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Bio Signal (EEG) Using Empirical Wavelet Transform In Time Frequency Analysis

D.Christy Rubella [1], M.karthick [2]
[1](PG Scholar,Department of ECE,K.Ramakrishnan College of Engineering,Samayapuram)
[2](Assistant Professor, Department of ECE,K.Ramakrishnan College of Engineering,Samayapuram)

Abstract: *Time-frequency analysis is used to reveal the valuable information hidden in the EEG data. The high resolution of the time-frequency representation is the one of the important thing to depict geological structures. In this project, we propose a EEG time-frequency analysis approach using the newly developed empirical wavelet transform (EWT). It is the first time that EWT is used for analysing multichannel EEG data for the purpose of ECG exploration. EWT is similar to the empirical mode decomposition; it is a thoroughly adaptive signal-analysis approach, which purely contains consolidated mathematical background. . EWT first estimates the frequency components presented in the EEG signal, then computes the boundaries, and extracts oscillatory components based on the boundaries computed. The real EEG datas are synthetic, 2-D, and 3-D.Which helps to demonstrate the effectiveness of the EEG time-frequency analysis approach. Results show that the EWT can provide a much higher resolution than the traditional continuous wavelet transform and offers the potential in precisely highlighting geological and stratigraphic information. Finally comparative results of the EWT and CWT were shown in MATLAB.*

Keywords: *Continuous wavelet transform (CWT), empirical wavelet transform (EWT), instantaneous frequency, sparse representation, time–frequency analysis.*

I. Introduction

Most of us directly experience such technologies daily: browsing the Internet, transforming/receiving emails, viewing television, or carrying out a phone conversation. Many of these experiences occur on mobile devices that we carry around with us, so that we are always connected to the cyber world of modern communication systems. In fact, there is a wide amount of communication take place from one machine to another machine that we cannot directly experience, but which are indispensable for the operation of modern society. Examples include- Internet: signaling between routers Computing devices: signaling between processors and memories.

We use the term message signals for such signals, since the term message is used to convey the information from one person to another through communication system. In natural condition both during generation and consumption the message signals are in analog form: these messages signal are continuous time signals in this value also occurring in a continuous manner. Geophysical properties of the local time-frequency variations are described by a **T**IME-frequency decomposition maps. In these TFD maps a 1-D signal in the time domain into a 2-D image in time-frequency space take place to describe the geophysical properties. In seismic data processing and interpretation the time-frequency analysis are used wider in range. The most commonly used approach is the short time Fourier transform (STFT) [1]. However, the predefined window length provides a fixed spectral resolution [2].

A wavelet-based method is the alternate method used for seismic time-frequency analysis. This wavelet-based method helps to overcome the limitations of STFT. [3]. and it shows superior spectral resolutions. Stockwell *et al.* [4] suggested the S transform, is a combination of both STFT and the wavelet transform (WT) [5], [6]. It not only discriminates as the multiresolution analysis of the WT, Meanwhile it also eradicates the further requirement of the standard window length for the STFT [7].

The Wigner-Ville distribution [8], [9] has a higher time-frequency resolution, but its application is restricted by the existence of cross-product terms or interference. Matching pursuit-It is one of the Time-Frequency Analysis methods. Due to the redundancy of the atom library at the expense of computation this occurs even though the time-frequency resolution is higher in range. Han and van der Baan [13] investigated about the chance of using empirical mode decomposition (EMD) and its expansion, the ensemble [EMD] + complete ensemble [EMD], in combination with instantaneous frequency. In spite of its considerable success, there is still a lack of mathematical foundation and low computational efficiency.

The authors of [14]-[17] applied the synchrosqueezed wavelet transform [18] to seismic time-frequency analysis and it gives significant higher resolution than the WT. To boost the spectral resolution [18] a redistribution method of the time-frequency plane information and a classic wavelet analysis are merged using the synchrosqueezed wavelet transform [19]. With a newly recommended transform called empirical wavelet transform (EWT) are used to expand our future studies of seismic time-frequency analysis [19].The EWT is a rapid and entirely adjusting wavelet technique. The scaling function and wavelets accept themselves according to the message contained in the evaluated signal, and no former message regarding the signal is required. Similar to EMD, EWT is a entirely modifying signal analysis approach that can be conveniently used. However, Empirical Wavelet Transform has a firm mathematical support and also powerful than the empirically defined EMD. Correlate with the conventional time-frequency analysis methods, the Empirical Wavelet Transform is ready to produce higher time-frequency resolution, which promotes seismic data processing and interpretation.

