EEG Signal Preprocessing using Wavelet Transform

Arun S. Chavan¹ and Mahesh Kolte²
¹Vidyalankar Institute of Technology, Wadala, Mumbai-400 037.
²Shree Chhatrapati Shivaraj Maharaj College of Engineering, Pune.
E-mail: arunschavan@yahoo.co.in

Abstract: The purpose of the study was to investigate the feasibility of using wavelet transform as a preprocessor for EEG spikes detection system. The study aimed at decreasing the information content of the signal without degrading the detection performance. Since routine clinical EEG requires recording from many channels (generally 32 to 44), input size becomes a critical design parameter for real – time multichannel spike detection systems.

The Short Time Fourier Transform (STFT) is used for time frequency analysis of signals on a routine basis. The STFT has some drawbacks, such as bandwidth can be arbitrarily small, and increasing the resolution in time decreases the resolution in frequency and vice versa. Another characteristic of the STFT is its fixed time-frequency resolution. Once a time window has been chosen, the time-frequency resolution remains the same for all the frequencies in the time-frequency plane. [6]

We proposed to use wavelet transform to overcome some of the shortcomings of the STFT by performing a multiresolution analysis of signals. In the wavelet transform, high frequency components are analyzed with a sharp time resolution than low frequency components. This is a desirable property, especially in analyzing fast transient waveforms such as EEG spikes. [6]

The wavelet transform is used to represent essential characteristics of EEG spikes and spike wave(SSW) complex with few coefficients. Since spikes contain high frequency energy, they will be represented in particular scale localized in a small time window. The wave portion of the spike wave complex will be represented in a lower scale of WT, covering wider span of time. Thus with the proper selection of WT scales and time spans a fewer number of WT coefficients may be used to represent the SSW complexes. [6]

In order to reduce the false detection, we can extend the contextual information by referring to other signals such as EOG for information about eye movements, EMG (ElectroMyoGram) for information about muscle electrical activity. With this it is possible to reduce greatly the false detection of sharp transients due to artifacts. [3]

1. WAVELET TRANSFORM

Wavelet theory provides a unified framework for a number of techniques developed for various signal-processing applications. Particularly, it is of immense interest for the analysis of non-stationary signals like EEG, because it provides an alternative to the classical Short-Time Fourier Transform (STFT) or Gabor transform. The basic difference is, in contrast to the STFT, which uses a single analysis window, the Wavelet Transform (WT) uses short windows at high frequencies and long windows at lower frequencies. This is similar to “Constant Q” or Conastant relative bandwidth frequency analysis.[6]

For some applications WT can be seen as signal decomposition onto a set of basis functions. Basis functions called Wavelets are obtained by a single prototype wavelet by dilation and contraction (Scaling) as well as shifts. The prototype wavelet can be thought of as a band pass filter, and the constant Q property of the other bandpass filter (Wavelets) follows because they are scaled version of prototype. [6]

Therefore, in a WT, the notion of the scale is introduced as an alternative to frequency leading to time scale representation. It means that a signal is mapped into a time-scale plane as compared to the time frequency plane used in the STFT. [6]

Non Stationary Signal Analysis

The aim of signal analysis is to extract relative information from a signal by transforming it. Perhaps the most well known tool for transforming is Fourier transform analysis, which breaks down a signal into constituent sinusoids of different frequencies. Another way to think of it as a mathematical technique for transforming view of signal from a time based one to frequency-based one[4]

For a signal \( x(t) \), Fourier transform is given as,

\[
X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} \, dt
\]

As it is clear from above equation, analysis coefficients \( x(f) \) can be computed as inner products of the signal with
sinewave basis functions of infinite duration. As a result, Fourier analysis works well if \( x(t) \) is composed of a few stationary components (e.g. sinewaves). However, any abrupt change in time in a non-stationary signal \( x(t) \) is spread out over the whole frequency axis in \( x(f) \). Most interesting signals contain numerous non-stationary or transitory characteristics as drift, trends, abrupt changes and beginning and end of events. These characteristics are often the most important part of signal, and Fourier analysis is not suited to detecting them. [6]

