

A New Technique for Multi Resolution Characterization of Epileptic Spikes in EEG

H. N. Suresh, Dr. V. Udaya Shankara

Abstract— A technique proposed for the automatic detection of spikes in electroencephalograms (EEG). A multi-resolution approach and a non-linear energy operator are exploited. The signal on each EEG channel is decomposed into three sub bands using a non-decimated wavelet transform (WT). The WT is a powerful tool for multi-resolution analysis of non-stationary signal as well as for signal compression, recognition and restoration. Each sub band is analyzed by using a non-linear energy operator, in order to detect spikes. A decision rule detects the presence of spikes in the EEG, relying upon the energy of the three sub-bands. The effectiveness of the proposed technique was confirmed by analyzing both test signals and EEG layouts.

Keywords—EEG, Spike, SNEO, Wavelet Transform

I. INTRODUCTION

THE 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 some times 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 waveforms, 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 requires highly trained professional who are in generally short supply. Hence a requirement for automatic detection of EEG spikes and seizures. In addition the use of EEG monitoring, which produces 24 hours or longer continuous EEG recording, is becoming more common thus further 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.

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H. N. Suresh is with Bangalore Institute of Technology, Bangalore-04, Karnataka India. (Tel.:91-80-26422726, M:9448685021, e-mail: hnsuresh@yahoo.com).

V. Udaya Shankara is with Sri Jayachamarajendra College of Engineering working as a Professor in the Department of Instrumentation Technology, Mysore, Karnataka. (e-mail: udaya@sjce.ac.in).

Although fairly successful this approach becomes increasingly difficult due to the proliferation of the rules and the need for computers with large memories and large processing power. In addition, EEGers cannot agree on a complete set of rules acceptable to all, limiting the success of this method. If we used Fourier Transform (F.T) to detect spikes, but that gives only frequency information of the signal. The Short time Fourier Transform gives time and frequency information simultaneously, but it suffers from resolution problems. In this research work, the smoothed non-linear energy operator (SNEO) has been proposed for the analysis of EEG signals.

II. METHODOLOGY

Spike detection in 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. our 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 generates 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 for an easier detection. Our 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 wavelet representation is a powerful technique that has been successfully exploited in the analysis of non-stationary signals, like biomedical signal processing [1, 2]. 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 [3]. The signal is decomposed into a series of sub-bands, each relative to a peculiar spectral region, whose bandwidth linearly increases with frequency [4]. The simplest approaches that can be devised for spike detection in a multi-resolution analysis framework consist of energy estimates in number of sub-bands [5]. Indeed, although very fast, a single-resolution approach like that in [6] has some limitations. In [7] a nonlinear energy operator

(SNEO) is proposed for the direct analysis of the EEG signal. We show that multi-resolution analysis combined with SNEO give some advantages and provide a useful tool for EEG analysis.

II. SUBBAND DECOMPOSITION PRINCIPLES

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

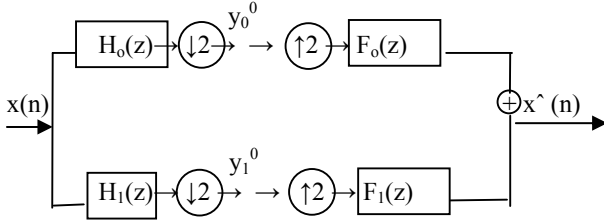


Figure 1: Two-channel subband system.

Consider the two-channel filter bank Fig. 1. 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 two. It is well known that it is possible to design the analysis filter $H_0(z)$, $H_1(z)$ and the synthesis filter pair $F_0(z)$, $F_1(z)$ 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 $h_0(n)$ such that its z -transform satisfies.

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

and choose $f_0(n) = h_0(-n)$, $f_1(n) = h_1(-n)$, $h_1(n) = (-1)^{1-n}H_0(1-n)$. Note that the above equations imply that the filter impulse response $h_0(n)$ is orthogonal to its even-translates, namely

$$\langle h_0, n, h_0, n+2k \rangle = \sum_n h_0(n)h_0(n+2k) = \delta(k),$$

and that $\langle h_1, n, h_0, n+2k \rangle = 0$, 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,

$$x(n) = \sum_k y_0^0(k)f_0(n-2k) + \sum_k y_1^0(k)f_1(n-2k) \quad (2)$$

Thus equation (2) can be interpreted as the series expansion of the input over the orthogonal family of function $\{f_0(n-2k), k \in \mathbb{Z}\}$.

