A systematic review on detection and estimation algorithms of EEG signal for epilepsy

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Abstract: Epilepsy is the most common neurological disorder characterised by a sudden and recurrent neuronal firing in the brain. As EEG records the electrical activity of the brain so it helps to detect epilepsy of the subject. Early detection of epileptic seizure using EEG signal is most useful in several diagnoses. So aim of the work is to study and compare the different techniques used for feature extraction and classification algorithm. Epilepsy detection research is oriented to develop non-invasive and precise methods to allow accurate and quick diagnose. In this paper, we present a review of significant researches where we can find most suitable method among existing members to improve computing efficiency and detect epilepsy of the subject efficiently and accurately with lesser computational time. The database which is publicly available at Bonn University is taken.

Keywords: EEG signal; epilepsy; seizure detection algorithm; performance analysis; wavelet; Hilbert transform; empirical mode decomposition; EMD.

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1 Introduction

Human brain is an organic electrochemical computer where neurons generate electricity through chemical reactions. This nature of neurons leads to action, behaviour and modes of human. The recording of electrical activity of brain over a small duration of time is called Electroencephalography and the waveform recorded is called EEG signal. EEG signal contains valuable information about brain activity. We can see the waveform recorded and find any abnormalities or disorder or diseases relating to brain. Some common diseases related to brain are epilepsy, Parkinson's disease, Alzemeir, etc. Epilepsy is one of the most common neurological disorder that 60 million people suffer worldwide reported by WHO (Acharya et al., 2013; Gajic et al., 2014). Seizures come without a symptom and are the temporary anomalies, causes abnormal electrical behaviour of brain cells. Epilepsy seizure may lead to situations like fractures, burns, submersion, motor vehicle accidents and even death. Hence a lot of research is being done for the early detection of seizure.

EEG is a non-invasive method to diagnose brain diseases. Epilepsy detection study focuses on classifying only the normal and ictal stages (two-class problem), or the methods for classifying all three stages, namely, normal, interictal and ictal (three-class problem). The two primary considerations for detection of epilepsy are the type of features to be extracted from the EEG input signal (feature extraction techniques) and the type of analysis techniques to be applied on these extracted features to detect the stage (classification techniques). There are a number of seizure detection techniques available to classify seizure and non-seizure EEG signals. Epileptic seizure detection can be done using pre-processing, feature extraction, feature selection and classification.

1.1 Motivation

Epilepsy can be detected by experienced neurologist by visual inspection of EEG recordings for ictal, interictal activity. But it is a very time consuming process for long term recording. Early days, epileptic seizure automatic analysis is done using Fourier transform and parametric methods. The epilepsy gives rise to frequency changes in sub bands [δ (0.4–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–30 Hz)]. The EEG analysis methods can broadly be classified in to time domain analysis, frequency domain analysis, time–frequency domain analysis, higher order spectral analysis, nonlinear dynamic analysis and artificial neural network analysis. Spectral parameters and features extracted from the Fourier transform are commonly used for detection and classification of epileptic seizure EEG signals, but assumption is that Fourier transform-based analysis, the signal being analysed is stationary. To overcome the problems associated with conventional frequency-based detection techniques, time-frequency analysis-based detection techniques have been employed (Tzallas et al., 2009). Various time-frequency domain methods are Short time Fourier transform (Parvez et al., 2015), wavelet transform (Ocak, 2009; Kumar et al., 2017), multi wavelet transform (Bajaj and Pachori, 2012). The behaviour of neuron is dynamic. It is decided by threshold and saturation phenomena. So, the functioning of the brain at the microscopic level, i.e., the interplay of neurons, is extremely nonlinear in nature. Hence, Nonlinear dynamics analysis methods may be preferred more for the analysis of the complex and nonlinear EEG waveform recorded from the brain than time and frequency domain methods. Finally, these nonlinear methods are used to extract parameters for analysis and classification of EEG signal.

The paper is organised as follows: Section 2 describes the detection methods available in literature. Section 3 outlines data collection method and Section 4 discusses the findings of different methods of the present work. Conclusion and future scope is discussed in Section 5.

