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DETECTION OF EPILEPTIC SEIZURES USING LabVIEW

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Abstract— **A significant portion of the population (0.5% - 0.8%) suffers from epilepsy. This study is an effort to predict seizures in epileptic patients. Electroencephalogram (EEG) continues to be an attractive tool in clinical practice due to its non-invasive nature and its real time depiction of brain function. The Short time Fourier Transform (STFT) is used for time frequency analysis of signals. In the present analysis, the authors adopted an effective technique for the denoising of EEG signals corrupted by non-stationary noises using Undecimated Wavelet Transform (UWT) which is implemented through Laboratory Virtual Instrumentation Engineering Workbench LabVIEW platform This Technique has overcome some of the short comings of the STFT by performing a multi - resolution analysis of signals. In the Wavelet Transform, high frequency components are analyzed with a sharp time resolution than low frequency components. This is the most desirable property, especially in analyzing fast transient waveforms such as EEG spikes. This paper deals with EEG spike detection based on wavelet representation using LabVIEW. The results obtained through this technique, show the superior performance of the Wavelet Transform Technique over the other techniques for detecting EEG spikes in terms of higher resolution and robust noise immunity.**

Keywords— Electroencephalogram, Epilepsy and wavelet transform, LabVIEW.

I. INTRODUCTION

The Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain. Epilepsy is a disorder characterized by recurrent seizures [1]. The seizures (ictal states) cause temporary disturbances of brain functions (e.g., motor control, responsiveness, recall), for periods ranging from few seconds to several minutes. Seizures may be followed by a postictal period of confusion or impaired sensorium that can last for several hours. The presence of noise in extracellular recordings of neural activity in the brain is inevitable in this technique according to Jean Gotmann [2]. Our current knowledge about the neural code relies on the assumption that information is carried in a train of action potentials that are fired by individual neurons within a population of neurons. Therefore, it is of utmost importance to reliably separate signal from noise under different scenarios that include variable Signal to noise ratios (SNR), Firing rates, sampling rates etc. Electrical recordings of action potentials have become an indispensable tool in neuroscience. While the use of EEG has an advantage of providing a non-invasive measure of electrical activity, the quantitative method for analyzing and interpreting EEG data remains an important field of study. Epileptic seizures are considered to be the result of sudden change in the synchronization of firing neurons in brain. [3]. Despite numerous algorithms for detection of extra cellular potentials in a background noise, a fully automated and robust detection system is yet to be formulated [3].

Beyond the diagnosis of epilepsy, automatic spike detection [3-6] is important because it may be able to answer questions like: can quantitative descriptions of spike density, topology and morphology help determine patient syndrome and surgical outcome. The comprehensive spike marking required for these types of studies is tedious and time consuming for visual identification by electroencephalographers.

A spike was loosely defined by Gloor (1975) as

(i) A restricted triangular transient is clearly distinguishable from background activity and should have amplitude of at least twice that of the background activity during the preceding 5s in any channel of EEG,

(ii) Having a duration of ≤ 200 ms, and

(iii) Including the presence of a field, as defined by the influence of a second adjacent electrode.

II. MATERIALS

EEG signals are normally recorded non- invasively using small (micro) electrodes attached to the surface of the scalp of a patient. The total number of electrodes attached to the scalp of a patient may vary from 1 to 256. The electrodes are placed at predetermined positions as per the international 10/20 system. The EEG signals from 16 surface electrodes are recorded simultaneously from each subject / patient under normally relaxed conditions for long term clinical procedures with the help of a bi-polar montage. The 16 scalp locations are

Fp1 , Fp2 , F3 , F4 ,C3 , C4 , P3 , P4 , O1 , O2 , F7 , F8 , T3 , T4 , T5 and T6 . The data is acquired at 256 samples / sec with 12 – bit uniform quantization. A commercially available 32 channel Nicolet EEG recorder with anti-aliasing filters with a -6dB / Octave roll – off at 70 Hz is employed in the present investigation [7]. The recordings are made for long periods while the patients are resting and hence may include periods of sleep and wakefulness with eyes open or closed. The data set has 45 normal persons and 33 generalized epileptic persons with age below 40 years. Each EEG recording is labeled by an experienced neurophysiologist and this is subsequently used as a reference for the evaluation of the detection methods.

III. METHOD

The problem of an adequate interpretation of epileptic EEG recordings is of great importance in the understanding, recognition and treatment of epilepsy. Our methodology consists of a combination of several techniques in LabVIEW. In first step, the required data from applied input is stored in to a Sub-array. In second step, the preprocessing of the signal is done. In third step, denoising of a signal and reconstruction of the signal are done .In fourth step, psd is analyzed, frequency is detected and respective classification is carried out which is shown in figure1.

