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Analysis of the ECG Signal Recognizing the QRS Complex and P and T Waves, Using Wavelet Transform

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ABSTRACT: *In this paper we study the role of the Wavelet Transform in the analysis method of time frequency of the electrocardiogram (ECG), in order to improve the cardiac disease diagnosis.To get this,we have designed an algorithm to detect the significant features of the ECG signal, in sinus rhythm normal, including the P wave, the QRS complex, and the T wave.*

Keywords -*Electrocardiogram (ECG) signal, Multiresolution analysis, QRS complex, Threshold method, Wavelet Denoising,Wavelets Transform.*

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I. INTRODUCTION AND OBJECTIVES

Over the past few years, the electrocardiogram (ECG) signal plays an important role in the primary diagnosis, prognosis and survival analysis of heart diseases. The electrocardiography has had a profound influence on the practice of Medicine.

The electrocardiogram (ECG) is a diagnostic tool that measures and recordsthe electrical activity of the heart with exceptional attention to detail. Interpretation of these details allows diagnosis of a wide range of heart anomalies. Automatic extraction ECG features is important for cardiac disease diagnosis.Significant features of the ECG signal include the P wave, the QRS complex, and the T wave.

The Wavelet Transform has emerged in recent years as a powerful analysis method of time frequency and preferred encoding tool for the study and analysis of complex non-stationary signals.

First of all, we have seen several works that have allowed us to see in detail the emerging role of the Wavelet Transform in the analysis of the ECG as [4, 10, 13, 16, 19, 21, 22] among others. Next, we have worked separately with Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform, in order to study the Analysis of the ECG.

Hereafter, we will use several acronyms which meaning is in the last section 6, in order to facilitate the reading of this paper.

Several objectives of applying the Wavelet Transform to the ECG signals are proposed in this work:

1. The Wavelet Analysis of ECG signals with normal sinus rhythm using the CWT and Morlet Wavelet [5, 14, 17, 20].
2. The identification of the various ventricular and supraventricular arrhythmias by observing the Wavelet energy scalograms after applying the CWT and the Multiresolution decomposition analysis (MRA)[6, 7, 8].
   In order to get this, we have been using the CWT with two Wavelet families:

a) Morlet Wavelet.
b) Gaussian Wavelet of order N=2 (Mexican Hat Wavelet).
   In Multiresolution analysis, the Daubechies Wavelet (Db8) has been applied with 8 levels of decomposition.

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3. To determine the best estimators for removing noise ECG signals using Wavelet thresholding methods [9, 15, 19].

The decomposition algorithm (MRA) has been applied using different Wavelet families:

a) Daubechies Wavelet (Db8 and Db4),
b) Symlet (Sym6), Coiflet (Coif5), and
c) Meyer and Haar Wavelet.

Experimental results showed that, Daubechies (Db8) family, for scaled white noise structure and the SURE method (soft); provided the best results as compared with to other wavelet families.

Finally, we use the above parts to arrive at the main objective, this is:

4. TodesignanalgorithmtodetectECGsignalsinsinusrhythmnormal,using MRA based techniques. This is, thisalgorithm have to detect the QRS complex and the P and T waves [8, 10, 12, 13, 14].

Moreover, we can say that we had covered with success this objective, since the accuracy achieved with this algorithm, in the detection of QRS complex with Daubechies Db8 and SURE thresholding method (Soft) in the ECG noise removal; has been 98 percent.

This value is a much higher value than the value obtained with other Detection methods based on Wavelet Transform (DWT), with values of 95.74 and 92.55 percent, even more if we take into account that the detection algorithm proposed in this paper (see (4) in Figure 1) is a very low computational cost.

In order to evaluate the proposed algorithm, we use several bases data [1, 2, 3] and in this evaluation has been very useful the identification of arrhythmia patterns, with the esteemed collaboration of the eminent cardiologist Dr. Enrique Fernández Burgos, who has been kind enough to study the ECG signals analyzed in this work and classify them in the different types of established arrhythmias. By this reason we want to thanks Dr. Enrique Fernández Burgos.

II. METHODOLOGY

In order to extract information from the ECG signal, the raw ECG signal should be processed. ECG signal processing can be roughly divided into two stages by functionality: **Preprocessing** (getting the ECG signals, baseline drift removal and denoising, noise removal) and Feature Extraction (continuous Wavelet Transform (CWT) and Wavelet analysis, Multiresolution decomposition (MRA), thresholding and reconstruction, QRS complex detection and Rwave and detection of P and T waves) as shown in Fig. 1.

