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WAVELET FAMILIES COMPARISON FOR R-PEAKS DETECTION IN ELECTROCARDIOGRAM SIGNAL

BY

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Abstract. A detection of R-peaks in electrocardiogram signal (ECG) based on modified threshold in wavelet transform domain is presented. In this paper, the threshold determination is based on segmentation approach and with help of different wavelet families. However, the decision about the possible R-peaks is done by using the physiological heart parameters. Our method has been applied to MIT-BIH arrhythmia database to show its practical efficiency in terms of sensitivity, median, mean and standard deviation values. A comparative study is done between the results of our proposed algorithm based on modified threshold with different wavelets combinations, and the work based only on Daubechies wavelet with simple threshold. The survey showed that the combination of Daubechies wavelet mother gives with Symlet, Coiflet and Biorthogonal wavelets mother the best results.

Keywords: threshold; BW artifact; sensitivity; median; standard deviation.

1. Introduction

The body can be considered as a chemical and electrical system supported by a mechanical structure. Measuring and quantifying such electrical

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activity provides a means for objective examination of health status (Reilly & Lee, 2010). Bioelectric potentials present the electrochemical activity in a certain class of excitable cells. The electrocardiogram (ECG) records the electrical activity of the heart, which is a noninvasive recording produced by an electrocardiographic device and collected by surface electrodes placed at designated locations on the body (Zhidong *et al*., 2011).

ECG signals are composed of five important waves: P, Q, R, S, and T as shown in Fig. 1. Sometimes, a sixth wave (U) may follow T. The Q, R, and S waves are grouped together to form the QRS-complex, which plays an important role to determine the heart rate, and hence it can be used to detect P, and T waves not only because of its location relative to them, but also due to its high amplitude which makes it easy to detect (Bsoul *et al*., 2009).

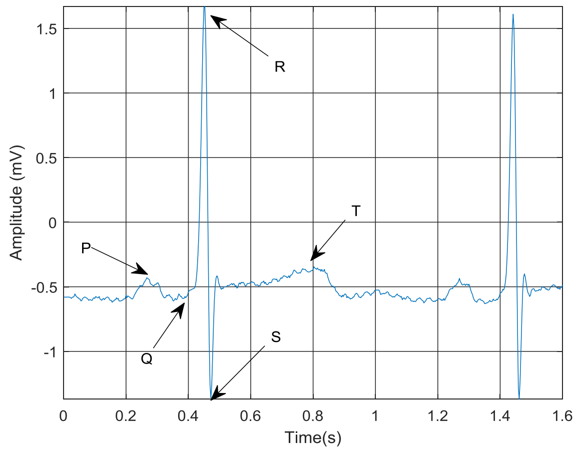

Fig. 1 − Sample of ECG signal with standard notations (MIT-BIH Arrhythmia record 115) (Belkacem *et al*., 2018).

A range of normal values in sinus rhythm of each wave is summarized in Table 1 according to Clifford *et al*., (2006).

Table 1
ECG Values

Waves	Values
P width, [ms]	110
PQ/PR interval, [ms]	160
QRS width, [ms]	100
P amplitude, [mV]	0.15
QRS height, [mV]	1.5
ST level, [mV]	0
T amplitude, [mV]	0.3

All of the different types of waves that can be seen on an ECG signal are demonstrations of two processes: depolarization and repolarization (Rai *et* *al*., 2014). If we record one electrical cycle of depolarization and repolarization from a single cell, we get an electrical tracing called an action potential (Thalor, 2012). The cardiac cell is not excitable during the absolute refractory period (ARP) of the action potential (Haddadi, 2014), which means there is no QRS complex in this period. ARP is marked by the onset of a Q wave and ends at the peak of the T wave. The absolute refractory period is followed by a relative refractory period (Brock, 2011).

