# Analysis of QRS Complex in ECG Signals Using New Continuous Wavelet Transform

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***Abstract*** — *The ECG (electrocardiogram), which records heart's electrical activity, is able to give information about the type of Cardiac disorders suffered by the patient depending upon the deviations from normal ECG signal pattern. We have plotted the coefficients of continuous wavelet transform using a new wavelet (raees wavelets). We used different ECG signal available at MIT-BIH database and performed a comparative study. We demonstrated that the coefficient at a particular scale represents the presence of QRS signal very efficiently irrespective of the type or intensity of noise, presence of unusually high amplitude of peaks other than QRS.*

**Keywords —** *ECG signal, Wavelet Analysis, Wavelet Scalogram.*

## I. Introduction

In recent paper we introduce a new continuous wavelet (raees wavelets) and in this paper we are using them in the wavelet transform to detect the presence of QRS signal very efficiently irrespective of the type or intensity of noise, presence of unusually high amplitude of peaks other than QRS.

The ECG (electrocardiogram), which is nothing but recording heart's electrical activity, provides very vital information about the wide range of Cardiac disorders depending upon the deviations from normal ECG signal pattern. In general, the frequency range of an ECG signal varies between 0.05–100 Hz with the dynamic range between 1–10 mV. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T. In some cases we also use another peak called U. The QRS complex is the most prominent waveform within the electrocardiographic (ECG) signal, with normal duration from 0.06 s to 0.1 s. The performance of ECG analysing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T- and P waves. However since the QRS complexes have a time-varying morphology, they are not always the strongest signal component in an ECG signal. In addition there are many sources of noise in a clinical environment, for example,
power line interference, muscle contraction noise,
poor electrode contact, patient movement, and
baseline wandering
due to respiration that can degrade the ECG signal. Previously applied algorithms commonly use nonlinear filtering to detect QRS complexes using thresholding, artificial intelligence using hidden Markov models, and time recursive prediction techniques. A General algorithm is passing the signal passed through a nonlinear transformer like derivative and square, etc., to enhance the QRS complexes after filtering the ECG signal using a band pass filter to suppress the *P* and *T* waves and noise and finally determining the presence of QRS complexes using decision. The main drawbacks of these techniques are that frequency variation in QRS complexes adversely affects their performance. The frequency band of QRS complexes generally overlaps the frequency band of noise, resulting in both false positives and false negatives. Methods using artificial intelligence are time consuming due to the use of grammar and inference rules as mentioned earlier. The hidden Markov model approach too requires considerable time even with the use of efficient algorithms. Wavelet analysis is a very promising mathematical tool 'a mathematical microscope' that gives good estimation of time and frequency localization. Wavelet analysis has become a renowned tool for characterizing ECG signal and some very efficient algorithms has been reported using wavelet transform as QRS detectors. In this paper we have reported methodologies that are very simple in order to develop algorithms to detect the QRS complex using continuous wavelet transform. We used the raees wavelet (rsw2) and plotted coefficients to detect the QRS.

## II. New Continuous Wavelet Transform

A new family of continuous Wavelet known as raees wavelets defined by

$$\psi_k(t) = C_k \frac{d^k}{dx^k}(\psi(t))$$

Where

$$\psi(t) = e^{-t^2} \cdot \frac{1}{1+t^2} \text{ and } C_k = \left( \int_{-\infty}^{\infty} \left| \frac{d^k}{dt^k}\left[\psi(t)\right] \right|^2 dt \right)^{-\frac{1}{2}}$$

Such that $\int_{-\infty}^{\infty} |\psi_k(t)|^2 dt = 1, \forall \quad k = 1, 2, 3........., 7$ .

i.e. $\psi_k(t)$ is a Mother Wavelet for each *k* are used.

This family is named as raees wavelet family, shortly rsw associated with numbers 1, 2……7, according to their order.

The wavelet transform of a continuous time signal, $x(t)$ using the above mother wavelet is defined as

$$W_{x(t)}(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty}x(t)\psi_k^*\left(\frac{t-a}{b}\right)dt$$

Where $\psi_k^*(t)$ is the complex conjugate of $\psi_k(t)$ and $a$ is the dilation parameter of the wavelet and $b$ is the location parameter of the wavelet.

