Multi-Stage, Multi-Resolution Method for Automatic Characterization of Epileptic Spikes in EEG

Ganesan.M, Sumesh.E.P, Vidhyalavanya.R
Department of Electronics and Communication Engineering
Amrita School of Engineering
Amrita Vishwa Vidyapeetham, Coimbatore, INDIA.
m_ganesan1@cb.amrita.edu, ep_sumesh@cb.amrita.edu,
r_vidhyalavanya@cb.amrita.edu

Abstract

In this paper, a technique is proposed for the automatic detection of the spikes in long term 18 channel human electroencephalograms (EEG) with less number of data set. The scheme for detecting epileptic and non epileptic spikes in EEG is based on a multi resolution, multi-level analysis and Artificial Neural Network(ANN) approach. Wavelet Transform (WT) is a powerful tool for signal compression, recognition, restoration and multi-resolution analysis of non-stationary signal. The signal on each EEG channel is decomposed into six sub bands using a non-decimated WT. Each sub band is analyzed by using a non-linear energy operator, in order to detect spikes. A parameter extraction stage extracts the parameters of the detected spikes that can be given as the input to ANN classifier. A robust system that combines multiple signal-processing methods in a multistage scheme, integrating wavelet transform and artificial neural network is proposed here. This system is experimented on a simulated EEG pattern waveform as well as with real patient data. The system is evaluated on testing data from 81 patients, totaling more than 800 hours of recordings. 90.0% of the epileptic events were correctly detected and the detection rate of non epileptic events was 98.0%. We conclude that the proposed system has good performance in detecting epileptic form activities; further the multistage multiresolution approach is an appropriate way of automatic classification problems in EEG.

Keywords: *SNEO, Multi resolution decomposition, ANN, Epilepsy Classification*

1. Introduction

Electroencephalography (EEG) is of utmost advantage in studying transient neuronal activity and its timing with respect to behavior of a person. Generally, EEG evaluation for the detection of epilepsy includes visual screening of EEG recordings for these sharp transients by an experienced electro encephalographer [1]. This process may be time consuming, especially in the case of long term recording. The routine clinical EEG requires recordings from many channels (generally 32 or 64); input data size becomes a critical design parameter for real-time multichannel spike detection systems. For a sliding window of 20 points, more than 300 input lines will be necessary for a 16-channel system, which is not easily manageable with current ANN technology. Such requirements could be fulfilled neither by single stage nor by simple method strategy, due to the extreme variety of EEG morphologies and frequency of artifacts. Thus Computer-assisted algorithmic analysis is resorted to [2]. Automated detection algorithms have been developed in the past and they can be roughly divided into orthogonal transform, template matching, Expert system, Artificial Neural Network and Wavelet transform. This work investigates the crucial issue of different epileptic pattern by adding additional parameters to artificial neural network for classification. Performance of the method is evaluated with both Epileptic and non Epileptic data compared with the different wavelets.

2. Processing of simulated EEG waveform SNEO approach

2.1. Background study

Let x(t) be a real band limited process with spectrum $S_{xx}(\omega)=0$; for $|\omega|>B$ and x(nT) is the uniformly sampled version with sampling interval $T<\pi/B$ $T<\pi/B$. For both the continuous and discrete time signals, Kaiser has defined a nonlinear energy operator Ψ [3], [4]. For continuous time energy operator ψ is defined as

$$\Psi\left[x(t)\right]=\left[x(t)\right]^2-x(t)x^1(t)\ , \tag{1}$$

where $x^1(t)$ is the second-order derivative of *x(t)*. For the discrete time case, Ψ is defined as

$$\Psi\left[x(n)\right]=\left[x(n)\right]^2-x(n+1)x^1(n-1)\ . \tag{2}$$

2.2. Smoothed Non Linear Energy Operator(SNEO)

The problem of detection of spike has been reduced to the problem of estimation of $E\{\Psi\left[x(n)\right]\}$, where the Expectation of the $\Psi\left[x(n)\right]$ is given by