II. Related Work

In 2014Ping Wang; Jinghuai Gao; Zhiguo Wang proposed,"Time-frequency analysis of ECG data using synchrosqueezing transform". The synchrosqueezing transform is a promising tool which can provide a detailed time-frequency representation for ECG signal processing applications. In 2013Jerome Gilles reported empirical mode decomposition (EMD), to decompose a signal accordingly to its contained information. Even though its adaptability seems useful for many applications, the main issue with this approach is its lack of theory. The main idea is to extract the different modes of a signal by designing an appropriate wavelet filter bank. This construction leads us to a new wavelet transform, called the empirical wavelet transform. In 1997 Amir-Homayoon Najmi and John Sadowsky proposed, "The Continuous Wavelet Transform and Variable Resolution Time–Frequency Analysis". Wavelet transforms have recently emerged as a mathematical tool for multiresolution decomposition of signals. In 1996R. G. Stockwell; L. Mansinha; R. P. Lowe anticipated, " Localization of the complex spectrum: The s transform". The S transform, which is introduced in the present correspondence, is an extension of the ideas of the continuous wavelet transform (CWT) and is based on a moving and scalable localizing Gaussian window.

III. Model And Problem Definition

3.1 Empirical Wavelet Transform

The objective of EWT is to extract different modes by building adaptive wavelets. This approach is performed in the following steps.

Step 1) Apply the FFT to the signal f(t), where f(t) is a discrete signal, t = {ti}i=1,2,...,M, and M denotes the number of samples, to obtain the frequency spectrum X(w), and find the set of maxima M = {Mi}i=1,2,...,N in the Fourier spectrum and deduce their corresponding frequencies w = {wi}i=1,2,...,N . Here, N denotes the number of maxima, and also, the number of filter banks is introduced hereinafter.

Step 2) Obtain proper segmentation of the Fourier spectrum and the set of boundaries. Now, define the boundaries Ωi of each segment as the center of two consecutive maxima

$$\Omega_i = \frac{w_i + w_{i+1}}{2} \qquad (1)$$

where wi and wi+1 are two frequencies and the set of boundaries isΩ = {Ωi}i=1,2,...,N−1.

Step 3) Define a bank of N wavelet filters composed of one low-pass filter andN − 1 band pass filters based on the boundaries. The expressions for the Fourier transform of scaling function φ1(w) and the empirical wavelets ψi(w) are given by

$$\phi_1 = \begin{cases} 1, & |\omega| \leq (1-\gamma)\Omega_1 \\ \cos\left(\frac{\pi}{2}\alpha(\gamma,\Omega_1)\right) & (1-\gamma)\Omega_1 < |\omega| \leq (1+\gamma)\Omega_1 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where α(γ,Ωi) = β((1/2γΩi)(|ω| − (1 − γ)Ωi)), γ is a parameter that ensures no overlap between the two consecutive transitions, and β(x) is an arbitrary function defined as

$$\psi_i = \begin{cases} 1 & (1+\gamma)\Omega_i < |\omega| < (1-\gamma)\Omega_{i+1} \\ \cos\left(\frac{\pi}{2}\alpha(\gamma,\Omega_{i+1})\right) & (1-\gamma)\Omega_{i+1} \leq |\omega| \leq (1+\gamma)\Omega_{i+1} \\ \sin\left(\frac{\pi}{2}\alpha(\gamma,\Omega_i)\right) & (1-\gamma)\Omega_i \leq |\omega| \leq (1+\gamma)\Omega_i \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$$\beta(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x \geq 1 \\ \beta(x) + \beta(1-x) = 1, & x \in (0,1). \end{cases} \qquad (4)$$

