

# Wavelet Scalogram for Detection of R-peaks in Noisy ECG Signal

Arunkumar H. M., Padmanabha Reddy A.

**Abstract:** The ECG (electrocardiography) which reports heart electrical action is capable to supply with valuable data almost the sort of cardiac disarranges endured by the patient based on the fluctuations obtained from the ECG signal design. In this paper, we considered noisy ECG signals [MIT-BIH database] and their different wavelet scalograms. Wavelet analysis performed in the ECG signals with continuous wavelet transforms and it has allowed to graphically identifying scalograms energy two-dimensional characteristics of the heartbeat QRS complex.

**Keywords:** Noisy ECG Signal, Continuous Wavelet Transform, Wavelet Scalogram.

## I. INTRODUCTION

Cardiology is advance to its show state for the foremost portion due to a few ECG signal handling algorithm connected in combination with the natural concepts by; anything we know of the cardiac function is for the most part due to the natural ECG signal represents a graphical representation of electrical action is called electrocardiography. ECG signal could be a two-dimensional representation of the cardiac possibilities plotted with regard to time. Many authors are worked on the ECG signal one of the authors A., Mukherjee [1] mentioned the ECG signal is seemingly-periodic because it could be a combined work of diverse wave, each wave implying the working of a specific portion of the human heart [1]. Related works are done by M., Rayeezuddin and B. Krishna Reddy [2], throughout each heartbeat, a beat prepare of excitation passes through the heart, contracting to begin with the atria coming about in bloodstream into ventricles, and after that the ventricles pushes forward blood outside. This traveling beat contains a speed of almost 0.5m/s and a characteristic length of approximately 8 to 10 cm. it is organized by electrical coupling between nearby cells of the heart muscle. Coming about ECG signal is created out of the muscles potential energy and its spatial and sifting impacts. In general algorithm is passing the signal passed through a nonlinear transformer like derivative and square, etc., the most disadvantaged of this calculation is that frequency variety in QRS complexes unfavorably influences their execution [2].

G., L., Sheean [3] worked on the conventional ghashly examination of ECG signal comprises of an FFT (Fast Fourier Transform) of the ECG signal. The yield shows the run and plentifulness of the component frequency but does not say anything around the conveyance of these frequencies over time. Realistic show of the FFT appears the vitality dissemination of the ECG signal but moreover, without localization in time [3], FFT contains universally found the middle value of ghashly data. Hence, the transitory ghostly data is misplaced [4]. R., J., Martis and et al [5], worked on noisy free conditions ECG signal. The range shifts with distinctive cardiac arrhythmias and control spectra are watched within the frequency run from 1 to 20 Hz. The spectrum is analyzed and all amplitude is normalized with most extreme sufficiency. The amplitude diminishes as the frequency increments and quickly disappear over 12 Hz, frequency components from 1 to 12 Hz are chosen for numerous ECG signal beat distinguishing proof. These spectra are not aggravated by high-frequency components over 20 Hz such as power-line impedance (50Hz) and commotion, and exceptionally low-frequency components (less than 1 Hz) such as standard float and breathe [6]. H. M. Arunkumar and A. Padmanabha Reddy [7], reduced noise and recognized P, R and T waves but did not discuss scalograms. Analytical wavelets are complex-valued whose Fourier transform disappear for negative frequencies. Analytical wavelets are a better choice when doing a time-frequency examination with the CWT (Continuous wavelet transform). In this paper, the symptomatic strategy comprises of a continuous wavelet transformation, the time-frequency based on futures with wavelet scalograms. Test information is gotten from the MIT-BIH arrhythmia database. The results appear computational proficiency and precise distinguish. The proposed strategy for speedy investigation of the ECG signals outwardly and without any numeric calculation of interims, so that indeed a non-pro can judge the condition of the heart fair by looking at the plot of the cardiac cycles be that as it may, for particular and nitty-gritty conclusion of the heart, the inclusion of a cardiac master may be a must and it is crucial to extricate the covered up data show within the ECG signals and move forward the QRS-wave execution.