$$E\{\Psi\left[x(n)\right]\}=r_x(0)-r_x(2)=\frac{1}{2\pi}\int_{-\infty}^{\infty}R_x(e^{j\omega})(1-\cos 2\omega)d\omega \tag{3}$$

where the $r_x(k)$ is the input process autocorrelation function and $R_x(e^{j\omega})$ is the spectral density of *x(n)*. But as the spike is a non stationary phenomenon, the operator E{ $\Psi\left[x(n)\right]$ } cannot be replaced by time-domain averaging. In this case the first attempt would be to drop the $E\{\Psi\left[x(n)\right]\}$ operator. The same idea has been applied in WT. The expression for WT can be written in the form

$$W(t,\omega)=\frac{1}{2\pi}\int_{-\infty}^{\infty}x(t+\tau)x(t-\tau)\exp(-j\omega\tau)d\tau\ . \tag{4}$$

In Eqn.(4) WT contains cross terms and few negative values. To alleviate these problems, time and frequency-domain windowing is suggested [5]. when $\Psi\left[x(n)\right]$ is convoluted with a time-domain window, the Smoothed Nonlinear Energy Operator (SNEO) is obtained; and can be expressed as

$$\Psi_s\left[x(n)\right]=\Psi\left[x(n)\right]\otimes w(n), \tag{5}$$

where $\otimes$ represents the convolution operator and *w(n)* represents the window. The SNEO , given in Equ.(5)can serve as an estimate of $E\{\Psi\left[x(n)\right]\}$. The choice of window type and width are optimized to achieve sufficient reduction of interference without loosing much of its time resolution; which is very important for spike detection. For this purpose Barlett window function with an integer filter implementation has been chosen to keep the complexity of algorithm as low as possible.

2.3 Detection of Spike by Thresholding

Peaks in EEG signal are identified by comparing output of the filter to a threshold. In any spike detection algorithm the threshold is optimized to minimize missing of true peaks, while keeping the number of false detection of peaks within a reasonable limit. For this, the threshold is taken as a scaled version of the mean of the output filter. This modification makes the detection algorithm robust. So, the threshold value for SNEO is chosen as

$$T = C \frac{1}{N} \sum_{n=1}^{N} \Psi_s \left[x(n) \right], \tag{6}$$

where N is the number of samples and C is the scaling factor. For a particular type of signal, the scaling factor C is first adjusted by experiment, and later used 1.25 as a constant.

2.4. Procedure

SNEO is used to estimate the energy levels. Spike detection is done using the threshold value Equ.(6). EEg signals with epileptic events are simulated. The detection of these events using SNEO approach is demonstrated in Figs. 1 and 2

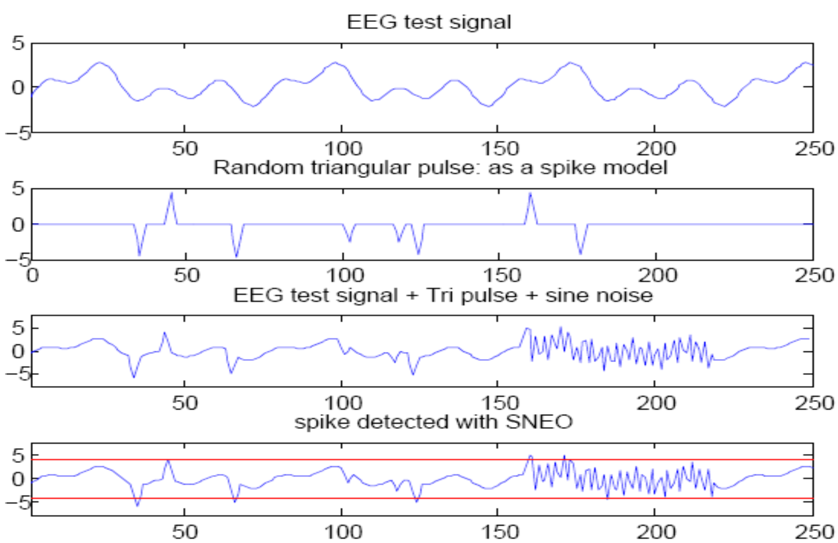

Figure 1. Spike Detection using SNEO.