The usual approach is to introduce time dependency in the Fourier analysis while preserving linearity. The idea is to introduce a “local frequency” parameter (local in time) so that the “local” Fourier transform looks at the signal through a window over which the signal is approximately stationary. Another, equivalent way is to modify the sine wave basis function used in the Fourier transform to basis functions which are more concentrated in time (but less concentrated in frequency). [6]

**Short-Time Fourier Analysis**

In an effort to correct the deficiency, Dennis Gabor (1946) adopted the Fourier transform to analyze only a small section of the signal at a time, a technique called windowing the signal. Gabor’s adaptation called the Short – Time Fourier Transform (STFT), maps a signal into a two dimensional function of time and frequency. [6]

Consider a signal \( x(t) \). Assuming that it is stationary when seen through a window \( g(t) \) of limited extents, centered at time location \( T \), the Fourier Transform of the windowed signals \( x(t) g(t-T) \) yields the Short-time Fourier Transform

\[
STFT(T, f) = \int_{-\infty}^{\infty} X(t) g(t-T) e^{-j2\pi ft} \, dt
\]

The STFT represents a sort of compromise between the time and frequency based views of a signal. It provides some information about both, when and at what frequencies a signal event occurs. However one can only obtain this information with limited precision, and that precision is determined by the size of the window. [6]

An alternative view is based on a filter bank interpretation of the same process. At a given frequency \( f \), equation above amounts to filtering the signal “at all times” with a bandpass filter having the window function modulated to that frequency as impulse response, Thus the STFT may be seen as modulated filter bank. [6]

**Fig. 1:** (a) Standard Time Domain Basis, (b) Standard Frequency Domain Basis.

**Fig. 2:** Time Frequency Plane Corresponding to Short Time Fourier Transform
Heisenberg Inequality

From the dual interpretation of equation for STFT, exists a drawback related to the time and frequency resolution. For a window function \( g(t) \) and its Fourier transform \( G(f) \), the ‘bandwidth’ \( \Delta f \) of the filter is defined as

\[
\Delta f = \frac{\int f^2 |G(f)|^2 \, df}{\int |G(f)|^2 \, df}
\]

Where the denominator is the energy of \( g(t) \). Two sinusoids will be discriminated only if they are more than \( \Delta f \) apart. Thus the resolution in the frequency of STFT analysis is given by \( \Delta f \). Similarly the spread in time is given by \( \Delta t \) as

\[
\Delta t^2 = \frac{\int t^2 |G(t)|^2 \, dt}{\int |G(t)|^2 \, dt}
\]

Where the denominator is the energy of \( g(t) \). Two pulses in time can be discriminated only if they are more than \( \Delta t \) apart.

Resolution in time and frequency cannot be arbitrary small, because their product is lower bounded.

Time-Bandwidth Product = \( \Delta t \times \Delta f \geq 1/4\pi \)

This is referred to as the uncertainty principle, or Heisenberg inequality. It means that one can only trade time resolution for frequency resolution or vice versa. That is one cannot know that exact time-frequency representation of a signal or one can not know what spectral components exist at what instances of time. What one can know are the time intervals in which certain band of frequencies exists.

More important is that once a window has been chosen for the STFT, then the time – frequency resolution given by equation for \( \Delta t \) & \( \Delta f \) is fixed over the entire time frequency plane (since the same window is used at all frequencies). Suppose if the signal is composed of small bursts associated with long quasi – stationary components like spikes and slow – wave complex in epileptiform EEG activity, then each type of component can be analyzed with good time resolution or frequency resolution, but not both.

Multiresolution Analysis

Anyone who would like to use STFT is faced with this problem of resolution. What kind of windows to use? Narrow windows give good time resolution, but poor frequency resolution; wide windows may violate the condition of stationary.

One Alternative to overcome this resolution limitation of STFT is by letting the resolution \( \Delta t \) and \( \Delta f \) vary in the time- frequency plane in order to obtain a multi resolution analysis. That is when the analysis is viewed as a filter bank; the time resolution must increase with the central frequency of the analysis filters. To make this happen, the \( \Delta f \) should be made proportional to \( f \) or \( \Delta f / f = c \); where \( c \) is a constant.