Preprocessing stage removes or suppresses noise from the raw ECG signal. Feature extraction is performed to form distinctive personalized signatures forevery patient.

The detection of the QRS complex is based on modulus maxima of theWavelet Transform, using the MRA decomposition and Daubechies Wavelet Db8.

QRS complexes identified the P and T waves in each R → R interval was delimited looking in a windo on the local maxima of the d4 signal.

The ECG signals were previously processed and filtered through a band-pass filter and the noise removed with Wavelet thresholding method, using the ”scaled white noise” structure and the SURE method (Soft).

Finally, we note that we have used the Morlet wavelet with cwtft MATLAB algorithm, to apply CWT [18].

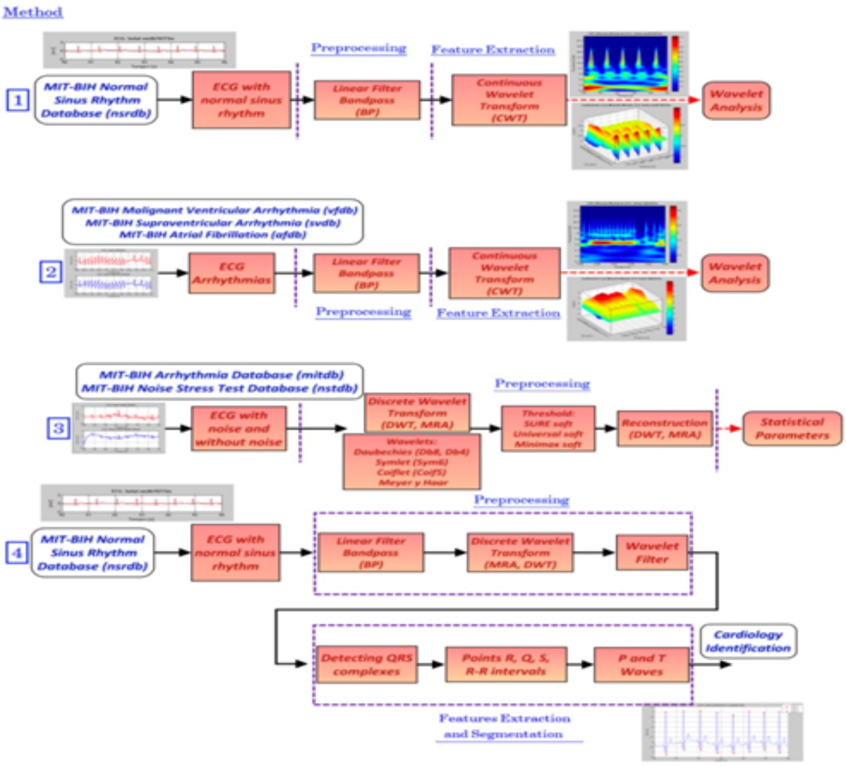

Figure 1: Methods of applying the Wavelet Transform to the ECG signals (1, 2, and 3). (4) Algorithm of the identification processes of the QRS complex, and P and T waves.

III. MAIN RESULTS

Research outcomes are categorized according to the four objectives described in the section 1 for this work, in which different methods have been used when applying the Wavelet Transform.

1.1. ECG signals with normal sinus rhythm

The analysis was performed on a total of 1519 beats from 18 different patients with normal sinus rhythm, processed through Continuous Wavelet Transform (CWT) and using the Morlet wavelet with cwtft MATLAB algorithm, as we have commented in the above section.

1. The CWT of the ECG signal with normal sinus rhythm presented QRS complex as a conical structure, where the coefficients of higher energy corresponded to the higher frequencies of the spectrum, converging on thehigh frequency component of the RS section. See Fig. 2 and Fig. 3.
2. P and T waves appear at intervals of frequencies around 3 Hz, 2 Hz to 5Hz, showing lower energy Wavelets coefficients in the QRS complex.
3. In 2D energy scalogram, a continuous band appears in the range of frequencies ranging from 1 Hz to the 1.75 Hz, which corresponds to thefrequency of a heartbeat from 60 bpm to the 105 bpm.
4. The QRS complexes are conical structures in the lowest scales, highest frequencies, in 3D wavelet energy scalograms, being its highest frequencycomponent in the RS section.