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II. DATA [8]

The data available at MIT-BIH, this database incorporates 12 half-hour ECG recordings and 3 half-hour recordings were made utilizing physically dynamic volunteers and standard ECG records, leads, and cathodes were set on the appendages in positions in which the subjects ECG were not unmistakable. The ECG recordings were made by the script “nstdbgen” (noise stress test database) utilizing two clean recordings (118 and 119) from the MIT-BIH arrhythmia database, to which calibrated sums of clamor from record ‘em’ (electrode motion) were included utilizing “nst”(noise stress test). The commotion was included starting after the primary five minutes of each record, amid two-minute sections substituting with two-minutes clean fragments. SNRs (signal to noise ratio) amid the boisterous portions of this record number is the 118e24 contained 24 SNR in dB and another record number is 119e06 it contained clamor 6 SNR in dB. We considered analyzing the ECG signals 10-seconds records.

III. THE CONTINUOUS WAVELETS TRANSFORMATION

A. Wavelets Theory [9]

Wavelet transform is prevalent to the Fourier transform and STFT (short time Fourier transforms) sense of its capacity to degree the time-frequency varieties in a signal at distinctive time-frequency resolutions. Fourier transformation contains all inclusive found the middle value of unearthly data. In this way, the transitory ghastly data is misplaced. The Heisenberg boxes in time-frequency domain illustrate the multi-scale zooming property of the wavelet transform wherein boxes or rectangles of detail coefficients at higher frequency components of the signal span have shorter time duration whereas those at lower frequency components have a wider time span. In our applications, the wavelet scalogram is based on the various CWT. The time arrangements of exploded form are analyzed on the time-scale or time-frequency plane utilizing the various CWT. In the real world problems, the ECG signal values CWT is a *a* by *N* here *a* is the scale and *N* represents the length of the original ECG signal. The least and most extreme scale is decided consequently based on the vitality spread of the wavelet in time and frequency. The scaling functions of continuous time are given below

$$\phi(s) = \phi(2s) + \phi(2s - 1).$$

In for the most part

$$\phi(s) = 2 \sum_{b=0}^N h_0(b) \phi(2s - b) \tag{1}$$

$\phi(s)$  is called a scaling function. The continuous-time work at two-time scale, continuous-time decided, by for the Haar wavelets discrete lowpass filter like  $h_0(0) = h_0(1) = \frac{1}{2}$ , the solution of equation (1) may

not continuously exist. If it does  $\phi(s)$  compact support i.e.,  $\phi(s) = 0$ , outside  $0 \leq s < N$ ,  $\phi(s)$  frequently has no closed frame arrangement.  $\phi(s)$  is to be probably not going to be smoothed, the constraint on  $h_0(n)$  defined

$$\int \phi(s) ds = 2 \sum_{b=0}^N h_0(b) \int \phi(2s - b) ds = 2 \sum_{b=0}^N h_0(b) \frac{1}{2} \int \phi(s) ds,$$

so

$$\sum_{b=0}^N h_0(b) = 1, \text{ assume } \int \phi(s) ds \neq 0$$

and wavelets functions of continuous time are defined below

$$\psi(s) = \phi(2s) - \phi(2s - 1)$$

In for the most part wavelets functions

$$\psi(s) = 2 \sum_{b=0}^N h_1(b) \phi(2s - b), \tag{2}$$

continuous-time determined by for the Haar wavelets discrete highpass filters like

$$h_1(0) = \frac{1}{2}, h_1(1) = -\frac{1}{2}.$$

The orthogonality of integer translates of both scaling and wavelets functions are mathematically defined

$$\int \phi(s) \phi(s - b) ds = \begin{cases} 1, & \text{if } b = 0, \\ 0, & \text{otherwise,} \end{cases} = \delta[b].$$

Similarly

$$\int \psi(s) \psi(s - b) ds = \delta[b],$$

no overlap. The scaling function is orthogonal to wavelet:  $\int \phi(s) \psi(s) ds = 0$ , since positive and negative regions cancel each other. Wavelet is orthogonal over scales,  $\int \psi(s) \psi(2s) ds = 0$ ,  $\int \psi(s) \psi(2s - 1) ds = 0$ , and in general  $\int \psi(s) \psi(2s - b) ds = 0$ , since, better scale forms alter sign whereas coarse scale form remains steady.

