.in
[2]Electronics and Communication Engineering Department, PEC University of Technology, Sector-12, Chandigarh – 160012, India; neelamrprakash@pec.ac.in

Abstract

Objectives: To study the different seizure detection techniques and find an efficient technique which results in optimum output parameters in terms of sensitivity and specificity. **Methods/Statistical Analysis**: Different seizure detection techniques were studied to find the efficient technique for early seizure detection. Past researches extracted different features from raw Electroencephalogram (EEG) signals. Features like time domain and frequency domain were extracted. Recently, wavelet parameters have been introduced which is the combination of time and frequency domain. For the classification, different classifiers like RNN, Artificial Neural Network, Modified Neural Network and Support Vector Machine were used. **Findings:** This review paper studies different types of seizure detection techniques. Development of early seizure detection techniques gains a major attention to provide an early alert to the epileptic patient. Different time domain, frequency domain and time-frequency domain features were extracted from the raw EEG signal. For the classification, different classifiers like RNN, Artificial Neural Network (ANN), Modified Neural Network and Support Vector Machine (SVM) were used. It was observed that the technique employing DT-CWT as a feature set and Support Vector Machine as a classifier resulted in maximum classification accuracy of 100% and 0 false alarm rate. So, from the findings, it is concluded that the combination of wavelet decomposition and a number of features extraction will improve the accuracy for early seizure detection in future. **Application/Improvements:** In future, the early seizure detection techniques can be used to provide an alert to the epileptic patient so that an effective diagnosis can be done before the occurrence of seizure onset.

Keywords: Daubechies Wavelet, Detection Techniques, Electroencephalogram, Osorio-Frei Algorithm and Seizure

Abbreviations:

DT-CWT	Dual Tree Complex Wavelets Transform
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
ECoG	Electrocardiogram
iEEG	Intracranial EEG

1. Introduction

Worldwide, about 1% of people i.e. 65 million have epilepsy and nearly 80% of cases arise from developing countries. In 2013, due to epilepsy 116,000 deaths had occurred and about 111,000 deaths in 1990. Epilepsy is more prominent in old age. Persons affected with epilepsy can be treated with drug therapy up to an extent of 67% or neurosurgical procedures up to an extent of 7-8 %.

Electroencephalogram (EEG) was discovered in 1929 by German psychiatrist 'Hans Berger'. It is a non-invasive method by which potentials generated from millions of neurons are recorded[1]. A non-invasive method of recording brain potentials is called as Electrocardiogram (ECoG) or intracranial EEG (iEEG). Long-term EEG and video monitoring can be very unpleasant for patients and performing analysis of EEG signals and video data is very exhaustive. Seizure is defined as the change in behavior

**Author for correspondence*

which is caused due to an abnormal neuronal activity in the brain. For the diagnosis of epileptic patients, detection of seizure must be carried out prior to occurrence of seizure onset. For refractory patients, who are prone to have frequent seizures, EEG and video monitoring over a long period contributes to the management of daily care and adjustment of drug therapy.

Seizure detection algorithms have been proposed by many researchers to alert the patient so that proper diagnostic action can be given to the patient at right time. Two main stages of these algorithms which provide a significant contribution in detecting seizure are feature extraction and feature selection stage.

1.1 Feature Extraction Stage

From the EEG recording, several features are extracted for the detection of seizure. Various features that can be extracted from EEG signals are time, frequency and joint time-frequency domain features. These features are described as:

1.1.1 Time Domain Features

Time domain features includes variance, zero crossings, curve length, non-linear energy[2], average amplitude and average duration of half wave, coefficient of variation of half wave amplitude and its duration[3], etc. Average amplitude[3] and average wave duration[3] are calculated as:

$$\text{Average Amplitude} = \frac{\sum_{i=1}^{N} Amp_i}{N}$$

$$\text{Average wave duration} = \frac{\sum_{i=1}^{N} Dur_i}{N}$$

where N=Number of half waves in one epoch
Amp_i=Amplitude of half wave
Dur_i=Duration of half wave

Coefficient of variation is the ratio of standard deviation and mean. It is also known as relative standard deviation which is used for calculating the degree of variation between data. Co-efficient of variation of half wave amplitude[3] and half wave duration[3] are calculated as:

