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Electrocardiogram features detection using stationary wavelet transform

Mounaim Aqil[1], Atman Jbari[2]
[1]Superior School of Technology (EST), Sultan Moulay Slimane University, Béni-Mellal, Morrocco
[2]National Higher School of Arts and Crafts (ENSAM), Mohammed V University in Rabat, Rabat, Morrocco

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ABSTRACT

The main objective of this paper is to provide a novel stationary wavelet transform (SWT) based method for electrocardiogram (ECG) feature detection. The proposed technique uses the detail coefficients of the ECG signal decomposition by SWT and the selection of the appropriate coefficient to detect a specific wave of the signal. Indeed, the temporal and frequency analysis of these coefficients allowed us to choose detail coefficient of level 2 (Cd2) to detect the R peaks. In contrast, the coefficient of level 3 (Cd3) is determined to extract the Q, S, P, and T waves from the ECG. The proposed method was tested on recordings from the apnea and Massachusetts Institute of Technology–Beth Israel hospital (MIT-BIH) databases. The performances obtained are excellent. Indeed, the technique presents a sensitivity of 99.83%, a predictivity of 99.72%, and an error rate of 0.44%. A further important advantage of the method is its ability to detect different waves even in the presence of baseline wander (BLW) of the ECG signal. This property makes it possible to bypass the filtering operation of BLW.

Corresponding Author:

Mounaim Aqil
Superior School of Technology (EST), Sultan Moulay Slimane University
Av Med V, BP 591, Beni-Mellal 23000, Morrocco
Email: mounaim.aqil@usms.ma

1. INTRODUCTION

The electrocardiogram (ECG) is the recording of electrical activity in the heart. The ECG is used in a variety of biomedical applications, such as the analysis of heartbeat rhythm, the detection of cardiac anomalies, the identification of emotions, and biometric recognition. The diagnosis of cardiovascular disease is undoubtedly the main area in which ECG analysis is essential [1], [2].

Modern electrocardiography enables the ECG signal to be analyzed and interpreted. These operations aim to detect and extract unobservable features from the signal. In addition, clinical information is hidden in the different waves of the ECG signal and their shapes. Therefore, it is essential to develop reliable and robust detection and extraction techniques [1]–[3].

The non-stationary nature of the ECG signal requires the use of high-performance mathematical tools for processing and analysis. These tools include wavelet transforms. Thanks to their powerful time-frequency localization property, these transforms are very powerful tools for processing, analyzing, and extracting the characteristics of non-stationary signals such as the ECG. These transforms use a set of basic functions called wavelets to observe and reveal signal changes in the time and frequency domains simultaneously [4], [5].

Two main categories of wavelets transform exist: continuous wavelets transform (CWT) and discrete wavelets transform (DWT). The CWT is characterized by the redundancy of the signal information.

In addition, this transform is greedy in terms of calculation time and energy consumed by the processors. Indeed, a calculation of the power consumption of this transform in [3] and [6] showed that it consumes four times more energy than the digital wavelet transform. This disadvantage of the CWT seems to be a good reason for using the DWT. Unfortunately, DWT also suffers from the following shortcomings: high shift dependence, weak directionality, and lack of phase information. In particular, when DWT is used to detect the characteristics of a non-stationary signal, it has two major drawbacks: dependence on the time-lag variance and poor resolution at small scales [7]–[9]. These drawbacks can be corrected by using a variant of DWT called the stationary wavelet transform (SWT) or un-decimated DWT (UDWT). The stationary property guarantees time invariance: the translation of a signal $x(n)$ implies a translation of its transform. Most uses of this transform are for denoising, while its use for detecting and extracting features from a signal is limited.

Many research works have focused on wavelet transforms for the detection and extraction of the different features of the ECG signal. A large part of the research work has exploited the Mallat and Hwang approach to detect singularity points and local maxima of the different coefficients of the transform [10]–[12]. Other methods have used the detail coefficients of the DWT to detect the quality rating system (QRS) complex [13], while other techniques have adopted multi-scale resolution for band-pass filter implementation to detect the QRS complex [14]. Finally, some approaches are based on the selection of the scale parameters of CWT [3], [15]. There are few research works on the use of SWT for the detection of ECG signal features, for example [16], [17] whose authors were interested in the detection of the QRS complex.

This work aims to use the SWT to detect the different P, QRS, and T waves of the ECG signal and to explore the capability of this transform in this domain. For this purpose, we will compare the proposed method with different wavelet-based detection methods. The structure of the rest of this article is as follows: section 2 will present a background theory on SWT with a precise description of the choice of wavelet to be used and the level of decomposition to be adopted. Section 3 is reserved for the description of the proposed algorithm. This section also includes a presentation of the SWT-based ECG features detection method. Section 4 is reserved for tests and validation of the proposed method as well as a comparison with other methods. This section also presents an advantage in terms of the robustness of our method. Section 5 will be devoted to conclusions and future work.

2. THEORETICAL BASIS ON STATIONARY WAVELETS TRANSFORM

2.1. Stationary wavelets transform algorithm

The stationary wavelets transform (SWT) can be seen as an extension of the discrete wavelets transform (DWT). The advantage of SWT is that it solves the transient invariance problem of DWT. In effect, SWT eliminates the down-samplers and up-samplers and replaces them with up-sampling filter coefficients by 2^{j-1} in the j^{th} level. SWT is a redundant method that is a hybrid of the high-redundancy continuous wavelet transforms (CWT) and the non-redundant DWT. The SWT of a signal $x(n)$ is the convolution product of $x(n)$ and filters (a low-pass then a high-pass) that procures the approximation $Ca_{j,k}$ and detail coefficients $Cd_{j,k}$ consecutively at the j level [7]–[9].