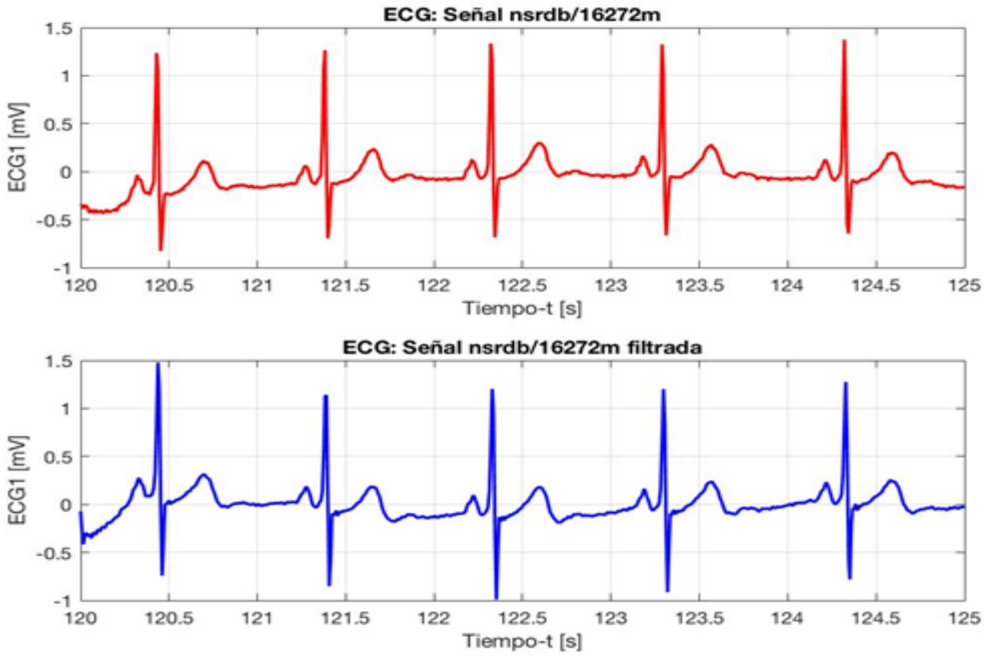

Figure 2: CWT of ECG signal with normal sinus rhythm.

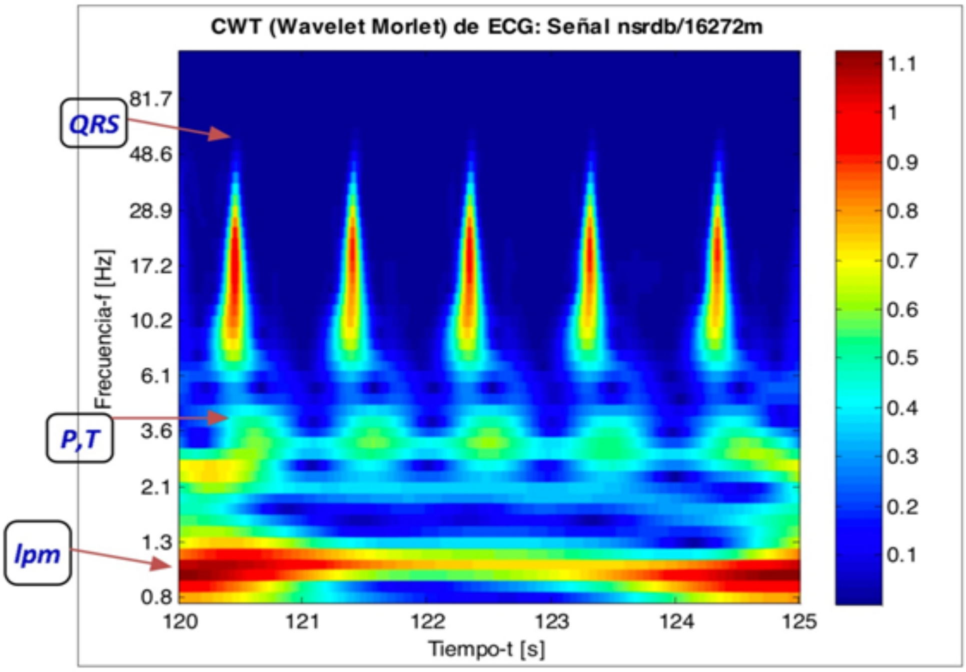

Figure 3: Energy scalogram of ECG signal with normal sinus rhythm.