In Fig. 1 a model EEG signal X is generated, a Spike model and a 50hz burst sine wave, where,

$$X = \sin(2*pi*n/75) - \sin(4*pi*n/75 + pi/2) + \sin(8*pi*n/75) \tag{7}$$

The EEG test signal is given by,

$$\text{EEG test signal} = (X) + \text{Spike model} + \text{burst sine} \tag{8}$$

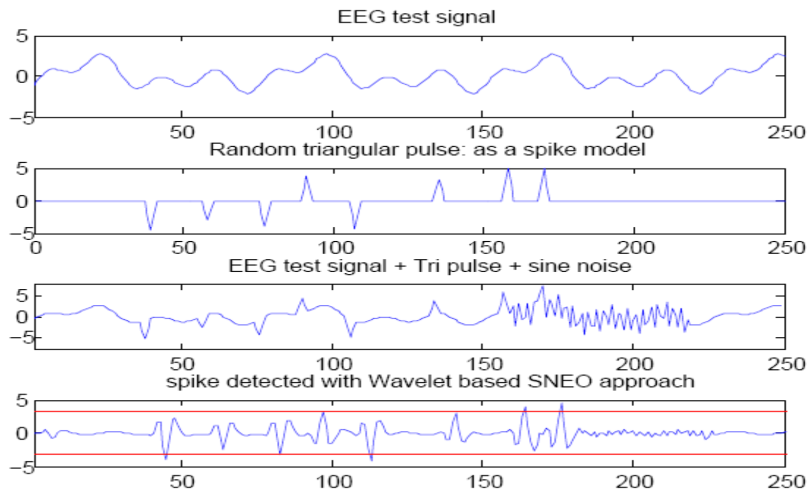

Figure 2. Spike detection with SNEO based wavelet approach.

It is evident from Figs. 1 and 2 by a adaptive thresholding SNEO based approach detects more number of non epileptic events(50Hz burst sine) from 160 to 220 samples,where as in the wavelet based SNEO approach it is minimized

Table I. Comparison of SNEO and Wavelet based SNEO approach using EEG signal with 8 random spikes added.

	With SNEO	With Wavelet based SNEO approach
Spikes Detected Correctly	5	7
False spikes Detected	3	1
*False positive ratio	0.75 ± 0.3	0.42 ± 0.2
*False negative ratio	0.25 ± 0.15	0.13 ± 0.1

*False Negative ratio = (Number of spikes missed) / (Actual number of spikes), and
*False Positive ratio = (Number of False spikes detected) / (Actual number of spikes).

From Table 1, it is significant to point out that Wavelet based SNEO approach significantly reduces False positive and negative ratios than the SNEO approach.

3. Processing of Epileptic and non Epileptic Patient Data

3.1. Preprocessing

In this processing stage signal on each channel is decomposed into six sub-bands using discrete wavelet transform[10-7][11-8]. For detecting spikes, a two level analysis is then performed on these sub-bands which fall in the frequency range of 4-8 Hz and 8-16 Hz [7-9] [8-10]. In this work four different Wavelet Db4, Db20, Haar and Coif3 are used[9-11]. In all these six levels of decomposed data the spikes are detected through thresholding by applying the smooth non-linear energy operator technique. The results using different wavelet coefficients [12][13] are compared. One of the major advantages of the proposed scheme is that the threshold for different scales are computed adaptively to suit to different epileptic patients.

