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Full Length Research Paper

A new technique for characterization of epileptic spikes using wavelet transform and neural network

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A technique proposed for the automatic detection of spikes in electroencephalograms (EEG). The important features of the raw EEG data were extracted using two methods: Wavelet transform and energy estimation. This data was normalized and given as input to the neural network, which was trained using back propagation algorithm. Energy estimation was used as an amplitude threshold parameter. The wavelet transform (WT) is a powerful tool for multi-resolution analysis of non-stationary signal as well as for signal compression, recognition and restoration, which uses Daubechies 4 as the mother wavelet. The details of the wavelet decomposition level, 1, 2, 3 and energy estimation parameters are given as input to the neural network in order to detect spikes. The codes are written in C and implemented on the DSP Processor TMS320VC5402. The waveforms were observed on MATLAB. The effectiveness of the proposed technique was confirmed with and EEG layouts.

Key words: Spike, wavelet transform, energy estimation, Back propagation.

INTRODUCTION

The electroencephalogram (EEG) is an important clinical tool for diagnosing, monitoring and managing neurological disorder related to epilepsy. This disorder is characterized by sudden recurrent and transient disturbances of mental function and/or movement of the body that results from excessive discharge of groups of brain cells. The presence of epileptiform activity in the EEG confirms the diagnosis of epilepsy, which sometimes can be confused with other disorders producing similar seizures like activity. During seizures, the scalp EEG of patients with epilepsy is characterized by high amplitude synchronized periodic EEG wave- forms, reflecting abnormal discharge of large group of neurons. Between seizures, epileptiform transient waveform which includes spikes and sharp waves are typically observed on the scalp EEG of such patients. Detecting and classifying sharp transient waveforms by visual screening of the EEG record is a complex and time consuming operation. Also, such EEG records require highly trained professionals who are generally in short supply. Hence, an automatic detection of EEG spikes and seizures is required. In addition, the use of EEG monitoring which produces 24 h longer continuous EEG recording is becoming more common thus increasing the need for automated detection methods. In the past, many methods have been investigated to detect the EEG spikes. Mimetic techniques have been widely used to detect spikes, but difficulties arise with artifacts. These problems increase the number of false detection's, which commonly plague all automatic systems. However, in recent years, an artificial intelligence approach using expert system methods have been introduced to solve these problems. Although fairly successful, this approach becomes increasingly difficult due to the proliferation of

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Abbreviations: EEG, Electroencephalograms; **WT,** wavelet transform; **FT,** Fourier transform.

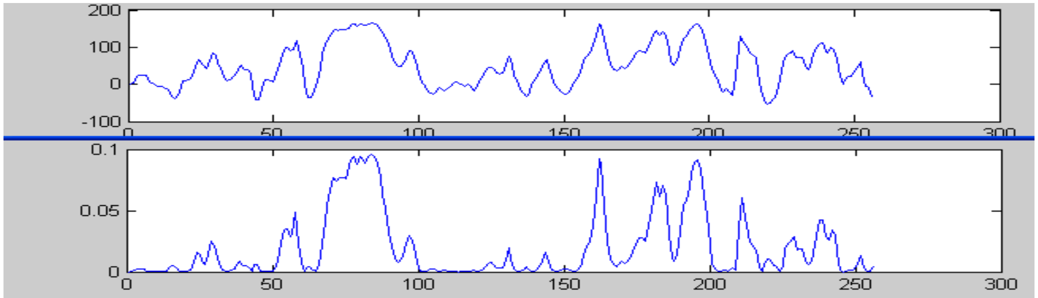


Figure 1. EEG signal and its energy.

the rules and the need for computers with large memories and large processing power. In addition, electroencephalographers (EEGers) cannot agree on a complete set of rules acceptable to all, limiting the success of this method. If we used Fourier transform (FT) to detect spikes, which gives only frequency information of the signal. However, the short time Fourier transform gives time and frequency information simultaneously, but it suffers from resolution problems. In this research work, the features of the raw EEG data were extracted using wavelet transform and energy estimation. Energy estimation was used as an amplitude threshold parameter. This data was normalized and given as input to the neural network which was trained using back propagation algorithm.

METHODOLOGY

Spike detection in electroencephalogram (EEG) is an important task for the diagnosis of epilepsy. The shape and size of epileptic spikes essentially change from one patient to the other. They appear in the EEG as isolated events, as well as quasi periodic oscillations of spike-and-wave. Epileptic spike detection is a very difficult task since normal brain activity, non pathological events that resemble pathological ones, noise and instrumental artifacts can be misinterpreted as epileptic spikes. In this study, the approach to spike detection relies on the observation that the impulse-like shape of spike would result in a broad-band signal, displaying large energy at all frequencies. Indeed, when analyzed with a filter bank like the one provided by the wavelet multi-resolution decomposition, a spike generated events in all the sub-bands. On the contrary, normal brain activity and non-pathological events likely have low frequency contents and appear only in low resolution sub-bands. In the presence of broadband noise, on the other hand, the mid-range frequency sub-bands have a large spike signal-to-noise-ratio, thus allowing an easier detection. This scheme does not decimate the EEG sub-bands, as in non-redundant representations, avoiding the problems arising from the shift-variant property of the wavelet transform. The energy of the input signal is used as an amplitude threshold and the wavelet transform is used to retain the time and frequency information.

Energy estimation

In signal processing techniques, the word "spike" refers to localized high frequency and an increase in instantaneous energy. The quantitative descriptions of the amplitude and spectrum of spikes vary from signal to signal, subject to subject; it even varies from time to time for the same subject. As the spike based width increases, energy is concentrated more in the low-frequency band where the energy of the background signal is also located and detection becomes more difficult in the frequency domain. Therefore, the instantaneous energy of the output was estimated. Since spike, by definition has high energy, this can be implement to detect the spikes. The energy is estimated by the formula:

$$\mathbf{E(n) = x^2(n)}$$

Where, E(n) is the output energy of the input. x(n) is the raw EEG input.

