

P-Wave Detection Combining Entropic Criterion and Wavelet Transform

Sawsan Rekik, Nouredinne Ellouze

Department of Electric Engineering, National School of Engineering of Tunis,
Tunis, Tunisia

Email: Sawsan.Rekik@enit.rnu.tn, n.ellouze@enit.rnu.tn

Received 2 June 2015; accepted 17 July 2015; published 21 July 2015

Copyright © 2015 by authors and Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

The objective of this paper is to develop an efficient P wave detection method in electrocardiogram (ECG) using the local entropy criterion (EC) and wavelet transform (WT) modulus maxima. The detection of P wave relates to the diagnosis of many heart diseases and it is also a difficult point during the ECG signal detection. Determining the position of a P-wave is complicated due to the low amplitude, the ambiguous and changing form of the complex. In a first step, QRS complexes are detected using the pan-Tompkins method. Then, we look for the best position of the analysis window and the value of the most appropriate width to the P wave. Finally, the determination of P wave peaks, as well as their onsets and offsets. The method has been validated using ECG-recordings with a wide variety of P-wave morphologies from MIT-BIH Arrhythmia and QT database. The P-wave method obtains a sensitivity of 99.87% and a positive predictivity of 98.04% over the MIT-BIH Arrhythmia, while for the QT, sensitivity and predictivity over 99.8% are attained.

Keywords

ECG, P-Wave, Entropy, Wavelet Transform, Modulus Maxima

1. Introduction

The analysis of the ECG is widely used for diagnosing many cardiac diseases, which are the main cause of mortality in developed countries. Since most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its significant points (characteristic wave peaks and boundaries), the development of accurate and robust methods for automatic ECG delineation is a subject of major importance, especially for the analysis of long recordings. In order to interpret the ECG and use it to diagnose abnormalities, it is important to know the normal characteristics of the ECG, and understand the mechanisms underlying the generation of each

segment of the ECG.

The P wave is caused by atrial depolarization. The duration is normally not greater than 120 ms. The normal shape of the P wave does not include any notches or peaks. It can be positive, negative, or biphasic in the remaining leads. An absent P wave in the ECG may signify sinoatrial block [1]. Some researchers present some P wave detection method based on wavelet transform [2]. Wavelet analysis provides important information about the mathematical morphology of a signal. Using this method, it is possible to describe the characteristic elements of a complex quasi-periodic signal. But P wave's amplitude is much smaller than other waves, so the accuracy of detection is limited.

We present here a new method for P wave's location combines entropic criterion and wavelets transform (ECWT). We are interested in entropy as a measure of the amount of information contained in a signal. The amount of information can also be interpreted as the unpredictability of events in a signal. More events are unpredictable, the more information it contains is important and its entropy is high. This measure is favorable to the segmentation or an unpredictable event will be proportional to the increase in entropy. The entropic criterion can indicate the maximum of P wave's energy.

The wavelet transform provides a description of the signal in the time-scale domain, allowing the representation of the temporal features of a signal at different resolutions; therefore, it is a suitable tool to analyze the ECG signal, which is characterized by a cyclic occurrence of patterns with different frequency content (QRS complexes, P and T waves). Moreover, the noise and artifacts affecting the ECG signal also appear at different frequency bands, thus having different contribution at the various scales.

For the singularity detection through local maxima, we rely on the approach Mallet and Hwang [3], using a first derivative Gaussian function as the prototype wavelet. The principle of this approach is, firstly, to use the entropy function for identifying the concentrated energy of the P wave and on the other hand to link the result with that of the modulus maxima allowing an exact location.

The paper is organized as follows: in Section 2, we present the theory of entropic local criterion and the notion of wavelets transforms modulus maxima. We show the detection method of P wave. Onsets and ends are performed in Section 3. Then, we interpret the results of P wave detection. The results of the validation on two databases (MIT-BIH, QT) and their comparison to other algorithms are given in Section 4. Finally, the conclusion is presented in Section 5.

2. Entropy and Wavelet Transform Modulus Maxima

This article proposes a method combining entropic criterion and Wavelet Transform Modulus Maxima to detect P wave. The two theories are introduced in the following.

