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# EXPLORING CWT BASED ALGORITHM AS ADDITIONAL AND ACCURATE TOOL FOR DETECTING ECG ABNORMALITIES

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**Abstract:** The wavelet transform has emerged in recent years as a key tool for time–frequency analysis and coding for ECG. The main advantage of this type of detection is that less time is allocated for processing the ECG signal with the continuous wavelet transform Db 5 (CWT). This paper aims to investigate a Db 5 continuous wavelet transform (CWT) analysis for selected ECG signals from the St.Petersburg Arrythmia Database. The results revealed that the flattened QRS complex and P and T waves containing low frequencies can be easily observed. The research findings emphasized the potential of Db5 technique as a powerful supplementary tool to investigate ECG features. This option can moderate rapid and precise diagnosis of cardiac diseases.
**Keywords:** ECG features, coronary disease, ischemia, Db wavelet, MATLAB

## INTRODUCTION

The electrocardiogram (ECG) is a graphical recording of the direction and magnitude of heart electrical activity, which is generated by depolarization and repolarization of atria and ventricles. ECG recording analysis is a subjective and difficult process due to its small graphical dimensions. Most of the time it is done in a very short time, imposed by the severity of the anomaly and the speed with which decisions must be made. Fine changes, even the very little obvious ones of the electrical potential for repolarization and depolarization are valuable indicators of the many diseases. Most useful information for ECG diagnostics is found in amplitudes of the P–QRS–T waves. The normal ECG waveform and anomalous waveforms are represented in Figures 1–3.

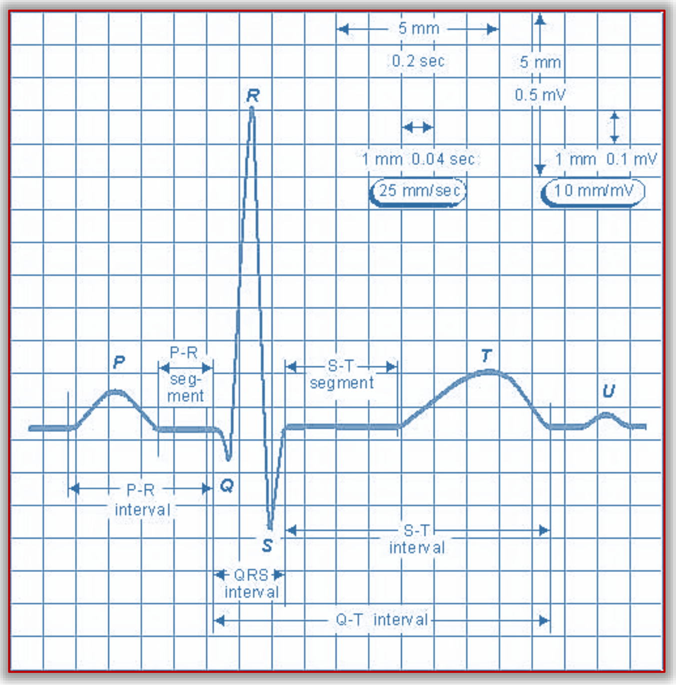



Figure 1. Normal ECG wave values. [1]

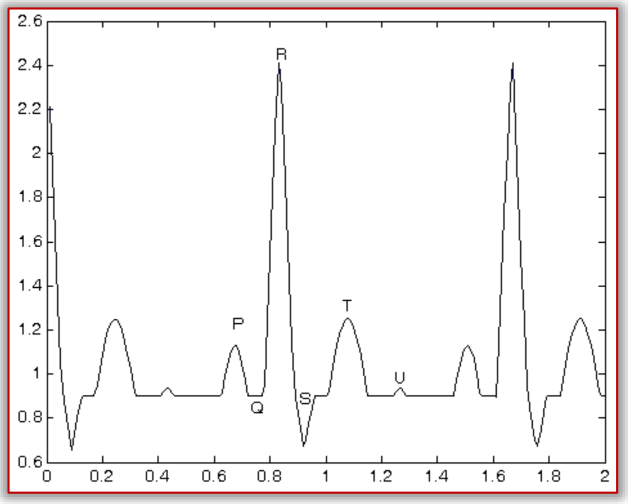



Figure 2. Normal sinus Rhytm.[2]