The resulting signal consists mainly of high amplitude spikes and this will emphasize the spike and de-emphasize the unimportant features of EEG. The wavelet representation is a powerful technique that has been successfully exploited in the analysis of non stationary signals, like biomedical signal processing (Unser and Aldroubi, 1996; Clark and Echeverria, 1995). Unlike classical Fourier analysis, the wavelet representation allows for trading frequency resolution and time resolution. In its discrete implementation, the wavelet transform can be viewed as a filter bank which provides a multi-resolution decomposition of the signal (Vetterli and Kovacevic, 1995). The signal is decomposed into a series of sub-bands, each relative to a peculiar spectral region, whose bandwidth linearly increases with frequency (Mallat, 1989).

The simplest approaches that could be devised for spike detection in a multi-resolution analysis framework consist of energy estimation, which is used as an amplitude threshold parameter (Attellis et al., 1997). Although very fast, a single-resolution approach like that in (Sartoretto and Ermani, 1999) has some limitations. In (Mukhopadhyay and Ray, 1998), a nonlinear energy operator (SNEO) is proposed for the direct analysis of the EEG signal (Figure 1). This study shows that multi-resolution analysis combined with energy estimation give some advantages and provide a useful tool for EEG analysis (Simoncelli and Adelson, 1991).

Sub-band decomposition principles

In this section we briefly review the discrete-time wavelet transform and its relations with sub band decomposition.

Consider the two-channel filter bank (Figure 2). The input signal x(n) is decomposed into two sub-bands by filtering with the low-pass filter $H_0(z)$ and the high pass filter $H_1(z)$. The output of the filters is decimated by a factor, 2. It is well know that it is possible to design the analysis filter $H_0(z)$, H_1 (z) and the synthesis filter pair

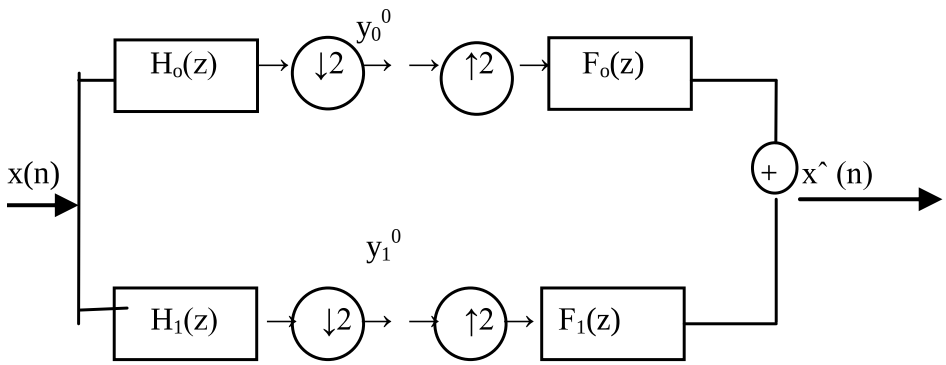


Figure 2. Two- channel sub-band system.

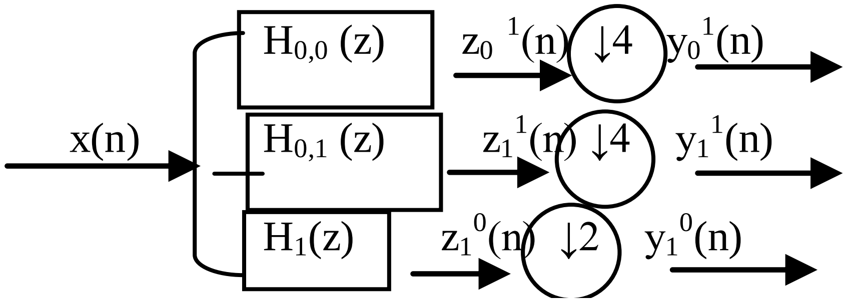


Figure 3. Equivalent scheme for two levels of multi-resolution analysis.

$F_o(z)$, $F_1(z)$ in order to have perfect reconstruction of x(n) at the output of the synthesis stage. One possible way to achieve perfect reconstruction is to design the analysis filter impulse response $H_o(n)$ such that its z-transform satisfies.

$$H_0(z)H_0(z^{-1}) + H_0(-z)\, H_0(-z^{-1}) = 2, \tag{1}$$

Choose $f_o(n) = h_o(-n)$, $f_1(n) = h_1(-n)$, $h_1(n) = (-1)^{1-n}$ ho(1-n). Note that the above equation implies that the filter impulse response $h_o(n)$ is orthogonal to its even-translates, namely

$$\langle h_o, n, h_o, n+2k \rangle \overset{\triangle}{=} \sum_n h_o(n) h_o(n+2k) = \delta(k),$$

And that $\langle h_1, n, h_o.n+2k \rangle = 0$, for all k. It is easy to see that the synthesis filters satisfy similar orthogonality conditions.

If we explicitly write the synthesis stage output as a function of the sub-band signal y_0^0 (n) y_1^0(n), we have for an orthogonal perfect reconstruction system,

$$x(n) = \sum_k y_o^U(k) fo(n-2k) + \sum_k y_1^o(k) f1(n-2k) \tag{2}$$

Thus Equation 2 can be interpreted as the series expansion of the input over the orthogonal family of function {fo(n-2k), kЄz}.