2.1. Entropic Local Criterion

In the case of the representation of the signal, entropy comes to measuring the fineness and precision of the location information, location in both time and frequency. Entropy will allow us to see where the energy signal is localized in the time-frequency plane. Specifically, it will allow us to know what time-frequency representation allows the best location information in the plan. The entropy associated with a discrete scalar random variable with X achievements $\{x_1, \dots, x_N\}$ and the probability distribution $\{p_1, \dots, p_N\}$ measures its mess [4]. It is defined by:

$$H[X] = -\sum_{k=1}^N p_k \ln p_k, \quad \text{with} \quad \sum_{k=1}^N p_k = 1 \quad (1)$$

Since entropy operator will be applied to a channel signal $\{x[n]\}, n \in [0, N-1]$, it has implicitly been normalized to 1, so that:

$$\sum_{k=0}^{N-1} |X[k]|^2 = 1, \quad \text{where} \quad \sum_{k=0}^{N-1} |X[k]|^2 = \sum_{n=0}^{N-1} x[n]^2 \quad (2)$$

With $X[k]$ the Discrete Fourier Transform DFT of $x[n]$ for $n \in [0, N-1]$ defined for $k \in [0, N-1]$ by:

$$X[k] = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} x[k] \cdot e^{-2\pi i k \frac{n}{N}} \quad (3)$$

For any signal $\{x[n]\}, n \in [0, N-1]$, the entropy in the sense of the energy distribution of frequencies is legitimate with the following definition:

$$H_{[0, N-1]}(x) = \sum_{k=0}^{N-1} \left(\frac{|X[k]|}{\nu} \right)^2 \cdot \log \left(\frac{|X[k]|}{\nu} \right)^2 \quad (4)$$

where

$$\nu = \sqrt{\sum_{n=0}^{N-1} x[n]^2}$$

2.2. Wavelet Transform Modulus Maxima

Most of the information in a signal is carried by its irregular structures and its transient phenomena, called singularities. A method that excels in finding and identifying these singularities is the Wavelet Transform; because of its capability of decomposing a signal into elementary building blocks that are well localized in both time and frequency. Because of this capability, the Wavelet Transform is capable of defining the local regularity of a signal. The local regularity of a function is often measured with the Lipschitz exponents [5], also called the Hölder exponent. We define what we mean by a local maximum of the wavelet transform modulus [3]. Let $Wf(x)$ is the wavelet transform of a function $f(x)$

- We note a local extremum any point x_0 such that $\frac{d(Wf(x))}{dx}$ has a zero crossing at $x = x_0$, when x varies.
- We note a modulus maximum; any point x_0 such that $|Wf(x)| < |Wf(x_0)|$ when x belongs to either a right or left neighborhood of x_0 , and $|Wf(x)| \leq |Wf(x_0)|$ when x belongs to the other side of the neighborhood of x_0 .
- We call maxima line, any connected curve in the scale space x along which all points are modulus maxima.

3. P-Wave Detection

Based on the waveform, Laurent Clavier [6] divide the different P waves encountered in five classes.

- Class 1: the P wave has a relatively symmetrical reflecting normal patient.
- Class 2: P wave has a normal climb, but relatively slow down.
- Class 3: the P wave has a relatively slow rise but a normal descent.
- Class 4: the P wave has a double hump.
- Class 5: P wave is biphasic; usually it is a pathological wave.

3.1. P-Peak Detection

The detection algorithm of P wave is generally designed according to three steps (Figure 1).

The first is based on a preliminary localization of the QRS complex and consists in seeking, in a window preceding the QRS, a trace of the P wave. The second step is based on the research for an analysis window well adapted to the width and to the position of the P wave by means of the local entropy criterion which measures the temporal unpredictability and disorder in the frequency signals and is an index for the segmentation. As part of the segmentation, the entropy changes reflect the presence of a change in the signal. The entropy is going to help us to adopt the width of the window to that of the P wave. In this case, our research becomes more efficient and more objective. By the way, we will gain in computing time for the next step of this method. We succeed and optimization the algorithm. The third is based on the detection of the P wave by modulus maxim's method.