Considering $\phi(n)$ is a scaling function, the discrete approximation coefficients at the resolution 2^j are given by (1) and (2) [8], [9].

$$Ca_{j,k} = \langle x(n), \phi_{j,k}(n) \rangle \tag{1}$$

$$\phi_{j,k}(n) = 2^{-j}\phi(2^{-j}n - k) \tag{2}$$

The discrete detail coefficients at the resolution 2^j are given by (3).

$$Cd_{j,k} = \langle x(n), 2^{-j}\psi(2^{-j}n - k) \rangle \tag{3}$$

where $\psi(n)$ is the wavelet function. In these equations, $\langle f, g \rangle$ denotes the convolution product of the functions f and g. The scaling function $\phi(n)$ and the wavelet function $\psi(n)$ can be expressed as convolution with high pass and low pass filters as [8], [9].

$$\frac{1}{2}\phi\left(\frac{n}{2}\right) = \sum_l h(l)\phi(n-l) \tag{4}$$

$$\frac{1}{2}\psi\left(\frac{n}{2}\right) = \sum_l g(l)\psi(n-l) \tag{5}$$

- $h(l)$ are the coefficients of the impulse response of a low-pass filter;
- $g(l)$ are the coefficients of the impulse response of a high-pass filter;

The approximate coefficients $Ca_{j+1,k}$ at level $(j + 1)$ can be directly computed from the previous $Ca_{j,k}$ as (6).

$$Ca_{j+1,k} = \sum_n h(n - 2k)Ca_{j,n} \tag{6}$$

Similarly, the detail coefficients at level $(j + 1)$ also can be computed as (7)

$$Cd_{j+1,k} = \sum_n g(n - 2k)Cd_{j,n} \tag{7}$$

These equations represent DWT multi-resolution analysis; in this case, the signal is down-sampled at each level of decomposition. As a result, the number of signal samples is halved at each level. In contrast, in the SWT algorithm, instead of down-sampling the signal, it is up-sampled before the filter is convolved. Thus, in the case of the SWT algorithm, the approximation and detail coefficients are obtained as shown below.

$$Ca_{j+1,k} = \sum_m h(m)Ca_{j,k+2^j m} \tag{1}$$

$$Cd_{j+1,k} = \sum_m g(m)Cd_{j,k+2^j m} \tag{9}$$

The method for computing detail and approximation coefficients of the SWT is shown in Figure 1.

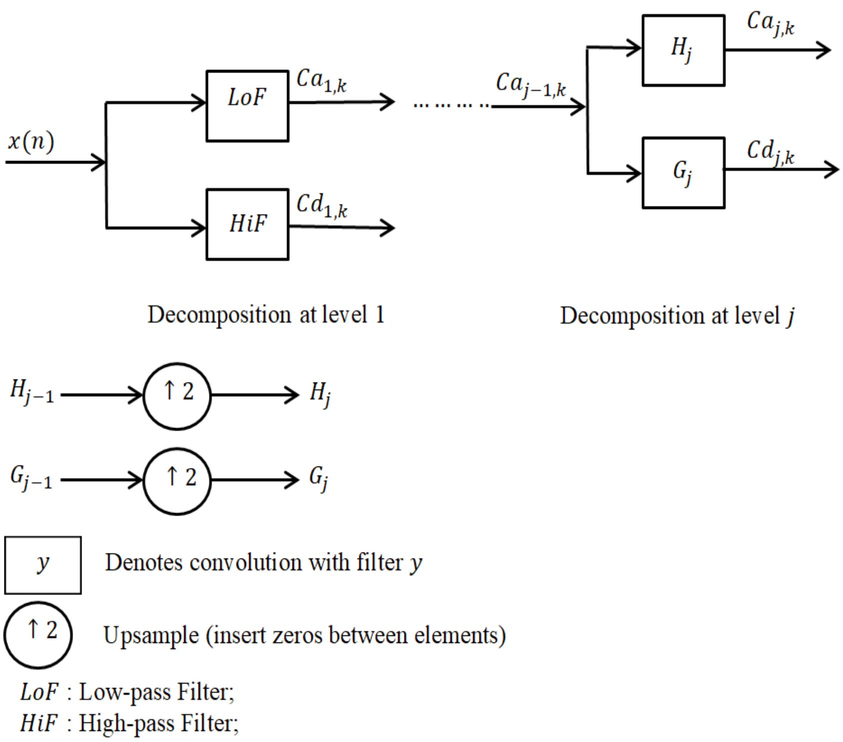


Figure 1. SWT algorithm

2.2. Selection of wavelet decomposition parameters

2.2.1. Selection of wavelet type

In literature, there is no predefined rule to select a wavelet for a particular application; rather the selection is application-oriented. It is a common practice to select a wavelet function with a similar shape to the subject signal. Moreover, the SWT requires that the wavelet be orthogonal or biorthogonal. Taking into account the previous considerations, we have chosen a Daubechies1 wavelet (db1).