B. Wavelets Bases

Our objective is to utilize  $\psi(s)$ , its dilations and translations, as structure blocks for continuous-time functions  $x(s)$ . Particularly, we are fascinated by the class of functions for which we will define the inner product as

$$\langle x(s), g(s) \rangle = \int_{\mathbb{R}} x(s) g(s) ds < \infty, \tag{3}$$

such functions  $x(s)$  must have limited vitality i.e.,



$\|x(s)\|^2 = \int_{\mathbb{R}} |x(s)|^2 ds < \infty$ , and that value belongs to the  $L_2(\mathbb{R})$  and  $g(s)$  is the scaling functions or wavelets functions.

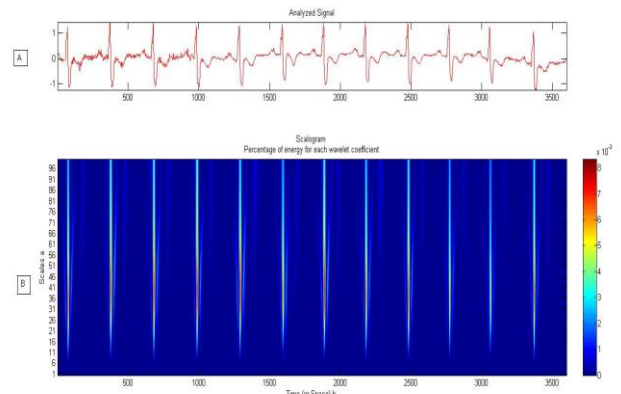
**C. The Continuous Wavelets Transform using Various Wavelets [8]**

The CWT is a generalization of the STFT that permits for the examinations of non-stationary signals at numerous scales. Comparable to the STFT, the continuous makes utilize of an examinations window to extricate signal portions, in this case, the window is called wavelet. Not at all like the STFT, the examinations window or wavelet isn't as it was deciphered but widened and contracted depending on has the scale of action beneath pondered. Wavelet dilation increases its affectability to brief time-scale occasions. The mathematical expression for the CWT is shown below

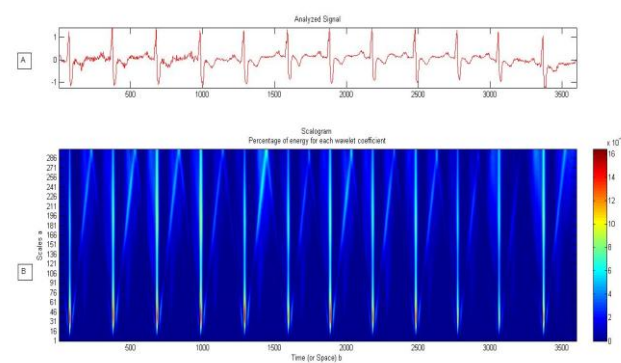
$$C(a, b) = \int \frac{1}{\sqrt{a}} \psi\left(\frac{s-b}{a}\right) x(s) ds, \quad (4)$$

The conditions appear that a wavelet  $\psi(s)$  is translated by  $b$  and dilated by the factor  $a$  ( $a > 0$ ) earlier to computing its inner product with ECG signals  $x(s)$ . The wavelet and inner product between signals characterized integral of their product. The CWT map  $x(s)$  is a function with exactly two variables function  $C(a, b)$  that can be utilized to decide the likeness between the signal and a wavelet scaled by  $a$  at a given time  $b$ . The inner product is localized in time, it is computed over an interim starting at  $s = sa$  an ending  $s = b + D$  here  $D$  is time length of wavelet. The plotting of time, inner product between signal and scaled wavelet is naming scalogram. Step for developing a scalogram are visualized in figures from 1 to 8. Through the wavelet is dilated (less than 1) the wavelet offers tall transient determination and well suited for the deciding onset of brief time occasions such as spike and transients. Through the wavelet is dilated (greater than 1) the wavelet offers toll ghostly determination and is well suited for deciding frequency of support, long term occasions such as pattern motions the scalogram of an ECG signal with directly expanding frequency. The scalogram highlights the signal expanding frequency substance by the nearness of vitality in progressively scales. We look at the scalogram of the spike and moderate wave ECG signal. At the lower scales (1 to 100) the scalogram appears limits shinning columnar groups are QRS- waves(see figures), which are lies in between thicker columnar groups, this contract band speaks to the spikes within the signal. At the higher scales (1 to 300) the scalogram appears thin, shinning columnar groups are QRS-waves (see figures) which speak to the waves components of the ECG signals. The different CWT is able to the same time capture the multi-scale action inside the ECG signal. The CWT is excess since it changes the wavelet scaling parameter  $a$  ceaselessly. Ordinarily, not much more