Step 4) Perform scaling and wavelet functions to extract the components of different modes. Therefore, the approximate coefficients can be expressed by the inner product of analyzed signal f with empirical scaling function

$$W_f(1,t) = \langle f, \phi_1 \rangle = \int f(\tau)\overline{\phi_1(\tau - t)}d\tau. \qquad (5)$$

Similarly, the detailed coefficients are obtained by the inner product of analyzed signal f with empirical wavelets

$$W_f(i,t) = \langle f, \psi_i \rangle = \int f(\tau)\overline{\psi_i(\tau - t)}d\tau. \qquad (6)$$

Here,Wf (i, t) denotes the detailed coefficients for the ith filter bank at the tth time point.

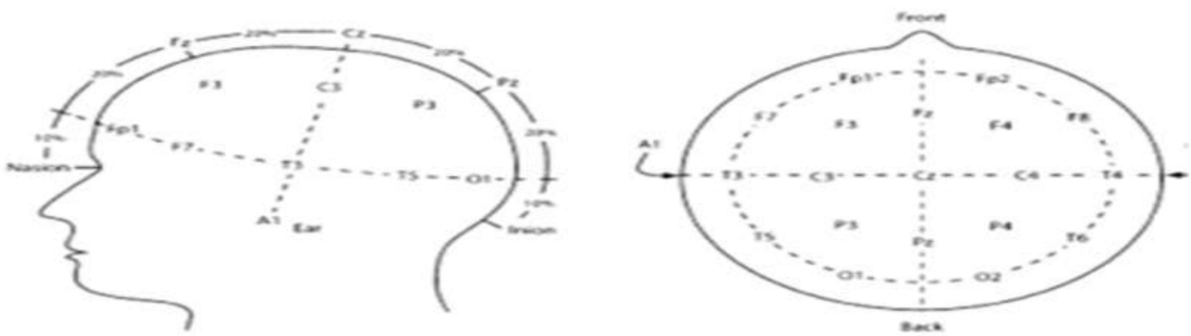
3.2 Wavelet bank of filter tree based analysis

As the computation of wavelet involves filtering, an efficient filtering process is essential in wavelet hardware implementation. Hence, the overall performance depends significantly on the precision of the intermediate wavelet coefficients as discussed in detail in next chapter. An alternative method for fast and efficient implementation of wavelet transform is based on parallel filter implementation.

In this, cascaded high-pass and low-pass filters at different resolution levels will be replaced by their equivalent filter. This necessitates number of filters to be of the order of decomposition level. The main advantage of the parallel filter algorithm is that it does not require storing intermediate coefficients. Another advantage of this architecture is that the word length can be arbitrary and is not restricted to be a multiple of two meters for m-resolution-level wavelet decomposition.

3.3 BIO MEDICAL SIGNAL ANALYSIS OF EEG

The EEG potentials were recorded at 10–20 EEG electrode positions over the scalp, with a cap and integrated electrodes. These electrodes measure the weak (5-100μV) electrical potentials generated by brain activity. Each electrode typically consists of a wire leading to a disk that is attached to the scalp using conductive paste or gel. The data acquisition was performed using Micromed Digital Acquisition System at a 256 sample per second sampling frequency. This system contains an amplifier, and an ADC.

