On the Algorithm for QRS Complexes Localisation in Electrocardiogram

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Summary
Various techniques have been utilized in computer-assisted arrhythmia recognition for the management of cardiac disorders. To identify any arrhythmias characteristics, generally, the QRS complex is taken as a reference because the important amplitude. Several algorithms are developed to localise the R peaks. Most physiologic signal detection algorithms are based on pre-processing and deciding stages if an incoming peak is a true component based on a user specified threshold. Some have significantly large processing times. In this paper, a simpler idea is proposed and developed to localise efficiency the occurrence time of R wave of electrocardiograms. The proposed algorithm treats the decision step. Our key idea is to equalize the maxima of the signal and to attenuate the lower amplitude of P and T. to accomplish the task, we introduce a characteristic function which acts essentially on the zone of the threshold action; consequently, the activated zone where the threshold occurs is enlarged and the amplitude of the other domains is attenuated. The evaluation of the tested algorithm is performed to pre-classified ECG data from the MIT-BIH database and The MIT-BIH Polysomnographic Database. The simulation result prove the efficiency by exhibiting over 99,5% of sensitivity and positive predictivity. Due to its fast time execution, this algorithm can be applied in routine ambulatory heart rate screening.

Key words:
Electrocardiogram, beat variability, QRS detection, wavelet transform, sensitivity.

1. Introduction

In recent years, computer-assisted ECG interpretation is playing an increasing role in assisting medical doctors in diagnosis and treatment of heart anomalies. So, significant amount of research has focused on the development of algorithms for accurate diagnosis of arrhythmias diseases. Because the form and the amplitude of the QRS complexes are the most perceptible parameters in electrocardiogram ECG, it is a subject of researches to any diagnosis or/and analysis of the beats heart. When processing long term ECGs, it is often not possible or at least very time consuming, to scroll through the whole signal in order to find interesting sequences within the ECG. Therefore, many automatic algorithms are developed to detect the QRS complexes.

The common physiologic signal detection algorithms are based on pre-processing and deciding steps. A user specified threshold is chosen to separate the amplitude considered as true or false R peak of the ECG. Usually the localisation of the QRS complex is performed by a well known optimized Pan-Hamilton algorithm [17]. In the literature, different approaches are developed. The overview of the principles is summarized in [12] [1]. Older detectors are reviewed in [8]. Recently new approaches are been introduced, like Artificial neural networks [19], genetic algorithms, wavelet transforms [20], and filter banc techniques [2]. A generalized scheme of the most QRS detectors structure presents two stages: a pre-processing stage, usually including linear filtering followed by a nonlinear transformation, and the decision rules one [13]. Other methods have been investigated as well, RR variability characteristics using wavelet and fractal analysis. They have reported high sensitivity and specificity for automatic Atria Fibrillation [7]. The performances of the most algorithms are demonstrated and the sensitivity exceeds the 99%.

In this paper, a new approach is investigated in order to identify and to localise the position of QRS complex efficiency. The proposed algorithm consists on filtering the recorded data by discrete wavelet technique and processing the filtered data by an adequate characteristic function which attenuates the lower level and equalizes the maxima. The activated domain where the threshold occurs is then enlarged and the amplitude of the other domains is attenuated. Consequently, the last transformation acts to suppress the P and T waves, and to pass or enhance the QRS wave. Other advantages of this proposed algorithm are the reduction of the computational time and the elimination of some weak points found in the earlier algorithms. The method is tested and evaluated in simulation, for MIT-BIH Arrhythmia and MIT-BIH Polysomnographic Database, manually annotated and developed for validation purposes. As a result, it is observed that the performances of the QRS complexes detector were attained a Sensitivity of 99,82%, a Positive Predictivity of 99,86% and False Discovery Rate of 0,32%.

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In this preliminary study we sought to quantitatively evaluate the performance by compare the results produced by the actual and different methods of simulated ECG signals.

2. Features of the ECG components

The electrocardiograph (ECG) is the electrical activity of the heart. The ECG can be generally divided into three components, P wave, QRS complex and T wave, corresponding to waves of depolarization and repolarization of cardiac muscle. The ECG of a single heartbeat and its relevant portions are indicated in figure 1.