3.2. Parameter Extraction

The second stage can describe briefly about threshold, relative amplitude of different spikes, number of data points between the start and the end points of the spike, the upslope and down slope of the spikes are extracted. The extracted samples are shown in table III and IV. The extracted features for all the 81 data containing both epileptic and non-epileptic spikes are used as the training set for the ANN. As we deal with binary decisions it is enough to consider only one output from the Neural network. Designing a separate hardware for this purpose is a difficult task. Moreover efficiency of basic signal classifier is undoubtedly low. So a better classifier, artificial neural network is preferred. Since a neuron is made of simple building blocks like adder, multiplier and limiting function, it is easy to model as hardware. Furthermore the network of neurons is formed by repeatedly using these blocks. Hence complexity of designing and implementing the hardware is reduced. A feed forward neural network having four neurons in input layer, four in hidden and one in output layer is designed for classifying the epileptic EEG signal.

Tables IV and V gives the comparison of energy of both epileptic and epileptic spikes at different levels for Coif3, Db4, Db20 and Haar wavelets.

3.3. ANN Classifier

The idea behind neural networks (ANN) is based on the simulation of the neurons in a human brain. It is a network of neurons, which processes incoming information and outputs information based on this input, very much like human neurons. And this is used to classify and take decisions according the way the ANN is trained. Modeled after properties of natural neurons, ANNs are composed of basic computing units, which learn and recognize patterns in ways similar to humans. ANNs do not need any specific rules but only examples for training. Thus, ANNs offer an attractive solution to recognition and classification tasks where complete rules cannot be written [14]. A neural network topology exists for layers of neurons. Typically one input layer, one or more hidden layers and one output layer. A neuron is referred to as the processing element (PE) of the NN. The PE performs an operation on its combined input. This combination of the input is usually linear summation according to weights. These weights can be adapted during training, to reflect the importance of each of the inputs. To reduce the data set in EEG spike detection by multilayer neural network we taken into account of four parameters namely, the amplitude of the spike, Duration, Upslope and Downslope of the detected spike.

4. Results and Discussion

The classification problem is simplified in the following aspects: it is evident from Table 2 and 3 the relative amplitude of epileptic spike is invariably larger than its counterpart for non epileptic spike. It is also observed from table 4 and 5 wavelet Db20 has higher energy levels in all the sub-bands for a epileptic event compared to a non epileptic event. Hence from our study we like to conclude wavelet db20 is better suited for our application and the parameters discussed above are enough for classification of epileptic spikes.

Region Of Convergence(ROC) is a measure of specificity and sensitivity[15]. In Fig. 3 the area under ROC curve is close to unity. This Indicates that the system can have high sensitivity and high specificity simultaneously

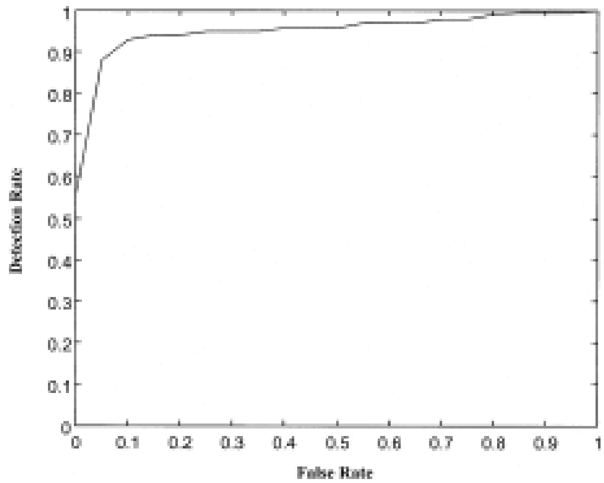

Figure 3. ROC curve for final threshold.

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5. Conclusion

Compared to previous studies, in the proposed method, automatic detection of epileptic activities in scalp EEG have the following attributes:

1. A two-level multi-resolution approach is used, which is effective in identifying different amplitude and width of epileptic spikes.
2. This algorithm is quite effective for single spike, multiple spikes and generalized spikes.
3. We have processed 18 channels of EEG data, which covers most of the area of the brain, and the system identified the channels at which the spikes has occurred.
4. The threshold for different scales are computed adaptively to suit to different epileptic patients.