In an octave filter bank, or discrete time wavelet transform, the low-pass signal y_o^0 (n) is further splited by a low-pass filtering and sub-sampling with the analysis filter. Figure 2 shows the equivalent scheme for a two-stage sub-band scheme, where $y_o^0(n)$ is split into y_o^1 (n) and y_1^1 (n), and Ho,o(z = Ho(z), Ho (z^2), $Ho,_1(z) = H_0(z)\, H_1(z^2)$. The equivalent scheme is obtained by applying the noble identities, which allow exchange of the role of decimators and filters in the iterated sub-band scheme (3). Note that, for an analysis filter, $H_o(z)$ with approximate bandwidth [0,fc/4], the equivalent filters Ho,o (z), $Ho,_1(z)$, and H_1 (z), have bandwidth [0, Fc/8], [fc/8, Fc/4], [F_c/4, Fc/2], respectively, where Fc is the input signal sampling frequency. Thus, the sub-bands $y_1^j(n)$ provide a multi resolution representation of the input, each relative to a different frequency band. In particular, y_o^1 (n) is a decimated smooth version of x(n), while $y_1^1(n)$ and y_1^0 (n) are detailed signals to be added in the synthesis stage. Note that the decimators in Figure 3 give rise to a ship-variant analysis stage. This is not a desirable feature when the goal for this research is performing time localization of events rather than providing a compact representation of the signal. To perform spike detection, the signals z_1^j (n) is considered before decimation in Figure 3, where j denotes the multi resolution level, and i Є{0,1}.

The SNEO operator in the frame work of multi-resolution analysis

Figure 4 shows original EEG and Energy output Data file 1. The smoothed Nonlinear Energy Operator (SNEO) has been proposed in [7] for the analysis of EEG signals. SNEO is a smoothed version of the nonlinear energy operator.

$$\psi[x(n)] = x^2(n) - x(n+1)\, x(n-1) \tag{3}$$

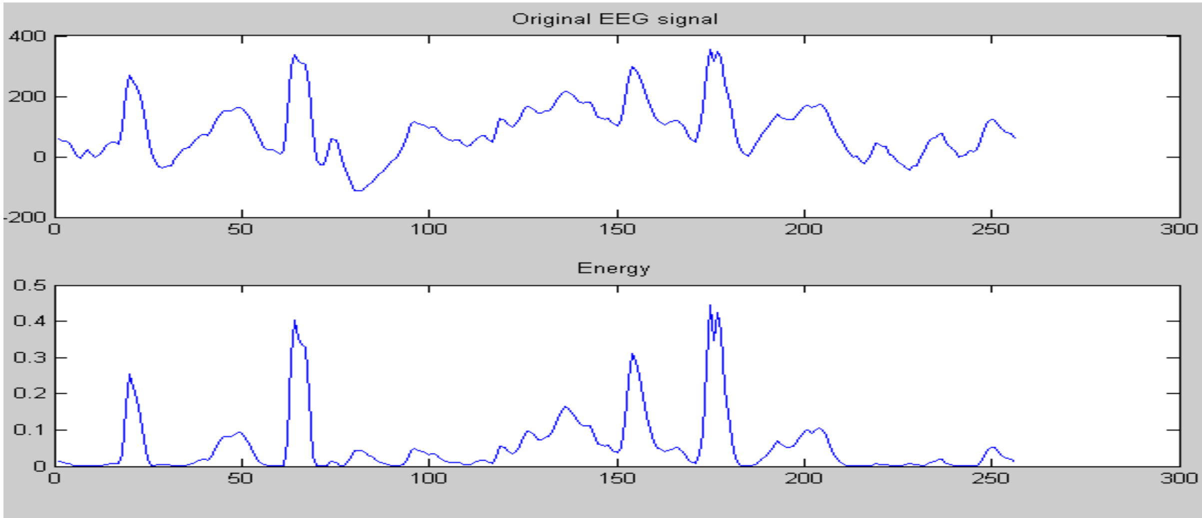


Figure 4. Energy output Data file1.

Smoothing is achieved by low-pass filtering $\psi[x(n)]$, in order to obtain an estimate SNEO $[x(n)]$ of the expectation $E[\psi(n)]$. Indeed, taking the expectation of Equation 3, for a stationary zero mean process $x(n)$ we obtain,

$$E[\psi[x(n)]] = r_x(0) - r_x(2) = \int_0^{2\pi} R_x(e^{j\omega})\,(1 - \cos 2\omega)\, d\omega/2\pi \qquad (4)$$

Where, $r_x(k) = E[x(n)x(n+k)]$ is the input process autocorrelation function and $R_x(e^{j\omega})$ is the spectral density of $x(n)$.

From Equation 4, one can see that SNEO $[x(n)]$ is an approximation of the power of a band pass filtered version of the input process. For non-stationary process, a similar interpretation can be given in terms of the evolutionary spectrum (Miroslaw and Ziemowit, 2002). Moreover, if the smoothing low-pass filter has a short compact support, the information provided by SNEO $[x(n)]$ is relative to the local characteristics of $x(n)$ around time n.

Beside its good properties for spike detection, the SNEO operator has dome disadvantages pointed out in the sequel, with respect to interference immunity in which multi-resolution approach obtained, should overcome. Assume first that a constant value K is added to the EEG signal $x(n)$, during a given time interval then such a phenomenon is produced, as an example of patient movements, which produce an offset in the EEG measurement. Thus:

$$\psi[x(n) + K] = \psi[x(n)] + K\,(2x(n) - x(n-1) - x(n+1)).$$

Although low pass filtering attenuates the interference term, it is apparent that SNEO $[x(n)]$ depends on the local DC value of the signal, and this is not a desirable effect in spike detection.