ECG signals with supraventricular ventricular and arrhythmias

We analyzed 88 episodes of Ventricular Tachycardia (VT), 13 Ventricular Fibrillation (VF), 28 Ventricular Flutter (VFL), 111 Supraventricular Tachycardia (SVTA) and 31 episodes of ventricular fibrillation. As example, it showsVF.

Ventricular Fibrillation (VF):

1. P waves initiating QRS complex are not identifiable. On the 2D energy scalogram (Figures 4 and 5) it does not present the conical structure of the QRS complex, but the presence of heartbeat frequencies from 3 Hz to 4 Hz.

2. There is the temporary presence of several undulations within the 10 Hz band on 3D scalogram. VF episodes are identifiable by the high frequency scales 2^4,2^5 and 2^6 showing no frequency variation on the scale pattern 2^4 in the MRA analysis. See Fig. 6.

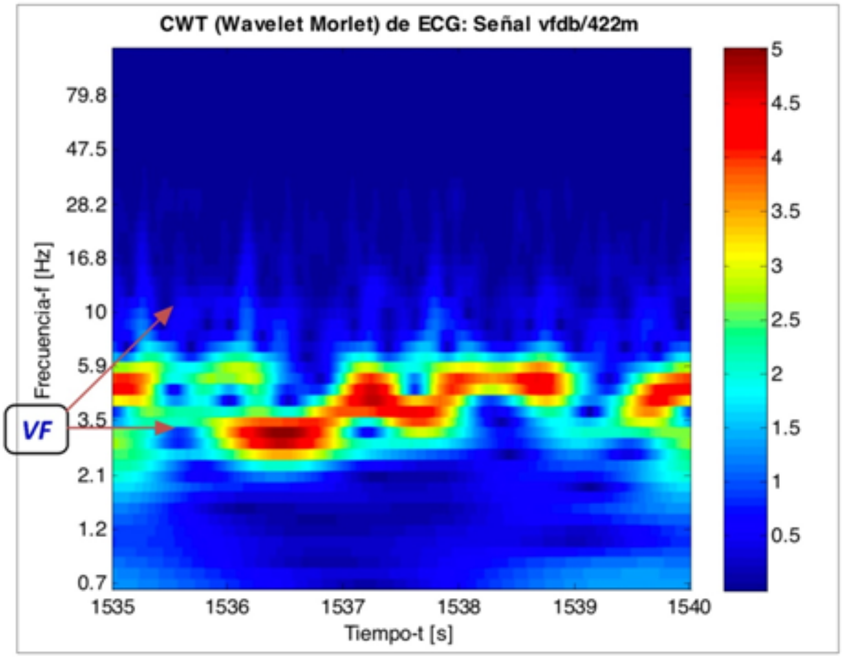

Figure 4: ECG vfdb/422m Wavelet energy scalogram with episodes of Ventricular Fibrillation (CWT).

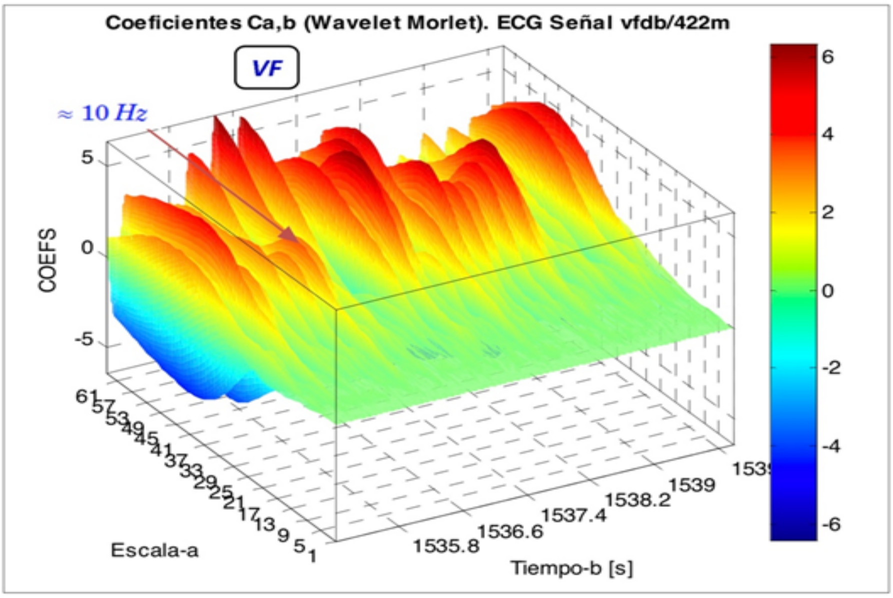

Figure 5: ECG vfdb/422m Wavelet energy scalogram with episodes of Ventricular Fibrillation (Coef).