In an octave filter bank, or discrete time wavelet transform, the low-pass signal $y_0^0(n)$ is further split by low-pass filtering and sub-sampling with the analysis filter. Fig. 2 shows the equivalent scheme for a two-stage sub-band scheme, where $y_0^0(n)$ is split into $y_0^1(n)$ and $y_1^1(n)$, and $H_{0,0}(z) = H_0(z)$, $H_{0,1}(z) = H_0(z^2)$, $H_{1,1}(z) = H_0(z)H_1(z^2)$. The equivalent scheme is obtained by applying the Noble Identities, which allow to exchange the role of decimators and filters in the iterated sub-band scheme (3). Note that,

the analysis filter $H_0(z)$ with approximate bandwidth $[0, f_c/4]$, the equivalent filters $H_{0,0}(z)$, $H_{0,1}(z)$, and $H_1(z)$, have bandwidth $[0, f_c/8]$, $[f_c/8, f_c/4]$, $[f_c/4, f_c/2]$ respectively, where f_c is the input signal sampling frequency. Thus, the sub-bands $y_1^1(n)$ provide a multi resolution representation of the input, each relative to a different frequency band. In particular, $y_0^1(n)$ 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 Fig. 2 give rise to a shift-variant analysis stage. This is not a desirable feature when our goal is performing time localization of events, rather than providing a compact representation of the signal. To perform spike detection, we consider the signals $z_1^j(n)$ before decimation in Fig. 2, where j denotes the multi resolution level, and $i \in \{0,1\}$.

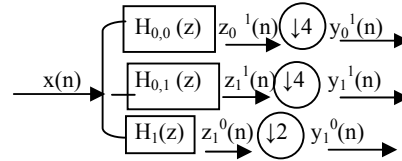


Fig. 2 Equivalent scheme for two levels of multi-resolution analysis.

III. THE SNEO OPERATOR IN THE FRAME WORK OF MULTI RESOLUTION ANALYSIS

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.

$$\psi[x(n)] = x^2(n) - x(n+1)x(n-1) \quad (3)$$

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 (3), for a stationary zero mean process $x(n)$ we obtain.

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

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 [8]. More-over, 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 some disadvantages, pointed out in the sequel, with respect to interference immunity, which our multi-resolution approach should overcome. Assume first that a constant value K is added to the EEG signal $x(n)$, during a given time interval. Such a phenomenon is produced, as an example, by patient movements, which produce an offset in the EEG measurement. We have

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

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.

A more important drawback is the SNEO response to sinusoidal interference. Remarkably enough, when $x(n) = \cos\omega_0 n$, we have

$$\psi[x(n)] = \frac{1}{2} - \frac{1}{2} \cos 2\omega_0 = \text{const.}$$

Indeed, due to the additive property of the SNEO operator [7], when a sinusoidal interference is added to the EEG signal in a given time interval, it increases the SNEO output, which is misunderstood by a threshold based detector.

Our scheme exploits the SNEO operator in the framework of multi-resolution analysis. The signal is analyzed using three level discrete-time wavelet decomposition. The 5-tap almost orthogonal linear phase filters of [8] are used in the experiments. The detail signals $z_1^0(n)$, $z_1^1(n)$ and $z_1^2(n)$ are then processed using the SNEO operator. Note that, when the EEG signal is 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 is present in some or none of the sub-bands. Our idea is to devise a spike detector based upon the values $\text{SNEO}[z_j^i(n)]$, $j = 0, 1, 2$, $i = 1$. Given a specific threshold on each of the three levels, we say that a spike is detected at time n what at that time $\text{SNEO}[z_j^i(n)]$, is above the level threshold, for all $j = 0, 1, 2$, $i = 1$. A specific threshold value is used in each subband, to take into account the peculiar subband amplitudes corresponding to a spike.

IV. DATA SELECTION

The EEG data used in the study were obtained from 10 patients who were diagnosed with epilepsy and were under evaluation in the centre, National Institute of Mental Health and Neuro Sciences, Bangalore.

V. EXPERIMENTAL RESULTS

In this section, we show some results obtained applying our technique. Following [7], we consider a 250 sample test signal.

$$x(n) = \sin(2\pi n/75) - \sin(4\pi n/75 + \pi/2) + \sin(8\pi n/75) \quad (5)$$

adding synthetic spikes in random positions. A synthetic spike is a triangular symmetric pulse having a 5-sample support, random amplitude which is uniformly distributed in the range $[2.5, 5]$, and a random sign. To avoid simultaneous spikes, we force a time separation of at least 11 samples between them. Fig. 3a shows a typical test signal including 4 spikes. In order to assess the immunity of our method to

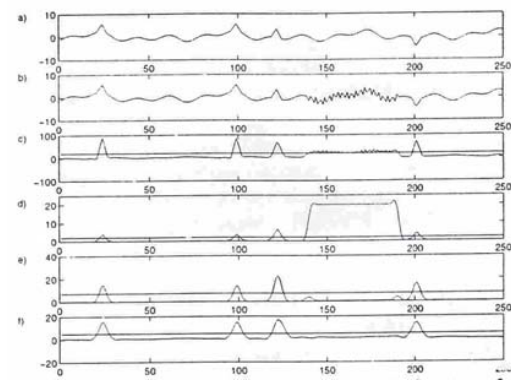


Figure 3 : a) Test signal, b) Test signal plus interference, c) SNEO and d)-e)-f) M-SNEO output, when applied to the signal in frame b).

Sinusoidal interference, we consider in Fig.3b the same test signal with a bursty 50 Hz sinusoidal interference around time sample $n = 170$.