This scheme exploits the SNEO operator in the framework of multi-resolution analysis (Suresh and Udaya, 2005). The signal was analyzed using three level discrete-time wavelet decomposition. The 5-tap almost, an orthogonal linear phase filters of [8] are used in the experiments. The detail signals $z_1^0(n)$, $z_1^1(n)$ and $z_1^2(n)$ were then processed using the SNEO operator. Note that, when the EEG signal was sampled by an F_s Hz frequency, the three details signals pertain to the frequency bands $[F_s/4, F_s/2]$ Hz, $[F_s/8, F_s/4]$ Hz and $[F_s/16, F_s/8]$ Hz, respectively. An impulse-like signal, as a spike, generates a significant output in all the three sub-bands. On the other hand, sinusoidal, band pass and low pass interference are present in some or none of the sub-bands. This idea was to devise a spike detector based upon the values SNEO $[z_i^j(n)]$, $j = 0, 1, 2$, $i = 1$. Given a specific threshold on each of the three levels, it could be concluded that a spike is detected at time n what at that time SNEO $[z_i^j(n)]$, is above the level threshold, for all $j = 0, 1, 2$, $i = 1$. A specific threshold value was used in each sub-band to take into account the peculiar sub-band amplitudes corresponding to a spike.

Data selection

The EEG data required for the detection of spikes was obtained from the National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore. The data acquired was from both normal and epileptic patients and these data was recorded using a "10-20" system with bipolar montages.

EXPERIMENTAL RESULTS

Energy estimation

The spikes are always associated with high energy. We can obtain the instantaneous energy of spikes by using squaring, the input EEG signal. Figures 5 and 6 consist of 256 and 512 data samples. On executing the C code, an ENERGY.TXT data file is generated, which has the normalized energy values. The values from this file were plotted using MATLAB and the raw EEG data was squared to obtain the energy output.

Wavelet transform

A feature extraction scheme using the wavelet transform (WT) has been applied. Through wavelet decomposition

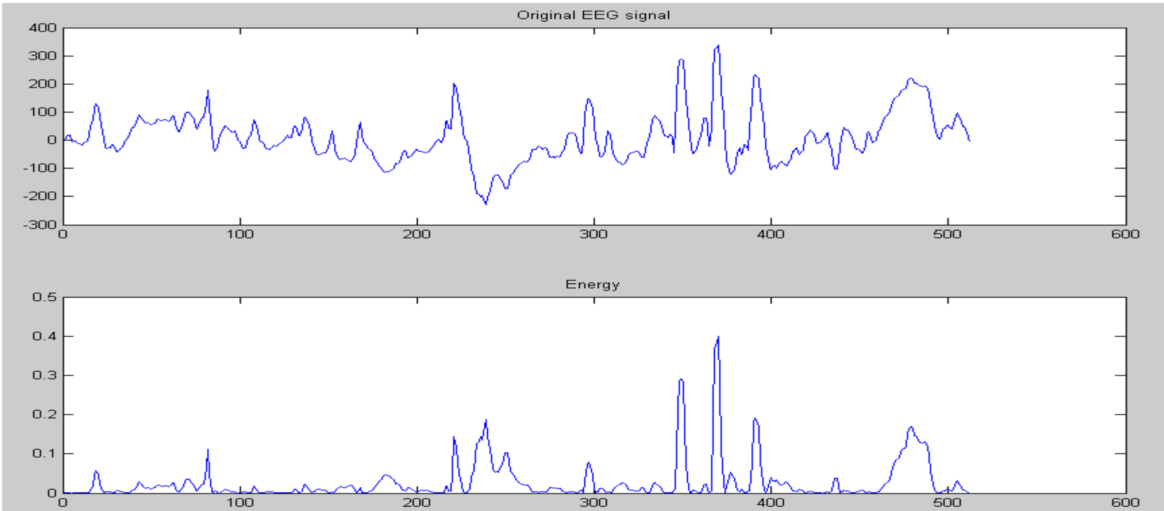


Figure 5. Energy output data file2.

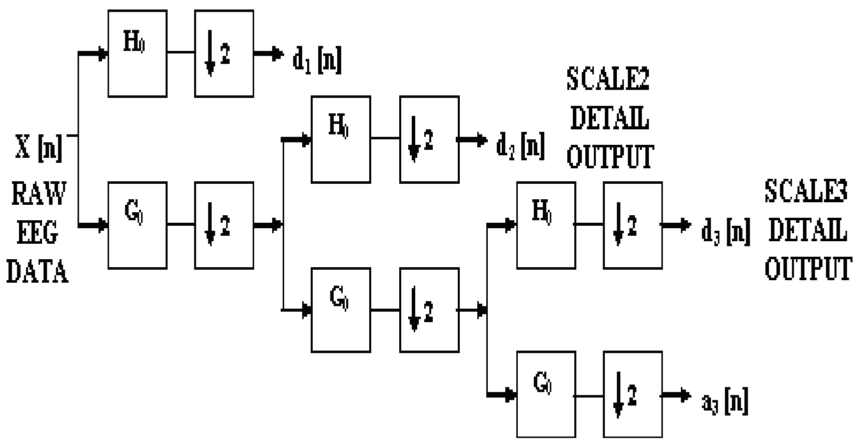


Figure 6. Wavelet transform decomposition.

of the EEG records, transient features are accurately captured and localized in both time and frequency context. The mother wavelet was chosen from the Daubechies family for its easy implementation in this application. Daub4 characterized by 4 vanishing moments was implemented here. Both scales 2 and 3 coefficients were given as input to artificial neural networks for training and testing, and the results obtained from these 2 were compared. The differential of this output was given as an input to the artificial neural network for training. Figure 6 shows the decomposition principle of wavelet transform.