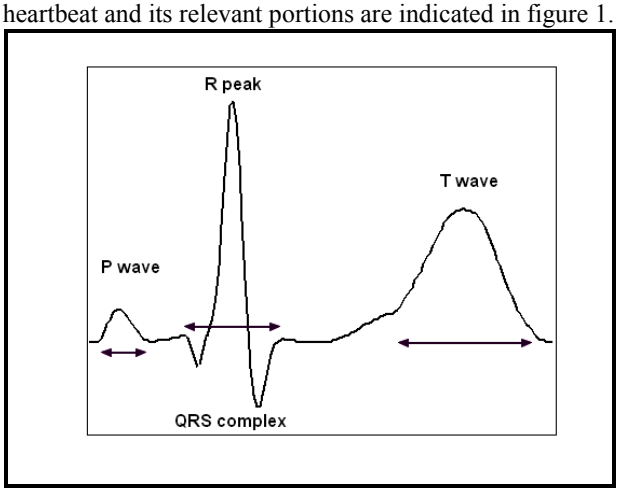

Fig. 1 Components of normal ECG

These waves are related to the activity of the auricles and the ventricles in the form of activation or recovery. The muscles contraction of the heart produces a visible wave of depolarization in the layout of the ECG and the return to the rest state constitutes a wave of repolarisation represented by an iso-electric tension which constitutes the base line. The frequencies relating to each wave present variations according to the rate of heartbeat. The change of the rhythmic beat is called Arrhythmia. The frequency band of the ECGs signals is approximately 60 Hz for a normal subject and can increases to 130 Hz for an abnormal patient. Table 1 gives the actions of the membranes of the heart in the normal case and the associated waves like their temporal and frequencies characteristics.

Tableau 1: Mechanical and Electrical features of normal arrhythmia.

Mechanical actions	*Associated wave*	*Duration (ms)*	*Amplitude (mV)*	*Frequency (Hz)*
auricular depolarization	P wave	80-120	≤ 0.3	10
ventricles depolarizatio	QRS Complex	85-120	Q<0-S>0-R (0.5-2)	20-50
relax state of ventricles or repolarization	T wave	200	0.2	5
auricular repolarization	Hidden wave			

3. Details of proposed method

Typical approaches for most QRS detectors implement one or more of three types of processing steps, i.e., linear digital filtering, nonlinear transformation, and decision rule algorithms [10]. The pre-processing stage traditionally relies on signal derivatives and digital filters or wavelets and filter banks for recent algorithms. The decision stage decides if an incoming peak is a true component based on a user-specified threshold.

The proposed contribution consists to transform the filtered data by an appropriate function which attenuates the lower level and equalizes the maxima in order to threshold efficiency the undesired part of the ECG signals. As shown in figure 2, the proposed QRS detection algorithm can be divided into three main steps: pre-processing, transformation and redundancy elimination.

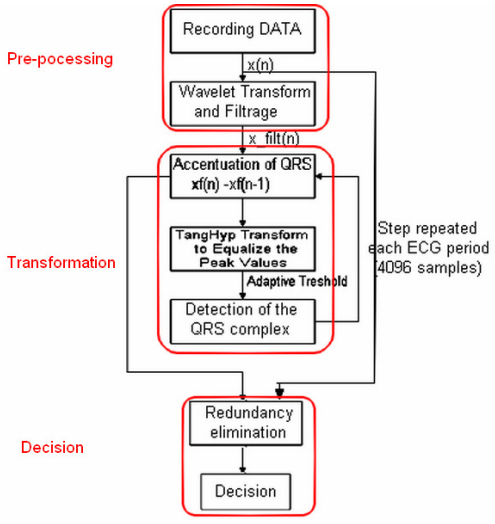

Fig 2. Flow chart of proposed QRS complex detection algorithm.

3.1 Preprocessing

In the ECG recording, there are two principal sources of noises, the 'technical' caused
by the physical parameters of the recording equipment, and the 'physiological' representing the bioelectrical activity of living cells not belonging to the area of diagnostic interest (also called background activity) (Aug 2003). The recording data must be filtered, in order to attenuate undesired components and artifacts, such as P-wave, T-wave, baseline drift and uncoupling noise. Whereas the attenuation of the P and T waves as well as baseline drift requires high-pass filtering, the suppression of uncoupling noise is usually accomplished by a low-pass filter. High and low-pass filtering can be carried out commonly or separately.
In this paper, The ECG signals are pre-processed by band pass filters (BPF) based on Discrete Wavelet Transform (DWT), retaining only three or four levels of details Dj of interest; that is

$$s\_filt = A_3 - A_7 = D_4 + D_5 + D_6 + D_7$$
$$BPF = [2.875;\ 45Hz\ ]$$

Where:
s-filt is the filtered ECG; Ai and Dj are the approximation and details signals of DWT.
A wavelet filter has many advantages. It is linear, so that it will scale properly when presented with ECGs of varying strength. It is time-invariant, so it will perform the same kind of filtering on each QRS component it sees (Kestler et al.1998).
As the figures 3(a) and 3(b) illustrate, the record 105 from the MIT-BIH standard database contains baseline wandering and the results after it passes through the wavelet filter.