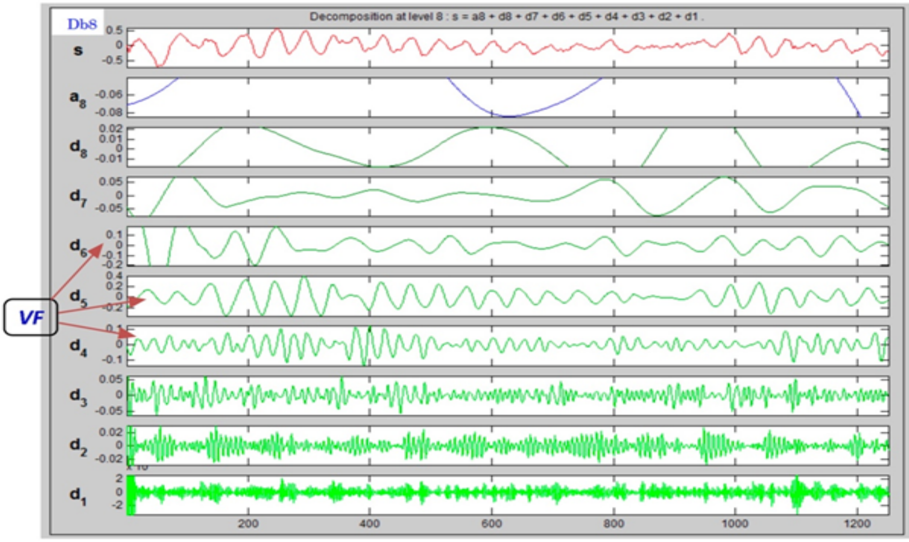

Figure 6: MRA decomposition of ECG signal vfdb/426m with an episode of VF.

1.2. Noise removal in ECG signals using the wavelet thresholding methods.

When comparing the statistical parameters, such as standard deviation and residues norms, and by removing noise by the MRA analysis with different Wavelet families, we note that:

The best results that we have obtained by reconstructing the decomposed signal, using the SURE (Soft) thresholding method, have been obtained with Wavelet Daubechies of order N=8.

This is, the techniques that have been used to remove noise in ECG signals with wavelet (Wavelet thresholding), decomposing signals without noise added to the decomposition algorithm (MRA) using different Wavelet families and applying SURE (soft), universal (soft) and minimax (soft) threshold methods with the structure of scaled white noise; allow us to conclude that, the best results were obtained by Daubechies Wavelet of order N = 8 with the SUREthreshold (Soft) method.

1.3. Detection Algorithm of QRS complexes and P and T waves.

With the proposed detection algorithm of QRS complex (see (4) in Fig. 1), we have evaluated 13 ECG signals from the database MIT-BIH Normal Sinus Rhythm Database (nsrdb) [1, 2, 3].We have evaluated these signals with a duration of 3600 seconds each ECG recording, in order to evaluate its effectiveness. See Fig. 7 and Fig. 8.