The analysis filter bank is then composed of bandpass filters with constant relative bandwidth (constant \( Q \) analysis). When above equation is satisfied, \( \Delta f \) and therefore also \( \Delta t \) changes with center frequency of analysis window. Of course, they still satisfy the Heisenberg inequality, but now, the time resolution becomes arbitrary good at high frequencies, while the frequency resolution becomes arbitrary good at low frequencies. For example, two very close short bursts can always be eventually separated in the analysis by going up to higher analysis frequencies in order to increase time resolution. This kind of analysis works best if the signal is composed of high frequency component of short duration plus low frequency component of long duration, which is often the case with the biomedical signals like EEG.

Fig. 4: Wave and Wavelet
Wavelet Transform

The wavelet transform of a sigmoid \( x(t) \) is defined as

\[
WTX(T,a) = \left( \frac{1}{\sqrt{a}} \right) \int_{-\infty}^{+\infty} x(t) h((t-T)/a)e^{-j2\pi a} dt
\]

\[
WTX(T,a) = \left( \frac{1}{\sqrt{a}} \right) \int_{-\infty}^{+\infty} x(at) h(t-(T/a))e^{-j2\pi a} dt
\]

In WT, analysis of a signal is carried out by the use of a special function, \( h(t) \), called the mother wavelet. This function is translated in time for selecting that part of the signal to be analyzed. The portion of the signal selected is then expanded or contracted using a scale parameter, \( a \), which is analogous to frequency. For small values of \( a \), the wavelet is a narrow function of the original function, which corresponds roughly to higher frequencies. For very large values of \( a \), the wavelets are expanded and correspond to low frequency. In the WT, high frequency components are analyzed with the sharper time resolution than low frequency components. This is desirable properly, especially in analyzing fast transient waveforms such as EEG spikes. [6]

The functions \( WTX(T,a) \) is the projection of signal onto the wavelet shifted by \( T \) and scaled by \( a \), and hence indicates the contribution of wavelet to the signal. Thus, such a transformation does not lead to time-frequency representation but instead, to, time – scale decomposition in which scales are related to frequency.

Advantages of Wavelet Transform

1. The Fourier transform represents a signal as combination of scaled and phase shifted sinusoids. Wavelet decomposition represents a signal as a combination of scaled wavelets; the mother wavelet shape selected depends on the application.
2. The Discrete Fourier transform assumes that the signal is periodic and in the case of non – periodic signals complex techniques must be used to estimate the Fourier components without misrepresentation. Wavelets decomposition is naturally amenable to represent non- periodic functions.
3. The wavelet expansion allows a more accurate local description and separation of signal characteristics. A Fourier coefficient represents a component that last for all time and therefore, temporary events must be described by a phase characteristics that allows cancellation or reinforcement over large time periods. A wavelet expansion coefficient represent a component that is itself local and is easier to represent.
4. The Fourier transform acts on a block of data simultaneously, therefore, information about the location of different components within the block is not available. In wavelet decomposition the time location of the wavelets is known directly from the position of the output Wavelet coefficients.

[5] The Fourier transform has equal time and frequency resolution for all the components. Wavelet decomposition has a large time aperture, but closely spaced frequency resolution for slow components; and small time aperture but broad frequency resolution for fast components.

2. METHODOLOGY

The methodology followed in the study is summarized below. It consists of three sequentially performed procedures.

- Data Selection
- Waveform Transformation
- Data Compression
- Signal Reconstruction

The EEG data used in the study in this study was obtained from Nasan Medical Electronics pvt. Ltd., Pune. The data was available in binary file format with 12 bit resolution and the sampling frequency of 250 samples per second. It was then preprocessed to separate the 20-channel waveform and stored in a separate file for subsequent transformation with wavelets.

Data Selection

The EEG is broken down into sections, or epochs, for the purpose of wavelet transform. An epoch of 2.0485 sec. is used for following reasons:

1. It is long enough to capture the main statistical characteristics of the EEG and short enough to capture the evolution of seizures.
2. To detect the seizures as soon as possible, a short epoch length may increase the chance of early detection.
3. The EEG being digitized at a sampling rate of 250 Hz, an epoch of 2.0485 contains 512 samples, a convenient length to complete wavelet Transform.

