International Journal of Future Generation Communication and Networking
Vol. 13, No. 2s, (2020), pp. 449–455

Epilepsy Detection Using ECG Signal Analysis

Shashank Teppalwar[1],N.M.Wagdarikar[2],Sanket Pawar[3],Pratik Patil[4]

[1,2,3,4] Dept. of E & TC Engg., Smt. Kashibai Navale College of Engineering, Savitribai Phule Pune University, Pune

[1]shashankteppalwar@gmail.com
[2]narendradsp@rediffmail.com
[3]sanketpwr100@gmail.com
[4]pratikpp820@gmail.com

Abstract

Epilepsy is an interminable neurological issue described by intermittent unjustifiable seizures came about because of anomalous, extreme and hyper synchronous neuronal action in brain.The proposed thought includes discovery of Epileptic seizures utilizing EEG signals which are chronicles on scalp of electrical action of the cerebrum. Since in mind there are a large number of neurons interconnected in an intricate way, the resultant EEG signal is unpredictable, nonlinear, non-stationary and non-Gaussian in nature. The proposed thought decays the EEG signals utilizing observational mode disintegration. The EMD adaptively breaks down a sign into wavering segments or Intrinsic Mode Functions (IMFs). The EMD is in actuality a sort of channel bank disintegration strategy whose sub groups are worked as expected to isolate the diverse common segments of the sign. The time and recurrence highlights of IMFS are then extracted. The significant highlights are chosen utilizing Lambda of Wilks. At long last the sign are delegated signals with epilepsy segments and flag with non-epilepsy components.

Keywords- *Epilepsy, ECG, EMD, IMFs*

I.INTRODUCTION

Epilepsyis a global disease with considerable incidence thanks to recurrent unprovoked seizures. These seizures being in the form of signals can be noninvasively diagnosed using electroencephalogram (EEG), a measure of neuronal electrical activity in brain recorded along scalp. EEG is extremely nonlinear, nonstationary and non-Gaussian in nature. Nonlinear adaptive models like empirical mode decomposition (EMD) provide intuitive understanding of data present in these signals. During this study a completely unique methodology is proposed to automatically classify EEG of normal, subjects using EMD decomposition. EEG decomposition using EMD yields few intrinsic mode functions (IMF), which are amplitude and frequency modulated (AM and FM) waves. Epilepsy being related to brainis be a chronic disorder that affects over 50 million people worldwide, characterized by recurrent seizures (World Health Organization [WHO], 2006).Convulsion could be a transient occurrence of signs andsymptoms thanks to abnormal excessive or synchronous neuronal activity within the brain (Fisher et al., 2005 & Berg et al., 2010). This electrical hyperactivity can have its source in numerous parts of the brain and produces physical symptoms like short periods of inattention and loose of memory, a sensory hallucination, or a whole-body convulsion. The frequency of those events can vary from one during a year to many during a day. The bulk of the patients suffer from unpredictable, persistent and frequent seizures which limit the independence of a private, increase the chance of great injury and mobility, and lead to both social isolation and economic hardship (Friedman & Gilliam, 2010). Additionally, the patients with epilepsy have an increased mortality risk of roughly two to three times that of the final population (Ficker, 2000). For any of the explanations exposed before the seizure detection is a very important component within the diagnosis of epilepsy and for the seizures control. Within the clinical practice this detection basically involves visual scanning of Electroencephalogram (EEG) long recordings by the physicians so as to detect and classify the seizure activity present within the EEG signal. Usually these are multichannel records of 24 to 72 hours length which means an awfully time-consuming task and it's also known that the conclusions are very subjective.

II.LITERATURE SURVEY

Empirical mode decomposition (EMD) is employed for classification of seizure and seizure-free EEG signals. The EMD method decomposes the EEG signal into a group of narrowband amplitude and frequency modulated (AM-FM) components called intrinsic mode functions (IMFs). the tactic proposes the utilization of the realm parameter and mean frequency estimation of IMFs within the classification of the seizure and seizure-free EEG signals. These parameters are used as an input in statistical procedure support vector machine (LS-SVM), which provides classification of seizure EEG signals from seizure-free EEG signals. The classification accuracy for classification of seizure and seizure-free EEG signals obtained by using proposed method for second IMF with radial basis function kernel of LS-SVM [1].