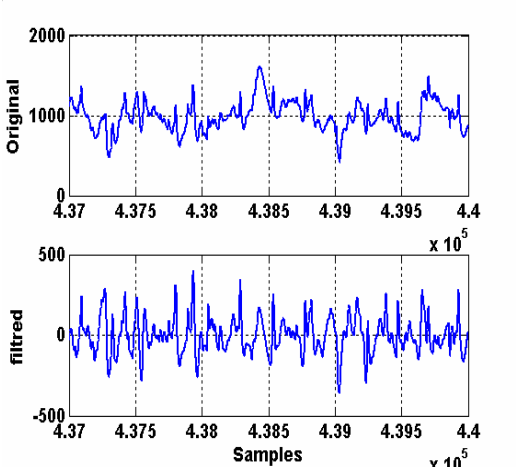

Fig 3. Process of Wavelet filtering of MIT 105. (a) fraction of original signal (b) Filtered signal.

3.2 Transformation of filtered signal

The first derivative of the filtered signal is estimated in order to accentuate the QRS variation and then its Hyperbolic Tangent is calculated. This function will saturate all peak values which take approximately same values. subsequently, the detection by the threshold becomes easier. Otherwise, the relative low amplitudes of P or T waves are attenuated. In other words, the algorithm acts to suppress the P and T waves, but to pass or enhance the QRS wave.
This task can be accomplished by any characteristic function represented by the figure 4.
Figure 5 shows an example of the output processing step performed by the detector during peak component detection.
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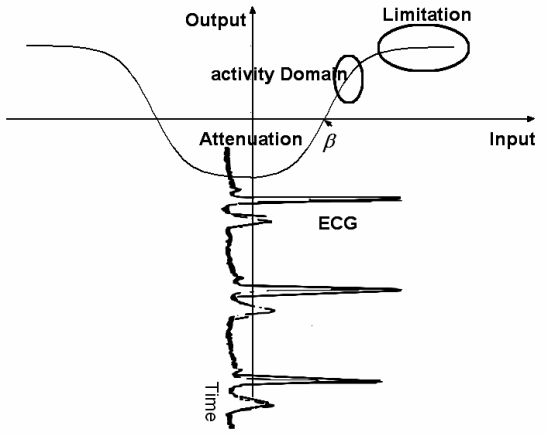

Fig. 4 Principle of amplification and attenuation

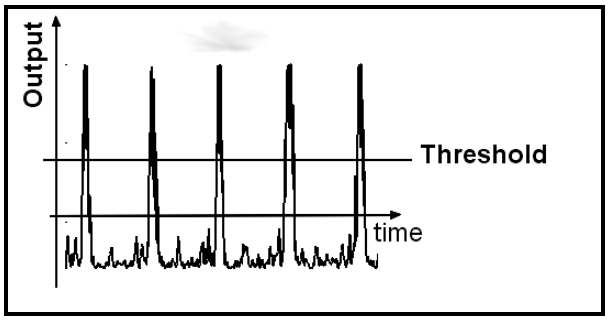

Fig. 5 Output signal treated

3.3 Peak detection and redundancy elimination

As shown in figure 4, the parameter β acts on the detection of the maximum. This parameter varies adaptively with the form and the power of the analyzed signal and it is calculated upon the mean of given ECG period as:

$$\beta = \frac{\alpha}{N}\sum_{i=1}^{N}|x_i|$$

Where: x_i is the amplitude of the filtered ECG, N is the number of beats and α is positive constant.
The value of the constant α is maintained practically the same for all simulated process (typically equals to 0,3).

As illustrated in figure 5, the QRS complex occurs if output stage is greater than any threshold thr, which is a positive real 0,3< thr <0,7. Practically, we observe the insensitivity of the algorithm on this parameter.
The last step consists for correcting the fiducially point time instant. The elimination of redundancy cycles are performed by taking the maximum of the filtered signal if the separation time between two successive R peak is the third of the estimated RR interval.
As illustrated in figure 6 and 7, the described steps of the proposed detection QRS method are illustrated for MIT 105. The differences between the maximum are clearly expanded.