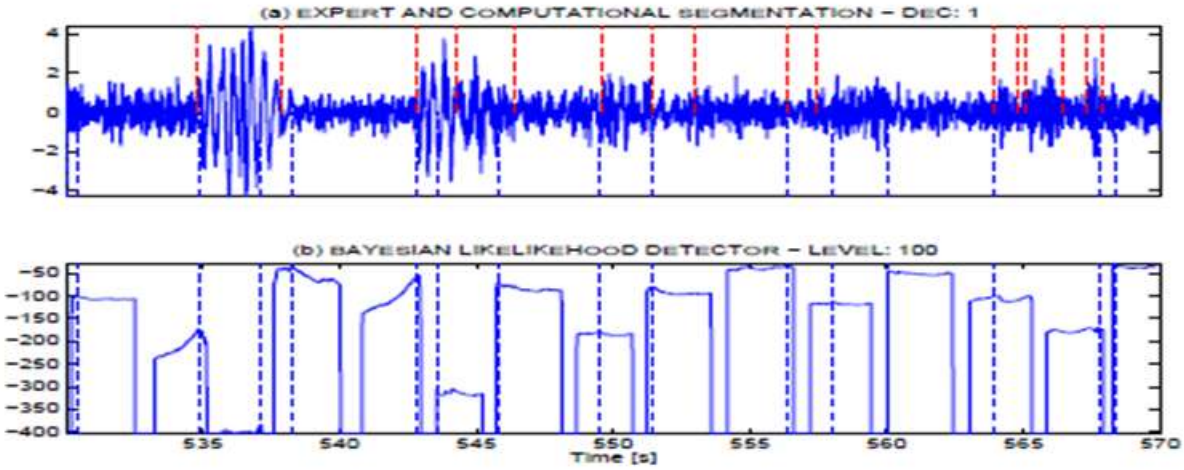


Channel Name	*Differential Electrodes*
Ch1	*Fp2- F4*
Ch2	*F4 - C4*
Ch3	*C4- P4*
Ch4	*P4 -O2*
Ch5	*Fp2- F8*
Ch6	*F8 - T4*
Ch7	*T4- T6*
Ch8	*T6- O2*
Ch9	*Fz- Cz*
Ch10	*Cz- Pz*
Ch11	*Fp1- F3*
Ch12	*F3 - C3*
Ch13	*C3- P3*
Ch14	*P3- O1*
Ch15	*Fp1- F7*
Ch16	*F7- T3*

Signal preprocessing is necessary to maximize the signalto-noise ratio (SNR) since there are many noise sources encountered with the EEG signal. Noise sources can be nonneural (eye movements, muscular activity, 50Hz power-line noise) or neural (EEG features other than those used for control. Notch filters with a null frequency of 50 Hz are used to ensure perfect rejection of the strong power supply. High pass filter with a cut-off frequency of than 0.3 Hz is used to remove the disturbing very low frequency components such as those of breathing. On the other hand, high-frequency noise is mitigated by using low pass filters with a cut-off frequency of 40 Hz. For eye-movement artifacts and muscular artifacts, it was tried to reject a trial containing any of these artifacts. Further preprocessing was not performed because the purpose is to be as close as possible from a BCI for real-time applications and preprocessing would slowdown the process of data analysis. Moreover, data recorded outside the laboratory are likely to be noisier than those recorded inside. So it is assumed that processing noisier data would have better generalization properties.

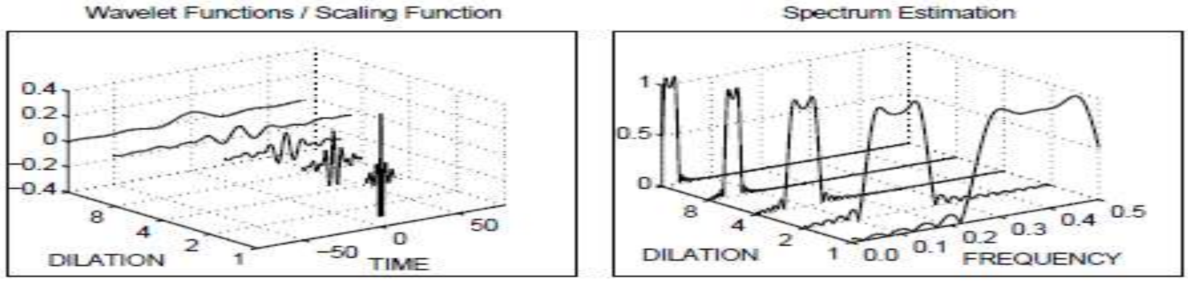
3.4 Analysis And Signal Feature Extraction