ANNOVA consists of decomposition of EEG signals using EMD to get eight intrinsic mode functions (IMFs). These IMFs were subjected to Hilbert transform computation to yield AM and FM frequencies. Three kinds of features were extracted from the IMFs (after Hilbert transform): (i) spectral peak magnitude, peak frequency, (ii) spectral entropy and (iii) spectral energy. In total, 32 features were used for this work [2].The MLP is feed-forward neural networks trained with the quality back-propagation algorithm. it's supervised. It learns the way to transform computer file into a desired response, so that they are widely used for pattern classification. so as to guage the efficiency of those features in discriminating normal data from epileptic called Intrinsic Mode Functions network (MLPNN) and self-organizing map (SOM)[3]. Many nonlinear methods are proposed to extract new parameters linked to the electrical activity of the brain. Among these parameters, the Lyapunov exponent can detect electroencephalo graphic changes the correlation dimension techniques can contain information about the various neurological states of the brain , the fractal dimension and entropy measure the complexity or the degree of disorder of the EEG signal while correlation integral, a measure sensitive to a large style of nonlinearities, utilized in might be wont to characterize the epileptogenic regions of the brain during the interictal period. The author proposed a completely unique scheme supported the discrete wavelet transform (DWT) and approximation entropy (ApEn) for epilepsy [4].

Wavelet transform may be implemented with a specially designed pair of FIR filters called a quadrature mirror filters (QMFs) pair which separate the high- and low-frequency components of the sign. The dividing point is typically halfway between 0 Hz and half the information rate (the Nyquist frequency). The outputs of the QMF filter pair are resampled by an element of two. The first signal is passed to the pairs of QMF filter and emerges as two signals[5].EMD of the EEG signals is achieved by computing IMF1 to IMF5 for each segments of every channel. Classifier used is LDA. During this paper two different convulsion detectors supported the EMD of EEG signals are going to be described. Within the first detector, the algorithm computes the energy of every IMF and performs the detection supported an energy threshold and a minimum seizure duration decision. The second detector consists on the extraction of several time and frequency features of IMFs, subsequently a feature selection supported a Mann-Whitney test and Lambda of Wilks criterion is performed and in an exceedingly last stage linear discriminant analysis (LDA) of the chosen parameters is employed to classify convulsion and normal EEG segments[6].

The author proposed method that employs two successive signal dependent techniques for classification of ictal and seizure-free EEG signals. Firstly, the EMD method is applied on the EEG signals for the extraction of the IMFs followed by second-order difference plot (SODP) which measures the speed of variability of individual IMFs[7].The purpose of this paper is to propose a brand new feature extraction method using empirical mode decomposition (EMD) and a multilayer perceptron neural network (MLPNN). The EMD algorithm decomposes a time segment EEG into intrinsic mode functions (IMFs) on which autoregressive (AR) parameters are extracted, combined and fed to the MLPNN classifier. Experimental results distributed on a publicly available dataset, comprising normal, inter-ictal and ictal EEG signals achieved classification accuracy up to 98 %. The

ISSN: 2233-7857 IJFGCN

end result of this research is especially intended to assist practioners within the diagnosis of epileptic portions within the EEG recordings[9].