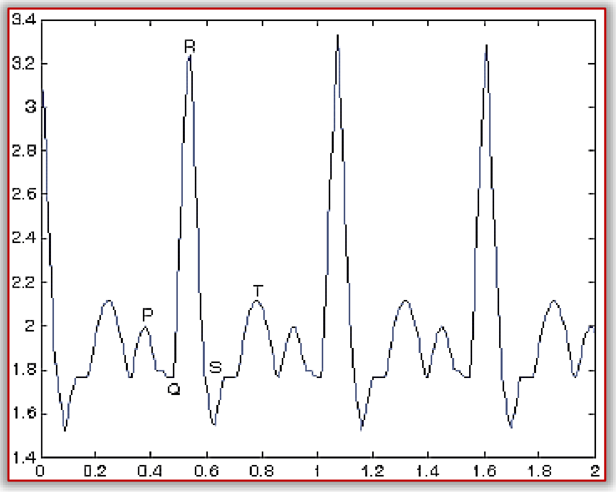



Figure 3. Sinus tachycardia. [2]

The P wave is the electrical fingerprint of the current that causes the atrial contraction. The QRS complex corresponds to the current that produces the ventricular contraction. Their repolarization generates the T wave, and the U wave, not always visible, is considered to be the representation of the activity of Purkinje fibers. The presence or absence of

these, as well as QRS and PR intervals, are significant parameters in the screening and diagnosis of cardiovascular disease.
The various cardiac abnormalities can be recognized according to ECG parameters (table 1).

Tabel 1. ECG parameter values related to cardiac diseases. [3]

| | |
|---|---|
| 1. Dextrocardia | P–wave inverted |
| 2. Tachycardia | interval R–R < 0.6 s, QRS between 0.1 şi 0.12 s |
| 3. Bradycardia | interval R–R > 1 s |
| 4. Hyperkalemia | high T–wave P–wave absent |
| 5. Myocardic Ischaemia | T–wave inverted |
| 6. Hypercalcaemia | QRS interval < 0.1 s |
| 7. Sinoatrial blockade | A complete absence of the cardiac cycle |
| 8. Supraventricular tachycardia (SVT) | QRS greater than 0.12 s, long duration of P wave (over 80 ms) |
| 9. Right or left branch block (BBB) | QRS greater than 0.12 s |
| 10. Paroxysmal atrial fibrillation | P–wave length (over 80 ms) |
| 11. Left ventricular hypertrophy | R peak over 2.6 mV in V5 |

Martis et al. [4] analyzes various computer–assisted cardiac diagnosis systems (CACD), methods of analysis, challenges for the future of cardiovascular disease screening.
These methods, ( including wavelet transforms), cannot alone accurately represent the inherent characteristics, but can serve as combined tools and help clinicians diagnose cardiovascular disease more precisely.
In recent years, the wavelet transform has become one of the topics in signal theory, which has enjoyed a big interest from numerous research groups. The multi–resolution analysis techniques, especially those based on the wavelet transform, have successfully become useful practical approaches.
The analysis of biomedical signals (ECG, EEG, EMG), solving differential equations or noise filtering are some of the areas of applicability of the functions called “wavelet”.
In the 19th century, the French mathematician J. Fourier, showed that any periodic function can be expressed as an infinite amount of complex periodic exponentials. This property of functions was first applied to non–periodic functions, then to discrete periodic and non–periodic signals, becoming an appropriate tool for calculations. In 1965, a new algorithm called Fourier Transform (FFT) was developed. [5].
The wavelet transform WT is defined as a convolution of the wavelet function $\psi_{a,b}(t)$, with signal x (t) [3]. The dyadic discrete orthogonal wavelet functions are associated with the scaling functions φ (t). The scaling function can produce the approximation coefficients a by convolution with the signal. The continuous wavelet transform (CWT) is given by the relationship:

$$C_{a,b} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^{*}{}_{a,b}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