The contribution to the signal energy at the specific $a$ scale and $b$ location is given by the two dimensional wavelet energy density function known as the 'Scalogram':

$$S(a,b)=\left|W_{x(t)}(a,b)\right|^2$$

The total energy in the signal may be found from its wavelet transform as follows:

$$S=\frac{1}{C_{\psi_k}}\int_{-\infty}^{\infty}\int_{0}^{\infty}\frac{1}{a^2}\left|W_{x(t)}(a,b)\right|^2 dadb$$

Where $C_{\psi}=\int_0^{\infty}\frac{\left|\hat{\psi}(\omega)\right|^2}{\omega}d\omega<\infty$ and $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$ and is given by

$$\hat{\psi}(\omega)=\mathcal{F}\left(e^{-t^2}.\frac{1}{1+t^2}\right)=\pi\sqrt{\pi}\int_{-\infty}^{\infty}e^{-\tau^2/4}.e^{-|\omega-\tau|}d\tau$$
$$=\pi^2\left[e^{1-\omega}\left(erf\left(\omega/2-1\right)+1\right)-e^{1+\omega}\left(erf\left(\omega/2+1\right)-1\right)\right]$$

Where $erf(\alpha)=\frac{2}{\sqrt{\pi}}\int_0^{\alpha}e^{-\xi^2}d\xi$

$$\therefore\hat{\psi}_k(\omega)=\mathcal{F}\left(\psi_k(t)\right)$$
$$=(i\omega)^k\pi^2\left[e^{1-\omega}\left(erf\left(\omega/2-1\right)+1\right)-e^{1+\omega}\left(erf\left(\omega/2+1\right)-1\right)\right]$$

In practice a fine discretization of the continuous wavelet transform is computed where usually the $b$ location is discretized at the sampling interval and the $a$ scale is discretized logarithmically. The $a$ scale discretization is often taken as integer powers of 2; however, we use a finer resolution in our method where scale discretization is in fractional powers of two. This discretization of the continuous wavelet transform (CWT) is made distinct from the discrete wavelet transform (DWT) in the literature. In its basic form, the DWT employs a dyadic grid and orthonormal wavelet basis functions and exhibits zero redundancy. Our method, i.e. using a high resolution in wavelet space as described above, allows individual maxima to be followed accurately across scales, something that is often very difficult with discrete orthogonal or dyadic stationary wavelet transforms incorporating integer power of two scale discretization.

## III. IMPLEMENTATION

The data has been taken from MIT-BIH arrhythmia database. We analyzed different signal of length 10 seconds for our algorithm and analysis have some different types of deviations from normal specifically. Namely, Record 105, which is more noisy than the others; Record 108 has unusually high and sharp *P* waves; Record 203 has a great number of QRS complexes with multiform ventricular arrhythmia; and Record 222 has some non-QRS waves with highly unusual morphologies and 109 having an base line drift in the signal which is one of the major problem causing failure of threshold type algorithms. As shown in figures 1.1, 2.1 … 6.1. We have analysed different signal with different types of noises, errors and fluctuations and we see that in the coefficient plot we get a band of high energy corresponding to exact number of the QRS peaks available in the signal. Very efficient and lucid algorithms can be developed to read this plot at a particular scale. We have done a localized analysis of a signal for a particular duration and one can count manually to check the results. For a very long duration signal, a variable scale can be defined to make the perfect count of QRS signal. Another inference that can be drawn from the Coefficients plot is about the exact positions where the energy scale representation is zoomed by the continuous wavelet transform. Here the transformation is done using rsw2 (raees wavelet of order 2).

## IV. TABLE AND FIGURE

**Table-1**

| Order of the Wavelet $(k)$ | $C_{\psi_k}$ | $C_k$ |
|---|---|---|
| 1 | −119.0753391489156 | 1.601616579725480 |
| 2 | 431.3058522364652 | 9.112718044441433 |
| 3 | −3441.012559088567 | 95.974203313082995 |
| 4 | 46109.58291987393 | 1596.419728602841 |
| 5 | −935295.5508285811 | 38948.93123589542 |
| 6 | 27136072.04053418 | 1330506.195338057 |
| 7 | −1081545882.025461 | 61348820.76589487 |