III. DIFFERENT TYPE OF CLASSIFIERS

A neural network model is comparable to human system. Because the human learn things by experience and practice or by repetition to develop the human like behavior in machine we use AI and neural network model uses the concept of AI that's why it's called as artificial neural network. the synthetic neural network is taught through a dataset. This dataset could also be known to us then ANN is trained in an exceedingly supervised manner, and it learns precisely and quickly about the pattern buried in dataset and Trained ANN is employed to spot the patterns that it's trained. But if the dataset isn't known to us before then the unsupervised training is used[9].The Support vector machine comes within the category of supervised learning.But it's popularly known for classification. It's a really efficient classifier. During this every object or item is represented by some extent within the n-dimensional space. the worth of every feature is represented by the actual coordinate[1]. The KNN is additionally the classifier of the category of supervised learning algorithm. In supervised learning the targets are known to us but the pathway to focus on isn't known. to understand machine learning nearest neighbor's forms is that the perfect example. Allow us to consider that there are many clusters of labelled samples. the character of things of the identical identified clusters or groups are of homogeneous nature. Now if an unlabeled item has to be labelled under one amongst the labelled groups. Now to classify it K-nearest neighbors is straightforward and best algorithm that have record of all available classes can perfectly put the new item into the category on the premise of largest number of vote fork neighbors. during this way KNN is one amongst the alternate to classify an unlabeled item into identified class[10].A multilayer perceptron (MLP) could be a class of feedforward artificial neural network (ANN). The term MLP is employed ambiguously, sometimes loosely to seek advice from any feedforward ANN, sometimes strictly to seek advice from networks composed of multiple layers of perceptron's (with threshold activation). An MLP consists of a minimum of three layers of nodes: an input layer, a hidden layer and an output layer[9].