The data files have shown Figures 7, 8, and 9 have 512 samples and the raw EEG data is decomposed into 3 levels. This is differentiated as this result is stored in the output file. On executing the C code, two data files were generated; COEFFS.TXT which has the details of the specific level and DIFF.TXT which has the differential of the details. The values from these files were plotted using MATLAB. Figures 7, 8 and 9 represent the detailed and differentiated results of Levels 1, 2, and 3 of wavelet transform.

Normalization

The operation on a digital computer system limits the size of the input number. So, the values of input must be restricted between 0 and 1. Since this does not affect the resolution of input data, the input values are normalized between the values 0 and 1. This makes the learning process simpler.

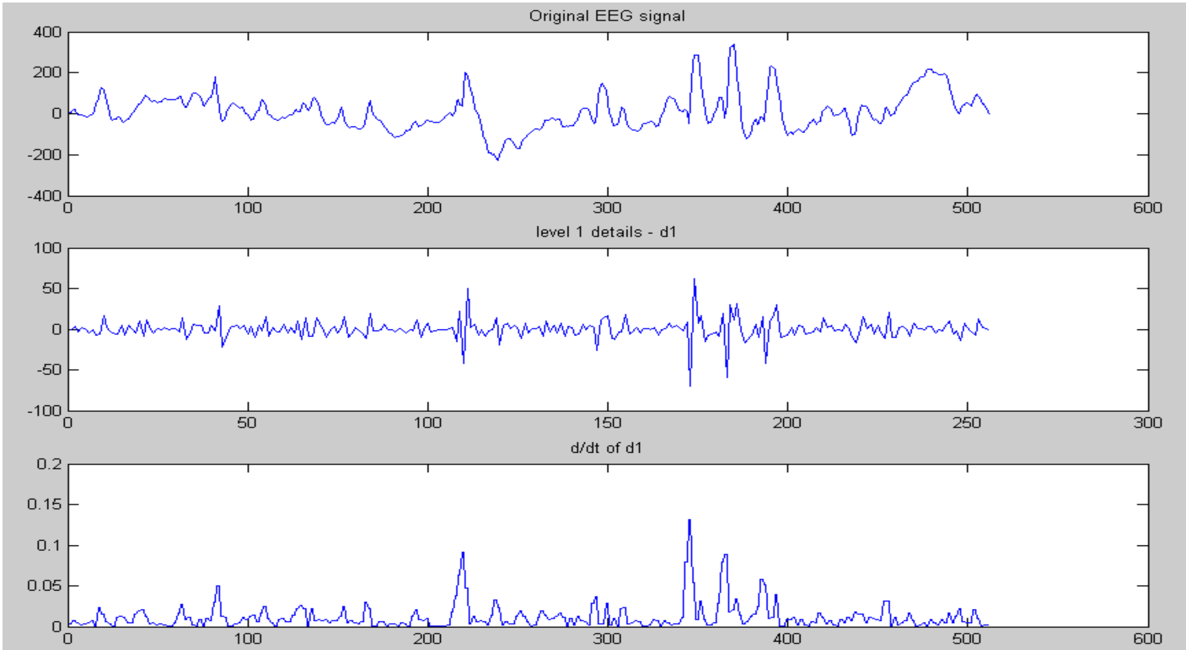


Figure 7. Level 1 Details (d1) and d/dt of d1 for Data file.

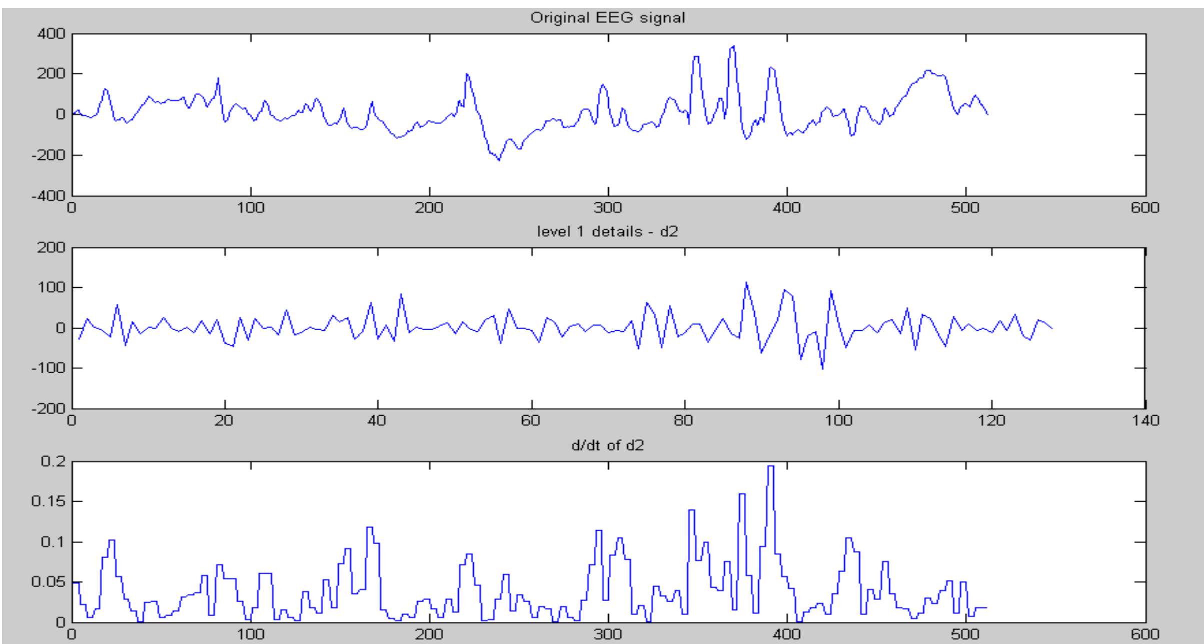


Figure 8. Level 2 Details (d2) and d/dt of d2 for Data file1.