Coefficient of variation of half wave

$$\text{amplitude} = \frac{\sum_{i=1}^{N} (Amp_i - Average\_wave\_amplitude)^2}{N * Average\_wave\_amplitude}$$

Coefficient of variation of half wave

$$\text{duration} = \frac{\sum_{i=1}^{N} (Dur_i - Average\_wave\_duration)^2}{N * Average\_wave\_duration}$$

1.1.2 Frequency Domain Features

Frequency domain features include relative power in delta (0-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (16-30 Hz), high frequency band (30-70 Hz), mean frequency, dominant frequency, dominant peak's width and bandwidth of peak frequency[3]. Relative power in particular band[3] is calculated as:

$$P = \sum_{f_i \in \Delta f} S(f)$$

where S(f)= power spectrum of an epoch

Δf =frequency band

$$\text{Mean frequency } (f_m) = \frac{\sum_{f_i \in \Delta f} S(f) f_i}{\sum_{f_i \in \Delta f} S(f)}$$

Dominant frequency[3] is defined as the peak frequency which has the largest average power. It is calculated as:

$$\text{Dominant frequency } (f_d) = \arg\max_{\Delta f} \{S(f)\}$$

1.1.3 Joint Time-frequency Domain Features

Joint time-frequency domain features are extracted by using the process of wavelet level decomposition. In wavelet level decomposition, the input signal is decomposed into approximation and detail coefficients. A filter bank, comprising of a number of LPF and HPF, is generally used for the wavelet decomposition as shown in Figure 1.

In the wavelet decomposition tree, the input signal is decomposed by using a number of filters. Basically, these filters divide the input signal frequency by 2. As shown in figure, at first level the input signal of frequency range (0-70 Hz) is decomposed into two resolution components. The first resolution component is detail coefficient

$d_1[n]$ having frequency range (35-70 Hz) and the second resolution component is a_1 [n] whose frequency range is (0-35 Hz). Similarly, at second and third level the signal decomposition is performed to generate detail and approximation coefficients. The decomposition levels can be set according to the requirement. Features that can be derived from wavelet coefficients are mean, variance etc. Mean of these coefficients[3] is calculated as:

$$M_j = \frac{1}{N_j}\sum_{i=1}^{N_j} W_i^j$$

Where j = decomposition level, W_i^j = ith wavelet at level j

N_j = number of wavelet coefficients at level j

Variance of wavelet coefficients[3] is a measure of how far a set of wavelet coefficients are spread out. Variance of identical wavelet coefficients is 0.

$$V_j = \frac{1}{N_j}\sum_{i=1}^{N_j}[W_i^j - M_j]^2$$

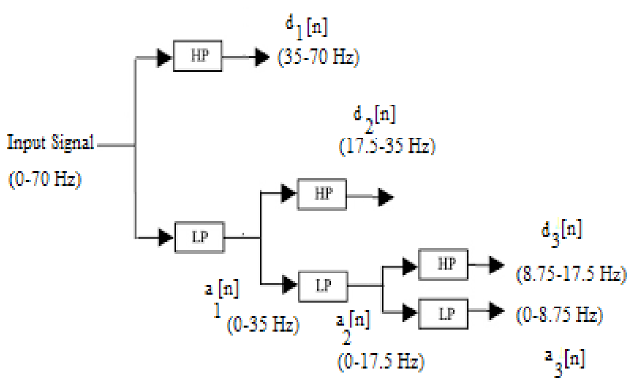

Figure 1. Wavelet decomposition tree.

1.2 Feature Selection Stage

After extracting several features from raw EEG data, the features are applied to classifier which separates seizure activity from non-seizure activity. The classifiers used are KNN, ANN, RNN and SVM etc. The different classifiers are explained below:

1.2.1 KNN

K Nearest Neighbor classifier classifies the seizure and non-seizure activity by storing the training data. Then the Euclidean distance between test data and training data is calculated while tracking k smallest distances.

1.2.2 ANN

Artificial Neural Network classifier works by feeding the feature vectors into a neural network which comprises of two layers i.e. hidden and output layer. Both of the layers have a particular transfer function. ANN do not need any information about data distribution, they form the model in training phase from the training set. The training process completes when the mean squared error starts to increase.

1.2.3 RNN

Recurrent Neural Network has the capability to classify the data with small amount of training data. This network can also represent and encode states in which output of the network depends on a number of previous inputs.