By choosing an orthonormal wavelet function basic $\psi_{a,b}(t)$, the original signal can be reconstructed [6]. Wavelet $\psi_{a,b}(t)$ is translated by b and dilated by the factor scale a (a > 0).
The CWT map x(t) is a two variables function C (a, b) that can be utilized to compare the original signal and a wavelet scaled by a at a given time b.
The commonly chosen set of scales is the dyadic scale, where a= $2^b$ for b=1, .. N.
An important aspect is the choice of a wavelet function that closely matches the signal to be processed [7]. A continuous function can be decomposing more efficiently via basic wavelet functions; thus edge artifacts are avoided. The wavelet function “mother” keeps the signal details, and the evolution information is stored in the coefficients obtained by decomposing the function “father”.
Daubechies wavelet functions are the best option for analyzing biosignals characterized by a sharp peak because they have much less energy stored in the high band. Daubechies wavelets implemented numerically via square filters provide adequate processing results. The large filters give a better energy concentration than those given by small filters.
ECG is a graphical recording of the direction and magnitude of electrical activity, which is generated by depolarization and repolarization of atria and ventricles (Figure 1). Most useful information for ECG diagnostics is found in the ranges and amplitudes of the P–QRS–T waves.
The development of the methods of automatic extraction of accurate and rapid information characteristic of ECG is of major importance for the long term analysis of ECG signals [7]. ECG features can be extracted and used in the subsequent automatic analysis.
One of the practical benefits of the ECG wavelet–based approach is related to the diagnosis of transient ischemia, namely the fact that the T–wave anomaly it can be evaluated without the need to identify the final point [7].
Another major advantage of the wavelet transform is its ability to highlight the details of the optimal frequency–time ECG signal. The peaks of the flattened QRS complexes and the P–T waves containing lower frequencies become more visible [3].
Daubechies 6 (Db6) functions have similar shape to the QRS complex and their energy spectrum is concentrated around low frequencies [8]. Figure 4 shows the details of an ECG signal with a short series of noise added at its end, decomposed with D6

wavelets. The original signal X is displayed on the top. Most of the signal details are kept at scale $2^5$, the high–frequency noise is captured at the smallest scales, namely $2^2$ and $2^1$. The signal details at scale $2^5$ reflect the similarity of the Db6 with the QRS complex.

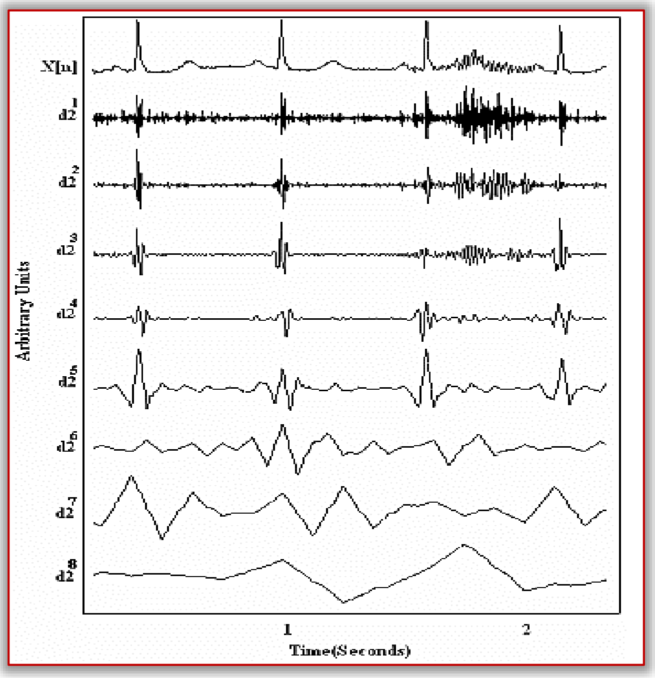
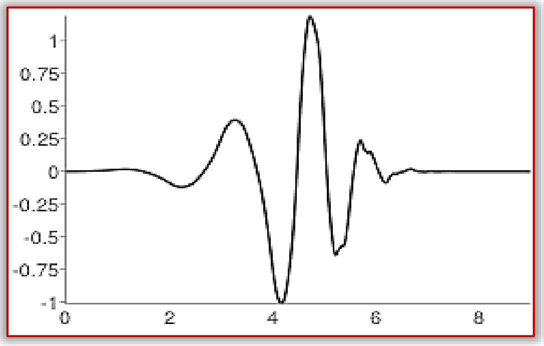
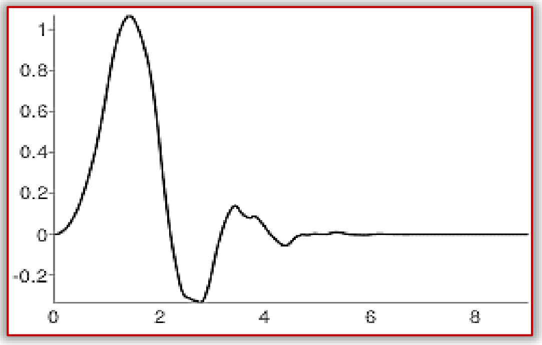