2 Research methodology

The detection methods available in literature consisting of following major steps:

1. pre-processing
2. feature extraction technique
3. feature selection
4. classification technique (Acharya et al., 2013).

Pre-processing is done on EEG signal to remove noise and artefacts from the signal. These artefacts can be removed using filtering methods (Orosco et al., 2013). Band pass Filter removes artefacts and allows the frequency range of 0.5 ~100 Hz of intracranial

EEG. Notch filter removes 50 Hz powerline interference. Independent component analysis (ICA) (Tong and Thakor, 2009; Sanei and Chambers, 2007), adaptive filtering methodologies are used for noise cancellation (He et al., 2005). Pre processing also helps to normalise the signal, putting all the data in a particular amplitude range so that comparison among the signals coming from different patient (Varsavsky et al., 2011) is possible. Similarly various feature extraction method used are some common spectral features are average band frequency, maximum power (Aarabi et al., 2006), central, mean, and peak frequencies (Orosco et al., 2011), and dominant frequency (Aarabi et al., 2009), power spectrum, spectral flux, spectral roll-off, spectral centroid, spectral entropy and spectral flatness (Greene et al., 2008; Mitra et al., 2006). Choosing best feature to best describe data reducing irrelevant variables and noise and provide good prediction results is called feature selection (Guyon and Elisseeff, 2003). The methods used for feature selection are:

1. filter
2. wrapper
3. embedded method.

The feature selection method used for epilepsy EEG classification are two stage feature selection algorithm, i.e., individual feature evaluation (IFE)) and sequential backward selection (SBS). This is a wrapper selection method (Mechmeche et al., 2016), sequential feature selection (SFS) for dimensionality reduction (Ghayab et al., 2016). After a successful feature selection process classification of data is done. This is the decision making stage of the EEG data in feature space. There are several classifiers used for epileptic EEG signal classification. Various machine learning algorithm like neural network (Husain and Rao, 2014), fuzzy inference system (Subasi, 2007), statistical analysis methods, wavelets (Adeli et al., 2003; Ocak, 2009), etc. used to give classification with high accuracy. Radial basis function neural network helps in discriminating the normal and seizure signal (Aslan et al., 2008). Multi-layer perceptron neural network is one of the widely used NN for classification (Ghosh-Dastidar et al., 2007; Yildiz et al., 2017).

3 Data collection (Andrzejak et al., 2001)

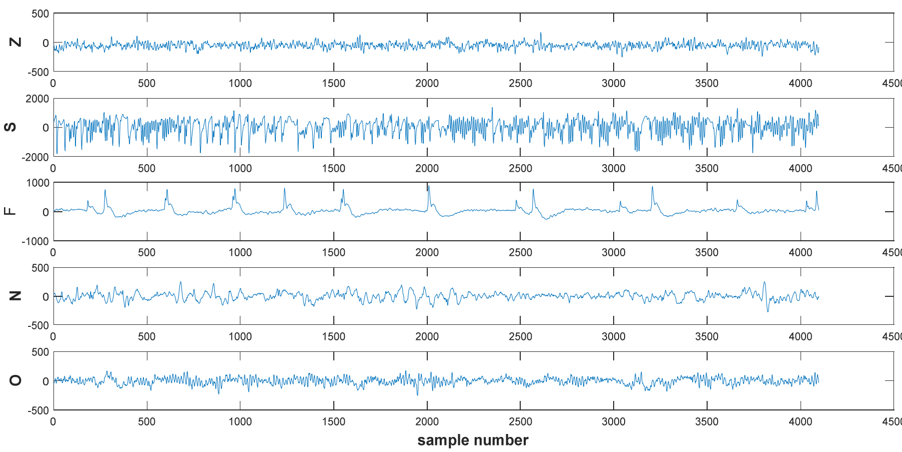
For classification of epilepsy, one of the publicly available dataset is used, i.e., Bonn University Epilepsy Dataset. It has five subsets. Each subset contains 100 EEG signals. Duration of each signal is 23.6 sec. Two subsets are collected from healthy persons, two from seizure free interval or interictal period and one during seizure period or ictal period of epileptic patients. Scalp EEG are used for two subsets and intracranial EEG are considered for three subsets. Epileptic EEG signals are captured by 32 electrodes and collected from five patients. Each segment has 4,097 data points and sampled at 173.61 kHz as presented in Table 1. The signals from each subset (Z, S, F, N and O) are shown in Figure 1.