Implementation using back propagation algorithm

The functional diagram gives a description of the method adapted for spike detection. Here, the features of the raw EEG data are extracted using wavelet transform and energy estimation technique.

This data was normalized and given as input to the neural network that is trained using back propagation algorithm. Hence, the spike output was obtained. The steps for this procedure and the output waveforms are

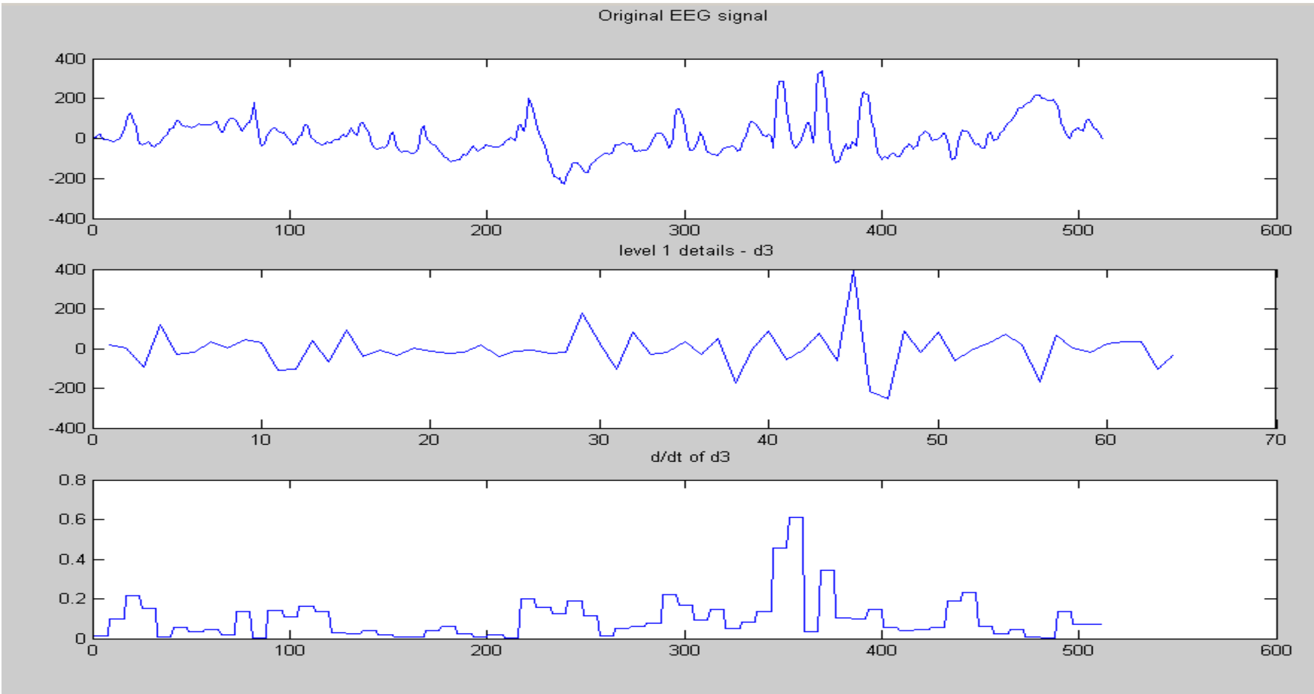


Figure 9. Level 3 Details (d3) and d/dt of d3 for Data file1.

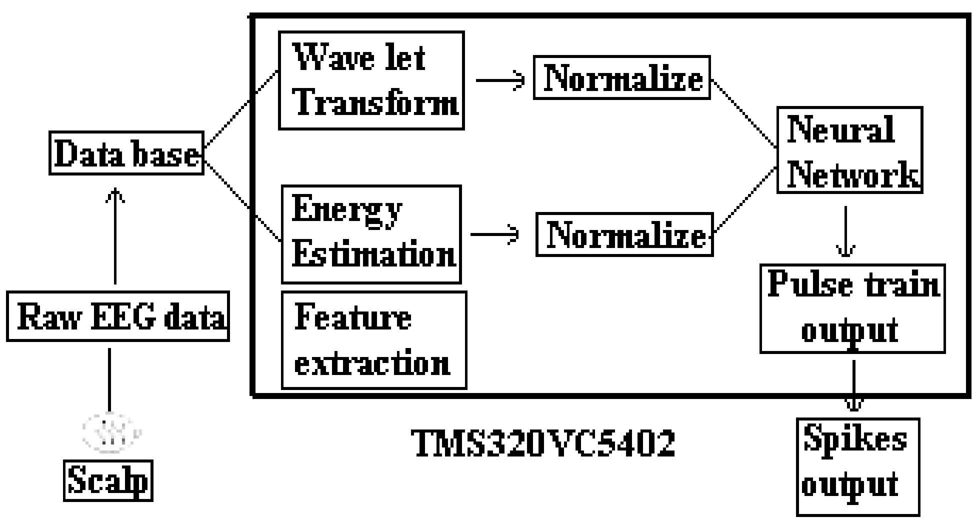


Figure 10. Functional diagram.

included in this chapter. Figure 10 shows the functional diagram of the neural network. The Input Data files shown in Figure 10 have 512 samples and the two extracted features were given as inputs to the back propagation algorithm and the output is obtained. On executing the C code, two files were generated, NETOUT.TXT which contains the output of the neural network (Figure 11) and PULSE.TXT which contains 1's at the points of spike occurrence. The values from this file were plotted using in MATLAB.