1.2.4 SVM

Support Vector Machine is used for classification of the data of two different classes. It finds the hyperplane for segregation of the data vectors. If the input data vectors are separated without any error then the hyperplane will provide optimal separation[4]. SVM is widely used for classification, regression and density estimation.

2. Early Seizure Detection Techniques

2.1 Seizure Detection Algorithm using Time Domain and Frequency Domain Features

A seizure detection algorithm was described in which time and frequency domain features were used for extraction[5]. Time domain features i.e. average amplitude and average duration of the wave; and its Coefficient of Variation (COVA) were extracted from an epoch. Dominant frequency and average power in the main energy zone were extracted in the frequency domain. For the classification of seizure and non-seizure activity modified Nearest Neighbor classifier was used.

The advantage of this system is that this algorithm achieved a detection rate of 100% as compared to traditional seizure detection methods, which only provided a detection rate of 83%; on the same database. But the limitation is that it has the capability of detecting only particular type of seizure template. If we apply this technique on different database, then this algorithm is not capable to provide the same efficiency.

A similar seizure detection system using time and frequency domain features was introduced, as shown in Figure 2, in which inspite of using Nearest Neighbor, Support Vector Machines was used for the classification[2]. The classification structure of Support Vector Machine is shown in Figure 3.

The EEG signal is down-sampled with an anti-aliasing filter of 12.8 Hz from 256 to 32 Hz and then it is segmented into epochs. A number of time and frequency domain features are extracted from each EEG epoch. The time domain features i.e. non-linear energy, number of maxima and minima, skewness, etc. are extracted directly by applying first and second derivative on each EEG epoch. From the power spectral density of each epoch, frequency domain features i.e. peak frequency of spectrum, total power etc. is extracted. These feature vectors are then classified using SVM. The individual outputs of all the channels are then merged using an OR operator. Then collar operation is applied which prevents cutting off the beginning and ending of data.

This algorithm was tested on a EEG database of 17 full-term newborns with seizures. Sensitivity of 89% was achieved with a FDR of 1/hr. For improving the performance of system further, Discrete Wavelet Transform was also used for seizure detection algorithms.

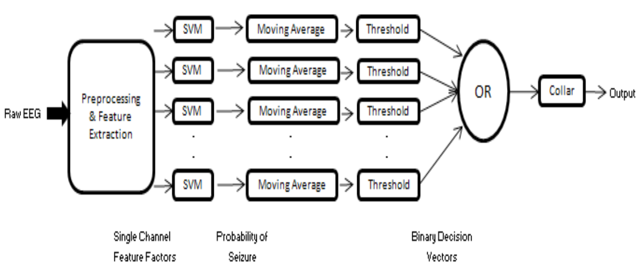

Figure 2. Seizure detection system.

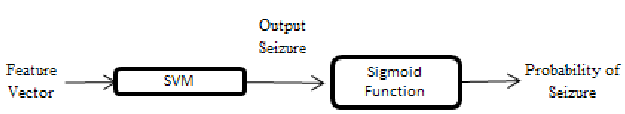

Figure 3. SVM classification structure.

2.2 Seizure Detection Algorithm using Joint Time-frequency Domain Features

Discrete Wavelet Transform provides the information in both frequency and time. Many algorithms have been developed using Discrete Wavelet Transform. A patient specific seizure detection algorithm using Discrete Wavelet Transform was also presented[6] as shown in Figure 4. The EEG signal recording from patients is first segmented into epochs of 2 seconds duration. Then from each epoch, a number of features i.e. morphology and spatial localization are extracted. Wavelet decomposition using 4 time scales was used for extracting the morphology of the EEG signal. The feature vectors are then segregated into seizure and non-seizure data using SVM. In order to avoid false detection, three consecutive 2 seconds epochs are monitored for detecting seizure event.

The disadvantage of this method is that the detection system declared 50 false detections on the EEG recordings because of the similarity in morphology of non-seizure data and training dataset. For further improvement in the performance of the system, the detector is trained with large number of recordings. Training the detector with additional recordings resulted in improvement in sensitivity but at the same time, it increases the false alarm rate, thereby deteriorating the system performance.

The performance of above algorithm was tested on another database for epileptic seizure detection[7]. The algorithm was tested on a database of 24 patients. Sensitivity of 96% with median detection latency of 3 s and median FDR of 2 FD/ 24 hr were achieved.