Table 1 EEG dataset

	Normal class (Z, O)	*SF class(N, F)*	*S class (S)*
Number of subjects	Five healthy	Five epileptic	Five epileptic
Electrode type	Extracranial	Intracranial	Intracranial
Electrode placement	Standard electrode placement scheme	Epileptic zone	Epileptic zone
Subject's state	Normal	Seizure-free (interictal)	Seizure (ictal)
Number of EEG signals	200	200	100
Signal duration	23.6 second	23.6 second	23.6 second

Source: Bajaj and Pachori (2011)

Figure 1 Example of EEG signal for Z, S, F, N and O (see online version for colours)



Source: Bajaj and Pachori (2011)

4 Performance evaluation of seizure detection methods

The nonlinear characteristic of the epileptic EEG and its detection methods needs a wide-ranging collection of criteria for their assessment. Reliability of seizure detection methods is generally measured by various traditional performance indices, such as classification accuracy, sensitivity, specificity, etc. These indices can be calculated as follows (Jaiswal and Banka, 2017):

$$SEN(\%) = \frac{TP}{TP + FN} \times 100 \tag{1}$$

$$SPE(\%) = \frac{TN}{TN + FP} \times 100 \tag{2}$$

$$ACC(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

where

- TP (true positive): correctly detected positive signals
- TN (true negative): correctly detected negative signals
- FP (false positive): erroneously detected positive signals
- FN (false negative): erroneously detected negative signals.

A combined value of the precision and recall can give a single numeric evaluation for an algorithm called F-measure (John et al., 1999). A constant β controls the trade-off between precision and recall (Satapathy et al., 2017). One additional parameter named Matthew's correlation coefficient (MCC) can also be used to evaluate performance (Azar and El-Said, 2014; Fawcett, 2006). MCC parameter provides more balanced measure of classification performance as compared to sensitivity, specificity and accuracy. Generally, the advantage of using MCC becomes apparent when number of observations in two classes differs very much.

$$MCC(\%) = \frac{TP * TN - FP * FN}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}} \times 100 \tag{5}$$

Ghosh-Dastidar et al. (2007) discuss the problem of improving classification accuracy from two different angles.

1 appropriate feature space needs to design by identifying combinations of parameters that increase the interclass separation

2 a classifier needs to design that accurately model the classification problem based on selected feature space.

Nine-parameter mixed band feature space is input to LMBPNN classifier with classification accuracy 96.7%. Similar comparative study of different Seizure detection techniques have been done based on the indices discussed above, and also using some other criteria, such as the type of feature extraction method, classifier etc. This analysis is illustrated in Table 2. However, the analysis doesn't include all the criteria for each method, because literature did not provide the information needed to obtain all of the criteria.