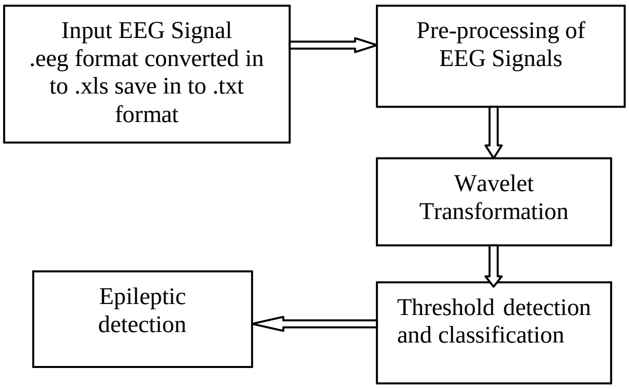

Fig 1: Block Diagram of EEG Signal Processing

In the Wavelet theory provides a unified framework for a number of techniques developed for various signal processing applications like detection of unknown transient signals [8-10]. A brief introduction to the Continuous Wavelet Transform (CWT) is presented below. The CWT of a function f(t) involves a mother wavelet $\Psi(t)$. The mother wavelet can be any real or complex continuous function that satisfies the following properties:

a) The total area under the curve of the function is zero, i.e.,

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \qquad \text{----} \qquad (1)$$

b) The total area of $|\Psi(t)|^2$ is finite, i.e.

$$\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt < \infty \qquad \text{----} \qquad (2)$$

c) The admissibility condition, as defined by the properties (a) and (b).

Property (a) suggests that the function oscillates about the time axis. Such a function tends to have a wavy appearance.

Property (b) implies that the energy of the function is finite, suggesting that the function is localized in some finite interval and is zero, or almost zero, outside this interval. These properties justify the nomenclature of a wavelet.

Once a wavelet Ψ (t) has been chosen, the CWT of a square integrable function f(t) is defined as

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \Psi^*\left(\frac{t-b}{a}\right) dt \qquad \text{----} \qquad (3)$$

The transform is a function of two real parameters a and b. The * denotes the complex conjugate. If we define a function $\Psi_{a,b}(t)$ as

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \Psi\left(\frac{t-b}{a}\right) \qquad \text{----} \qquad (4)$$

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \, \Psi_{a,b}(t) \, dt \qquad \text{----} \qquad (5)$$

Mathematically, the transform is the inner product of the two functions f(t) and $\Psi_{a,b}(t)$.

The quantity $\frac{1}{\sqrt{|a|}}$ is a normalizing factor that ensures that the energy of $\Psi(t)$ remains independent of 'a and b' i.e.,

$$\int_{-\infty}^{\infty} |\Psi_{a,b}(t)|^2 \, dt = \int_{-\infty}^{\infty} |\psi(t)|^2 \, dt \qquad \text{----} \qquad (6)$$

For any 'a' , $\Psi_{a,b}(t)$ is a copy of $\Psi_{a,0}(t)$ shifted through 'b' units along the time axis. Thus, 'b' is a translation parameter. Setting b = 0 shows that

$\Psi_{a,0}(t). = \frac{1}{\sqrt{|a|}} \Psi\left(\frac{t}{a}\right)$, implies that 'a' is a scaling (or a dilation) parameter. For values a > 1 stretch the wavelet, while for values 0< a<1 the wavelet shrinks.

The inverse CWT is defined by

$$f(t) = \frac{1}{C} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\frac{1}{|a|}\right)^2 w(a,b) \, |\Psi_{a,b}(t) \, da \, db \qquad \text{----} \qquad (7)$$

where the quantity C is defined as

$$C = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} \, d\omega \qquad \text{----} \qquad (8)$$

The inverse CWT exists if C is positive and finite.

Wavelet Denoising: Wavelet signal decomposition can be seen in Fig 2. as an iterative process whereby a signal is decomposed into finer resolution signals in time and frequency. First of all, two symmetric filters are created from a “mother” wavelet and a scaling function associated to that wavelet. These filters will provide an orthogonal basis dividing the signal frequency spectrum and generating high and low frequency signals in each iterative step. These signals are decimated by two before the next iterative step. Details on wavelet decomposition can be found in[1]. Figure 2. Illustrate this wavelet decomposition tree of an EEG signal, where the Approximations) boxes represent the low frequency components obtained by the low pass filter (LPF), and the D boxes represent the high frequency components obtained by the symmetric high pass filter (HPF).