3.1.1. Step 1

The ECG signal gotten at the time of the registration is contaminated generally by different sources of noises that can disrupt the phase and the amplitude characteristics of the useful signal, from where the necessity of a

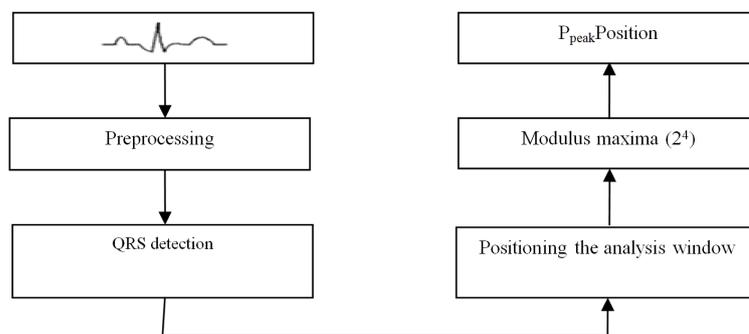


Figure 1. Algorithm of P peak detection.

good filtering [7]. We apply a band pass filter [8] to eliminate the noises caused by the breathing, the movements of muscles and the baseline. This filter is constituted by the combination of a passes low filter and another passes loud. The two are based on a sampling rate of 360 Hz [9].

In general, the normal ECG rhythm means that there is a regular rhythm and waveform. However, the ECG rhythm of the patient with arrhythmia will not be regular in certain QRS complexes. We use the different characteristics that arrhythmias exhibit to detect the abnormal ECG waveform. We first need to find the location of every QRS complex.

The locations of QRS complex have the maximum variation in the slopes. This property was used to detect the location of QRS complex. The method of Pan-Tompkins was adopted to detect the QRS complex [10]. The Pan and Tompkins QRS detection algorithm identifies the QRS complexes based upon digital analysis of slope, amplitude, and width of the ECG data. The algorithm implements a special digital band pass filter. It can reduce false detection caused by the various types of interference present in the ECG signal.

3.1.2. Step 2

The P wave is a rounded peak occurred before the QRS complex. Therefore, the P wave can be found based on the location of the QRS complex. The method consists in finding the right and better position of the analysis window (Figure 2).

The detection algorithm P-wave refers to the R peak backwards t_r ($t_{Rpeak}-200$ ms) so as to be in advance phase by report to the QRS complex (Figure 3).

t_r depends on the RR period in 5 seconds. Statistically, over a period for many patients and healthy on a recording time of one hour for each, P wave holds 10%, the QRS complex occupies 8% and the T wave occupies 20% of the RR period. The choice of the window is taken of such way as the energy in the side of lobes being as small as possible to minimize the errors in the entropy and increase the accuracy of positional. We perform the decomposition of the ECG signal for 4 levels (2^1 , 2^2 , 2^3 and 2^4) in which his higher energy is. For scales larger than 2^4 , the energy of the QRS complex is very low, only the P and T waves have significant components.

The detection of the P wave is based on the variations in local entropy rather than the entropy itself. It uses the local entropy criterion. Entropic Local Criterion is a time function, measuring variations in the energy concentration of the short-term spectrum of the signal. The measurement of concentration of energy or spectral disorder is used Shannon [11] entropy (Equation (1)). Due to significant changes in this measure in the context of the one part and the position of the analyzed frequencies, we add to this extent the notion of stability. In this case, we talk about the criterion entropic local stabilized

We set the first W_i analysis window, which L_i its width, from t_r . For that, we calculate the normalized and localized entropy of analysis window W_i (L_i) for 2^4 scale according to the Equation (4). The value of entropy H_i calculated through the W_i window is saved in a table.

The search for the best width of the window operates according to an iterative algorithm. In every iteration the width of the window is multiply by 2 ($L_i \times 2$) to look for the maximum of quantity of information contained in the wave P. The same steps are applied on the next analysis window W_{i+1} with $L_{i+1} = L_i \times 2$. So, we create an increasing dyadic table for the window's various values (Table 1).

