DETECTION OF VISUAL EVOKED POTENTIALS IN ELECTROENCEPHALOGRAM

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Abstract:

The signals which are obtained as a result of electrical activity of the brain are called as electroencephalogram (EEG) Experimental studies have pointed out that EEG's characteristics change due to the mental activity of the human. Evoked potential (EP) are responses of the brain corresponding to visual, auditory and electrical stimulus. Central nervous system's functions have been determined by analysis of the EPs. In this study, Visual Evoked Potentials (VEP) have been detected by a non-linear operator. Firstly, we studied artificial data sets then tested real EEGs with VEP coming from the data base.

I. INTRODUCTION

EPs are responses of the central nervous system to stimulus applied to controlled manner [1]. Their signal-noise ratios are between 0-10 dB and they have his frequency components with short term also and low frequency components with long term [2]. The hardest subject in clinic neuro-physiology is the extraction of evoked potentials from background EEGs [3]. These signals which are recorded from the scull, are much smaller than background EEG. In the injury of brain, EEGs and EPs have very important diagnostic features. The sources of these kind of injuries are; cerabral hypoxia or ischemia, cerebral hypotentian or hypertention, drug overdose, occlusion of a blood vessel and injury of a nerve [4]. Especially, VEPs have been used for the diagnosis of pituitary tumours and multiple sclerosis.

In the analysis of biomedical signals, the spikes have great importance for diagnosing. Epileptic seizures have been represented as typical spike characteristics in EEG. Also QRS complex in electrocardiograph is a spike. Spike detection is very important in case of many illnesses. In the signal processing, a spike has been represented a feature which is located in high frequency region and has an increasing instantaneous energy [5]. The quantitative evaluation of the spike has changed from signal to signal, time to time for the same person. As spike's width is increased, its energy is located in low frequency region so detection becomes harder.

In our study, VEPs have been assumed as spikes and have been extracted from background as spikes and EEG by using a non-linear operator. Our algorithm has been applied to a noisy artificial spike train then to a real EEG set with VEPs coming from a data base

II. ANALYSIS OF THE EVOKED POTENTIALS

In the analysis of EPs, generally stimulus synchronised ensemble averaging has been used since the amplitudes of EPs are smaller than those of the background EEGs. The essence of this method depends on following assumptions; 1-EPs have a deterministic-repeatable pattern, 2- Background EEG is a fully random signal and 3-EEG and EP are completely dependent on each other. Despite these assumptions have met challenges in case of changing EP pattern. To eliminate these challenges, following methods have been used; auto regressive moving average (ARMA), auto regressive model (AR), Fourier transformation. wavelet transformation and artificial neural networks.

In applications for interpretation of EP responses; analysis duration, sampling frequency and bandwidth of recording amplifier must be in a suitable manner. Because a noisy effects could have remained after ensemble averaging EP responses must be filtered by digital filters which have same band width without any phase distortion We can name following filtering methods as well known methods; a posterior Wiener filter and Adaptive Wiener filter. In our study, the method which is based on a non-linear operator has less computational complexity than those of above mentioned methods. Therefore, this method has been suitable for simulated signals and real EEGs, too.

III. ALGORITHMIC STUDY

Today the non-linear energy operator has been used for estimation of instantaneous frequency and amplitude signal. This operator is sensitive to a discontinuity of the signal.

A. Mathematical background

We consider a band limited signal x(t), Kaiser has defined a non-linear energy operator φ, for continuous and discrete domain .It can be written as follows in continuous time,

$$\varphi[x(t)] = [x(t)]^2 - x(t)x''(t) \quad (1)$$

and in discrete time,

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

If x(t) were a linear combination of x_1 (t) and x_2 (t). We would write as x(t)=x_1 (t)+x_2 (t) in discrete time. If these signals are uncorrelated each other,

$$E\{\varphi[x(n)]\} = E\{\varphi[x_1(n)]\} + E\{\varphi[x_2(n)]\} \quad (3)$$

where E[.] expectation operator (statistical average). Auto correlation function is a follows.