Spike output

The pulse train output obtained from the back propagation algorithm is logically ANDed with the original

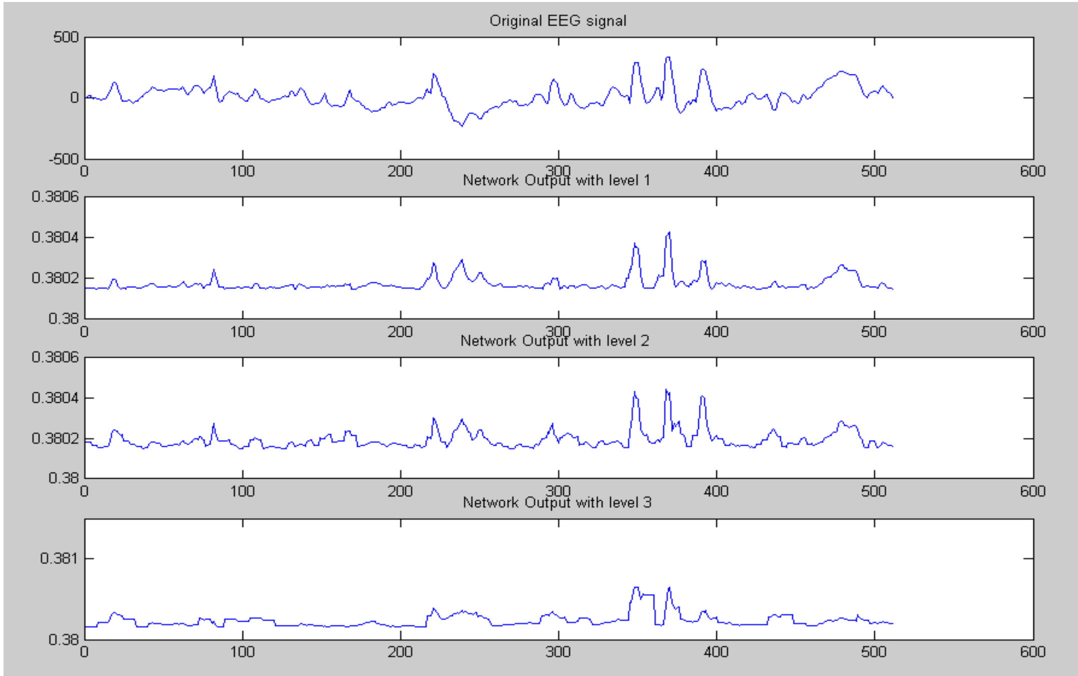


Figure 11. Network outputs for data file 1.

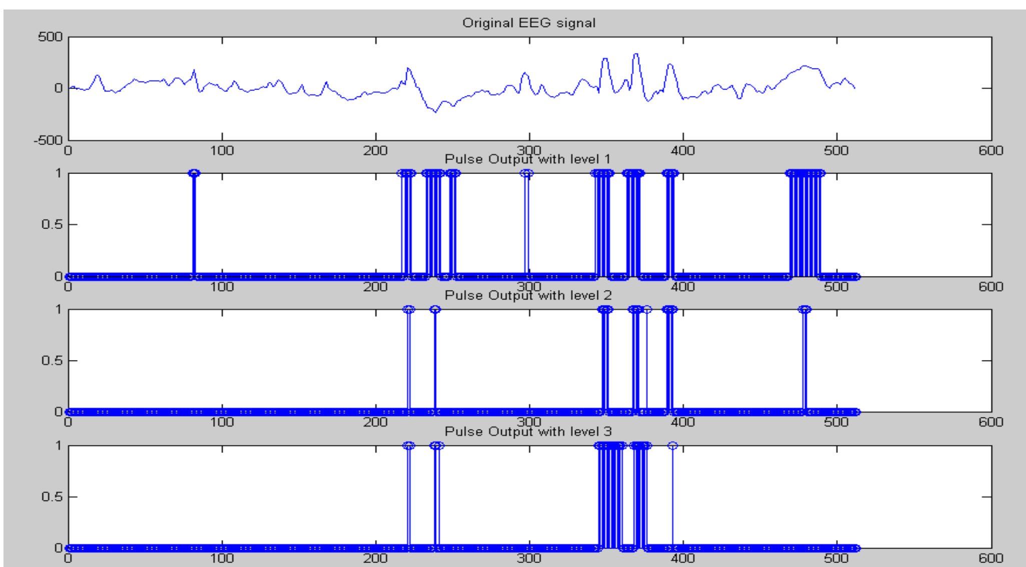
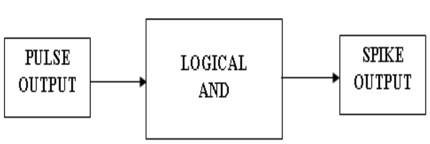


Figure 12. Pulse outputs for Data file1.

signal (Figure 12); that is, raw EEG data to retain only spikes as the output.



The Input Data files have 512 samples. The pulse train is given as input which is logically ANDed and the spike output was obtained (Figures 13 and 14). On executing the C code, an output file SPIKE.TXT was generated which contains only spikes and the values from this file were plotted using MATLAB.