By comparing the last two values of the found entropies, we start again calculating next entropy for the window W_{i+1} until the value of two successive entropy (H_{n+1} , H_n) remains constant. We retain the window W_n of L_n

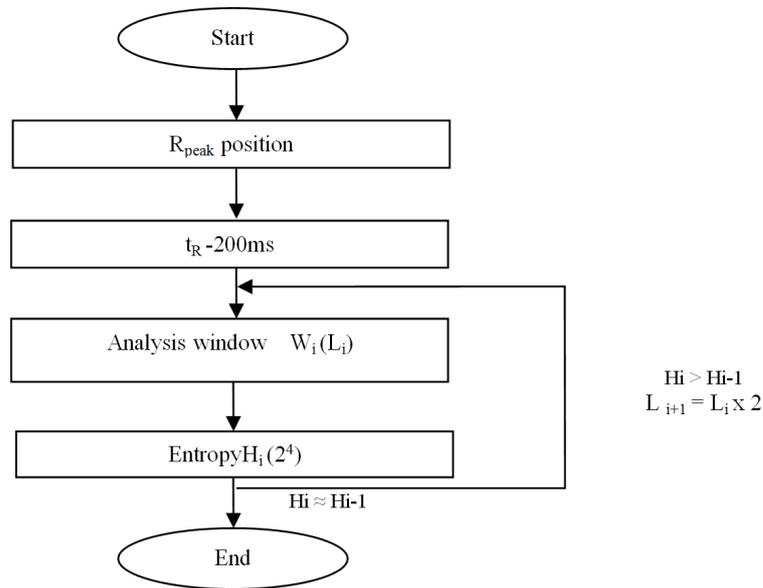


Figure 2. Algorithm of positioning analysis window.

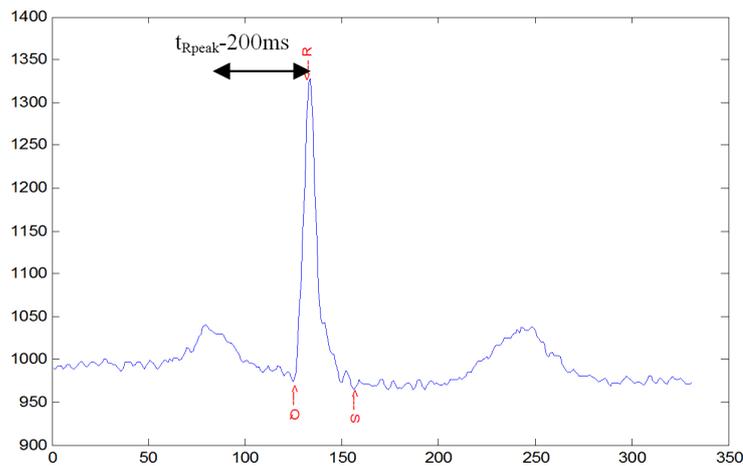


Figure 3. Back period t_{R} .

Table 1. Various values of windows.

Windows W_i	Width L_i
W_0	L_0
W_1	$L_1 = L_0 \times 2$
W_2	$L_2 = L_1 \times 2$
W_3	$L_3 = L_2 \times 2$
W_4	$L_4 = L_3 \times 2$
W_5	$L_5 = L_4 \times 2$

width.

Figure 4 shows three successive analyzes of windows (W_0, W_1, W_2, W_3) showing the growth of their width. We note that the value of the entropy increases when the width of the window widens at each iteration since the

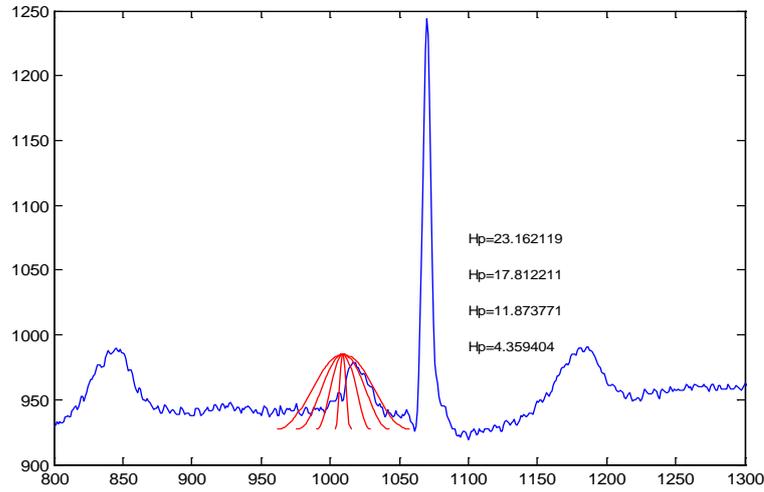


Figure 4. Successive analysis windows and their entropies' values.

detection of the information is more and more centralized on the P wave.