Figure 4. The original ECG signal (X) and decomposed with Daubechies D6 wavelet/different scaling orders $d2^m$ [3].

Another ECG–shape suitable wavelet is Db5 (Figure 5).




(a)




(b)

Figure 5. Wavelet and scalar function forms for Daubechies 5. [9]
(a) Wavelet function ψ DB5, (b) Scaling function φ

The detection of P wave, QRS complex and T wave in an ECG signal is a difficult problem due to the variation in time of signal, physiological conditions and the presence of noise. Senhadji et al [8] compared the potential of different types of wavelets (Daubechies, splines and Morlet) to recognize and describe isolated heartbeats. Sahambi et al [6,10], used dyadic wavelet maxima analysis to detect and measure different features of the signal, especially QRS localization, P and T waves. The algorithm was validated as a method of determining ECG signal synchronization intervals, including QRS. Romero Legarreta et al [11] used the continuous wavelet transform (CWT), which offers high time–frequency resolution, better definition of the maximum values of QRS parameters.

In a study with D4 transform, Pichot et al [12] analyzed the night heart rhythm of subjects who performed tiring exercises for three weeks, with a resting week. This rhythm had a significant progressive decline during the study. Gamero et al [13] reported that Daubechies D12 wavelet used in myocardial ischemia analysis is an important tool for dynamic assessment of ECG parameter changes.

Chen [14], using Daubechies D8 DWT, found that sympathovagal balance, estimated by the low and high (LF / HF) frequencies, increases before the onset of unsupported ventricular tachycardia.

In recent studies, potential of NN classifiers is exploit for the automatic detection and classification of ECG parameters [15,16]. Al–Fahoum and Howitt [15] proposed a network for the automatic detection and classification of arrhythmias that employ ECG preprocessing using Daubechies D4 wavelet. They obtained the correct classification of 97, 5% arrhythmias from a data set of 159 arrhythmia files from three different sources, with the correct classification of 100% for both ventricular fibrillation and ventricular tachycardia.

**METHODOLOGY**

Based on literature documentation, an investigation was designed centered on the idea that Db5 of the Daubechies family, are suitable for studying the characteristic ECG parameters for different cardiac diseases and normal signal.

The importance of this research lies in shedding light on the status quo of the complementary techniques of ECG processing among the signal and image in real–time evaluation. The research findings may hold benefits to fast investigation of ECG features and rapid and precise interpretation diagnosis of cardiac diseases.

The samples used were original records collected from patients with coronary heart disease (17 men and 15 women, ages 18–80; average age: 58 years, included in St. Petersburg Arrythmia Database [17]. These signals were chosen for the pathological features, which could be studied with this type of wavelet. Like all signals from the Physionet database, these sample recordings are noted for normal heart rate, RR intervals, presence of premature atrial (APC) and ventricular (PVC) contractions), tachycardia and bradycardia episodes, branch blockages (BBB; RBBB; LBBB), etc.

The experimental group comprises sequences of ECG signals, coming from:

- patients with normal heart (P4 and 6) – further noted with N;
- patients with coronary heart disease and hypertension (noted with CAD);
- patients with a transient ischemic attack (noted with TIA).