Daubechies formulated the most commonly used set of DWT in 1988 which was named as Daubechies Wavelet Transform. This formation uses recurrence relations to generate the discrete samples of mother wavelet function. A generic Osorio-frei algorithm using Daubechies Wavelet Transform was described which compares the signal's current seizure content with past seizure content[8].

The adaptation procedure for generic Osorio-frei algorithm comprises of two steps. In step 1, to improve sensitivity, the ECoG signal is filtered out using three level DAUB4 wavelet. The seizure recognition task is not altered using DAUB4 wavelet[9]. If input signal is $x_k[k = 1,2,\_ \_ \_]$ and DAUB4 wavelet coefficients are given by $[b_0, b_1, b_2, b_3,\_ \_ \_ \_, b_{p-1}]$, then output of filter is given by:

$$y_k = \sum_{j=0}^{p-1} b_j x_{k-j}$$

The output is then squared using the algorithm. In second step, specificity is increased by using an order statistic median filter. Normalization of foreground signal is performed with respect to background signal.

The background signal is obtained by using three steps:

- The foreground signal is firstly decimated. Foreground sequence is given by:

$$FG_k = median\{y_k^2, y_{k-1}^2, y_{k-2}^2, \_\_\_\_, y_{k-q1+1}^2\}$$

- The resultant signal is then passed by a median filter.
- For smoothening the output, an IIR filter is used.

The background sequence[9] is given by:

$$BG_k = \begin{cases} (1-\lambda)median\{FG_k, FG_{k-1s}, FG_{k-2s}, \_\_\_, FG_{k-(q2-1)s}\} \\ +(\lambda)BG_{k-1}(if\_k = ns) \\ BG_{k-1}(if\_n(s-1) \le k < ns) \end{cases}$$

Then the algorithm computes foreground to background ratio $r^{(i)}{}_k = \frac{FG_k^{(i)}}{BG_k^{(i)}}$ and compares with a pre-specified threshold value. The seizure event is declared if the ratio exceeds the threshold.

The effect of varying the threshold on output parameters is studied. Initially using Threshold (T) =10, an average false prediction rate of 2.8/hr and a detection delay of 15.5 s was achieved. Doubling the threshold value i.e. T = 20 resulted in increasing the detection delay to 1.2 s and decreasing the false alarm rate to .36/hr.

Discrete Wavelet Transform was also used as preprocessing step for automatic detection of epileptic seizures[10]. It was observed that without using DWT as initial stage, sensitivity was reduced to 73% from 96%. Approximate entropy feature was extracted after decomposing the EEG signal into wavelet features. Differences were found in approximate entropy of a normal and epileptic EEG. EEG epochs whose approximate entropy value is less than the threshold were detected as seizure pattern and epochs having approximate entropy value greater than the threshold were detected as normal pattern. A modified system was also introduced in which instead of using the comparison between approximate entropy value and the threshold, the difference between approximate entropy value and the mean approximate entropy value was compared with the threshold value. If the difference is greater than the threshold, the epoch is declared as epileptic otherwise it is declared as normal. This modified system achieved a sensitivity of 97%.

A binary classification approach for seizure detection was proposed[11]. In this technique, feature vectors are derived from an epoch. Then the function f(X) maps the feature vector X into labels Y= +1 depending on whether X represents seizure activity or non-seizure activity. Derivative filter is used as preprocessing step to eliminate the effect of frequency. Feature vector X_T with M*N elements is formed by concatenating the M spectral energies extracted from N EEG channels as shown in Figure 5.

Each feature is then scaled and normalized using training data. This feature vector does not capture the relationship between past and present epochs. To overcome this difficulty, stacking of the vectors from W contiguous and non-overlapping L = 1 second epoch is performed. The time delay embedded feature vector X_t obtained is $X_T, X_{T-L}, \_\_\_\_\_, X_{T-(W-1)L}$. This time delay embedded feature vector[11] X_t is classified using linear Support Vector Machine[7]. SVM is a classification technique used to separate seizure activity from non-seizure activity.

Limitation of this algorithm is that the detector misses or it has long detection latency in cases in which test seizure is very different from the training seizure pattern. The effect of varying the window size on detection latency is also studied here. It is observed that increasing the window size results in increase in detection latency. The detection latency is improved when the window size is 1 second but at the same time it increases the false alarm rate.