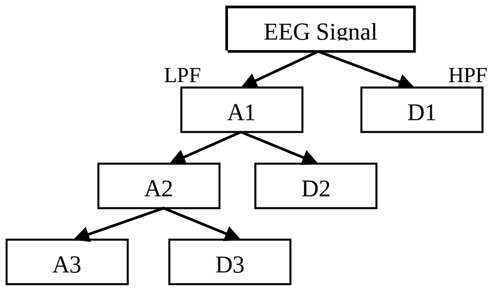

Fig 2: Wavelet Decomposition Tree.

Removal of Baseline Wandering:

Baseline wandering usually comes from respiration at frequency wandering between 0.15 Hz and 0.3 Hz and it can be suppressed by a high pass digital filter. Wavelet transform can also be used to remove the baseline wandering by eliminating the trend of the EEG signal which is shown in the Figure 3.The wavelet transform based approach is better because it introduces no latency and less distortion than the digital filter based approach.
The LabVIEW ASPT (Advanced signal processing toolkit) provides the WA Detrend virtual instrument which removes the low frequency trend of the signal.

$$trend\ level = \left[\frac{\log_2 2t}{\log_2 N}\right] \quad ---- \quad (9)$$

Where t is the sampling duration and N is the number of sampling points. The data used here has a sampling duration of 30.06 Min and with a sampling frequency of 256 samples /sec, therefore the trend level is 0.01 according to the above equation. Trend level specifies the number of levels of the wavelet decomposition, which is approximately,

$$\text{No. of decomposition level} = (1\text{-Trend level})*\log_2(N) \quad (10)$$

and for the data base we used here it is 8. The WA detrend virtual instrument has an option to specify the wavelet type used for the discrete wavelet analysis. The one selected here is Daubechies(db6) wavelet because this wavelet is similar to the real EEG signal and also Daubechies wavelet being orthogonal wavelet is suitable for signal denoising where as biorthogonal wavelet is suitable for feature extraction.

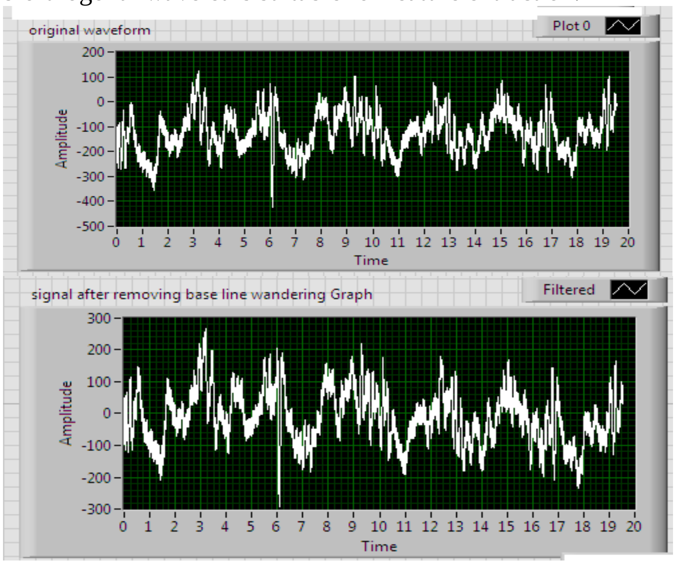

Fig 3: EEG signals before and after Baseline wandering.

After removing baseline wander the resulting EEG signal is more clean and explicit than the original signal shown in Fig 4. However, some other types of noise might still affect feature extraction of the EEG signal. The noise may be complex stochastic processes within a wideband, so one cannot remove them by using traditional digital filters[3]. To remove the wideband noises, the Wavelet Denoise Express Virtual instrument is used here. Which decomposes the EEG signal into several sub bands by applying the wavelet transform and then modifies each wavelet coefficient by applying a threshold or shrinking a function and finally reconstructs denoised signal.

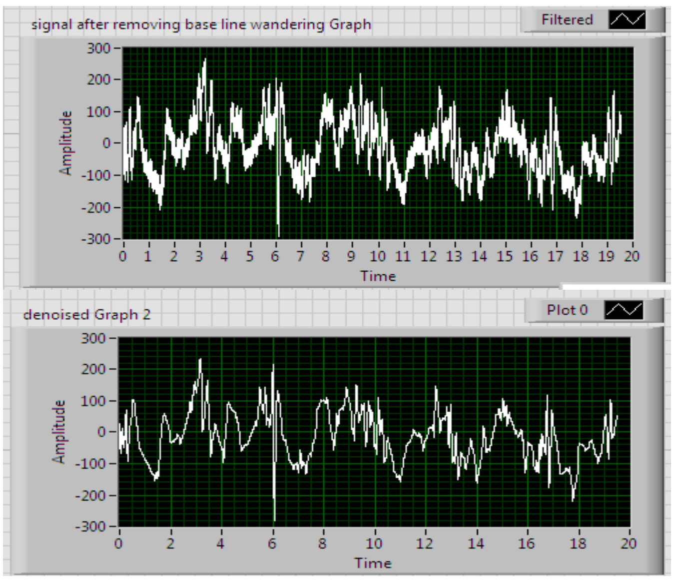

Fig 4: Signal before and after Denoising.