The amplitude value of the bioelectrical ECG signal is low, generally of the order of a few millivolts. When recording cardiac activity different types of noises coming from sources other than signals from the heart can contaminate the ECG signal notably: power line interference, electrode pop, contact noise, patient electrode motion artifacts, electromyographic (EMG) noise and baseline wandering artifact (Akshay *et al*., 2010). Baseline wandering artifact usually comes from respiration and lies between 0.15Hz-0.3Hz (Faezipour *et al*., 2009). However, the presence of this noise in an ECG signal changes the morphology of the waves, which makes detection of R-peaks difficult, and therefore lead to false diagnosis and interpretation. The determination of R-peaks in an ECG signal provides information about heart rate. An example of baseline variation up and down is visualised through the record 118 of MIT-BIH database is shown in Fig. 2.

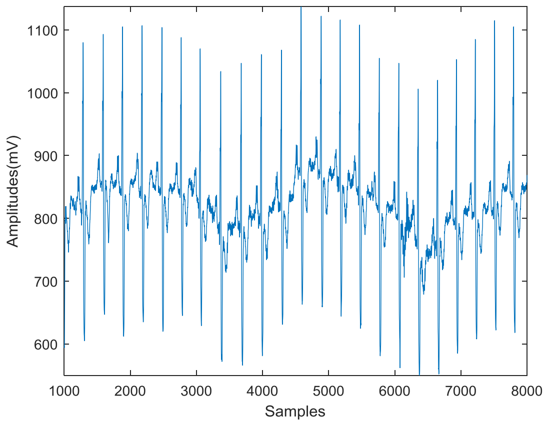

Fig. 2 – ECG with BW of record 118 from MIT-BIH database.

ECG denoising algorithms must keep the original characteristic waveform and especially the sharp Q, R, and S waves, without distorting the P and T waves.

ECG signals are non-stationary, pseudo periodic in nature and whose behaviour changes with time (Bindhu *et al*., 2014). Several methods have been applied to model and denoise of ECG signals, such as band pass filters (Bagheri *et al*., 2013). However, digital filtering methods are suitable only for stationary signals, whereas ECG signal is one of the bio-signals that are considered as non-stationary signal. Recently, several processing techniques for the non-stationary signals are applied to the ECG signal to denoise it. We cite here, wavelet transform (WT), empirical mode decomposition (EMD) and variational mode decomposition (VMD), a comparison of the performances of these methods are given in (Lahmiri, 2014). Hence, time-frequency methods are the appropriate tools in its analysis for non-stationary signal analysis (Jaffery *et al*., 2010; Lahmiri & Boukadoum, 2015; Silva, 2015).

In R-peaks detection, the thresholding is necessary, such a signal peak which exceeds the threshold (th) is considered as R-peak. The thresholding of a signal can be done by two methods: fixed or adaptive thresholding. Since the noise characteristics change with time, then fixed thresholds are not able to adapt the changing situation. Hence, the adaptive thresholding is better than the fixed thresholding. A high threshold value will increase the false negative rate, and a low threshold value will increase the positive false rate. For this purpose, we suggest some modifications concerning the existing R-peaks algorithm proposed in (Haddadi *et al*., 2014).

To improve the performance of the detection algorithm by selecting an optimal combination among proposed wavelet mother, our algorithm of R-peaks detection is based on a modified threshold value obtained from non-overlapping segments of the divided ECG signal.

The remaining part of the paper is organized as follows. Section II includes the previous research works in QRS complex detection. The principles of wavelet transform and wavelets mother selection are explained in section III. In section IV we explain our R-peaks detection algorithm based on modified threshold and wavelet mother combination. Next, in section V, we show the simulation plots and the obtained results performed with the recording of the MIT-IH database. Finally, conclusion is presented in section VI.

2. Previous Works

Detection of ECG features is mainly depended on the accurate determination of R-peaks; these techniques have been used for different applications like heart rate variability analysis, arrhythmia classification, heart rate calculation, feature extraction, ECG compression, R-R interval analysis, and P, S, and T waves detection (Rodríguez *et al*., 2015).

Originally slope-amplitude detection algorithm in real time was proposed by Pan and Tompkins, (1985), and after this period the detection algorithms are expanded in transformed domains, as wavelet transform.