data is picked up by analyzing an ECG signal at a little scale i.e.,  $a = (1:100)$  and in usual procedure a discrete set a scales chosen. The foremost commonly chosen set of scales is known as the dyadic scale, it incorporates all scales such that  $a = 2^b$  for  $b = 1, 2, \dots N$ . There is no misfortunate of data in this handle of sub-sampling the parameter  $a$ , the ECG signal can be flawlessly reproduction from the information of the CWT over the dyadic scales. The below graphs 1 to 8 are scalograms of ECG signals are analyzed by various CWT. Constructing a scalogram outlines the ECG signal movement inside a extends of time-scale advances over time. The scalogram is built by assessing the inner product between signal and wavelets with diverse scales, and after that plotting, the inner product with each wavelet shifts the time, the scalogram of ECG signal with the unexpected alter in frequency.



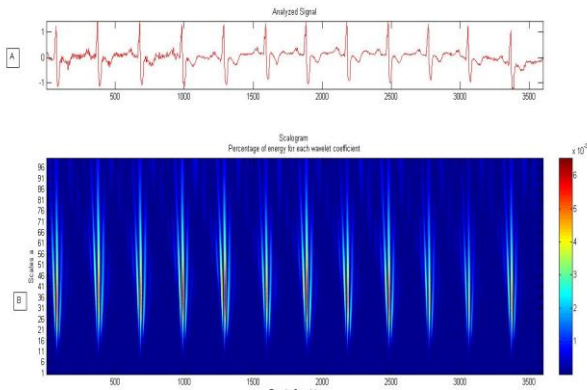
**Figure1. ECG signal analyzed using CWT with db1 to the MIT-BIH the record no 118e24 and scale lies between 1, 2 . . . 100. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db1.**



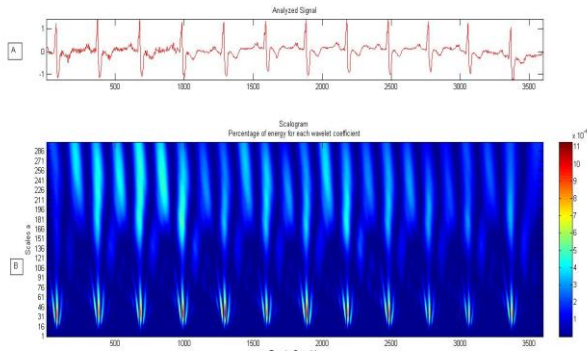
**Figure2. ECG signal analyzed using CWT with db1 to the MIT-BIH the record no 118e24 and scale lies between 1, 2 . . . 300. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db1.**



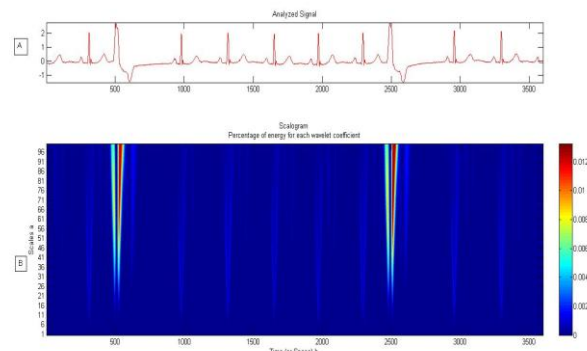
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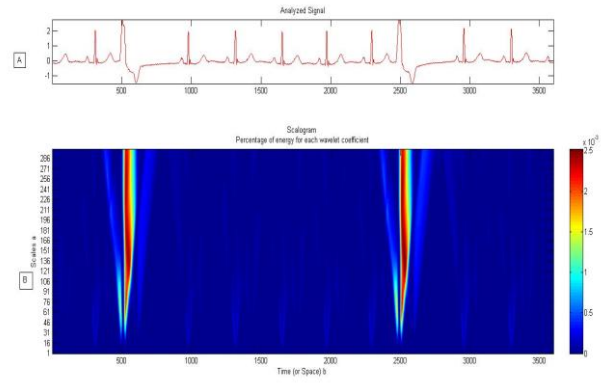
**Figure3.** ECG signal analyzed using CWT with db5 to the MIT-BIH the record no 118e24 and scale lies between 1, 2 . . . 100. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db5.