IV.BLOCK DIAGRAM

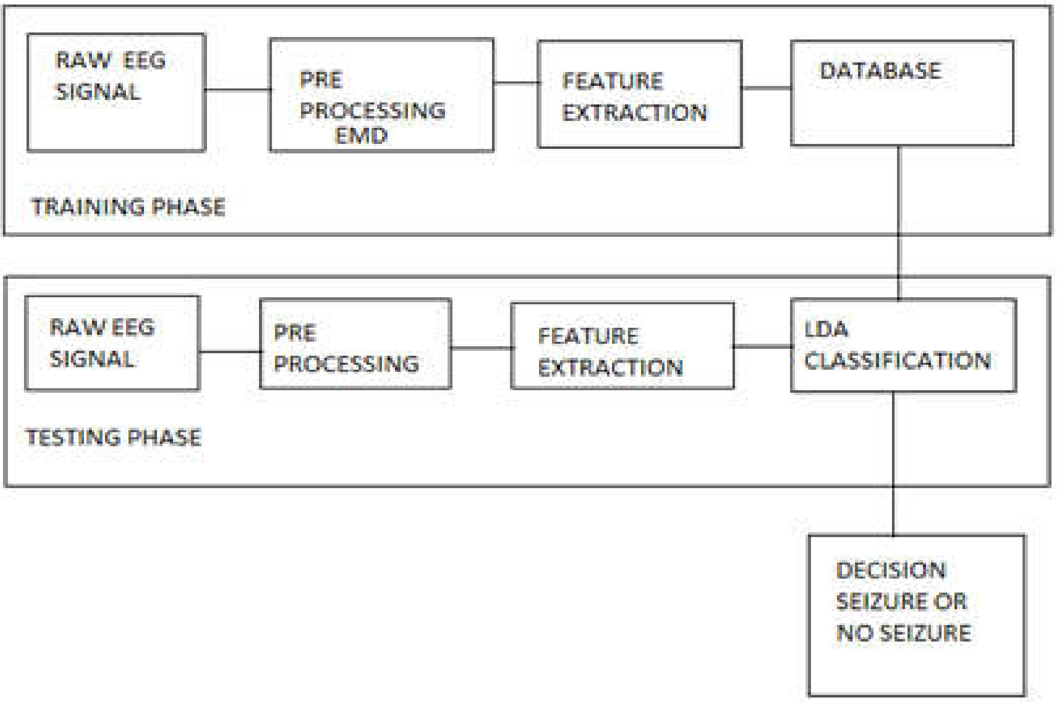

Figure 1 : System block diagram

V.DESCRIPTION

The EEG dataset of Seizure Prediction Project of Freiburg is employed. The dataset includes recordings for both healthy and epileptic subjects. A trainee data set is taken. All EEG records are initially filtered with a second order, bidirectional, Butterworth, 50 Hz notch filter so as to get rid of the ability line interference. Then, the EEG signals are band-pass filtered with a second order, bidirectional, Butter worth filter with a bandwidth of 0.5 - 60 Hz. Next, all EEG records are resampled to 128 Hz so as to cut back computation time of EMD decomposition. This operation doesn't have any influence on the results since the bandwidth of the signal of interest doesn't exceed the 60 Hz. The EMD is of course a sort of filter bank decomposition method whose sub bands are built as required to separate the various natural components of the signal. so as to characterize the EEG signals several features are computed upon these 3 IMFs series calculated for every channel.For each IMF, a group of parameters in time and frequency domains are computed. To detect the EEG segments with convulsion a linear discriminant analysis (LDA) was implemented using the classification functions h. These functions are a linear combination of the discriminant variables (Xm) which allows maximize the differences between groups and minimize the differences within-group. during this classification a trained data set is compared with test data set and eventually EEG signals are classified as signals with epileptic components and non-epileptic components.

A. The EMD Algorithm

The EMD may be a general nonlinear non-stationary signal decomposition method. The aim of the EMD is to decompose the signal into a sum of Intrinsic Mode Functions (IMFs). An IMF is defined as a function that satisfies two conditions:
1. Within the entire signal, the amount of extrema and also the number of zero crossings must be equal or differ at the most by one.
2. At any point, the average of the envelope defined by the local maxima and also the envelope

ISSN: 2233-7857 IJFGCN

defined by the local minima must be zero (or near zero). The major advantage of the EMD is that the IMFs are derived directly from the signal itself and doesn't require any a priori known basis. Hence the analysis is adaptive, in contrast to Fourier or Wavelet Transform, where the signal is decomposed during a linear combination of predefined basis functions. Given a proof x(t), the algorithm of the EMD will be given by following 6 steps.
1. Find local maxima and minima of d0(t)=x(t).
2. Interpolate between the maxima and minima so as to get the upper and lower envelopes Eu(t) and El(t), respectively.
3. Compute the mean of the envelopes m(t)=(Eu(t)+ El(t))/2.
4. Extract the detail d1(t)= d0(t)-m(t)
5. Iterate steps 1-4 on the residual until the detail signal dk(t) will be considered an IMF (accomplish the 2 conditions): c1(t)= dk(t)
6. Iterate steps 1-5 on the residual rn(t) so as to get all the IMFs c1(t) to cN(t) of the signal.
The procedure terminates when the residual cN(t) is either a relentless, a monotonic slope, or a function with just one extrema. The results of the EMD process produces N IMFs (c1(t), …, cN(t)) and a residue signal (rN(t)). The EMD may be a technique essentially defined by an algorithm and there's not an analytical formulation to get the IMFs.