Different wavelet mother are used for R-peaks detection: Haar, Daubechies, Symlet and Coiflet, with different level decomposition. In the literature we found researchers who are interested in the choice of approximation coefficients while other researchers prefer the use of the detail coefficients for signal decomposition in wavelet transform. Li *et al*., (1995), introduced spline quadratic wavelet for QRS complex detection. Alvarado *et al*., (2005) have used continuous wavelet transformation (CWT) with splines to detect characteristic points of QRS and T waves. Pachauri *et al.*, (2009) have developed a robust R wave detector using wavelets. The wavelets used for detection are Daubechies and Symmetric, and the detail coefficients (d4) have been selected. In the works of authors in Bsoul *et al.*, (2009), the wavelet mother Haar and detail coefficients are used with fourth level decomposition for QRS detection. In Rai *et al.*, (2014), the DB6 mother wavelet is used with 8 level decomposition. In the work of Haddadi *et al.*, (2014) and Alvarado *et al.*, (2005), the Daubechies wavelet is used with a 4 level decomposition.

3. Wavelet Transform and Mother Wavelet Selection

The wavelet transform (WT) describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis function (Mukhopadhyay *et al.*, 2012). WT is able to simultaneously provide time and frequency information.

By applying the wavelet transform, signals were decomposed to the approximate coefficients (low frequency) and detail coefficients (high frequency).

The approximation is then itself split into a second-level approximation and detail coefficients, and the process is repeated for n-level decomposition (Karami & Eshaghi, 2009).

To get the best results from the used wavelets, it is important to select well the mother wavelet function similar to the shape of the oscillation in the data. Several researchers have suggested the use of the well-known Daubechies (DB4) wavelet for ECG signal decomposition in wavelet transform, due to the similarity of its scaling function to the shape of the QRS complex in ECG signal (Haddadi *et al.*, 2014; Mohamed & Deriche, 2014).

Concerning the mother wavelet used for R peaks detection, we have proposed some mother wavelet, which have similar shape as QRS complex given by the names: Daubechies-4 (DB4), Symlet-4 (Sym4), Coiflet-2 (Coif2), and Biorthogonal-2.8 (Bior2.8). The comparison between their shapes and typical QRS complex shape of ECG signal is shown in Fig. 3.

It is clear that the shape of the QRS complex is similar to the four proposed mother wavelets. The simulation result shows the best representative of the QRS shape of the ECG signal.

For ECG data with sampling frequency Fs, its Nyquist frequency Fn = = Fs/2 (Tan & Perkowski, 2017).

The frequency components of the QRS complex range is from 10 Hz to 25Hz (Rufas & Carrabina, 2015). In Table 2, we describe the frequency band of approximate and detail coefficients in wavelet transform with respect to Nyquist rule for any ECG signal taken from MIT-BIH database sampled at 360Hz (www.physionet.com). It is clear that most energy of the QRS complex is concentrated at detail decomposition of level 4 (d4).

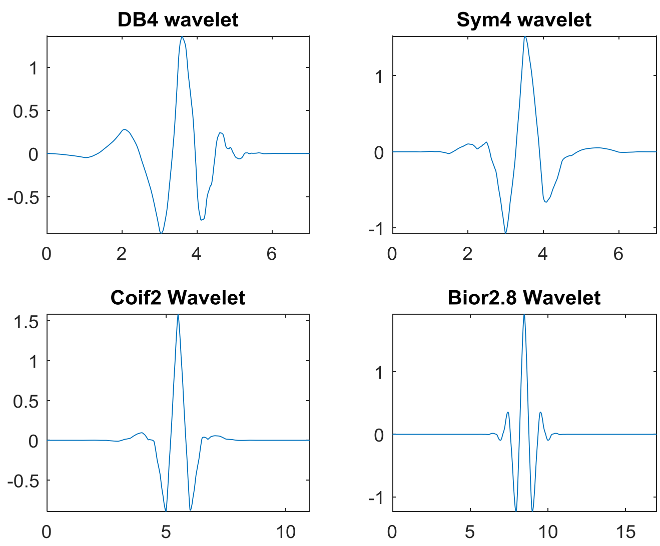

Fig. 3 – Comparison shape between different mother wavelets.