RNN was used as a classifier for the prediction of seizure onset[12]. The subbands are derived from EEG data using wavelet decomposition. It was demonstrated that preictal stage of some minutes duration is feasible before seizure onset. RNN was also used as classifier for every EEG channel[3]. All the RNN are independently trained with specific EEG patterns. Recurrent neural network has two output nodes i.e. preictal node for detecting preened patterns and octal node for detecting seizure onset patterns. Then the decision making module makes a decision whether the seizure has occurred or not.

A statistical method for seizure detection using dual tree complex wavelet transform was introduced[4]. It computes the complex transform of signal using two decomposition trees. DT-CWT has advantages over

DWT such as reduced redundancy and improvement in directionality. This transform produces two types of coefficients i.e. real and imaginary coefficients. Variance was used as feature in this method because variance and kurtosis features have shown significant contribution at sub-band level in segregation of seizure and non-seizure activity[13]. ANN and SVM were applied on EEG data of five sets in which two sets were collected from 5 healthy patients and the remaining three sets were collected from 5 patients which were selected for respective surgery. It was observed that SVM based approach provided 100% accuracy on all the sets.

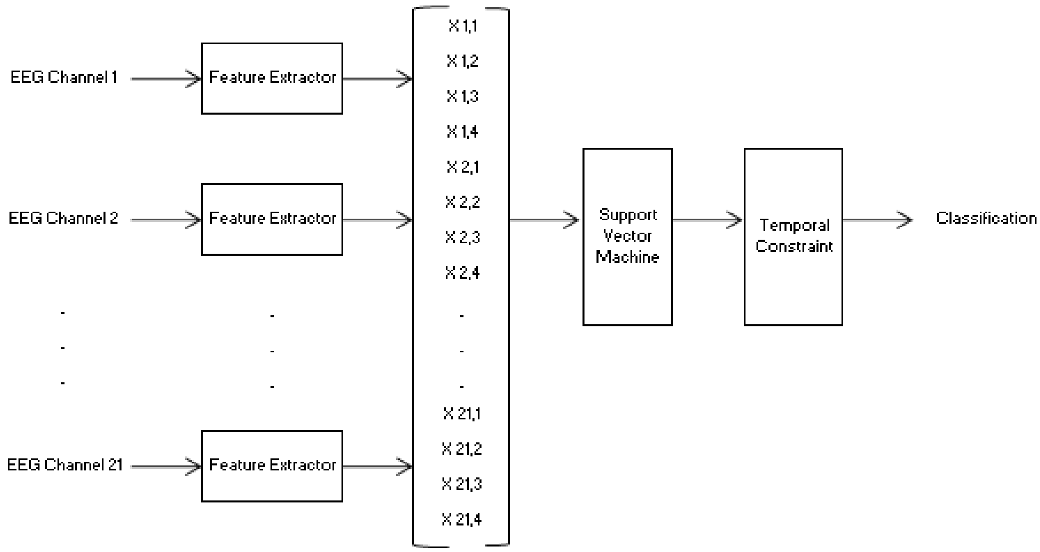

Figure 4. Architecture of detection system.