We assume a sampling frequency $F_s = 128$ Hz. Fig. 3c shows the output of the SNEO operator, while Figs 3d, 3e, and 3f, show the results obtained by applying the SNEO operator to the three subbands $z_1^0(n)$, $z_1^1(n)$ and $z_1^2(n)$ (such three-fold out-put is hereafter called M-SNEO). Figure 3 also shows the thresholds, represented by solid lines, on each resolution level. On each level, the threshold was set to 80% of the M-SNEO magnitude corresponding to spike having minimum amplitude (i.e.2.5). Inspecting Figure 3 one can see that the use of detection criterion that takes into account the simultaneous presence of energy in the three subbands can be beneficial, providing a better immunity to interference than single resolution SNEO. In order to assess the noise sensitivity of the proposed procedure, we performed a set of 100 simulations where gaussian noise is added to the test signal (5). In these simulations, 8 spikes with random positions and random amplitude, are added to $x(n)$. The signal to noise ratio is calculated on the basis of the signal variance before the addition of the spikes. For a given spike-detector, let the false-negative ratio be $FN = (\text{Number of spikes missed}) / (\text{Actual number of spikes})$, and the false-positive ratio be $FP = (\text{Number of False spikes detected}) / (\text{Actual number of spikes})$. Table 1 reports FN and FP, together with the standard deviation of the results obtained applying the SNEO and M-SNEO detectors to both 100 synthetic signals with 30 dB SNR, and 100 synthetic signals with 5 dB SNR. Note that M-SNEO, with respect to single resolution SNEO, almost halves the number of missed spikes, simultaneously displaying a comparable or lower number of erroneous identifications.

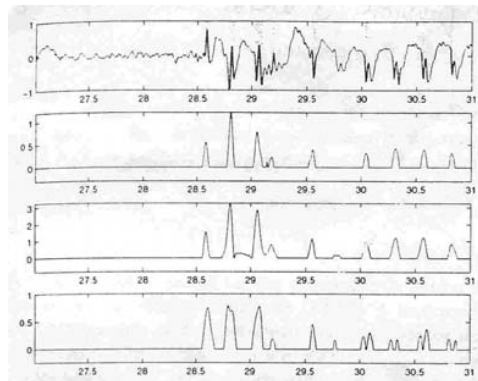


Figure 4: a) EEG signal, and b)-c)-d) M-SNEO

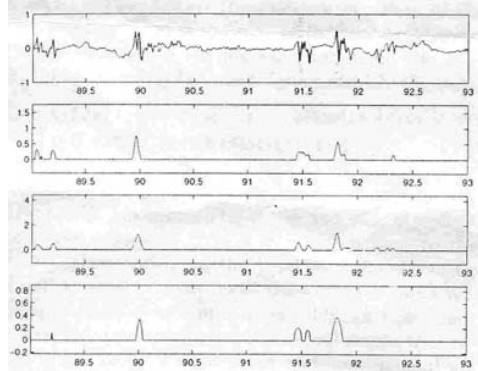


Figure 5: a) EEG signal, and b)-c)-d) M-SNEO

TABLE I
DETECTION RATIOS FOR THE TEST SIGNAL

Type	SNR	SNEO	M-SNEO
FN	30dB	0.05±0.07	0.02±0.06
FP	30dB	0.003±0.02	0.003±0.02
FN	5dB	0.11±0.09	0.06±0.09
FP	5dB	0.17±0.14	0.14±0.13

Eventually, let us consider EEG tracings. A set of 36 long-term EEG layouts, recorded by an 8 channel MEDLOG 9000 system, was processed. Analog signals were converted into digital ones by an A/D converter, having a 128 Hz sampling rate on each channel. Performing statistical computations on a distinguished subset encompassing 15 of our EEG tracings identified the threshold value on each resolution level. These tracings are representative of clinically relevant activity, in terms of morphology, spatial distribution, and discharge duration. They include also several artifacts. The computed thresholds were subsequently exploited for analyzing the remaining EEG layout. Figures 4 and 5 show the M-SNEO output obtained analyzing one channel of two EEG layouts. On each resolution level, the threshold is shifted to zero, and the (shifted) M-SNEO output values larger than the threshold are plotted. The marked time intervals are shadowed in the frame showing the EEG signal. Inspecting Fig.4, we see that epileptic spike-and-waves are correctly detected. Figure 5, on the other hand, shows that non-epileptic spikes can be marked (in this case, chew artifacts). Note, however, that the number of marked time intervals was a small fraction of the overall recording time, thus reducing the cost for subsequent human analysis. Such reduction was our main goal.

CONCLUSION

Results found that, the multi-resolution analysis combined with SNEO give some advantages and provide a useful tool for EEG analysis.

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Prof. H.N. Suresh received his BE (E&C) and M Tech degree in Bio-medical engineering from the University of Mysore, Mysore in 1989 and 1994 respectively. Since 1989, he has been actively engaged in teaching and research at Bangalore & Mysore University, Karnataka, India. Currently Assistant Professor of Electronic and instrumentation Technology, Bangalore Institute of Technology, Bangalore. His main professional interest are in Bio-medical signal processing, artificial neural network, & Adaptive systems. He is a member of IEEE, BME & ISTE.