Table 2

The Frequency Values for the Approximate and the Detail Coefficients

Decomposition level	Frequency band of approximate coefficients, (Hz)	Frequency band of detail coefficients, (Hz)
1	0 to 90 Hz	90 Hz to 180 Hz
2	0 to 45 Hz	45 Hz to 90 Hz
3	0 to 22.5 Hz	22.5 Hz to 45 Hz
4	0 to 11.5 Hz	11.25 Hz to 22.5 Hz

4. Our Method

The block diagram of R-peaks detection involves four blocks, which are shown in Fig. 4, and the explanation of each block is detailed below.

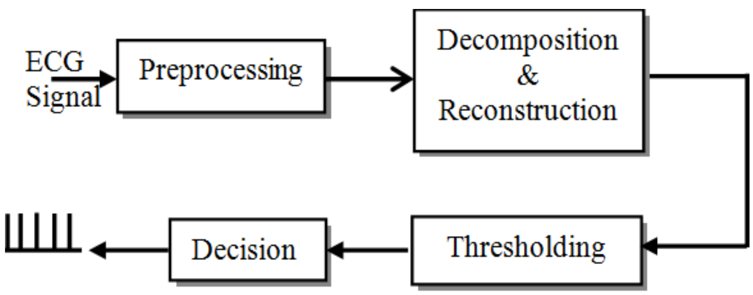

Fig. 4 – Block diagram of R peaks detection.

Block: Preprocessing

In this work, preprocessing consists of eliminating the baseline (BW) in the wavelet domain. BW artefact is represented by low frequency (Approximation coefficients) of the wavelet decomposition. Hence, to remove baseline, we need to ignore the approximation coefficients during the reconstruction phase (Inverse Wavelet Transform). So, the ECG signal without the BW, is the result of the construction of the details coefficients (d1, ... d8) of the ECG signal decomposed in wavelet, with respect to the Daubechies mother wavelet (Haddadi *et al*., 2014).

Block: Decomposition & Reconstruction

In several research studies, researchers have shown empirically that the DB4 wavelet is the best wavelet representative of the QRS complex of an ECG signal. In our algorithm we adopted DB4 only for decomposition, and we proposed several mother wavelets such as: Symlet, coiflet and biorthogonal for the reconstruction of the ECG signal; these operations are noted successively by the combinations: (DB4,Sym4), (DB4,Coif2) and (DB4, Bior2.8). It is already shown in paragraph 3 that the frequency content of the QRS complex is in the range 10 HZ up to 25 HZ which corresponds to the detail coefficients of the 4th level decomposition (d4). In this step, we will extract only the signal y that represents d4 in the time domain.

Block: Thresholding

Our proposed procedure for the threshold determination can be sectioned as follows:

In this step we have proposed to divide the signal into segments of small time intervals, so as not to spread the influence of the noise on the ECG signal, and then the formula used by the authors (Behbahani & Dabanloo, 2011) and (Haddadi *et al*., 2014) given by equation (1) is applied:

$$th = 0.15 \times \max(y). \tag{1}$$

Then, the value of the final threshold will be the mean value of all thresholds previously found, calculated as follows:

$$th\_mean = \frac{1}{n}\sum_{i=1}^{n} th(i), \tag{2}$$

where n represents the number of segments.

Block: Decision

After the application of the previous steps, the decision is made according to the following criteria:

– All amplitude values exceeding the threshold *th* are candidates for R peaks and placed in a vector called *R_condidat*, and their positions are stocked in another vector called '*R_locs*'.

– The R-peaks are determined by removing peaks which are occurring within less than the refractory period. Following the assumption that no two QRS complexes maybe found during less than 200 ms (Pachauri & Bhuyan, 2009).

5. Simulation Data and Results

Several established ECG databases are available to evaluate the QRS detection algorithms for ECG signals. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979 (www.physionet.com). The following results were obtained using MATLAB software.

An example of ECG signal for record 222 of MIT-BIH database with BW artifact is shown in Fig. 5 *a*, therefore it must be removed from ECG signal. The ECG signal reconstructed from detail coefficients after baseline elimination is plotted in Fig. 5 *b*.