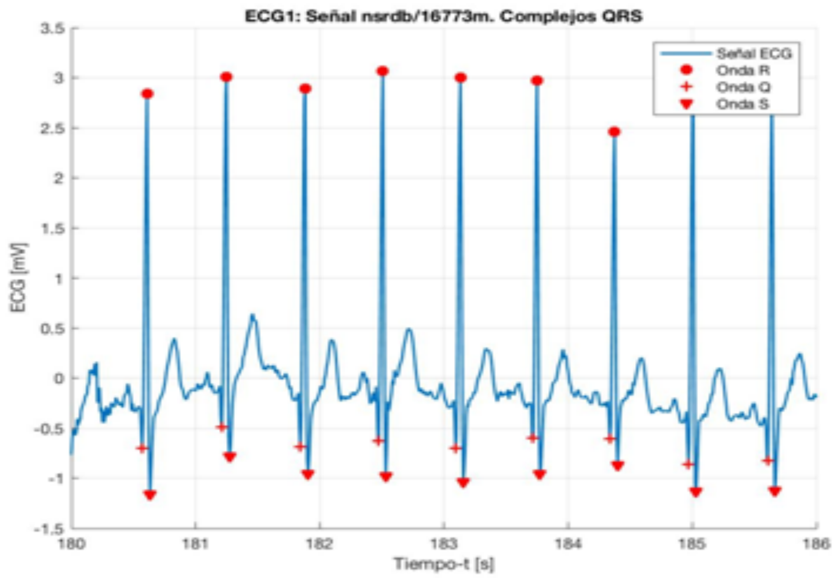

Figure 7: Detection of QRS complex in an ECG signal.

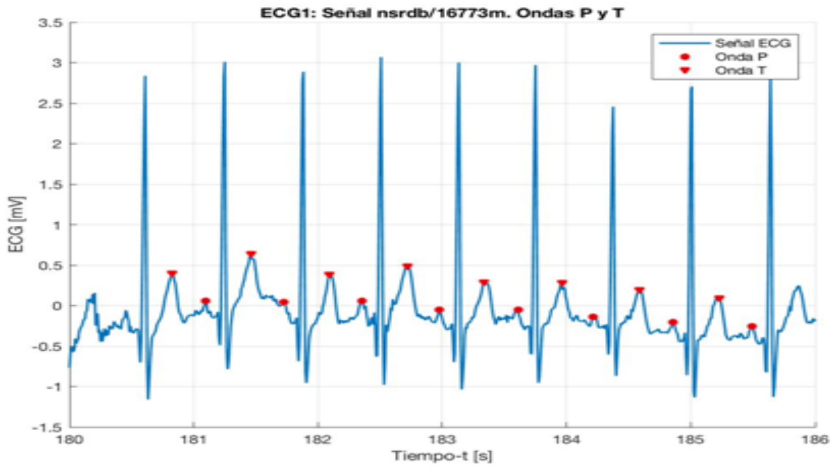

Figure 8: Identification of the P and T waves in an ECG signal.

1. The results of identification of the QRS complexes of ECG signals with different patients with different morphologies are shown in Table 1 (Fig. 9). We can note that:
2. Accuracy achieved with this DWT algorithm is 98 percent with a very low computational cost.

Nº	ECG Signal	No. QRS Complexes	Detected QRS	%
1	nsrdb/16 265 m	5281	5267	99.73
2	nsrdb/16 272 m	3736	3461	92.64
3	nsrdb/16 273 m	4976	4941	99.30
4	nsrdb/16 420 m	5907	5565	94.21
5	nsrdb/16 483 m	5481	5441	99.27
6	nsrdb/16 539 m	5247	5134	97.85
7	nsrdb/16 773 m	4424	4412	99.73
8	nsrdb/16 786 m	4406	4405	99.98
9	nsrdb/16 795 m	4112	4066	98.88
10	nsrdb/17 052 m	4463	4455	99.82
11	nsrdb/17 453 m	4963	4894	98.61
12	nsrdb/18 177 m	5832	5458	93.59
13	nsrdb/18 184 m	5208	5191	99.67
	Total QRS	64 036	62 690	**98 %**

Figure 9: QRS complexes identified by the algorithm (DWT).

IV. CONCLUSIONS

1. Wavelet analysis performed in the ECG signals with normal sinus rhythm with CWT and Morlet Wavelet has enabled to graphically identify (scalograms energy Wavelet 2D and 3D) characteristics of the heartbeat: QRS complex, P and T waves and heart rate.
2. Ventricular and supraventricular arrhythmias studied by the CWT Morlet Wavelet, and the Multiresolution (MRA) Wavelet analyses using DaubechiesDb8, have established patterns in terms of regular rhythm, absence of the P wave, fast heart rhythms, ripples in 10 Hz band, and presence of potential in the absence of P wave.
3. It is experimentally verified that the best results are obtained by recomposing the decomposed Daubechies Wavelet signal of order N=8 with the SURE threshold (Soft).
4. The algorithm designed in this work, based on Wavelet Transform (WT), for detecting the QRS complex and P and T waves, using Multiresolution (MRA) decomposition of ECG signal, through orthogonal Daubechies Wavelet of order 8, generated 8 scales in the coefficients of detail; has of- fered 98 (percent)

accuracy rate at very low computational cost. A higher value, if compared to what has been achieved by other DWT methods, 95.74 percent and 92.55 percent obtained with the ”So and Chan” method.