Table 2 Comparative study of different seizure detection techniques

References	*Feature extraction method*	*Features extracted*	*Classifier*	*Accuracy (ACC)*	*Sensitivity*	*Specificity*
Altunay et al. (2010)	Error energy method	Energy	Linear prediction filter	93.6%		
Joshi et al. (2014)	Fractional prediction filter	Prediction error energy, signal energy	SVM	95.33%		
Aarabi et al. (2006)	Mixed-band wavelet chaos methodology, PCA	9 parameter mixed band feature space	RBFNN	95.8%–96.6%, for normal and interictal EEGs 99.3%.		
Polat and Günes (2007)	FFT	FFT based features	Decision tree	98.72% for 10 fold cross validation		
Srinivasan et al. (2005)		Time and frequency domain features	Elman network	99.6%		
Fu et al. (2014)	HHT	Mean, variance and skewness	SVM	99.125%		
Oweis and Abdulhay (2011)	HHT	Weighted frequency	t-test, Euclidean clustering	$P < 0.02$ 94%		96%
Ghosh-Dastidar et al. (2007)	Chao's analysis	STD obtained from statistical analysis, corelation dimension	LMBPNN	96.7%		
Ocak (2009)	DWT	ApEn	Thresholding	96.7%		
Bajaj and Pachori (2012)	DWT	Statistical features	MLPNN, ME	94.5%	95%	94%
Subasi and Gursoy (2010)	DWT-PCA, ICA, LDA	Statistical features	SVM	98.75% (PCA), 99.50% (ICA), 100% (LDA)		
Chen et al. (2014)	Wavelet	ApEn, SampEn, recurrence quantification analysis	ELM	False detection rate 0.078	92.6%	

Notes: BPNN – back-propagation neural network; SVM – support vector machine; DT – decision tree; RF – random forest; EMD – empirical mode decomposition; Ls-SVM – least square support vector machine; WT – wavelet transform; ApEn – approximate entropy; SampEn – sample entropy; STD – standard deviation; MLPNN – multi layer perceptron neural network; EEMD – ensemble empirical mode decomposition; CEEMD – complete ensemble empirical mode decomposition; DQ – direct quadrature; KNNC – K-nearest neighbour classifier.

Table 2 Comparative study of different seizure detection techniques (continued)

References	*Feature extraction method*	*Features extracted*	*Classifier*	*Accuracy (ACC)*	*Sensitivity*	*Specificity*
Guo et al. (2010a)	Multi wavelet transform method	ApEn	MLPNN	99.85%		
Li et al. (2017)	Dual tree-complex WT method	Hurst component, fractal dimension and permutation entropy	SVM	98.87		
Pachori and Bajaj (2011)	EMD	Surface area of the circular complex plane	LS-SVM	98.33%		
Pachori (2008)	EMD	Mean frequency	Kruskal-Walis test	P < 0.01		
Alam and Bhuiyan (2013)	EMD	Coefficient variations, fluctuation index	SVM		98%	99.4%
Patidar and Panigrahi (2017)	EMD	obtain higher order statistical moments such as variance kurtosis, skewness	ANN	Better performance than other time frequency technique		
Patidar and Panigrahi (2017)	Tuned Q WT	Kraskov entropy	SVM	97.75%	97%	99%
Satapathy et al. (2017)	DWT	Entropy, min, max, mean, energy	RF	98%		
Guo et al. (2010b)	WT	Line length features	ANN	99.85%		
Acharya et al. (2012)	DWT-ICA	DWT, ICA coefficients	SVM	96		
Zahra et al. (2017)	MEMD	Weighted mean frequency	ANN	87.2		
Abdulhay et al. (2017)	DQ	Shanon entropy of instantaneous amplitude and frequency	Random forest	98.3~99.7%		
Fergus et al. (2016)	LDAb	Peak frequency, median frequency, variance, etc	KNNC	91%	84%	85%

Notes: BPNN – back-propagation neural network; SVM – support vector machine; DT – decision tree; RF – random forest; EMD – empirical mode decomposition; Ls-SVM – least square support vector machine; WT – wavelet transform; ApEn – approximate entropy; SampEn – sample entropy; STD – standard deviation; MLPNN – multi layer perceptron neural network; EEMD – ensemble empirical mode decomposition; CEEMD – complete ensemble empirical mode decomposition; DQ – direct quadrature; KNNC – K-nearest neighbour classifier.