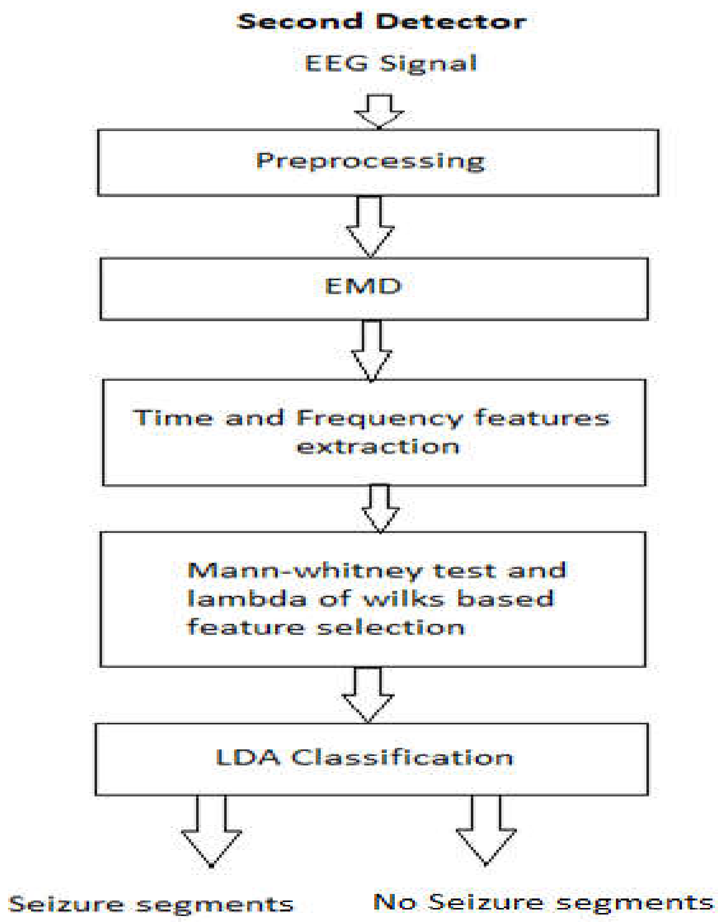

Fig 2 : Block diagram of epileptic seizure detectors

B. Preprocessing And EMD

All EEG records were initially filtered with a second order, bidirectional, Butterworth, 50 Hz notch filter so as to get rid of the ability line interference. Then, the EEG signals were band-pass filtered with a second order, bidirectional, Butter worth filter with a bandwidth of 0.5 - 60 Hz. Next, all EEG records were re sampled to 128 Hz so as to scale back computation time of EMD decomposition. This

ISSN: 2233-7857 IJFGCN

operation doesn't have any influence on the results since the bandwidth of the signal of interest doesn't exceed the 60 Hz.

C. Second Detector

In this case the preprocessing stage and also the EMD computation are the identical because the first detector. Next several time and frequency features of the IMFs are computed so selected employing a Mann-Whitney test and Lambda of Wilks criterion. Finally, a linear discriminant analysis (LDA) is performed to discriminate epileptic seizures and normal EEG segments.

D. Feature Extraction

In order to characterize the EEG signals several features were computed upon these 3 IMFs series (IMF1 to 3) calculated for every channel. for every IMF, a collection of parameters in time and frequency domains were computed. during this stage so as to enhance the statistical stationary of EEG records each IMF was divided in segments of 15 s. Hence the full IMFs selected of the all EEG records analyzed computes a complete of 45517 segments, 4828 of them without convulsions and 689 segments denoted as having just one epileptic seizure each. So as to characterize the EEG signals several features were computed upon these 3 IMFs series (IMF1 to 3) calculated for every channel. for every IMF, a collection of parameters in time and frequency domains were computed. during this stage so as to enhance the statistical stationary of EEG records each IMF was divided in segments of 15 s. Hence the full IMFs selected of the all EEG records analyzed computes a complete of 45517 segments, 44828 of them without convulsions and 689 segments denoted as having just one epileptic seizure each. In time domain, the subsequent parameters were calculated on each IMF: coefficient of variation (VC), Median Absolute Deviation (MAD), variance (STD), mean (MV), Variance (VAR) and Root Mean Square Value (RMS). For frequency domain, the facility spectral density (PSD) of IMF1, IMF2 and IMF3 was estimated by the periodogram method with a Hanning window. Then, classical parameters of descriptive statistics were computed on the PSD. Therefore, the subsequent frequency features were obtained on the spectrum of every IMF: Central, Mean and Peak Frequencies (CF, MF and PF), variance Frequency (STDF). 10 frequency domain parameters and 6 time domain features were computed. Thus, for IMF1 we've 16 parameters for every 15 second segment obtaining during this way a series with the time evolution of every feature. The identical procedure is repeated for IMF2 and IMF3. Hence this suggests a computation of 48 features series for every EEG channel and a complete of 144 series considering the three EEG channels.

E. *LDA Classification*

In order to cut back the dimensionality problem, the median of the individual values of every features series for the three channels were initially computed. As an example, we take CF of IMF1 of channel 1, CF of IMF1 of channel 2 and CF of IMF1 of channel 3 and calculate the median of this parameter leading to one series for this feature in IMF1. The procedure is repeated for all the parameters and IMFs. Thus, the amount of the entire features series is reduced to 48. although the vector of features was reduced, its dimension continues to be large. As a second approach, a stepwise method supported the statistical parameter Lambda of Wilks (WL) is performed. In an n-dimensional space constructed with n variables and with the matrixes Bnxn and Wnxn representing the square sum and cross products between groups and within groups, respectively; the WL are often defined because the ratio between their determinants. In other words, the WL measures the ratio between within-group variability and total variability, and it's an on the spot measure of the importance of the variables. Therefore, the foremost important features for the analysis should be selected, i.e. the variables (features) that contribute with more information.