2.2.2. Selection of decomposition level

The choice of the decomposition level l depends on the following parameters: i) The number of samples N of the signal to be decomposed must be a multiple of 2^l; ii) The level l must allow the extraction of the different P, QRS, and T waves from the ECG signal; iii) The level l must allow the conservation of the signal energy; and iv) The decomposition time must be as short as possible. In the proposed method, we have opted for a selection of detail coefficients to extract a specific wave from the ECG signal. As a result, the choice of decomposition level must respect the conservation of wave positions in the ECG signal as well as their frequency spectrum.

3. METHOD AND MATERIALS

3.1. Materials

To validate the method proposed in this article, we used two databases of ECG recordings: the apnea database [18] and the Massachusetts Institute of Technology–Beth Israel Hospital (MIT-BIH) arrhythmia database (MITDB) [19]. The apnea database consists of 70 records, divided into a learning set of 35 records (a01 through a20, b01 through b05, and c01 through c10), and a test set of 35 records (x01 through x35). Several files are associated with each recording [18]: a data file (*.*dat*), a header file *(*.hea*), an apnea annotation file (*.*apn*), and a QRS annotation file (*.*qrs*). The MIT-BIH database can be considered as a validation standard for any algorithm developed for QRS complex detection. The database consists of 48 half-hour recordings. These recordings were digitized using the following parameters: a sampling frequency of 360 Hz and 11-bit coding. Each recording was annotated by several cardiologists. Three files were provided for each recording [19]: a data file (*.*dat*), a header file (*.*hea*) and an annotation file (*.*atr*). This last file contains the manual annotations made by cardiologists. These annotations consist of the positions and times of appearance of the R peak of the ECG signal and a mark indicating whether the QRS complex is normal or not. The latter represents a standard for the validation of ECG R-peak detection algorithms. Indeed, a manual annotation is provided with the different records of this database.

3.2. Methodology

The algorithm used for the detection and extraction of the different P, QRS, and T waves of the ECG signal is given in the flowchart of Figure 2. Each step in the algorithm is a set of processing operations. These operations are described below.

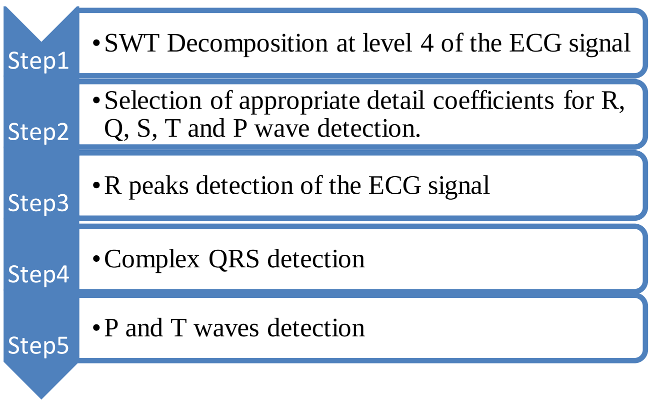


Figure 2. Flowchart of the proposed method

Step 1: SWT decomposition at level 4 of the ECG signal

In this step, we applied the SWT to decompose the signal into detail coefficients. We also looked at the time pattern of these coefficients and compared it to the ECG signal. The idea is to determine the appropriate detail coefficient for each type of waveform. The result of this step is given in Figure 3.

Step 2: Selection of appropriate detail coefficients for R, Q, S, T, and P wave detection

Several techniques for the selection of detail coefficients have been proposed. Indeed, Mahmoodabadi *et al.* [20] chose the detail coefficients $Cd3 - Cd5$ for the detection of the R peaks. Saxena *et al.* [21] proposed the use of the coefficients $Cd1 - Cd5$. These methods were applied with the use of the DWT. Another SWT method was proposed by Merah *et al.* [16] who chose the detail coefficient $Cd4$ to detect the QRS complex. In our work, we suggest that the choice of the appropriate detail coefficient to extract any wave from the signal is based on two criteria: the first criterion is determined by the appearance of the different waves in the temporal plot of the detail coefficients, the second criterion is based on the distribution of the power spectral density (PSD) of the different waves compared to that of the detail coefficients. The results of this step are given in Figure 3. These results are obtained using the record $a01m$ from the apnea Database.

By analyzing the time plots of the coefficients of detail, we see that the R peaks of the ECG signal coincide with the maxima present in the level 2 coefficient of detail ($Cd2$). The analysis of this coefficient is given in Figure 4 particularly the time analysis shown in Figure 4(a). Furthermore, the spectrum of this coefficient matches that of the QRS complex. This result is given in the frequency analysis given in Figure 4(b) and Figure 5. Therefore, we will use this coefficient to detect the R peaks. Regarding the Q and S waves, we notice that on the temporal representation of the level 3 coefficient ($Cd3$), the amplitude of these waves is more significant, see Figure 4(a). The frequency analysis of this coefficient also shows that its spectrum is close to the QRS complex. Therefore, we will exploit this coefficient to detect Q and S waves in Figure 4(b) and Figure 5. The detection of P and T waves in the ECG signal will also be based on the $Cd3$ coefficient. This is because the temporal representation of this coefficient maintains the appearance of these waves. In addition, the low-frequency part of the spectrum of this coefficient corresponds to the spectrum of these waves. The level 4 detail coefficient has a spectrum similar to that of the P and T waves, but the temporal analysis shows a significant shift between the positions of these waves on the ECG signal and those on the $Cd4$ plot.