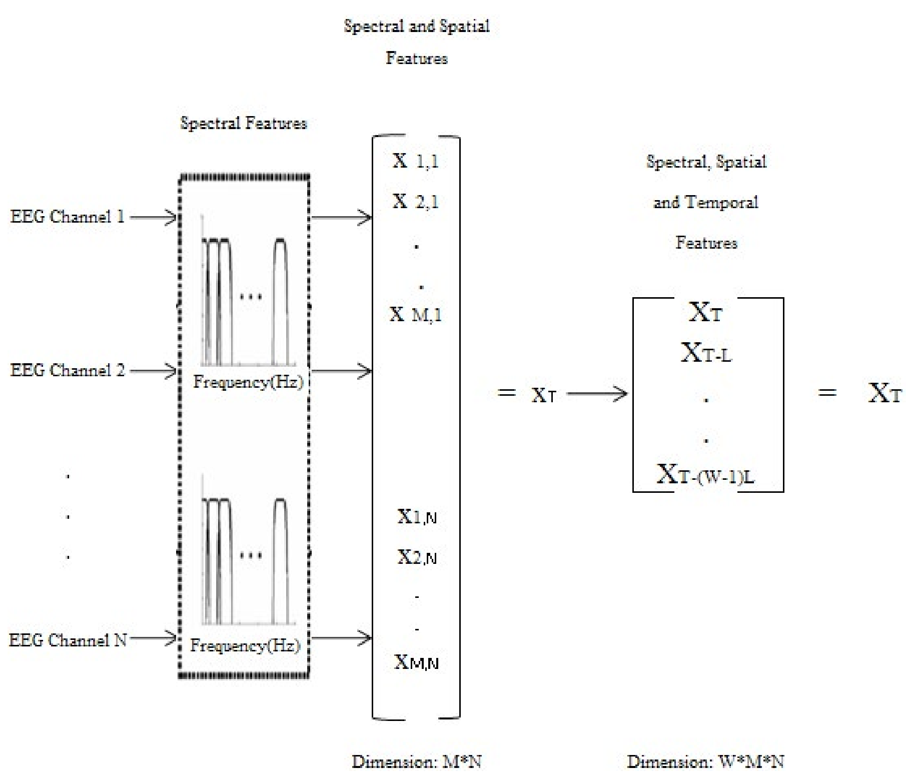

Figure 5. Feature vector formation steps.

3. Comparative Analysis

In this work different seizure detection algorithms were studied to propose efficient method for early seizure detection. The seizure detection technique using time domain and frequency domain features were described[5,12]. The main difference between these two methods was that the first method used Nearest Neighbor as classifier whereas the second method used Support Vector Machine for classification. The sensitivity provided by these algorithms are 100% and 89% respectively. The second method is still better as compared to other method, because first method only detects seizure which is similar to a particular template. On the other hand, second method can detect seizure of any kind of template.

Seizure detection technique was presented by calculating foreground to background signal ratio using wavelet decomposition[9] and achieved a sensitivity of 92% with a detection latency of. 8s. A patient specific seizure detection algorithm was described using Support Vector Machines[6]. Morphology and spatial distribution features were extracted from the EEG signal. This algorithm provided 97% sensitivity with a detection latency of 7.1+1.9 seconds. The limitation is that this detection system declared 50 false detections due to similarity in the morphology of EEG signals. The sensitivity increases by training the algorithm with large number of recordings. When algorithm is trained with one recording, 91% sensitivity is achieved; with two recordings 96% sensitivity is achieved. Similarly, when three recordings were used for training,

Table 1. Overview of previous work on seizure detection algorithms

Reference	Features, Classifier	Database	No. of patients	Total seizures	Recording Duration	Sensitivity	False alarm rate	Detection latency
[5]	Time domain and frequency domain; modified NN	Montreal Neurological Hospital	12	47	-	100%	0.02/hr	9.35 s
[7]	Daub4 wavelet, Foreground to background signal ratio	-	16	125	-	92%	2.8/hr	.8 s
[12]	DWT, Morphology; SVM	Clinical data	36	139	60 hrs	97%	6/hr	7.1 ± 1.9 s
[8]	DWT, Approximate Entropy	Clinical data	-	-	-	96%	-	-
[10]	DWT, Spectral Energy; SVM	CHB-MIT Database	24	173	916 hrs	96%	2/24hr	3 s
[3]	Time domain, frequency domain, wavelet and complexity measures, RNN	Thomas Jefferson University, Dartmouth University, University of Virginia, UCLA and University of Michigan medical centers	25	86	-	Preonset: 72% Onset: 100%	0.023/ hr	4 s
[2]	Time domain, frequency domain and Information theory; SVM	Cork university maternity hospital	55	705	267.9 hrs	89%	1/hr	-
[9]	DWT, Spectral Energy; SVM	Massachusetts General Hospital	10	67	875 hrs	97%	.6/24hr	5 s
[4]	DT-CWT, Skewness; ANN and SVM	-	10	-	-	100%	0	-

97% sensitivity is achieved. The mean detection latencies achieved with these recordings are 9.5+5.0 s, 7.6+2.4 s and 7.1 + 1.9 s respectively. The effect of using DWT as preprocessing step for automatic detection of seizures was studied[10]. The sensitivity was dropped to 73% from 96% without using wavelet transform. It was demonstrated that seizure can be detected prior to its onset[3]. Experiments were conducted on a database of 25 patients. Pre-onset detection was successful in 14 patients[14]. Sensitivity was 100% for post-onset detection with a false detection rate of 0.0023/hr and a detection latency of 4 seconds.