ISSN: 2233-7857 IJFGCN

VI. PERFORMANCE EVALUATION

In order to gauge the achievement of the algorithm the subsequent diagnostic categories were considered on the detection stage: true negative (TN), false positive (FP), true positive (TP), false negative (FN). The obtained values for these indexes are contrasted with the segments indicated within the database as having seizure or no seizure by the neurologists. Then the statistical diagnostic indexes of sensitivity (SEN) and specificity (SPE) were also computed. The performance of proposed seizures detector is obtained. Following diagnostic categories are considered on the detection stage: true negative (TN), false positive (FP), true positive (TP), false negative (FN). The obtained values for these indexes are contrasted with the segments indicated within the database as having seizure or no seizure by the neurologists.

VII. CONCLUSION

Epileptic seizure location in EEG records is a valuable and significant apparatus because of their different applications, for example, epilepsy investigate medications like convenient tranquilize conveyance, electrical incitement and seizure ready frameworks other than indicative applications. In this sense it is a genuine need the advancement of programmed calculations that might identify seizures freely of its mind source. It is likewise essential to set up some sort of institutionalization of the identifiers utilizing to test them a similar database so a powerful correlation of their exhibition could be completed. In this part two epileptic seizure identification strategies dependent on the Empirical Mode Decomposition (EMD) of EEG signals has been proposed. On one hand, the utilization of EMD for seizures identification it is an ongoing methodology. Likewise, as a commitment to the settled-out issue, long haul epileptic EEG intracranial records with various central epilepsies are utilized to assess the exhibition of the two seizures detectors.

REFERENCES

1. Varun Bajaj and Ram Bilas Pachori (2012). EEG Signal Classification Using Empirical Mode Decomposition and Support Vector Machine. AISC131, pp. 623–635.
2. [Roshan Martis, E. Y. K. Ng, Jen Hong Tan (2012). Application of empirical mode decomposition (emd) for automated detection of epilepsy using eeg signals. International Journal of Neural Systems, Vol. 22, No. 6.
3. AzadehTafreshi , Ali M. Nasrabadi, Amir H. Omidvarnia (2008). Epileptic Seizure Detection Using Empirical Mode Decomposition. IEEE pp. 239-242
4. Ram Bilas Pachori, Varun Bajaj (2011). Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition. Computer methods and programs in biomedicine 104 (2011) pp.373–381.
5. JR. Panda, S. Khobragade, D. Jambhule, P. R .Pal, K. Gandhi (2010). Classification of EEG Signal Using WaveletTransform and Support Vector Machine for Epileptic Seizure Detection. International Conference on Systems in Medicine and Biology.
6. Lorena Orosco, Eric Laciar (2011). Epileptic Seizures Detection Based on Empirical Mode Decomposition of EEG Signals.
7. Ram Bilas Pachori, Shivnarayan Patidar (2014). Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions. computer methods and programs in biomedicine 113(2014) 494–502.
8. S M Shafiul Alam, M. I. H. Bhuiyan (2013). Detection of Seizure and Epilepsy Using Higher Order Statistics in the EMD Domain. IEEE Journal Of Biomedical and Health Informatics, vol. 17, no. 2.
9. DjemiliRafik1,Boubchir Larbi (2019).Autoregressive Modeling Based Empirical Mode Decomposition (EMD) for Epileptic Seizures Detection Using EEG Signals. Traitement du Signal Vol. 36, No. 3, pp. 273-279.
10. AnnushreeBablani, Damodar Reddy (2018).Classification of EEG Data using k-Nearest Neighbor approach for Concealed Information Test,volume 143 2018, pp. 242-249.

ISSN: 2233-7857 IJFGCN