$$R_x(t+\tau, t-\tau) = E\{x(t-\tau)x(t+\tau)\} \quad (4)$$

The Fourier transform of R_X is;

$$W(t,w) = \frac{1}{2}\int_{\infty}^{\infty} R_x(t+\frac{\tau}{2}, t-\frac{\tau}{2})\exp(-j\omega\tau)dt \quad (5)$$

W is known as Wiener distribution. If x_1 and x_2 are background EEG and spike respectively, we can write,

$$E\{\varphi[x(n)]\} = K_{x1}(n)R_{x1}(n,n) + K_{x2}(n)R_{x2}(n,n)$$
(6)

where K_X is instantaneous high frequency term and R_X is instantaneous energy respectively If there is a spike in the signal, second term is dominant . Otherwise this term is zero E{x[.]} could have been used for spike detection and is a non negative term.

B. The smoothed non linear energy operator

E[.] can not be defined by time-averaging since the spikes are not stationary. It suggests that a windowing has been used in time and frequency domains. Time-domain windowing is defined as follows,

$$\varphi_s[x(n)] = \varphi[x(n)] \otimes w(n) \quad (7)$$

where $\otimes$ is convolution operator and w(n) is window function respectively. This equation can be used for estimation of E{ φ (t)}. Window's type and width are very important for reduction of interferences without loss of time resolution.

C- Spike detection by thresholding

The signal which has a spike train needs to pass through equations (2) and (7) and thresholding operation successively Thresholding level must be optimised so that loss of true peaks is minimum and number of false detection will be in a reasonable interval. The smoothed energy operator's thresholding level can be determined as follows,

$$T = C\frac{1}{N}\sum_{n=1}^{N}\varphi_s[x(n)] \tag{8}$$

where C is scaling factor and is determined as experimental manner.

D- Performance Indices

False- negative ratio (FN);

FN=(number of missed peaks / number of real peaks),

and

False positive ration (FP);

FP=(number of false detected peaks / number of real peaks)

Signal to noise Ration (SNR);

SNR=10 $\log_{10}$(signal energy / noise energy)

IV- APPLICATIONS

A- Simulation studies

Firstly we made simulations for testing of algorithm. We have generated a composite signal like a background. EEG signal which has slowly changed as follows,

$$s(n) = Sin(wn) - Sin(2wn + \varphi) + Sin(4wn)$$

where $w = 2\pi/75$ and $\varphi = \pi/2$. Also, w is randomly. Artificial EEG is shown in Figure 1.

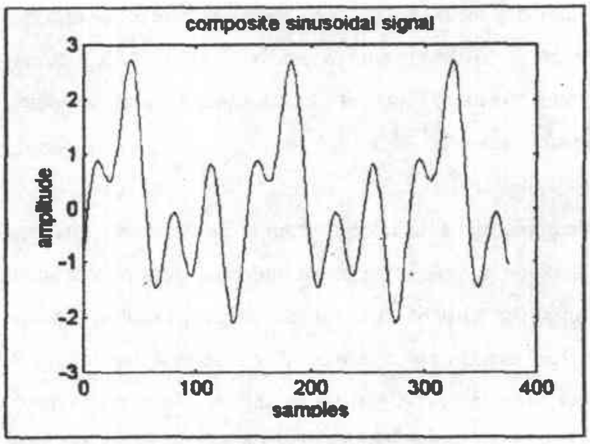


Figure 2. Artificial background EEG.

A spike train d(n) with random amplitude and duration, which has 10 spikes is generated. Finally general artificial signal is,

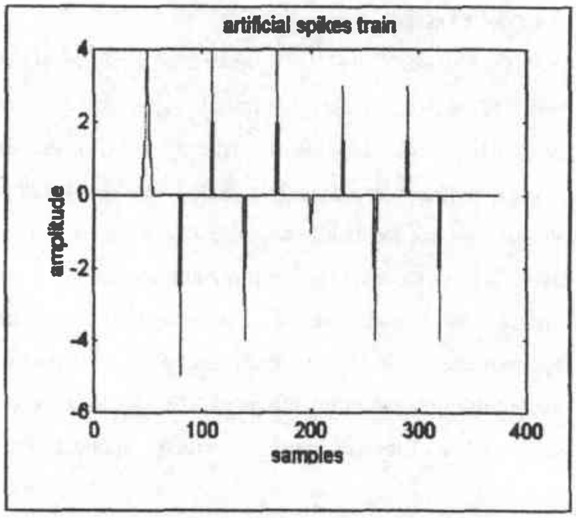
$$x(n) = s(n) + d(n) + v(n)$$

where v(n) is Gaussian distribution with unit variance distribution. Calculated performance criteria as a result of application are shown in Table 1.