Step 3: R peaks detection of the ECG signal

For the detection of R-peaks, we applied the following process for the detail coefficient $Cd2$:
- Apply a rectifier to the $Cd2$ signal to eliminate the negative parts;
- Evaluate the energy content E_R of the rectified $Cd2$ signal;
- Thresholding using the following expression:

$$th = \frac{\max(E_R)}{2} \tag{10}$$

- Detect peaks in the energy content of the $Cd2$ coefficient using the threshold th. These peaks match the R peaks of the ECG signal.

The results of this process are presented in Figure 6.

Step 4: Detection of Q and S points

After detecting the R peaks in the signal, it is the Q and S points that we're looking to detect. In addition, the Q and S points are local minima around each peak R. To achieve this, all we need to do is locate the first zero slope on either side of the R peak.

The location of these points will be done using the detail coefficient $Cd3$. Indeed, we used the following procedure:
- we performed the derivative of $Cd3$;
- we specified a window $w = 10$ on either side of the positions of each R peak;
- we looked for the points in the window w for which the derivative is zero;
- we have located the local minima in the window w around the positions of the R peaks;
- These local minima detected on $Cd3$ coincide with the positions of the Q and S points of the ECG signal.

The results of this procedure are shown in Figure 7.

Step 5: detection of T and P waves

After detecting the QRS complex, we proceed to locate the P and T waves of the ECG signal. For the detection of these waves, we have chosen to use the detail coefficient $Cd3$. The idea of using this coefficient comes from the fact that in the temporal representation, we noticed that the P-wave has a more significant amplitude than the one on the ECG signal while the P-wave has kept the same amplitude. This fact is shown in Figure 8. The P wave will be detected by identifying the first maxima before each Q point position in the plot of $Cd3$. To detect this wave, we proceed as follows: i) We used the derivative of $Cd3$ performed in the previous step; and ii) We have looked for P points that meet the following conditions:
- The point P is before the Q point;
- the derivative of $Cd3$ is null;
- $Cd3$ is increasing before P and decreasing after.

For the detection of T wave, we use the same process of P wave detection. Indeed, the T wave is considered as the first maxima after each S point position in the plot of $Cd3$. The results of this step are illustrated in Figure 9. The result of the detection and extraction of the different waves of the ECG signal using the proposed algorithm is shown in Figure 10.

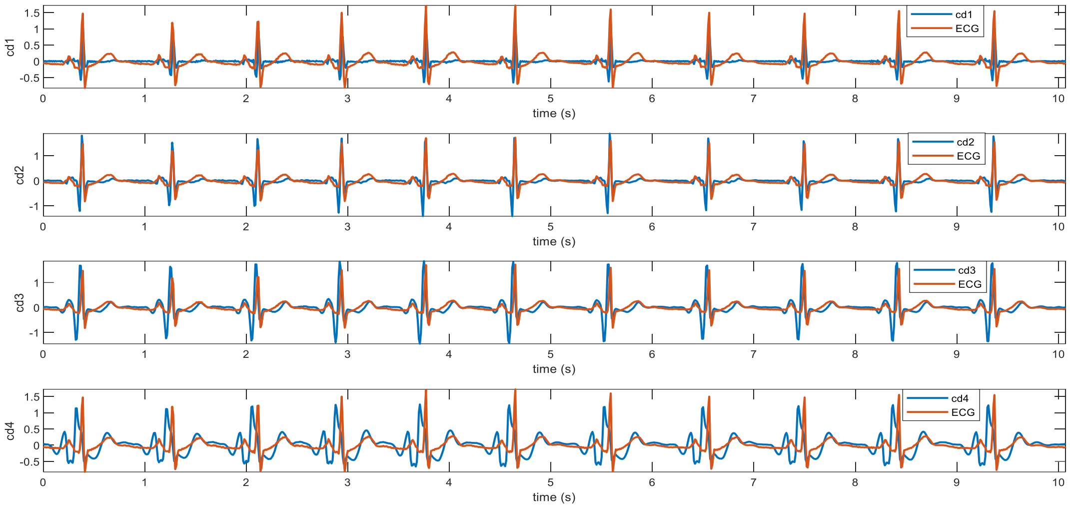
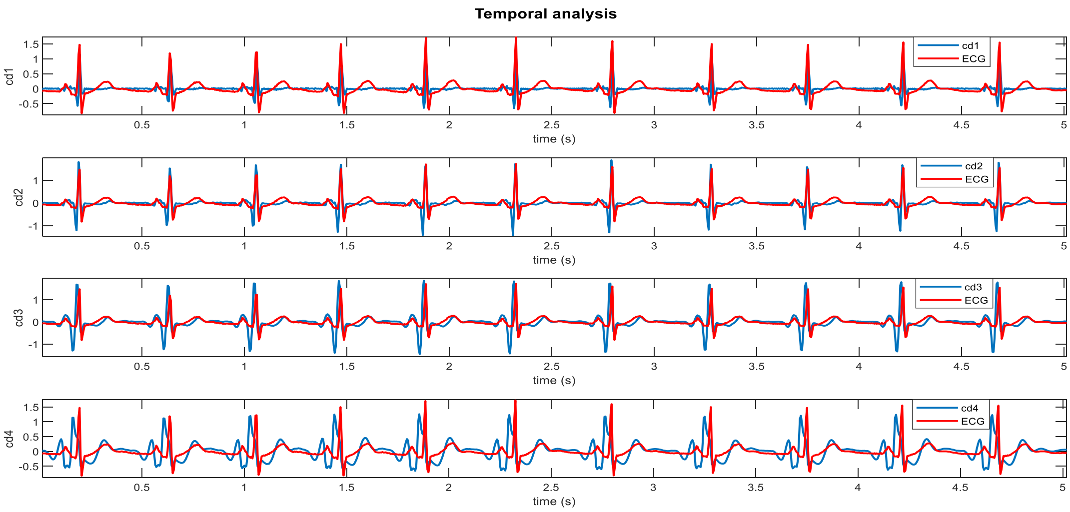
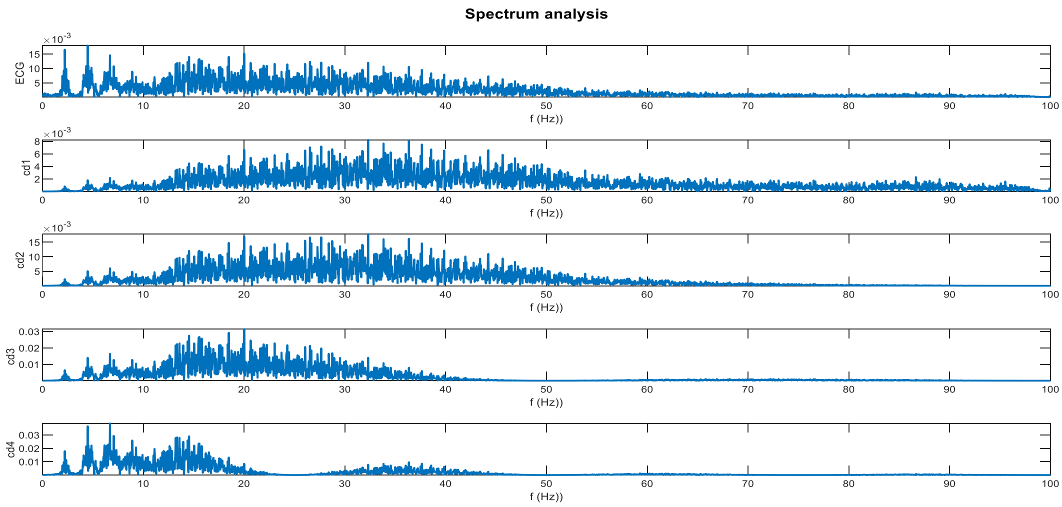