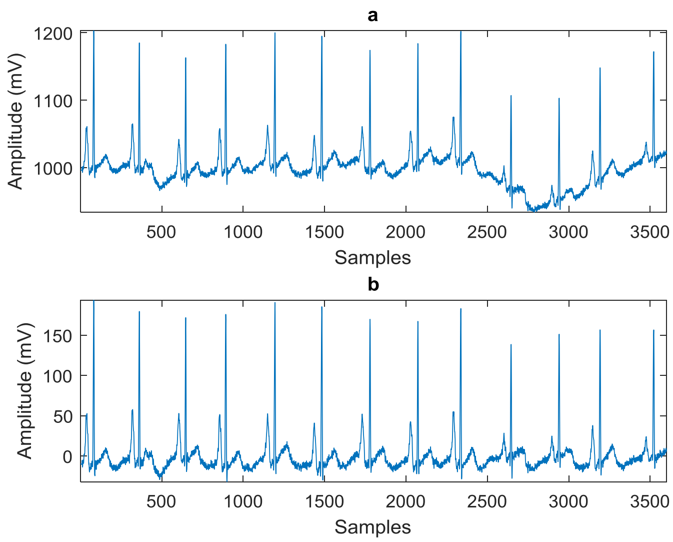

Fig. 5 – Denoising results (*a*): ECG signal 222 with BW; (*b*) : ECG signal reconstructed from detail coefficients.

It is noted that the reconstruction of ECG signal from the detail coefficients allows the elimination of the baseline signal.

The application of our algorithm on some real ECG signals from the MITBIH database is shown in Figs. 6 *a*, *b*, *c*, *d*), that will make it possible to obtain the positions of the R peaks that have been detected. The identified positions of the R peaks are marked on the original signal by 'Δ', for ECG records namely: 112, 118, 119, and 219.

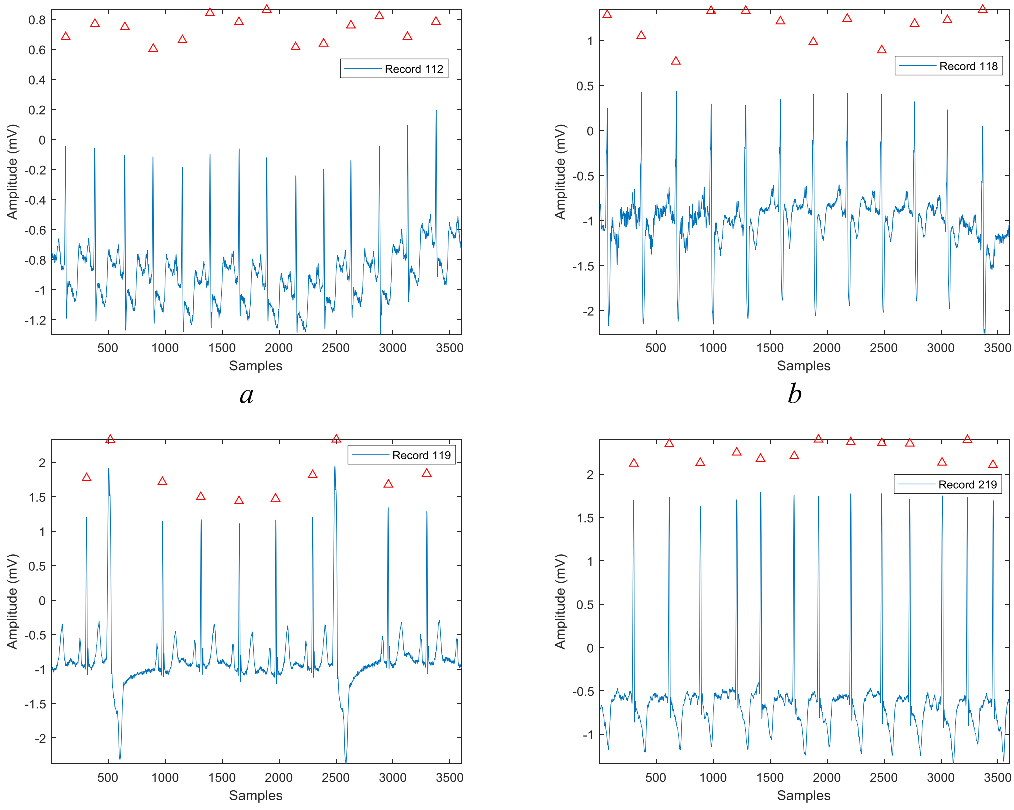

Fig. 6 − Examples of ECG signal and its identified R-peaks in original ECG signal for records named from left to right and from top to bottom:
a – 112, *b* – 118, *c* – 119, *d* – 219.