For this purpose were selected various sequences of ECG, recorded at the V5 level (precordial). This channel was chosen for several reasons: here begins the S wave; in V5 it can be measured the duration of the QT interval; V5 is often used as a reference for different values of the ECG parameters (for example, the R wave with a value greater than 2.7 mV is a sign of left ventricular hypertrophy (LVH).

The sampling frequency of these signals is 257 Hz. The sample signals were processed with the continuous wavelet transform Db 5 (CWT), Matlab for Windows Professional. The frequency and energy spectra of the reconstructed signals are highlighted and compared with those of the normal signal.

## EXPERIMENTAL RESULTS AND DISCUSSIONS

The ECG signals with coronary heart disease and hypertension (CAD) and transient ischemic attack (TIA) analyzed with CWT were compared with those of normal signals. The various abnormalities are highlighted by the changes in the value of the coefficients. [18]

The main categories of data obtained are revealed in Figures 6–9. Local maxima (or minima) have been detected after wavelet transformation, at different levels, occurring at different times during the cardiac cycle.

The decomposition of the input signal highlights the different frequency content of characteristic ECG waves so that they are distinguished by decomposition at different scales.

The wavelet transform is suitable for approaching ECG signals, characterized by high–frequency components with short durations and low–frequency components with long durations. [19]

We observe the ordered and symmetrical form of the local maxima lines in the case of the normal rhythm, versus the variable interval and the distribution of maxima lines in the case of the signal 1 (CAD, HTA). The dashed lines highlight the disturbances in ECG form.

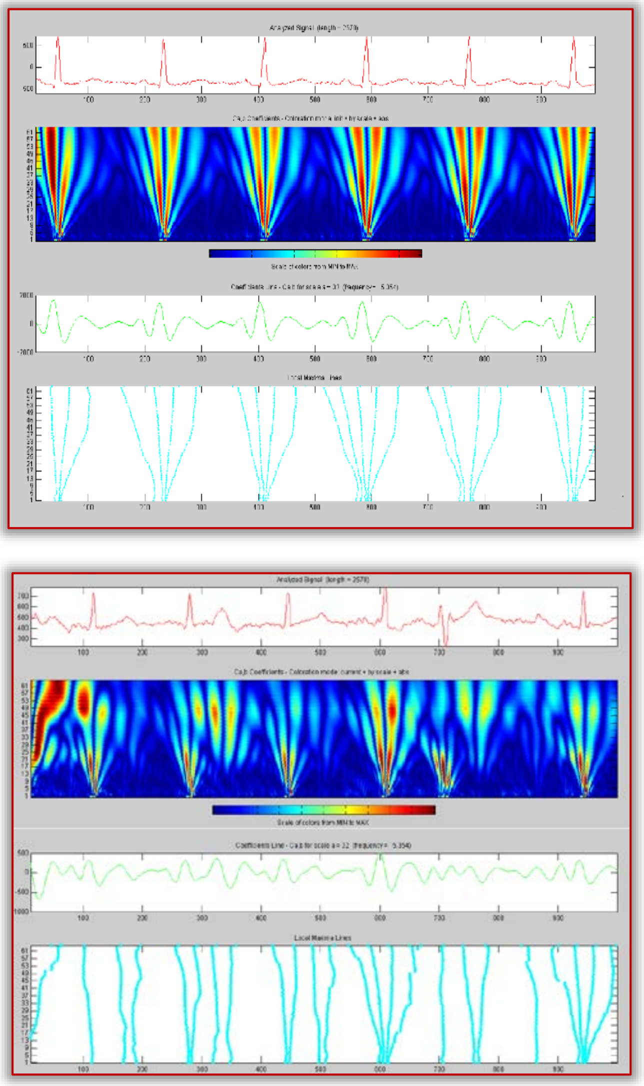


Figure 6 – Spectrogram for signal 12, normal sinus rhythm (top) and signal 1, patient with CAD and HTA (bottom)