**Figures:**

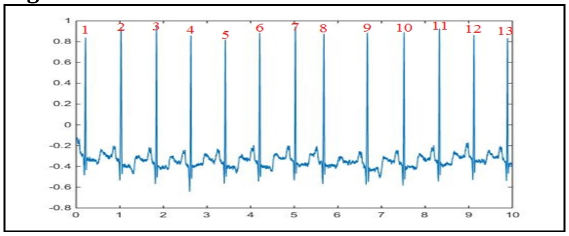

**Figure 1.1: ECG-signal of record 100 from MIT-BIH database**

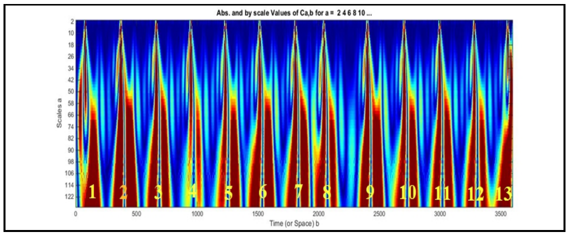

**Figure 1.2: Coefficient Plot of ECG-signal of record 100 after Applying Wavelet Transform**

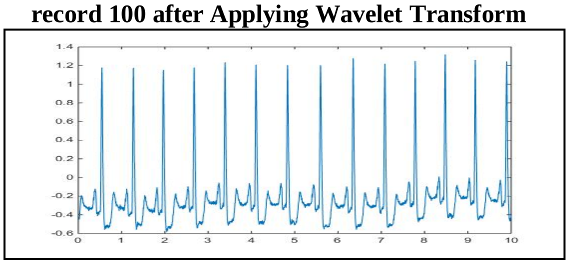

**Figure 2.1: ECG-signal of record 105 from MIT-BIH database**

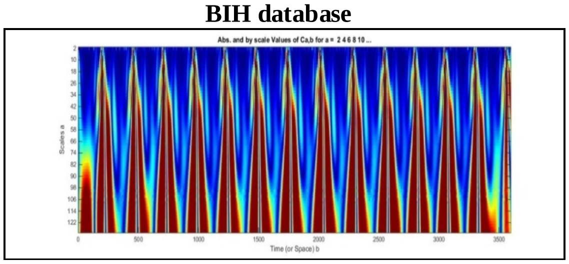

**Figure 2.2: Coefficient Plot of ECG-signal of record 105 after Applying Wavelet Transform**

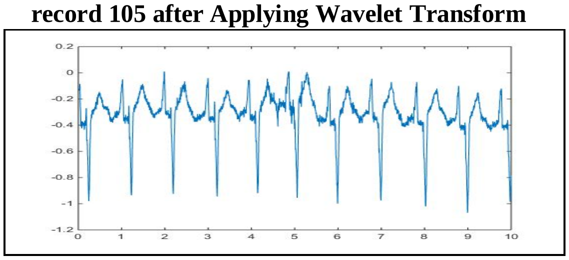

**Figure 3.1: ECG-signal of record 108 from MIT-BIH database**

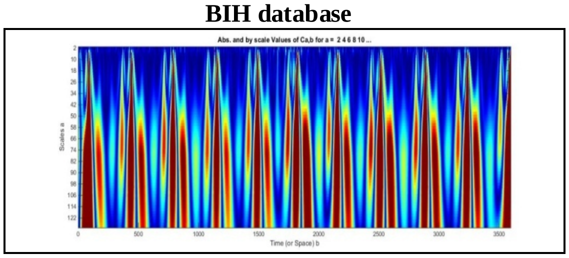

**Figure 3.2: Coefficient Plot of ECG-signal of record 108 after Applying Wavelet Transform**

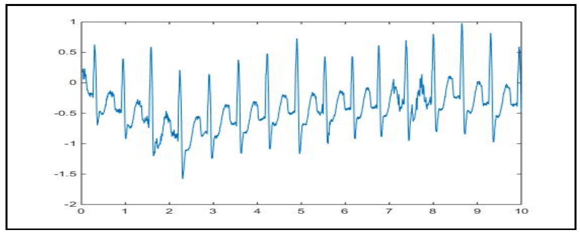

**Figure 4.1: ECG-signal of record 109 from MIT-BIH database**

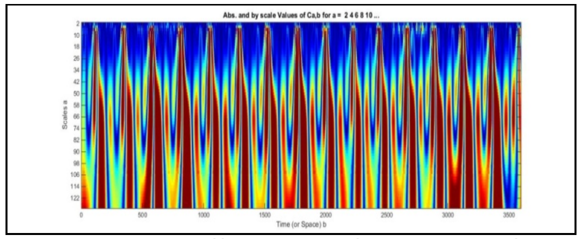

**Figure 4.2: Coefficient Plot of ECG-signal of record 109 after Applying Wavelet Transform**

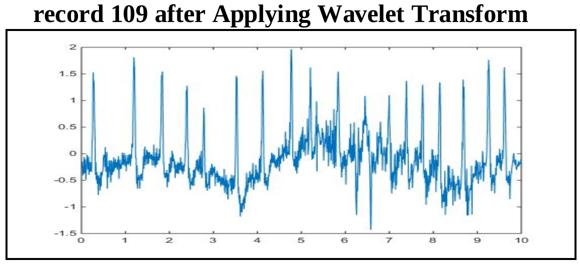

**Figure 5.1: ECG-signal of record 203 from MIT-BIH database**

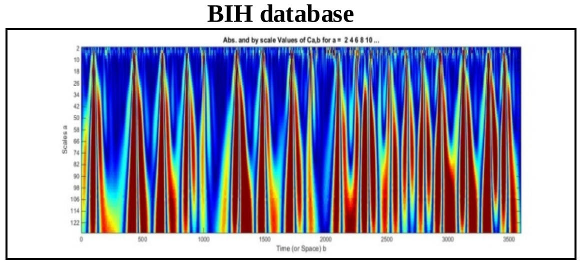

**Figure 5.2: Coefficient Plot of ECG-signal of record 203 after Applying Wavelet Transform**

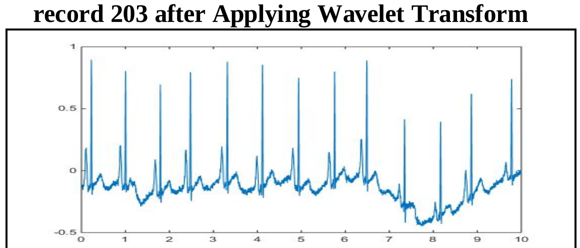

**Figure 6.1: ECG-signal of record 222 from MIT-BIH database**

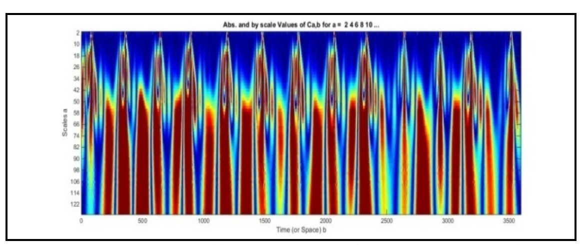

**Figure 6.2: Coefficient Plot of ECG-signal of record 222 after Applying Wavelet Transform**

## V. Conclusion

In this paper we have reported a time-frequency multiresolution analysis of an ECG signal. We have plotted the coefficients of continuous wavelet transform using raees wavelet. We used different ECG signal available at MIT-BIH database and performed a comparative study. We demonstrated that the coefficient at a particular scale

represents the presence of QRS signal very efficiently irrespective of the type or intensity of noise, presence of