A binary classification approach for seizure detection was described[11]. K parameter (number of consecutive epochs) used for analysis was varied to reduce the detection latency. Setting K = 1, causes the algorithm to wait for only single window, thereby improving the detection latency but at the cost of increased false alarm rate. Setting K = 2 improves the false alarm rate but it increases the detection latency. DT-CWT was used for decomposition and compared the performance of ANN and SVM classifier[4]. Both the classifiers were used on a number of data sets. It was observed that SVM based approach provides 100% accuracy on all the datasets. An overview of previous work on early seizure detection techniques is also shown in Table 1.

With reference to Table 1, among all the techniques described here, the technique based upon DT-CWT provides best efficiency in terms of both sensitivity and specificity. Technique described in[9] also achieved better results in terms of sensitivity, false alarm rate and detection latency.

4. Conclusion

So, based upon this study, decomposition of EEG signal into wavelet coefficients is carried out at initial stage and important features are extracted. Later on, classifiers i.e. SVM, ANN, RNN etc. have been used for the classification of extracted features. So, the combination of wavelet decomposition and a number of features extractions resulted in improvement in accuracy for early seizure detection.

5. References

1. Sanei S, Chambers JA. EEG signal processing. England: John Wiley and Sons. Ltd; 2007. p. 1–312. crossref
2. Temko A, Thomas E, Marnane W, Lightbody G, Boylan G. EEG-based neonatal seizure detection with Support Vector Machines. Clinical Neurophysiology. 2011; 122(3):464–73. crossref
3. Minasyan GR, Chatten JB, Chatten MJ, Harner RN. Patient-specific early seizure detection from scalp EEG. Journal of Clinical Neurophysiology: Official Publication of the American Electroencephalographic Society. 2010; 27(3):163–78.
4. Das AB, Bhuiyan MIH, Alam SSA. Statistical method for automatic detection of seizure and epilepsy in the dual tree complex wavelet transform domain. 2014 International Conference on Informatics, Electronics and Vision (ICIEV); 2014. p. 1–6. crossref
5. Qu H, Gotman J. A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: Possible use as a warning device. IEEE Transactions on Biomedical Engineering. 1997; 44(2):115–122. PMid: 9214791. crossref
6. Shoeb A, Edwards H, Connolly J, Bourgeois B, Treves ST, Guttag J. Patient-specific seizure onset detection. Epilepsy and Behavior. 2004; 5(4):483–98. PMid: 15256184. crossref
7. Shoeb A, Guttag J. Application of machine learning to epileptic seizure detection. Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, Massachusetts; 2010. p. 1–8. PMCid: PMC2946978.
8. Haas SM, Frei MG, Osorio I. Strategies for adapting automated seizure detection algorithms. Medical Engineering and Physics. 2007; 29(8):895–909. PMid: 17097325 PMCid: PMC2339717. crossref
9. Osorio I, Frei MG, Wilkinson SB. Real-time automated detection and quantitative analysis of seizures and short-term prediction of clinical onset. Epilepsia. 1998; 39(6):615–27. PMid: 9637604. crossref
10. Ocak H. Automatic detection of epileptic seizures in EEG using Discrete Wavelet Transform and approximates entropy. Expert Systems with Applications. 2009; 36(2):2027–36. crossref
11. Kharbouch A, Shoeb A, Guttag J, Cash SS. An algorithm for seizure onset detection using intracranial EEG. Epilepsy and Behavior. 2011; 22(1):S29–35. PMid: 22078515 PMCid: PMC3713785. crossref
12. Petrosian A, Prokhorov D, Homan R, Dasheiff R, Wunsch D. Recurrent Neural Network based prediction of epileptic seizures in intra-and extracranial EEG. Neurocomputing. 2000; 30(1):201–18. crossref
13. Alam SM, Bhuiyan MI, Das AB. Statistical parameters in the dual tree complex wavelet transform domain for the detection of epilepsy and seizure. 2013 International Conference on Electrical Information and Communication Technology (EICT); 2014. p. 1–6. PMCid: PMC5598519. crossref
14. Shoeb A. Patient-specific seizure onset detection. [Master of Engineering Thesis]. Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology; 2003. p. 1–124.