Figure 3. SWT decomposition of a01m record



(a)



(b)

Figure 4. Analysis of the detail coefficients (a) temporal analysis and (b) spectrum analysis

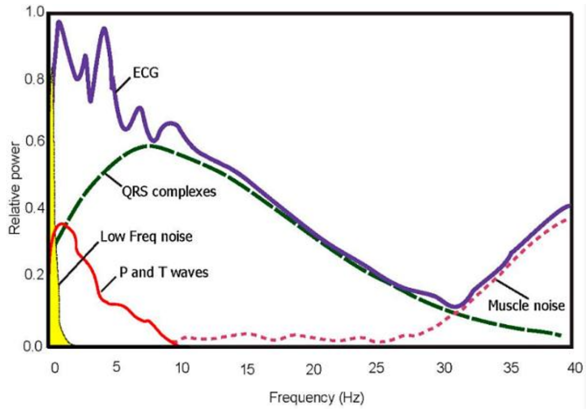


Figure 5. PSD of normal ECG signal [22]

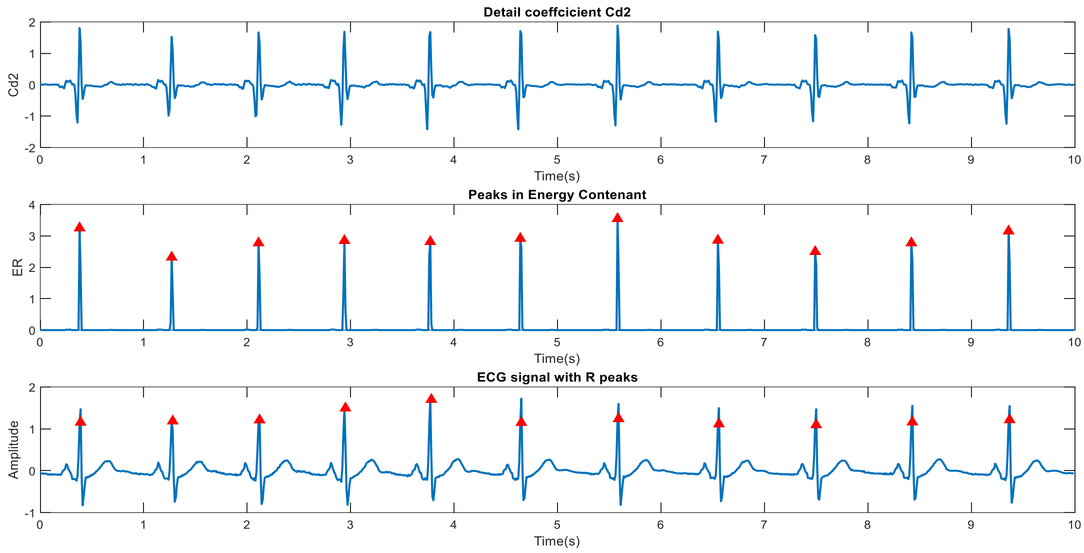


Figure 6. R peak detection

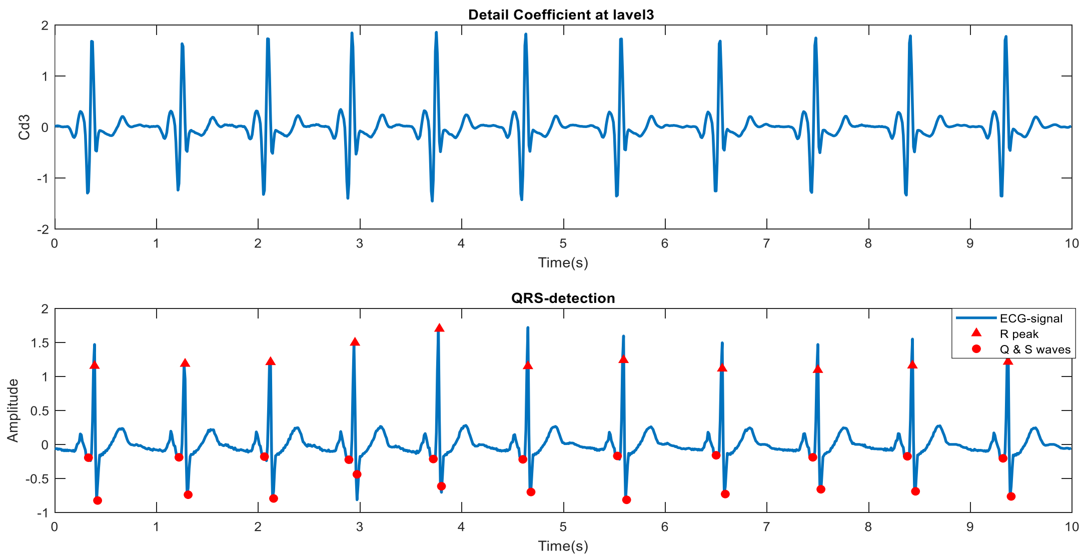


Figure 7. Q and S detection

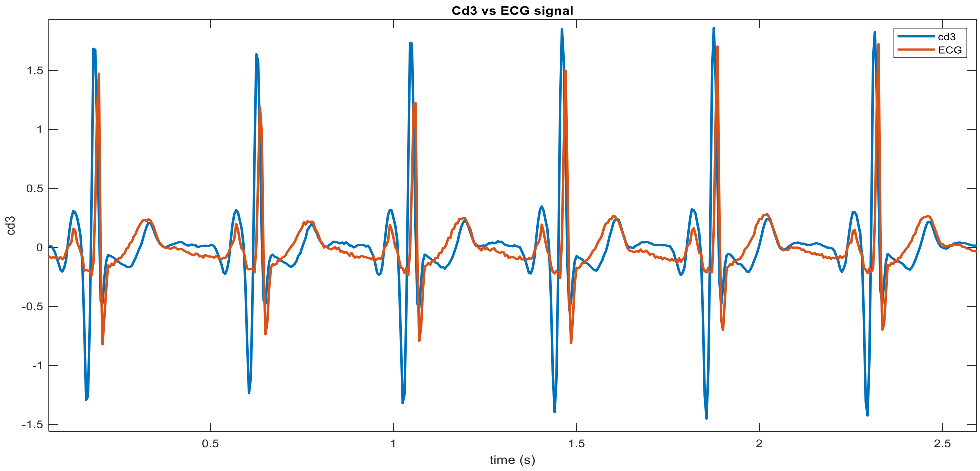


Figure 8. Comparison of P and T wave amplitudes in Cd3 versus ECG

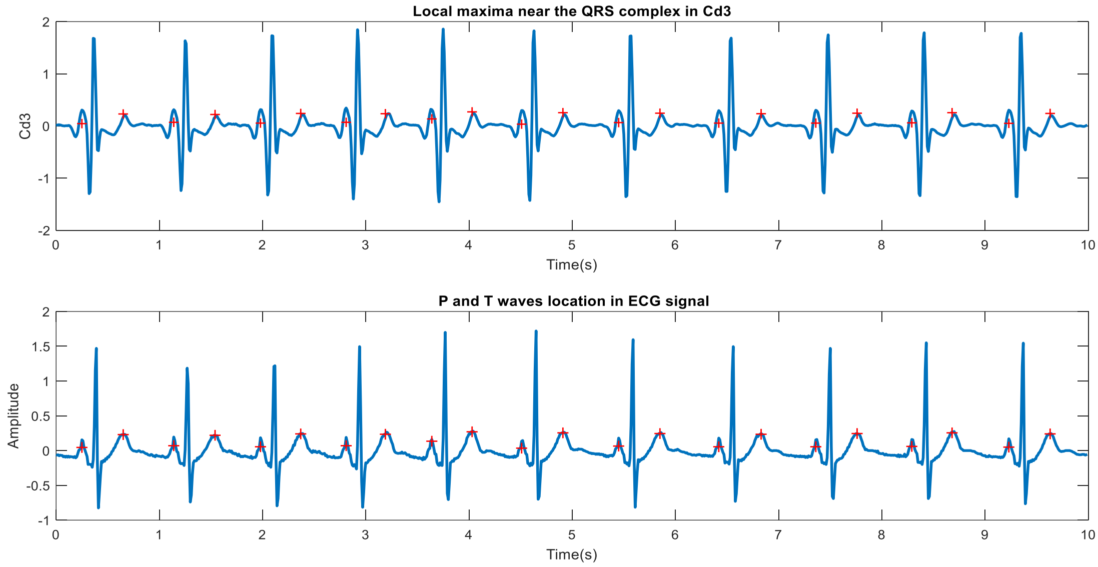


Figure 9. Detection of P and T waves

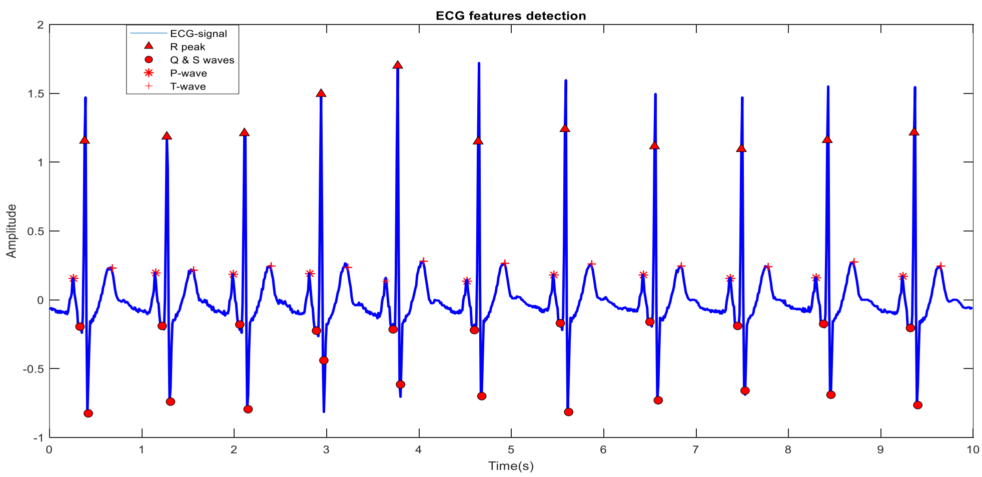


Figure 10. Extraction of ECG features

4. RESULTS AND DISCUSSION
4.1. Assessment parameters
The main assessment parameters used in ECG analysis algorithms are listed as:
- Sensitivity (Se): It is defined as (11):

$$Se(\%) = \frac{TP}{TP+FN} \times 100 \tag{2}$$

- Positive predictivity (P^+): It is given by (12):

$$P^+(\%) = \frac{TP}{TP+FP} \times 100 \tag{12}$$

- Error rate (ER): It is expressed in (13):