unusually high amplitude of peaks other than QRS peaks and Base line drift errors. In postscript we suggest that with few modifications of the current work can reveal the features and characteristics of other ECG waveform viz. P and T waveform which can also provide with some important information about physiological conditions of patient suffering from heart disease.

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## References

[1] I. Daubechies: *The wavelets transform, time frequency localization and signal analysis,* IEEE Transactions on Information Theory, vol. 36, no. 6, Sept. 1990, pp. 9611005.

[2] Daniel T. L. Lee, Akio Yamamoto, 1994. *"wavelet analysis: Theory and applications"*, Hewlett –Packard Journal.

[3] Swapnil Barmase, Saurav Das, Sabyasachi Mukhopadhyay. "Wavelet Transform-Based Analysis of QRS complex in ECG Signals", Indian Institute of Science Education and Research, Kolkata, Mohanpur campus, Nadia 741252.

[4] Aguiiar-Conrariia,, Luíís e Mariia Joana Soares: *"The Continuous Wavelet Transform:: A Priimer"*, NIPE WP 16/2011

[5] Paul S Addison : *The Illustrated Wavelet Transform Handbook, Introductory Theory and Applications in Science, Engineering, Medicine and Finance* Napier University, Edinburgh, UK.

[6] Misiti Yves Misiti Georges Oppenheim Jean-Michel Poggi *Wavelet Toolbox for use with Matlab Michel Computation, Visualization and Programming User's Guide Version 1.*

[7] Mathworks, Inc. Wavelet Toolbox Help, Wavelet Scalogram Using 1D Wavelet Analysis.

[8] Mohammed Rayeezuddin, B Krishna Reddy "*A New Continuous Wavelet Family and its Application to Analysis of Elementary Periodic Signals*" International Journal of Science and Research (IJSR), Volume 4 Issue 10, October 2015

[9]Robi Polikar, the Wavelet Tutorial, http://users.rowan.edu/~polikar/WAVELETS/WTpart1.html