From the results given in Fig. 6, we note that the position of the identified R peaks really corresponds to the R peaks in the ECG signal. In other words, the R peaks are well detected over the period of 10 s for signals 112, 118, 119, and 219.

Given the good results found on ECG record for R peaks detection of time 10s, we will apply our algorithm on persons of MITBIH database with a long recording time (30min) that were chosen by reference paper for performance comparison purpose (Haddadi *et al.*, 2014).

To evaluate the performance of our algorithm with application of different wavelet mother combination ((DB4,DB4), (DB4,Sym4), (DB4,Coif2) and (DB4,Bior2.8)) for R peaks detection, sensitivity (Se), median value (M), mean value (m) and standard deviation (std) are calculated, and compared with results found in the reference paper (Haddadi *et al*., 2014).

The sensitivity (Se) can be calculated using the following equation as in Pachauri and Bhuyan, (2009):

$$Se(\%) = \frac{TP}{TP + FN}, \tag{3}$$

where, TP (true positive) is the number of R peaks correctly detected as peaks and FN (false negatives) is the number of missed peaks.

The simulation results of the three statistics can be seen in the following figures.

In Fig. 7, it is found that the median sensitivity value obtained by our modified thresholding method is higher than that obtained by (Haddadi *et al*., 2014). However, the median sensitivity value in reference paper is close to the quartile q0.25, on the other hand, the distribution of the sensitivity values of the detection of R-peaks by our algorithm is close to the quartile q0.75, that are close to 100% value, which ensures the efficiency and the choice of the proposed method for the detection of the R-peaks of the ECG signal.

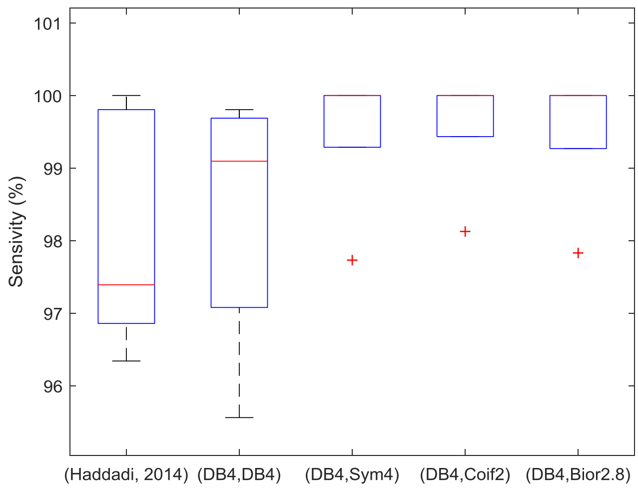

Fig. 9 − Boxplot of the sensitivity comparison among algorithms. Left box to right box shows the sensitivity of the detection of R-peaks with reference paper and our algorithm based on the use of the four combination of wavelets: (DB4,DB4), (DB4,Sym4), (DB4,Coif2) and (DB4,Bior2.8). The ‘’+’’ signs indicate the outliers exceeding the range of the corresponding box by more than 1.5 times its inter-quartile range.

Regarding the minimum value outside the box (outliers) for (DB4,Sym4), (DB4,Coif2) and (DB4,Bior2.8), their sensitivity value remains higher than the median value of the sensitivity found in the reference paper (Haddadi, 2014), and the greatest median value of the sensitivity is achieved by the three combinations of wavelet (DB4,Sym4), (DB4,Coif2) and (DB4,Bior2.8).

The mean and standard deviation of the sensitivity parameter were determined for reference paper and each wavelet combination parameters are summarized in Table 3, and shown in Fig. 8.

Note that the mean value of the detection sensitivity of R peaks obtained by our algorithm based on the new threshold method is higher than that found by the reference paper (Haddadi *et al*., 2014). Hence, the mean value of the sensitivity obtained by the combination of the wavelets is greater than that obtained by the use of a single type of wavelet (DB4,DB4).