3.1.3. Step 3

At this level of the algorithm, we have a window (W_n) adapted in width and in position to the P wave. Once the analysis window is fixed, we calculate the modulus maxima for the 2^4 scale to detect the position of the P peak applied to the W_n . Mainly at scales 2^4 , P wave has its major component, whereas artifacts produce isolated maximum or minimum lines which can be easily discarded. If the signal is contaminated with high-frequency noise, the most affected scales are and, being higher scales essentially immune to this sort of noise.

Using a first derivative Gaussian function as mother wavelet due to having one zero moment. It is therefore well adapted to detect the amplitude discontinuities in the signal; it delivers more to the spread of the maximum fine scales [12]. It is defines as follows

$$\Psi(t) = -\frac{\sqrt{2}}{\pi^{1/4} \sigma^{3/2}} t \exp\left(\frac{-t^2}{2\sigma^2}\right), \text{ with } \sigma = 0.25 \quad (5)$$

The waves produce a positive maximum-negative minimum pair along the scales, with a zero crossing between them. Each sharp change in the signal is associated to a line of maxima or minima across the scales. The passages by zero or zeros-crossings of the wavelet transform correspond in maxima premises or minima of the signal smoothed in the various scales and the maximal absolute values of the transformed it waves are associated with the maximal slopes. Using the information of local maxima, minima and zero crossings at 2^4 scales, the algorithm identifies the significant points P wave detection and delineation.

3.2. Onset/Offset Detection

Our detection method of P wave is also responsible for detecting P_{on}/P_{off} which is the start and end of the P waves. Our algorithm comprises two steps defined as follows (Figure 5), the beginning and the end of the P wave is determined based on the detection of P_{peak} .

The onset of P wave is before the first slope of the position of P peak. In the same way, the offset of P wave is after the last slope of the position of P peak. We calculate the modulus maxima of the (first/last) slope of the P peak's position for the 2^4 scale. We considered the modulus maxima calculated for the analysis window W_n already attached to the P peak search step.

4. The ECWT Method Results and Performance

The ECG signals under test of the transformations are taken from the website of MIT-BIH Arrhythmia Database [13]. The sampling frequency of the data is 360 Hz. We will discuss certain parts of signals chosen.

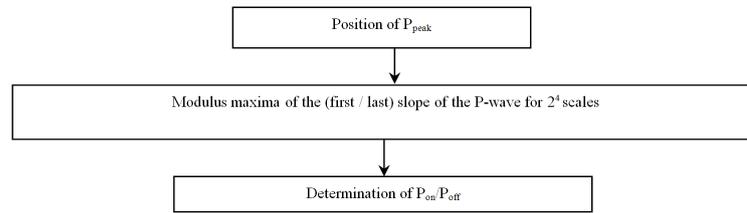


Figure 5. Successive analysis windows and their entropies' values.

4.1. Baseline Drift

The ECWT based method only considers variations of the signal that has a certain resemblance with the P-wave. Therefore, it is insensitive to baseline drift (**Figure 6**).

4.2. Noise (EMG)

Most methods require frequently adapted thresholds in order to detect a low amplitude P-wave. In most cases these thresholds are used to distinguish the wave from the noise. By using scales that contain most part of the energy of the P-wave it is possible to acquire a precise detection (see **Figure 7**).

4.3. Low Amplitude

Most methods require frequently adapted thresholds in order to detect a low amplitude P-wave. In most cases these thresholds are used to distinguish the wave from the noise (**Figure 8**). By using scales that contain most part of the energy of the P-wave it is possible to acquire a precise detection.

4.4. Ambiguous Amplitude

As most methods, the ECWT method uses certain decision rules to distinguish different kinds of P-waves. The difference with the other methods lies in the fact that the rules are applied to the transformation instead of to the pure signal. The transformation gives a clearer view of the signals information and therefore it is better suited for decision rules (**Figure 9**).