$$ER(\%) = \frac{FN+FP}{TB} \times 100 \tag{13}$$

where: TP is the number of true positives; TN is the number of true negatives; FP is the number of false positives; FN is the number of false negatives; and TB is the total number of beats.

The assessment parameters for our algorithm are presented in Table 1. The proposed algorithm produces 98 FN beats and 163 FP beats for a total detection of 60,981 beats. The algorithm achieved very interesting performances such as a sensitivity of 99.83%, a positive predictivity of 99.72%, and an error rate of 0.44%.

Table 1. Performance of the proposed method

Record	TB	TP	FN	FP	Se (%)	P+ (%)	ER (%)
100	2274	2274	0	0	100	100	0
101	1874	1874	0	14	100	99.26	0.75
102	2192	2191	1	0	99.95	100	0.05
103	2091	2091	0	0	100	100	0
104	2311	2307	4	16	99.83	99.31	0.87
105	2691	2687	4	16	99.85	99.41	0.74
106	2098	2094	4	6	99.81	99.71	0.48
107	2140	2140	0	0	100	100	0
108	1824	1819	5	25	99.73	98.64	1.64
109	2535	2535	0	0	100	100	0
111	2133	2129	4	1	99.81	99.95	0.23
112	2550	2547	3	5	99.88	99.80	0.31
113	1796	1795	1	4	99.94	99.78	0.28