Feature extraction is necessary to enhance the spike

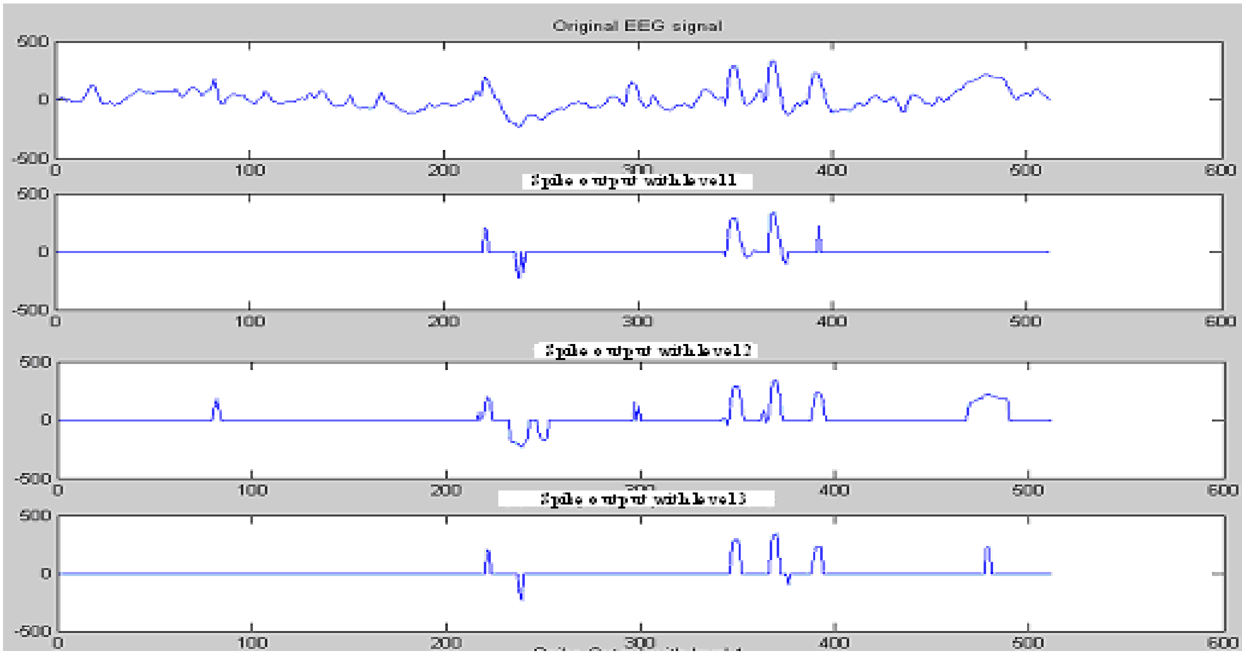


Figure 13. Spike outputs for Data file 1.

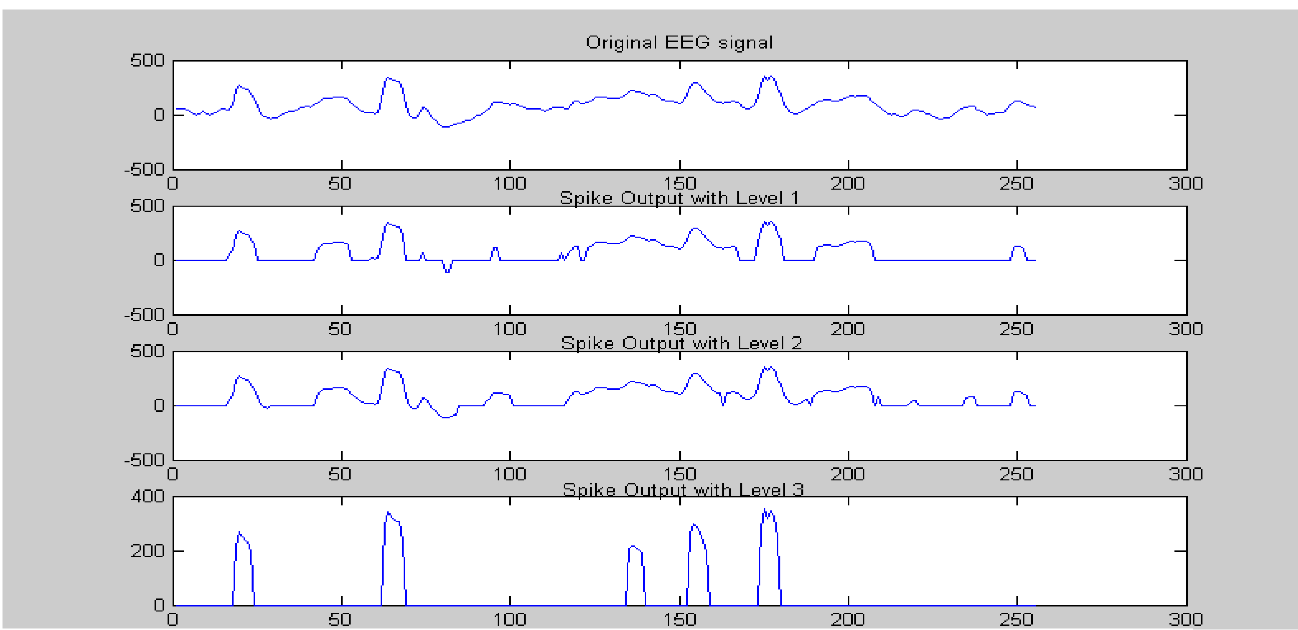


Figure 14. Spike outputs for Data file2.

information and suppress the unwanted background activity. The two chosen features; energy of the EEG signal and the wavelet decomposed signal of the raw EEG data are given as inputs to the neural network.

The neural network uses back propagation algorithm for training. However, the efficiency of the back propagation algorithm depends on the choice of learning rate and the momentum. Variations in the input thus have little effect on the output. Also, if the values are very small, the learning process is slow. After executing the code several times, the value of learning rate and momentum have been chosen to be 0.35 and 0.15, respectively. Then the network was trained to give an output pulse train in the presence of spike activity. The pulse train was used to window the original signal so as to retain only the spikes.

In this research, the outputs obtained from three different levels of wavelet decomposition were compared with the energy of the raw EEG signal and this was given as one of the inputs to the neural network. However, it was observed that the implementation with level 3 produced better results as compared to d1 and d2.

Conclusion

Results found reveal that, the spikes were successfully detected using neural network based on wavelet transform and energy estimation as a preprocessor.

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