4.5. Absent Wave

In some cases, the P-wave is absent. The figure below illustrates the case where the P wave is present with an important amplitude in start of signal but absent after (**Figure 10**).

4.6. P-Wave Performance

The datasets are signals coming from the MIT-BIH Arrhythmia Database [13] and QT Database [14]. However not every long signal contains large amounts of useful information. When there is no change in a wave throughout the whole signal, it is not useful to analyze every peak. Therefore, only the parts which define the ECG will be discussed. The performance of the methods will be tested by using several cases with certain difficulties. The results are detailed in the table below (**Table 2**).

- Number of True Positive detections (TP).
- Number of False Positive detections (FP).
- Number of False Negative detections (FN).
- Percentage of detected P-waves (S_e).

$$S_e = \frac{TP}{TP + FN}$$

- Percentage of positive predictivity (P^+)

$$P^+ = \frac{TP}{TP + FP}$$

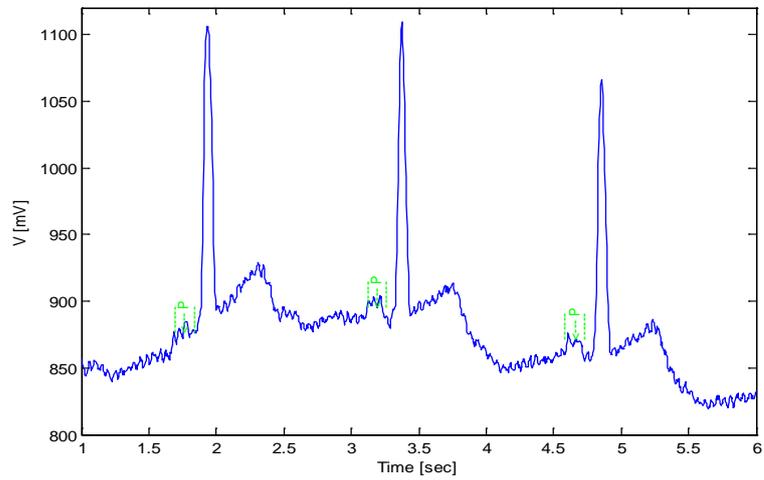


Figure 6. P wave detection (121.dat).

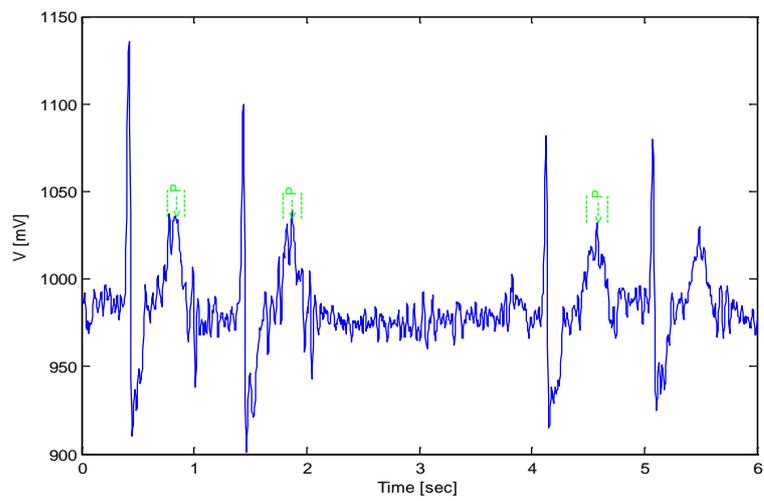


Figure 7. P wave detection (232.dat).