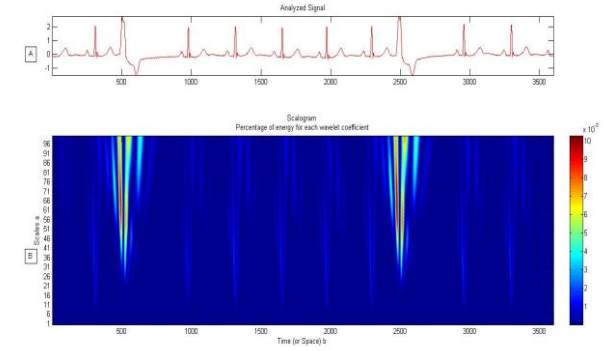
**Figure4.** ECG signal analyzed using CWT with db5 to the MIT-BIH the record no 118e24 and scale lies between 1, 2 . . . 300. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db5.



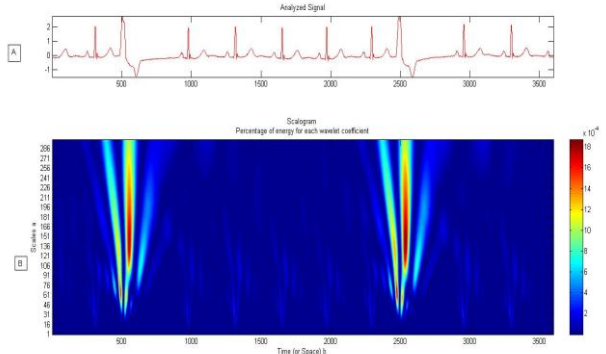
**Figure5.** ECG signal analyzed using CWT with db1 to the MIT-BIH the record no 119e06 and scale lies between 1, 2 . . . 100. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db1.



**Figure6.** ECG signal analyzed using CWT with db1 to the MIT-BIH the record no 119e06 and scale lies between 1, 2 . . . 300. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db1.



**Figure7** ECG signal analyzed using CWT with db5 to the MIT-BIH the record no 119e06 and scale lies between 1, 2 . . . 100. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db5.



**Figure8.** ECG signal analyzed using CWT with db5 to the MIT-BIH the record no 119e06 and scale lies between 1, 2 . . . 300. A). Original analyzed ECG Signal, B). Scalogram percentage of energy for each wavelet coefficients analyzed by CWT with db5.

#### IV. RESULT AND DISCUSSION

The ECG signal contains noise components like white Gaussian noise (WGN). But in most of the articles which are surveyed within the study, straight calculations have provided good execution. In any case, there is not much work performed to ponder the scalogram execution within the nearness of common clamor forms. As a practical example of comparing deferent wavelets, it is observant the above figures 1 to 8. The smaller scale comparison with large scale and various contiguous wavelets transform comprising with Daubechies (db5). The smaller scales are coarser visible for various continuous wavelet transform, i.e., Haar wavelet (db1), Daubechies family i.e., db2 and db5. The scale increasing as the more and more the result becomes finer and finer for visible QRS-waves scalograms and the observant Daubechies (db5) wavelets give accuracy QRS-waves visible, comparing with the Daubechies (db2) and Haar wavelet (db1).

#### V. CONCLUSION

This paper has used noisy ECG signal from MIT-BIH database to show continuous wavelet analysis algorithms that can be used at MATLAB command. When signals are dynamic over time, it is advantageous to use wavelet analysis instead of Fourier analysis. Wavelet analysis is able to maintain temporal characteristics whereas Fourier analysis removes the temporal characteristics. The algorithm can be an inner product both in amplitude and phase and non-linear interactions. Analysis results presented in figures 1 to 8 show the ECG signals of scalograms, both in amplitude and phase, and document the necessity to determine the time translates or delay between the investigated signals in order to show the more consistent inner product of visible events.

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