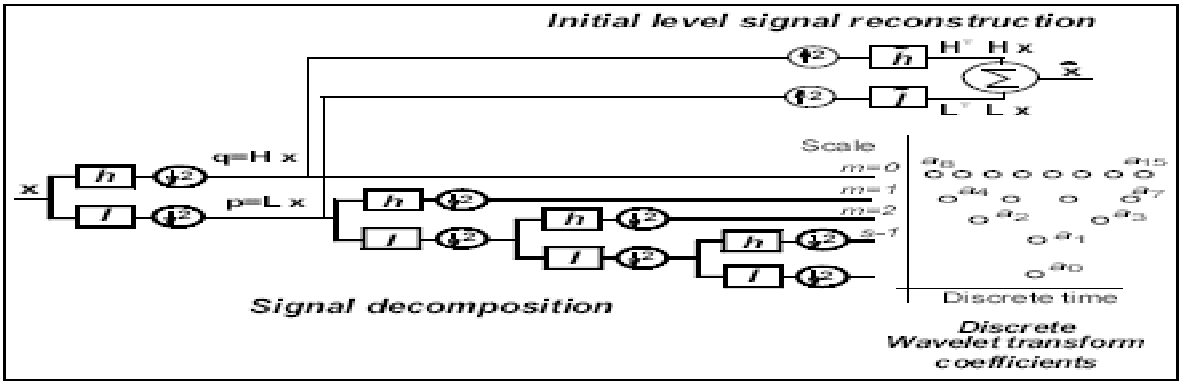
Wavelet transform forms a general mathematical tool for signal processing with many applications in EEG data analysis Its basic use includes time-scale signal analysis, signal decomposition and signal compression.

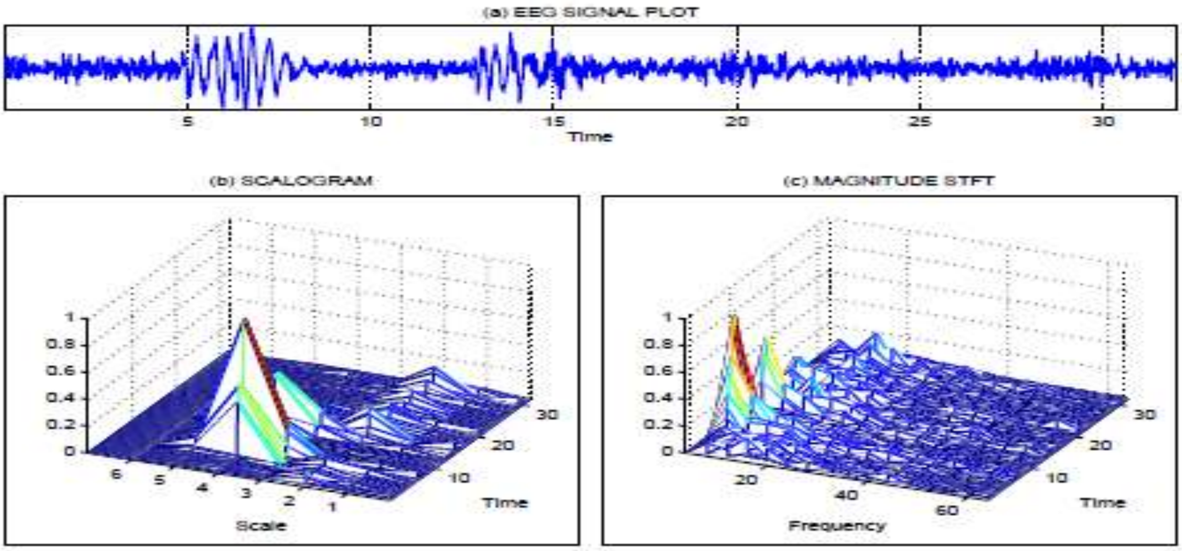


Both continuous or discrete signals can be then approximated in the way similar to Fourier series and discrete Fourier transform. The initial wavelet can be considered as a pass-band filter and in most cases half-band filter covering the normalized frequency band _0.25, 0.5). A wavelet dilation by the factor $a = 2m$ corresponds to a pass-band compression.

The set of wavelets define a special filter bank which can be used for signal component analysis and resulting wavelet transform coefficients can be further applied as signal features for its classification. Signal decomposition performed by a pyramidal algorithm is interpreting wavelets as pass-band filters. Another approach is based upon a very efficient parallel algorithm using the fast Fourier transform.