V. FUTURE SCOPE

Some prospective research directions are outlined:

1. Extension of the Wavelet Transform to the supervision of other biomedical signals: electromyographic (EMG) and electroencephalographic (EEG) signals, clinical sounds, breathing patterns, trends of blood pressure and sequences of deoxyribonucleic acid (DNA).
2. Classification and feature extraction in many types of cardiac arrhythmias in the field of Cardiology.
3. Using other Wavelet methods, as the Spline Wavelets, in the characterization of the ECG signals.
4. Using ECG signal as a feature biometric tool for identification and verification of people, as is distinctive for each individual.

VI. LIST OF SYMBOLS AND DEFINITIONS

bpm: Beats per minute.

1. **cwft MATLAB algorithm**:cwtstruct = cwtft (sig) returns the continuous wavelet transform (CWT) of the 1D input signal sig. cwtft uses an FFT algorithm to compute the CWT. sig can be a vector, a structure array, or a cell array. If the sampling interval of your signal is not equal to 1 , you must input the sampling period with sig in a cell array.
2. **CWT**: Continuous Wavelet Transform.

Interpreting Continuous Wavelet Coefficients Ca and b. If we assume that you have a wavelet supported on $[-C,C]$. Shifting the wavelet by b and scaling by a results in a wavelet supported on$[-C\,a + b, Ca + b]$. For the simple case of a shifted impulse, (t), the CWT coefficients are only nonzero in an interval around equal to the support of the wavelet at each scale.For the impulse, the CWT coefficients are equal to the conjugated, time-reversed, and scaled wavelet as a function of the shift parameter, b.

3. **Db8**: Daubechies Wavelet with 8 levels of decomposition.
4. **DWT**: Detection algorithm based in Wavelet Transform.
5. **ECG**:The electrocardiogram (ElectroCardioGraph).

Each portion of a heartbeat produces a different deflection on the ECG. These deflections are recorded as a series of positive and negative waves. On a normal ECG, there are typically up to five visible waveforms: the P wave,the Q wave,the R wave,the S wave and the T wave.

Moreover, atrial and ventricular depolarization and repolarization are represented on the ECG as: the P wave followed by the QRS complex and the T wave.

6. **MRA**: Multiresolution decomposition analysis.
7. **nsrdb**: Normal Sinus Rhythm Database [1, 2, 3].
8. **P wave**: Is the first deflection and is associated with right and left atrial depolarization.
9. **QRS complex**: is a name for the combination of three of the graphical deflections seen on a typical electrocardiogram (EKG or ECG). It is usually the central and most visually obvious part of the tracing. Thiscombination of the Q wave, R wave and S wave; QRS complex, represents ventricular depolarization and it corresponds to the depolarization of the right and left ventricles of the human heart.
10. **Q wave**: wave representing septal depolarisation. This is the first downward deflection after the P wave and the first element in the QRS complex. When the first deflection of the QRS complex is upright, then no Q wave is present. The normal individual will have a small Q wave in many, but not all, ECG leads.
11. **R wave**: wave representing ventricular depolarisation. This is the first upward deflection after the P wave (even when Q waves are absent) and part of the QRS complex. The R wave is normally the easiest waveform to identify on the ECG and represents early ventricular depolarisation. The R wave may be enlarged with ventricular hypertrophy, a thin chest wall or with an athletic physique. The R wave morphology itself is not of great clinical importance but can vary at times.
12. **Soft**: SURE thersholding method is the wavelet thresholding method.
13. **Sym 6**:Symlet wavelet,**Coif5**: Coiflet wavelet.
14. **S wave**: wave representing depolarisation of the Purkinje fibres. In the ECG we will also have seen a small negative wave following the large R wave. This is known as an S wave and represents depolarisation in the Purkinje fibres. The S wave travels in the opposite direction to the large R wave because, the Purkinje fibres spread throughout the ventricles from top to bottom and then back up through the walls of the ventricles.
15. **T wave**: In electrocardiography, the T wave represents the repolarization, or recovery, of the ventricles. The

interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period.

16. **VF**: Ventricular Fibrillation.

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