114	1890	1887	3	5	99.84	99.74	0.42
115	1962	1962	0	0	100	100	0
116	2421	2420	1	4	99.96	99.83	0.21
117	1539	1532	7	5	99.55	99.67	0.78
118	2301	2300	1	2	99.96	99.91	0.13
119	2094	2080	14	10	99.33	99.52	1.15
121	1876	1872	4	5	99.79	99.73	0.48
122	2479	2474	5	5	99.80	99.80	0.40
123	1519	1513	6	5	99.61	99.67	0.72
124	1634	1632	2	4	99.88	99.76	0.37
200	2792	2787	5	5	99.82	99.82	0.36
201	2039	2029	10	6	99.51	99.71	0.78
202	2146	2140	6	4	99.72	99.81	0.47
203	3108	3104	4	10	99.87	99.68	0.45
205	2672	2668	4	6	99.85	99.78	0.37
Total	60981	60883	98	163	99.83	99.72	0.44

4.2. Comparison with other approaches
To better assess the performance of an ECG R-peak detection algorithm, it should be compared with other published methods in this field of research. Indeed, Table 2 summarizes the performance of the main techniques developed in QRS complex detection and extraction. According to this table, it seems clear that the proposed method is ranked among the best techniques developed in the field of ECG signal feature extraction.