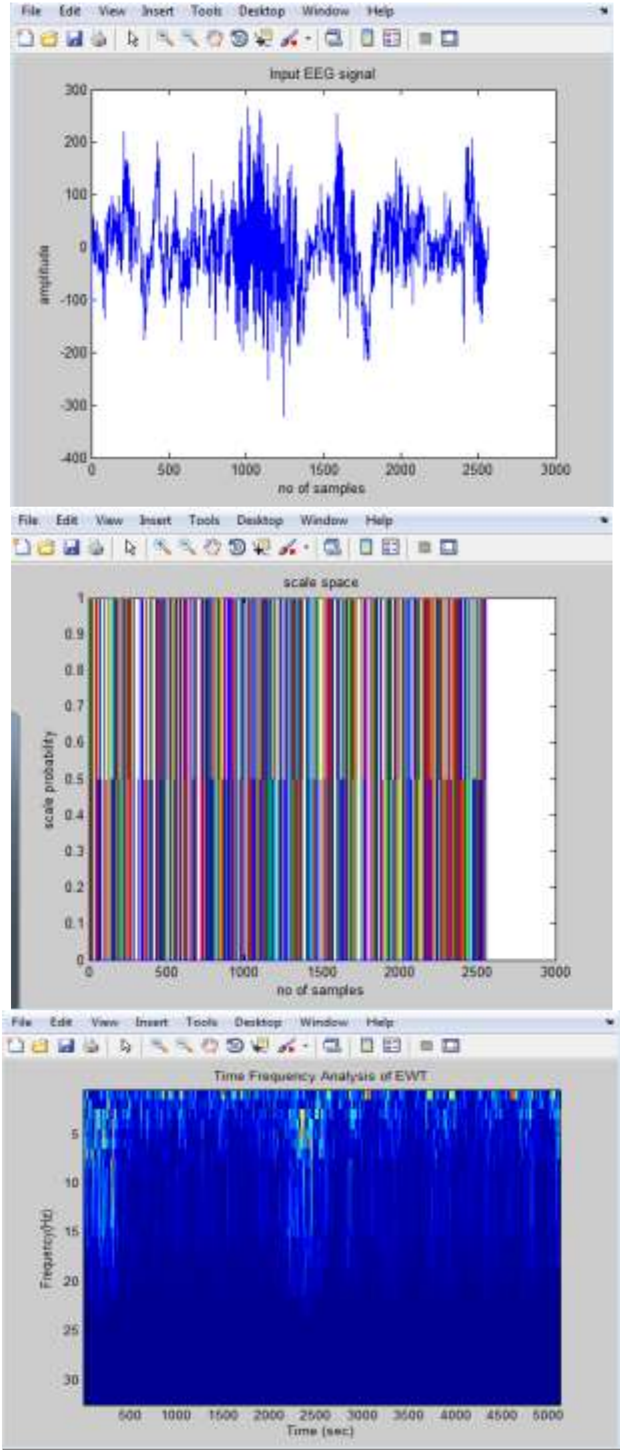






The scalogram and spectrogram of the selected part of the EEG signal comparing results achieved by the DWT and DFT. It is obvious that owing to the principle of the wavelet transform short time signal components can be better detected and more precisely localized by the DWT comparing to results obtained by the DFT.

IV. Simulation Result



Methods	PSNR(dB)	MSE
EWT	31.92	0.0143

Figure (1) Simulation of EEG signal (2) Simulation of Scale Space (3) Simulation of Time Frequency Analysis of EWT (4)value of PSN for EWT

V. Conclusion

In this letter, we have proposed a novel EEG time– frequency analysis approach using the EWT. The EWT approach first estimates the frequency components and then adapts the scaling function and wavelets based on the detected boundaries to decompose the signal. No prior information regarding the signal is required in this decomposition process, and thus, EWT can be a fully adaptive approach for conveniently analyzing the time–frequency information of EEG data. The EWT-based instantaneous frequency spectra can produce much sparser representation and much higher time–frequency resolution than the traditional CWT approach.

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