Detection of Epileptic Seizures using Power Spectral Density (PSD):

Seizures are often accompanied by an increase in EEG power at high frequencies. This frequency increase is particularly pronounced in the 10-100 Hz range, and the power at these frequencies may increase by as much as a factor of 10^4. The cellular mechanisms responsible for the frequency increase involve the increased frequency of generation of action potential of neurons, with action potentials occurring as soon as the refractory period of the previous cycle ends.

After the removal of noises, the power spectral density which computes the averaged auto power spectrum of time signal is applied. Wire data to the time signal input to determine the polymorphic instance to use or manually select the instance which is shown in Figure 5.

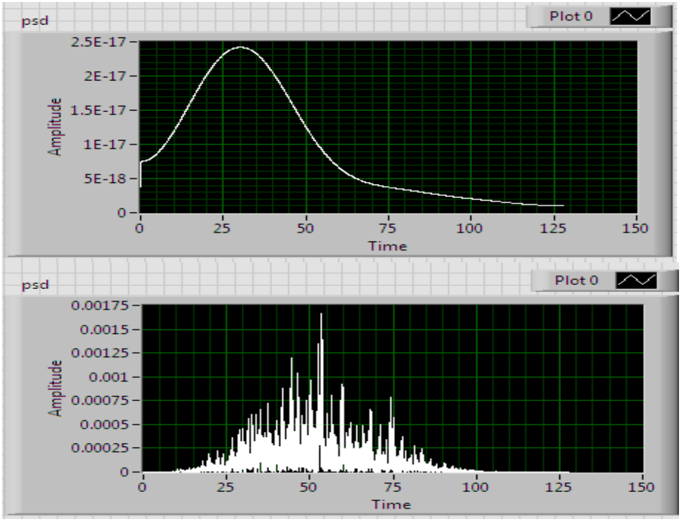

Fig 5: PSD Graph for Epileptic and Non-Epileptic

TABLE 1: RESULTS

S. No	Subject Name	P.S.D OF Fp1*	P.S.D OF F3*	*P.S.D OF C3**	P.S.D OF T5*	P.S.D OF T6*	R
1	KARTHIK	64.33	41.67	41.40	52.44	49.93	NE
2	CHARY	38.96	38.95	50.30	38.96	50.04	NE
3	UPENDRA	48.95	48.95	48.90	54.24	54.13	E
4	K.V.RAO	49.47	49.47	49.47	39.97	39.97	E
5	KAMALA	38.72	37.21	40.06	40.98	40.37	E
6	LAXMAN	48.98	37.08	43.69	48.99	40.49	E
7	RAJU	48.99	49.00	48.99	48.99	48.99	E
8	NITIN	49.04	52.29	52.29	52.26	37.83	E
9	P.UMA	37.12	32.00	32.00	44.11	32.00	E
10	KRISHNA	41.38	37.83	52.77	42.14	32.00	E
11	MANASA	49.03	49.03	54.01	41.58	41.52	E

* P.S.D – Power spectral Density, the letters F, T and C stands for frontal, temporal, central respectively. Even number 6 refer to electrode positions on the right hemisphere, whereas odd numbers 1, 3, 5 refer to those on the left hemisphere. The notation Fp stands for electrode position between frontal and parietal lobes. R, E, N.E Stands for Results, Epileptic and Non-Epileptic.

IV. CONCLUSION:

In summary, the CWT method proposed by the authors seems particularly suitable for accurate and reliable identification of bioelectric states of the cerebral, whether from the background EEG activity or from a preponderance of spontaneous single events. The method is capable of distinguishing sharp waves or spikes in some instances for healthy subjects as well as in patients with epilepsy. The method, described by the authors is an efficient system capable of automatic EEG evaluation for the detection of epileptic seizures using Wavelet Transform Analysis. This technique eliminates the manual examination of EEG for the identification of spikes. Hence this method reduces the work load of an expert physician substantially and can become a lucrative tool for mass screening.

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