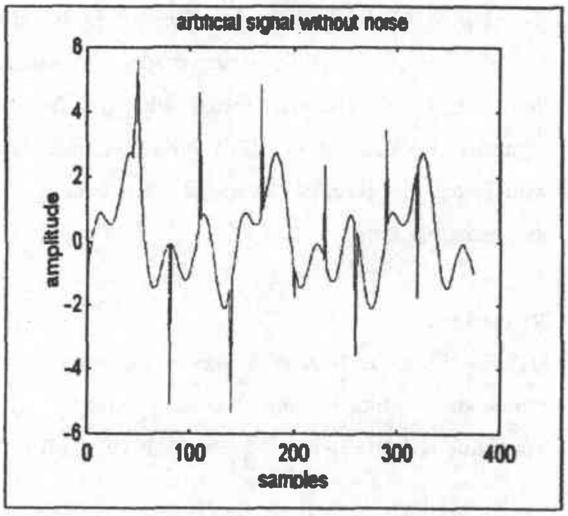
YN(avrg.)	0,09
YP(avrg.)	0,06
SNR	12.76 dB

Table 1: Performance criteria for artificial signal

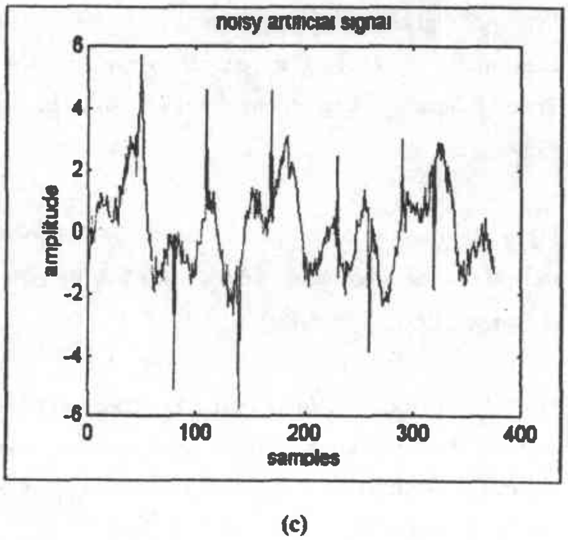
The wave shapes of some output signals coming from different stages of algorithms are shown in Figure 2.



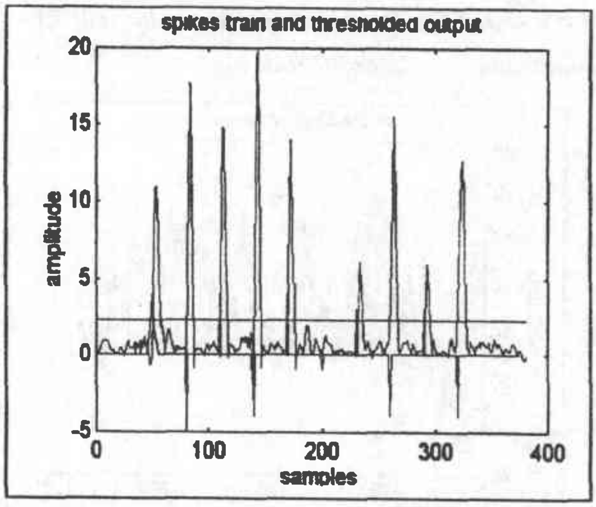
(a)



(b)



(c)



(d)

Figure 2. (a) Spike train (b) artificial signal without noise (c) noisy artificial signal (d) thresholded output and spike train.