From the above study it is found that the features that alpha, beta, gamma, theta and delta waves provide gives higher classification accuracy and best average classification. Many authors have used EMD and its variants to obtain finite set of band-limited signals called IMFs. IMFs provide a set of proper rotations. This behaves as a feature to detect the epileptic seizure. To illustrate IMFs are produced as shown in Figures 2–4. The first IMF imf1 produced is the highest frequency by its construction. Residue signal less oscillated than the original signal. Remaining signal still may be compound of several frequencies. The same procedure is applied on the residue signal to obtain the next IMF. By the construction, the number of extrema will eventually decrease as the procedure continues so that a signal is sequentially decomposed into the highest frequency component imf(1) to the lowest frequency component imf(n), for some finite n. Though there are five subsets of epileptic EEG signal set (Z S N F O) are present but they are basically Normal (Z, O), ictal (S) and interictal (N, S). Figures 2, 3 and 4 show the band limited IMFs of 23.6 second normal, ictal and interictal EEG signals. Though EMD is widely used now-a-days, it has some drawbacks as:

1 presence of oscillations of very disparate amplitude in a mode

2 presence of very similar oscillations in similar modes called 'mode mixing'.

But EEMD performs EMD over an ensemble of signal plus white Gaussian noise (WGN). WGN solves mode mixing by populating the whole time frequency space.

Figure 2 EMD of 23.6 sec duration normal EEG signal (see online version for colours)

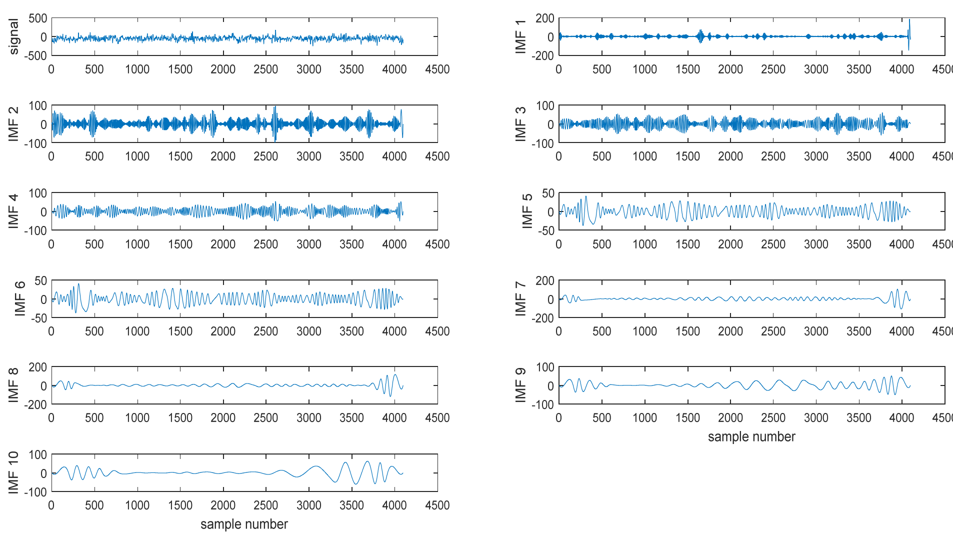


Figure 3 EMD of 23.6 sec duration seizure (ictal) EEG signal (see online version for colours)