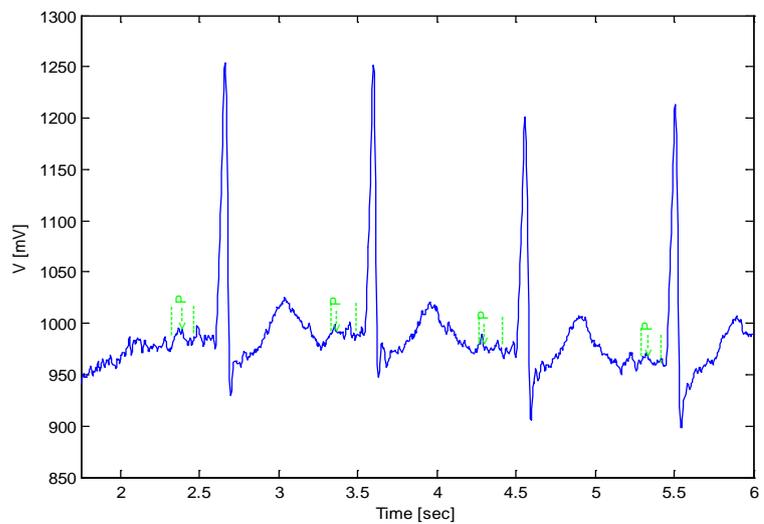


Figure 8. P wave detection (200.dat).

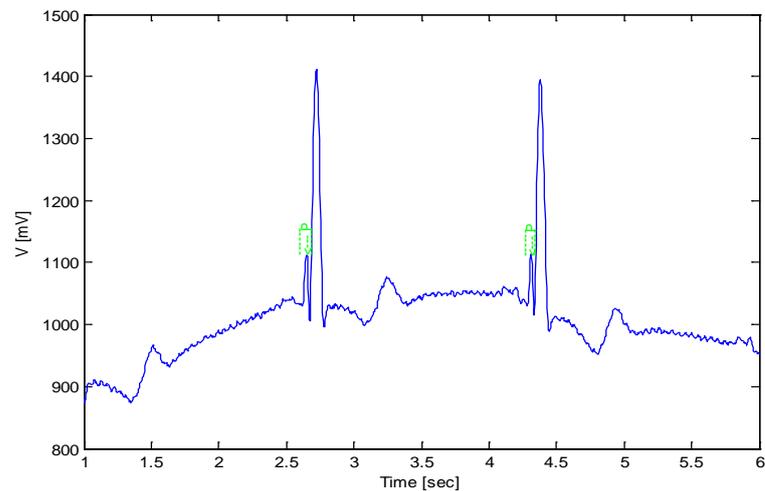


Figure 9. P wave detection (124.dat).

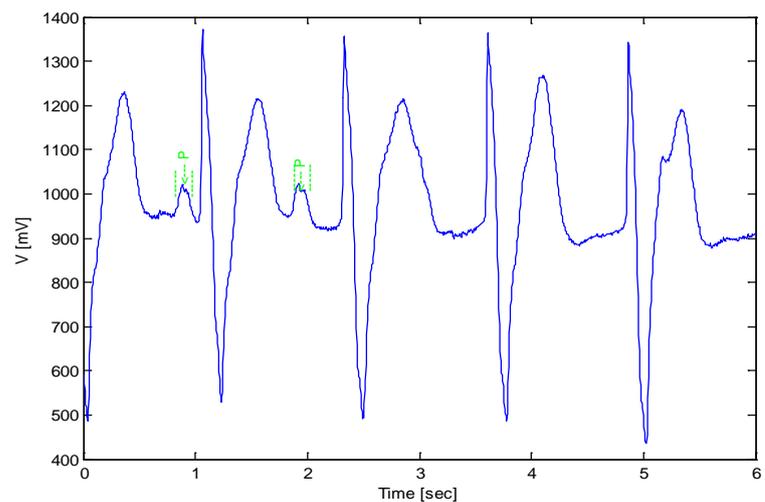


Figure 10. P wave detection (107.dat).

Table 2. P wave detection performance.

Database	P-wave detection	Beats	TP	FP	FN	S_e (%)	P^+ (%)
MITBIH	ECWT (this work)	54,714	54,557	76	109	98.87	98.04
	Pan <i>et al.</i> [10]	54,904	54,766	253	138	99.75	99.54
QT	ECWT	63,210	63,184	54	37	99.94	99.89
	Martinez <i>et al.</i> [15]	64,387	64,395	57	41	99.92	99.88

The detection results on the MITDB and QTDB obtained by our ECWT of P detection and other published detectors are given in **Table 2**. Our algorithm does not need any learning period. The proposed ECWT detection algorithm achieves very good detection performance on the two studied databases. This algorithm attains $S_e = 98.87\%$ and $P^+ = 98.04\%$ for the MITDB. On QTDB, our algorithm presents a positive predictivity (P^+) about 99.89% and sensitivity (S_e) about 99.94%.