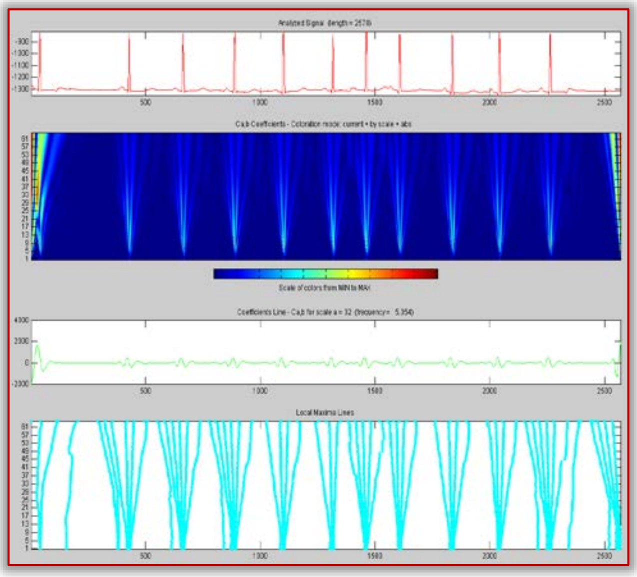


Figure 7 – Energy spectrogram of the QRS complex for ECG signal 20, with ventricular couplings, premature atrial contractions (APCs), atrial couplings, paroxysmal tachycardia

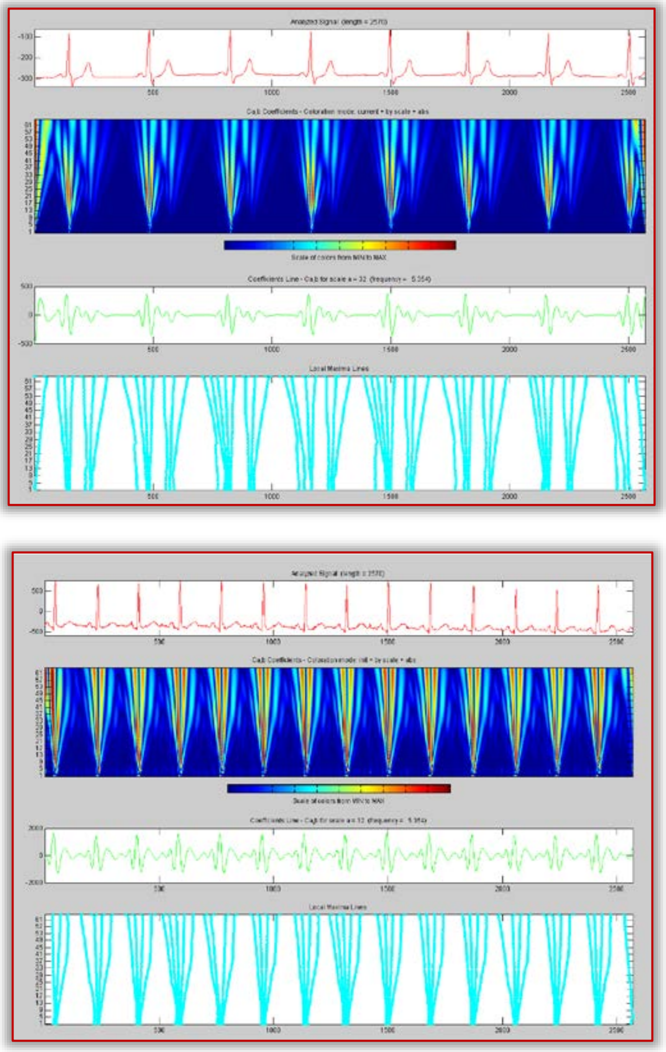


Figure 8 – Spectrogram ptr. Signal 16, TIA, with RBBB, polymorphic PVC (top). Normal sinus rhythm bottom

It easy to notice the different sizes of the R–R intervals and the large value of the T–wave amplitude (which appears in the spectrogram as a "shadow" of the QRS complex) (Figure 8)