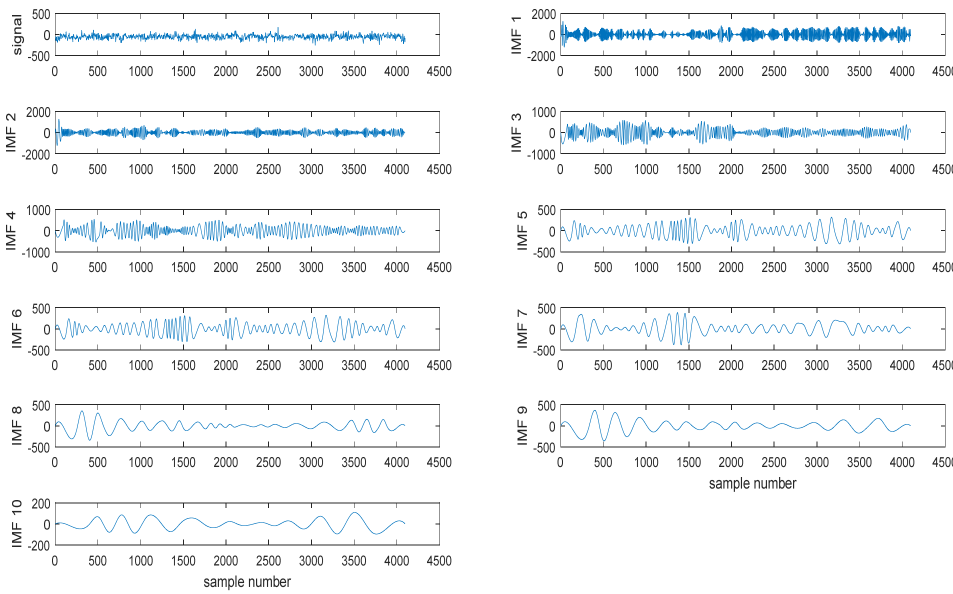
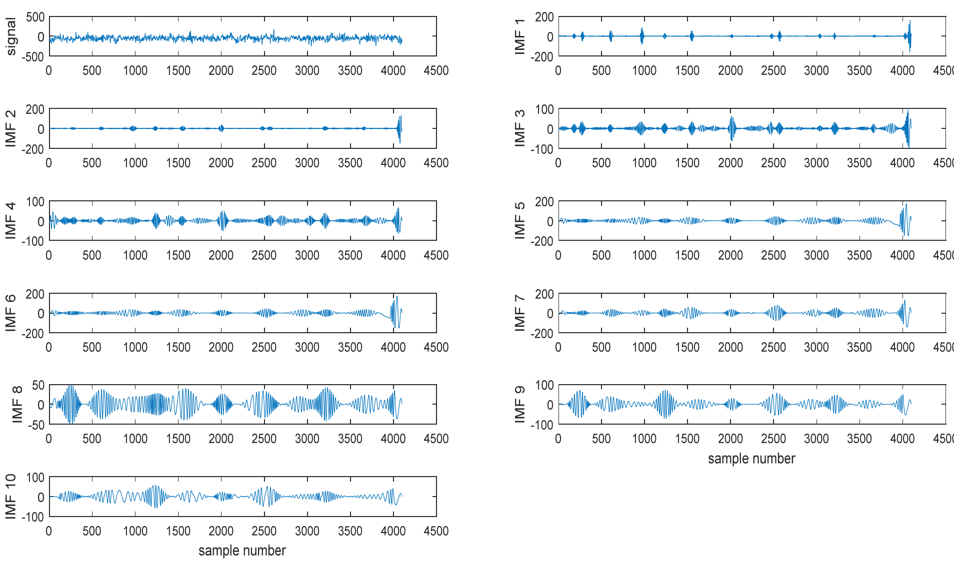


Figure 4 EMD of 23.6 sec duration non-seizure (interictal) EEG signal (see online version for colours)



5 Conclusions and future scope

EEG signal is highly nonlinear. Visual inspection is a tedious job and variations while observation is an issue for analysis of the signal. Abrupt and uncertain nature of epilepsy causes a serious discomfort to the patients. The difficulties motivated for developing automated seizure detection technique to assist neurologist to diagnose more accurately and faster. In this paper a detailed review of seizure detection methods that best classify the normal, ictal (seizure) and interictal (seizure free) signal has been done. Various signal analysis techniques such as linear, time-domain, frequency domain, time-frequency methods are presented in this review. In addition to this, a comprehensive literature survey on issues related to the techniques is highlighted in Table 2. Furthermore, various criteria to evaluate the performance of different detection techniques are also presented in details in Section 4. A wide range of research has been performed to diagnose the risk of epilepsy. Although certain development has been made, but an accomplish solution has not been obtain. Advancements in various aspects of utility operations may reduce risks from epilepsy. From the comparative studies of various techniques it has been observed that accuracy is higher in some methods but the challenges require further advancement of methods. More research is going on and need to be done to achieve 100% result with faster response in every aspect of the treatment of epilepsy.

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