5. Conclusions

We have presented in this paper a new method for P wave's locations using the local entropic criterion, in order

to focus on the maximum of P wave's energy, and wavelet transform over some successive scales. The algorithm has been validated using two standards databases MIT-BIH Arrhythmia and QT, with different sampling rates and a wide diversity for P wave forms.

Our method achieves very good detection performance on the two studied databases. This algorithm attains $S_e = 98.87\%$ and $P^+ = 98.04\%$ for the MITDB. On QTDB, it presents a positive predictivity (P^+) about 99.89% and sensitivity (S_e) about 99.94%.

References

- [1] Le Page, R. and Boucher, J. (2001) Détection et Analyse de l'Onde P d'Un Electrocardiogramme. Colloque GRETSI'01, France.
- [2] Li, C., Zheng, C. and Tai, C. (1995) Detection of ECG Characteristic Points Using Wavelet Transform. *IEEE Transactions on Biomedical Engineering*, **42**, 21-28. <http://dx.doi.org/10.1109/10.362922>
- [3] Mallat, S. and Hwang, W.L. (1992) Singularity Detection and Processing with Wavelets. *IEEE Transactions on Information Theory*, **38**, 617-643. <http://dx.doi.org/10.1109/18.119727>
- [4] Djafari, M. (1998) Entropy in Signal Processing. *Laboratory of Signal and System CNRS-SUPELEC-UPS*, **15**, 541-551.
- [5] Mallat, S. (1991) Zero-Crossings of a Wavelet Transform. *IEEE Transactions on Information Theory*, **37**, 1019-1033. <http://dx.doi.org/10.1109/18.86995>
- [6] Clavier, L. (1997) Analyse du signal électrocardiographique en vue du dépistage de la fibrillation auriculaire. Thèse de l'Université de Rennes I.
- [7] McNames, J. (2005) Optimal Rate Filters for Biomedical Point Processes. *27th Annual International Conference of the Engineering in Medicine and Biology Society*, Shanghai, 17-18 January 2006, 145-148. <http://dx.doi.org/10.1109/iembs.2005.1616363>
- [8] Belgacem, N., Chikh, M. and Reguig, F. (2003) Détection et Identification des Arythmies Cardiaques Par Application des Réseaux de Neurones. *Conférence Internationale sur les Systèmes de Télécommunications d'Electronique Médicale et d'Automatique CISTEMA*, Tlemcen, 27-29 September 2003, 236-239.
- [9] Khelil, B., Kachouri, A. and Ben Messaoud, M. (2006) Nouvelle Tendence Technologiques en Génie Electrique et Informatique. Springer, New York.
- [10] Pan, J. and Tompkins, W. (1985) A Real Time QRS Detection Algorithm. *IEEE Transactions on Biomedical Engineering*, **32**, 230-236. <http://dx.doi.org/10.1109/TBME.1985.325532>
- [11] Shannon, C. and Weaver, W. (1948) The Mathematical Theory of Communication. *Bell System Technical Journal*, **27**, 379-423, 623-656. <http://dx.doi.org/10.1002/j.1538-7305.1948.tb00917.x>
- [12] Mallat, S. and Zhong, S. (1992) Characterization of Signals from Multiscale Edge. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **14**, 710-732. <http://dx.doi.org/10.1109/34.142909>
- [13] Moody, G.B. and Mark, R.G. (2001) The Impact of the MIT-BIH Arrhythmia Database. *IEEE Engineering in Medicine and Biology Magazine*, **20**, 45-50. <http://dx.doi.org/10.1109/51.932724>
- [14] QT ECG Database (1997) Massachusetts Institute of Technology. <http://www.physionet.org/physiobank/database/qtdb>
- [15] Almeida, R., Martinez, J.P., Olmos, S., Rocha, A.P. and Laguna, P. (2004) A Wavelet-Based ECG Delineator: Evaluation on Standard Databases. *IEEE Transactions on Biomedical Engineering*, **51**, 570-581.