Table 3
Sensitivity Values in Term of Mean and Standard Deviation for Different Wavelet Combinations

	Sensitivity (Se%)				
	(Haddadi *et al*, 2014)	DB4,DB4	DB4,Sym4	DB4,Coif2	DB4,Bior2.8
Mean	98.1	98.3381	99.507	99.599	99.5155
Standard deviation	1.4864	1.5953	0.89144	0.73858	0.84873

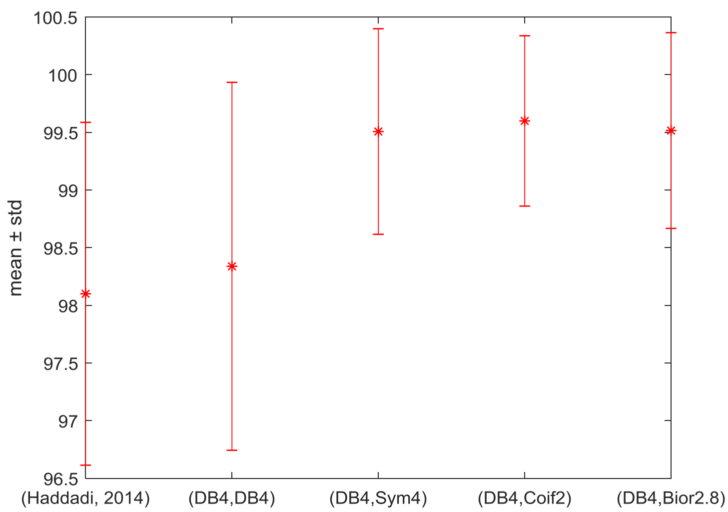

Fig. 8 − Mean and standard deviation comparison among algorithms. Left to right shows the mean and standard deviation sensitivity for R peaks detection with reference paper and our algorithm based on the use of the four combination of wavelets: (DB4,DB4), (DB4,Sym4), (DB4,Coif2) and (DB4, Bior2.8).

However the value of the standard deviation found by the reference paper algorithm and by our algorithm with the use of a single type of wavelet is with no significant difference. Hence, the standard deviation of our wavelets combinations method (DB4,Sym4), (DB4,Coif2) and (DB4, Bior2.8) are closed, and the lower value is obtained by (DB4, Coif2). The best results in term of the higher sensitivity and lower standard deviation is obtained by the combination of (DB4,Coif2). This validates the choice of the wavelet combination (DB4, Coif2) with the modified thresholding for the detection of R peaks of QRS complex.

6. Conclusion

The comparison of results in term of sensitivity value achieved by the application of our algorithm based on the new threshold with the four mother wavelet combinations are better than those found by the works cited in (Haddadi *et al*., 2014). The comparison of the performances of our algorithm, by estimating the mean and variance of each method, was found that a greater part of sensitivity is detected by (DB4,Sym4), (DB4,Coif2) and (DB4,Bior2.4). The obtained results done by the combination of wavelet (DB4,Coif2) may achieve the greater value in term of median and mean value sensitivity and present the lower value of standard deviation.

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COMPARAŢIE ÎNTRE FAMILIILE WAVELET DESTINATE DETECŢIEI UNDEI R DIN ELECTROCARDIOGRAMĂ

(Rezumat)

Se prezintă detecţia undei R bazată pe modificarea pragului în domeniul transformatei wavelet. Determinarea pragului este bazată pe o abordare pe segmente şi făcând apel la diferite familii de wavelets. Totuşi, decizia privitoare la detecţia undei R se ia pe baza parametrilor fiziologici ai inimii. Metoda a fost aplicată semnalelor din baza de date MIT-BIH privitoare la aritmie, în vederea evaluării eficienţei sale în ceea ce priveşte valorile senzitivităţii, medianei, mediei şi dispersiei. S-a efectuat un studiu comparativ între metoda prezentată, cea bazată pe pragul modificat, în cazul unor combinaţii de wavelets şi rezultatele anterioare, obţinute cu wavelets de tip Dubechy cu prag simplu. S-a pus în evidenţă faptul că wavelet-ul mama de tip Dubechy dă cele mai bune rezultate în combinaţie cu cele de tip Symlet, Coiflet şi cea biortogonală.