B- Real EEG applications

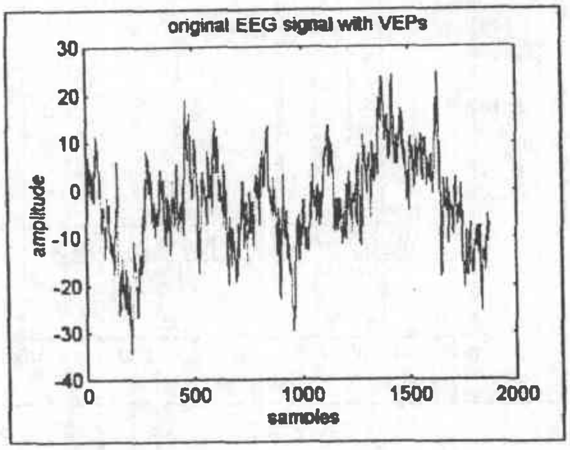
The aim of our study is detection of visual evoked potentials (VEP). VEPs are smaller than background EEG and they have short terms with high frequency components. Therefore above algorithm could be used for detection of VEPs Real EEGs coming from data-base have been recorded by Pz electrodes from the scull. They were sampled at 250 Hz and their recorded duration stars at 1.5 sec. before stimulus and continues until 2 sec. after stimulus. Complete EEG set has 100 responses each 375 samples.

In application, we have chosen a EEG set with 5 segments and decimated by a factor 2 and then haven not add any noise components. After removing d.c. level we have implemented 15 trials so that algorithm could be tested. The performance criteria are given as follow in Table 2.

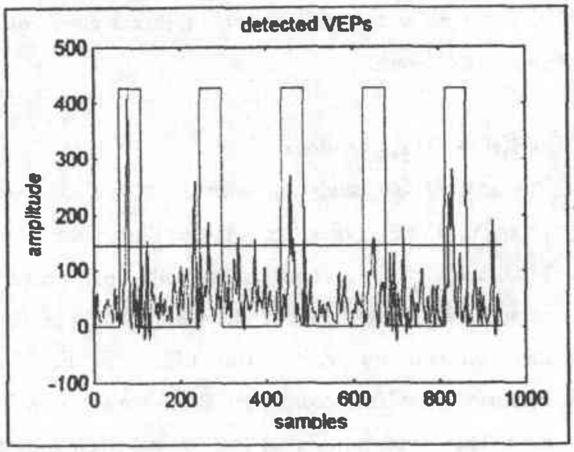
YN(avrg.)	0.08
YP(avrg.)	0.3

Table 2: Performance criteria for real EEGs application

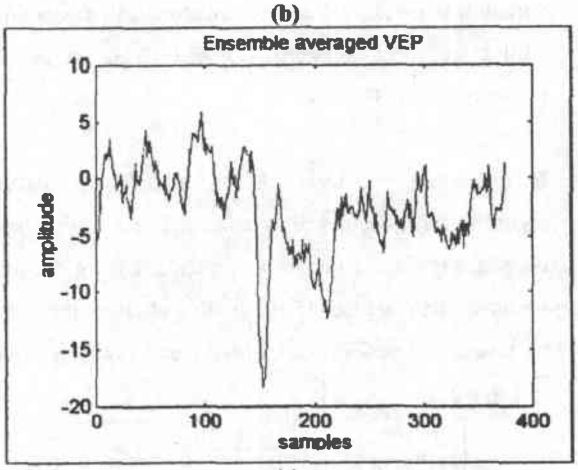
The Wave-forms of some output signals for real EEGs application are shown in Figure 3.



(a)



(b)



(c)

Figure 3. a) database EEG with VEP, b) detected VEP c) ensemble average VEP

V-CONCLUSION

In this study, firstly we have generated artificial signal with 10 spikes. In this , sinusoids frequencies and amplitudes and duration of spikes are generated randomly. They noisy signal is added to this artificial signal. Also, we have chosen real EEG signal sets from data base randomly. The performance indices are are given Table.1 and Table.2. False-negative ratios are approximately similar for each group of applications, while false positive ratios of real EEGs applications are smaller than those of artificial signal applications..

VEPs coming from thresholding have been interpreted according to localisation region. These results do not give any idea of VEP's wave shapes. We assumed that VEPs are generated periodically in data base segments. Localisation of VEPs have been determined with respect to ensemble averaged VEP coming from data base segments.

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