Wavelets transforming of 512 data points produced eight resolution scales consisting of 256, 128, 64, ……………......2 data points. Scale 1 represented the highest frequency region with 256 points. The next scale presented the next lower frequency region with half the number of the data points and so on. Since the seizure can be characterized to have a theta (4 – 7.75HZ) and beta (16 to 25Hz) dominate monofrequency at the beginning, which rapidly evolves to a dominant alpha monofrequency for the rest of the seizure,, the scale corresponding to the alpha(8 – 13 Hz) is selected. Three types of mother Wavelets used; db1 (or Haar) wavelets & db-4. Daubechies wavelets were found to be ideally suited for detection of spike/spike and wave (SSW) activity due to their compact support.
Waveform Transformation
Wavelet transformation is done using db-1 & db-4 wavelets producing eight resolution scales. The wavelet coefficients for different channels are stored in an array, which then are used for wave reconstruction and compression.

Data Compression
Data compression is done by setting different threshold levels. The basic idea is to ignore the samples which are not contributing for the study of different characteristics of EEG. Software is developed for decompression & to reconstruct the wave form after compression. Since it is also necessary to know the amount of energy restored after compression, the software is accordingly modified to calculate and display the amount of energy restored.

Signal Reconstruction
Signal is reconstructed after compression. The original and reconstructed signals are displayed simultaneously for comparison. The reconstructed signal is displayed with compression ratio and amount of energy restored.

3. RESULTS AND CONCLUSION
The purpose of the study was to investigate the feasibility of using wavelet transform as a preprocessor for EEG spikes detection system. The study aimed at decreasing the information content of the signal without degrading the detection performance. Since routine clinical EEG requires recording from many channels (generally 32 to 44), input size becomes a critical design parameter for real – time multichannel spike detection systems.

The results of the study now that the use of the WT drastically decrease the input size, without much compromise in performance. The most important factor in performance, however, was the proper selection of the scale. Scale 4 performed the best for the Haar as well as Daubechies Wavelets indicating that it contained most content of the relevant information for detection. [2]

Out of two wavelets analyzed namely Haar (Daub-1), Daub-4, it was found that Daub-4 gives good results. Daubechies Wavelets were found suitable for analysis due to the compact support and their similarity with the SSW wave.

Programs are developed to display the sample waveform for different channels, for decomposition of the waveform using DB-1 & DB-4 as well as for the display of original, denoised and compressed waveforms for each channel.

In the following figures the sample waveforms for channel-2 are shown.

Fig. 5: Waveform for Channel No-2

Fig. 6: The Wavelet Decomposition for Channel-2 Using DB-1 Wavelets
4. FUTURE SCOPE

In order to reduce the false detection, we can extend the contextual information by referring to other signals such as EOG (Electroculogram) for information about eye movements, EMG (Electromyogram) for information about electrocardiography activity. With this it is possible to reduce greatly the false detection of sharp transients due to artifacts.

For more reliable detection of epilepsy, number of clinical and pathological information such as age, sex, body temperature, pulse rate, body sugar etc. and behavioral status of patient like co-operative or non-co-operative, Introvert or extrovert, right handed or left handed etc. and different EEG recording with photic stimulations, hyperventilation may be used.

Although in this study, the accuracy of Daub-4 found to be satisfactory, other type of wavelets such as morlets wavelet or spline wavelets need to be analyzed. Designing the mother wavelet that matches the shape of frequency characteristics of Spike and Spike Wave (SSW) events may also offer higher accuracy. These possibilities are open for future studies.

The method was implemented and tested off-line. However, this can be further extended for on-line implementation by taking into account memory management and computational load.

This method can be further extended with ANN to classify the EEG into normal or abnormal depending upon its frequency distribution. It can be extended to further classify the abnormalities.

In order to replicate the reasoning of EEGer, the expert system provided with the knowledge of spatial context may be designed.

Finally, the system must be evaluated by comparing its performance after applying it to large number of abnormal cases, including normal cases with visual scoring by EEGer.

REFERENCES