Table 2. Comparison of QRS detector performance

Algorithm name	Se (%)	P+ (%)	ER (%)
Karimipour and Homaeinezhad [23]	99.81	99.7	0.49
Pan-and Tompkins [24]	99.75	99.53	0.675
Li *et al*. [12]	99.89	99.94	0.14
Poli *et al*. [25]	99.6	99.5	0.9
Madeiro *et al*. [26]	99.15	99.18	1.69
Zidelman *et al*. [13]	99.64	99.82	0.54
Yochum *et al*. [27]	99.85	99.48	0.67
Martinez *et al*. [28]	99.8	99.86	0.34
Hamilton and Tompkins [29]	99.69	99.77	0.54
Merah *et al*. [16]	99.84	99.88	0.28
Aqil *et al*. [3]	99.84	99.53	0.62
Proposed method	99.83	99.72	0.44

4.3. Detection robustness

In the proposed method, we made a selection of the detail coefficient of the SWT decomposition to extract a specific wave from the ECG signal. In addition, the approximation coefficients were not used. These coefficients contain the low-frequency components of the signal. Therefore, the possibility of analyzing the signal in the presence of some noise such as the baseline wander (BLW) seems feasible. To highlight this important result, we applied the algorithm to an ECG signal comprising a BLW. This last is synthesized using the sinusoidal model as given (14).

$$Bw(t) = A\,sin(2\pi f t) \tag{14}$$

where the amplitude $A = 0.2\, mV$ and the frequency $f \in [0 - 0.5\, Hz]$. The result of feature extraction from the ECG signal containing BLW noise is given in Figure 11.

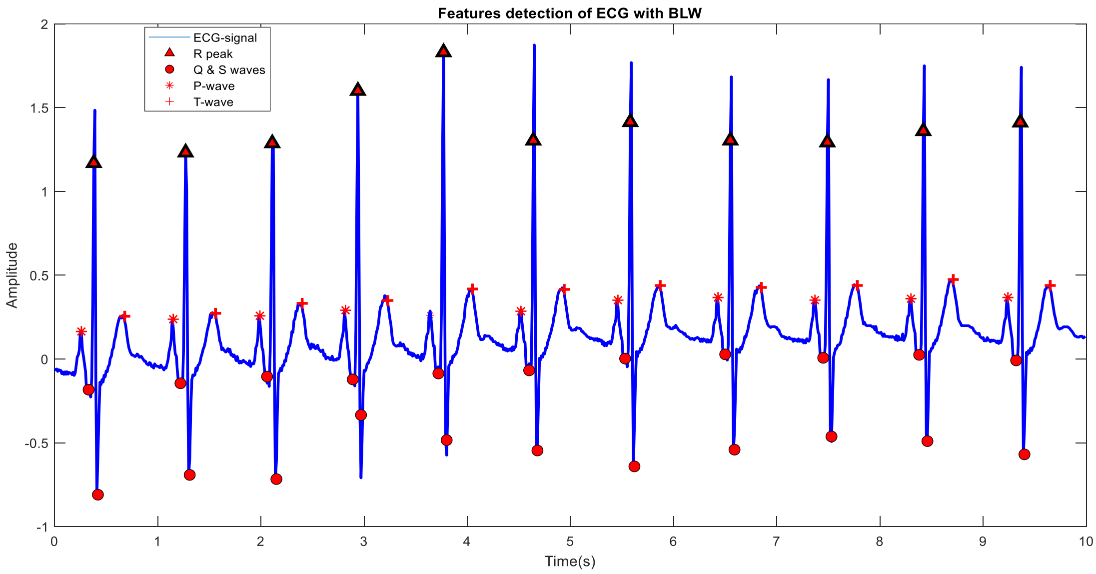


Figure 11. Features detection of ECG with BLW

5. CONCLUSION

In this paper, we have presented a new method for detecting the different waves of the ECG signal. This method is based on the selection of the appropriate detail coefficients for the detection of each wave of the signal. Indeed, the choice comes from a temporal and frequency study of the different detail coefficients obtained by the SWT transformation of the signal. The choice of this type of transform is justified by the fact that it achieves the best compromise between the CWT and DWT transforms. We have shown that the SWT has excellent performance in detecting ECG signal features and therefore should not be limited to the use of signal denoising.

To take full advantage of this transform, it is necessary to make a good choice of the wavelet and the level of decomposition. In this context, the wavelet to be chosen should have a similar shape to the signal to be analyzed and the level of decomposition has been determined by the analysis of the energy content of the detail coefficients. This level of decomposition must be as low as possible to reduce the processing time.

The proposed algorithm presents excellent performances in terms of sensitivity, predictivity, and error rate. Compared to other methods, our algorithm can be ranked among the most efficient. Indeed, the technique presents a sensitivity of 99.83%, a predictivity of 99.72%, and an error rate of 0.44%. Moreover, most of the methods are limited to the detection of the QRS complex without considering the P and T waves of the signal. A further important advantage of the proposed method is its ability to detect different waves even in the presence of baseline wander (BWL) of the ECG signal. This property makes it possible to bypass the filtering operation of BLW.

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BIOGRAPHIES OF AUTHORS

Mounaim Aqil is currently a full professor in the Mechatronics Department at Higher School of Technology, Sultan Moulay Slimane University, Béni-Mellal, Morocco. In 2018, he received his PhD in electrical engineering from Mohammed V University. His current research interests include signal processing, embedded electronic systems and IoT. He is member of engineering and applied physics team. He can be contacted at email: mounaim.aqil@usms.ma.

Atman Jbari is currently a full professor at the Electrical Engineering Department of national higher school of arts and crafts (ENSAM), Mohammed V University in Rabat, Morocco. In 2009, he received his Ph.D. in computer and telecommunications from Mohammed V-Agdal University. He is a member of electronic systems, sensors and nanobiotechnology research group. His current research interests include signal processing, blind source separation and embedded electronic systems. He can be contacted at email: atman.jbari@um5.ac.ma.