The data set includes four parameters namely amplitude, spike duration, upslope and down slope. The extracted features given to the feed forward back-propagation Network gives an automatic detection of epilepsy from the EEG test samples with a accuracy of 90% towards the EEG epileptic spike and 98% towards the non-epileptic spike samples tested. The effectiveness of the proposed technique was confirmed by analyzing the test signals and real patient data.

The advantages of these diversified fields namely SNEO, wavelets, and artificial neural networks are combined to give a better performance.

Table II. Extracted features of few epileptic spike data

Data	Relative Amplitude	Duration (samples)	Upslope	Downslope
E1	1345	12	184.62	-170.51
E2	484	12	196.76	-168.1
E3	760	11	100.25	-119.56
E4	665	10	64.824	-100.67
E5	1034	10	126.37	-160.96

Table III. Extracted Features of few non-epileptic spikes data

Data	Relative amplitude	Duration (samples)	Upslope	Down slope
NE1	308	11	129.74	-161.24
NE2	527	13	184.66	-208.53
NE3	588	15	16.691	-30.45
NE4	392	12	87.349	-76.739
NE5	146	15	35.787	-15.832

Table IV. Comparison of energy of epileptic spikes at different levels for Coif3, Db4, Db20 and Haar wavelet.

Wavelet	*Spike Energy D3*	*Spike Energy D4*	*Spike Energy D5*
coif 3	*1.4634*	*18.069*	*26.848*
Db4	*1.1053*	*45.03*	*16.827*
Db20	*5.4964*	*9.9229*	*32.075*
Haar	*9.6316*	*8.7494*	*28.914*

Table V. Comparison of energy of non-epileptic spikes at different levels for Coif3, Db4, and Db20 and Haar wavelet.

Wavelet	Spike Energy D3	Spike Energy D4	Spike Energy D5
coif 3	2.4009	16.75	15.154
Db4	2.175	22.089	23.14
Db20	0.98594	7.1219	23.592
Haar	9.2784	25.546	20.168

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Ganesan M received his B.Tech Degree from Madurai Kamaraj University in 2001, M.Tech Degree from Calicut University in 2007 He have the experience as Assistant professor in ECE department, Amrita Vishwa vidyapeetham, Ettimadai, Coimabtore and currently pursuing his Ph.D in Amrita Vishwa vidyapeetham , India. He has authored many research publications in International and NationalConferences. His areas of interest are Wavelets and Bio Medical Signal processing.

Sumesh EP received his B.Tech Degree from University of Calicut in 1995, M.Tech Degree from Cochin University of science and technology, Kerala, India in 1999 in Opto-Electronics and Laser Technology with Gold medal. He received his PhD degree for his thesis – " Multiwavelets for solving partial differential equations" Electronics Engineering from the National Institute of technology, Calicut, Kerala, India. He have the experience as Associate professor in ECE department, Amrita Vishwa vidyapeetham, Ettimadai, Coimabtore and currently pursuing his Post Doctral Fellowship in TKK Helsinki University of Technology, Finland. He has authored many research publications in International and National Journals and Conferences. His areas of interest are Wavelets and Signal processing.

Vidhyalavanya R received her BE Degree from Madras University in 2001, ME Degree from National Institute of Technology, Calicut, Kerala, India in 2006 in Electronics and Communication Engineering. She is currently pursuing her PhD degree in Electronics Engineering from the Anna university, Coimbatore, Tamilnadu, India. She is working as Assistant professor in ECE department, Amrita Vishwa vidyapeetham, Ettimadai, Coimabtore. She has authored many research publications in International and National Journals and Conferences. Her areas of interest are VLSI signal processing, and Embedded systems.