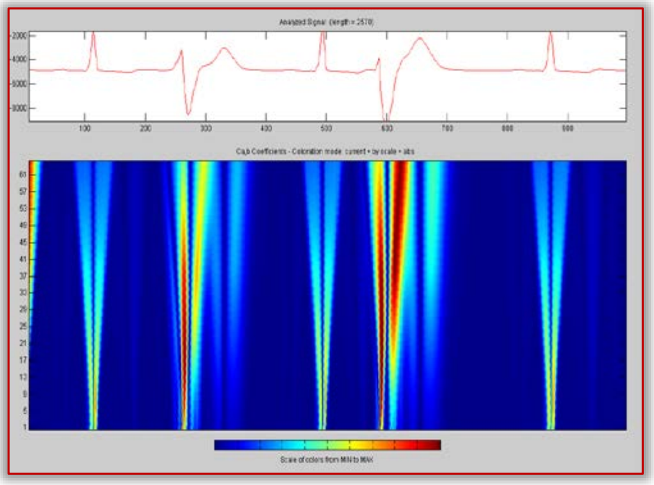


Figure 9 – Spectrogram ptr. Signal 72, CAD, with PVC and tachycardia couplings

The characteristic of this signal (Figure 9) is the sharp form of the P wave, the high R–R rhythm and the long duration of QRS (bradycardia). It should be noted that the shape of the QRS complex is atypical, with the Q wave almost absent, relatively small value of the R wave, deformation of the ST segment, high value of the T wave.

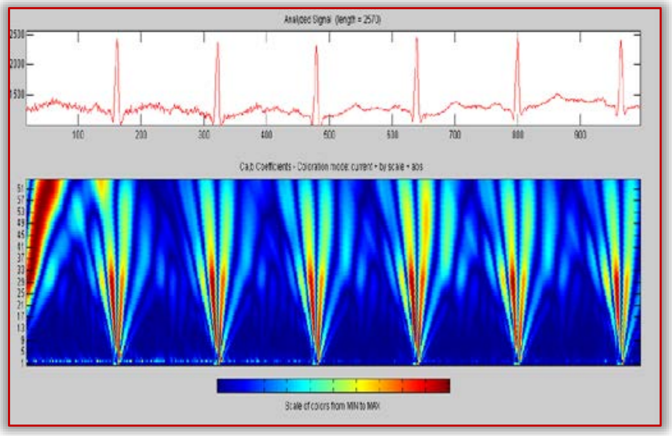


Figure 10 – Spectrogram for ptr. Signal 57, CAD, ventricular coupling (VC) of tachycardia

In this case (Figure10) it is evident the deformation of both pre and post QRS waves, ie P and T.

In all cases, the flattened QRS complex and the P and T waves containing low frequencies can be easily observed. At the same time details appear on small scales about the high frequency spectrum of the signal.

## CONCLUSIONS

The wavelet transform has emerged in recent years as a key tool for ECG time–frequency analysis and coding. The main advantage of this type of detection is that less time is allocated for processing the ECG signal.

The choice of the Db5 transform was made after rigorous research of the recent results in ECG processing with different families of Wavelet. Although the Daubechies wavelet algorithm is conceptually more complex and requires a larger volume of calculation, its advantage is that it takes over the detail, which is lost by other Wavelet transforms. Db5 continuous wavelet transform (CWT) of selected signals from the St.Petersburg Arrythmia Database revealed that the flattened QRS complex and P and T waves containing low frequencies can be easily observed and analyzed. At the same time, details about the high–frequency spectrum of the signal appear on small scales.

The practical benefit of wavelet–based experimental approaches is that T–wave anomalies can be detected without the necessity to identify the initial and final T–wave moments. Also, it can be emphasized the choice of the Db families is also conditioned by the spectrum of frequencies, values and orientations of the ECG characteristic parameters we want to study. This is at the same time a major disadvantage of this technique.

The findings of this paper show the ability to separate the relevant signal components and emphasized the wavelet–based techniques potential in case of particular medical field–interpreting the pathology of CAD and TIA diseases. This present Db5 approach can complements other minimally invasive investigation and diagnostic techniques, like neural network algorithms.

In order to improve and point out the clinical utility of this processing technique as a diagnostic and prognostic tool in different fields of cardiology, laborious future studies must be incorporated.

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