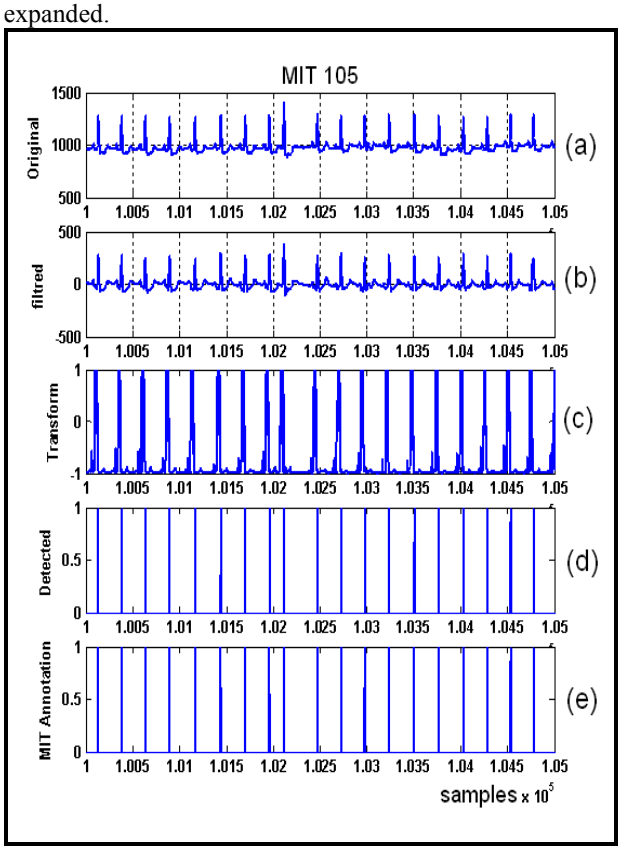

Fig. 6 Stages of the algorithm applied to MIT 105 (a) Original signal (b) Output of wavelet filter (c) Transformed signal (d) Result of QRS detector: output pulse (e) MIT annotations.

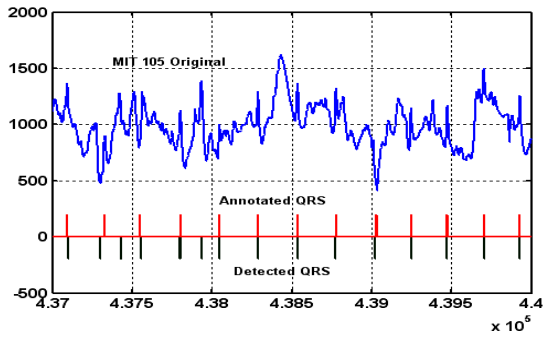

Fig.7. Result of QRS detection of MIT 105 between 437.000 and 440.000 samples

4. Simulation results

4.1 Materials and database

In this study, the proposed algorithm is designed for QRS complex event and tested using ECG registrations from the MIT-BIH database [21] and The MIT-BIH Polysomnographic Database [22]. The MITDB contains 48 half-hours recordings of annotated ECG with a sampling rate of 360. Altogether there are 116137 QRS complexes in this database. While some records contain clear R-peaks and few artifacts (e.g., records 100-107), for some records the detection of QRS complex is very difficult due to abnormal shapes, noise, and artifacts (e.g., records 108 and 207). The MIT-BIH Polysomnographic Database is a collection of recordings of multiple physiologic signals during sleep with sampling rate 250. The database contains over 80 hours' worth of four-, six-, and seven-channel polysomnographic recordings, each with specifically an ECG signal annotated beat-by-beat.
Lead 1 is selected for the whole analysis due to its representative characteristics for identifying the common heart beats. This method has the advantage of requiring at least one recording lead, thus being less memory intensive than two leads recordings. The adaptive constant was set for each 4096 points window.

4.2 Evaluation and Comparison of the results

The threshold coefficient value thr, if chosen in a certain considerably wide interval, doesn't influence the detection ratio, which provides stability for the algorithm.
The accuracy of our QRS detection algorithm was assessed by comparing their marked QRS annotations with those generated by the MIT algorithm. The evaluation of the detection algorithm performance uses the Sensitivity (Se) and the positive predictivity (Spp) factors defined as:

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

$$Spp(\%) = 100\frac{TP}{TP + FP}$$

Where:
FP = false positives;
FN = false negatives;
TP = true positives;
TN = true negatives; and
UN = classified as "uncertain", if applicable.

Another widely used measurement, the False Discovery Rate (FDR) is used to examine how well the classifier performs in recognizing arrhythmias and to compare it with other methods [9]. FDR quantifies the expected proportion of false predictions in the set of predictions, rather than quantifying the chance of any false positives:

$$FDR(\%) = 100\frac{FP + FN}{FP + FN + TP + TN + UN}$$

The verification process was performed using a developed program that allows us to measure the QRS annotation differences and deliver the number and the position of the True Positive, False Positive and the False Negative peaks. Excluding record 207 where there is an occurrence of atrial flutter and the QRS complex haven't a high slope (Dinh), a total of 47 records (duration 23.5 hours) of the MIT-BIH arrhythmia database and 8 records (34H15mn) for MIT-BIH Polysomnographic Database have been considered. The performance criteria are taken into account regarding to the different locations of QRS.

The results of QRS detection algorithm for the 47 recording of MITDB in the case of 30 mn duration is summarized in Table 2.

Tableau 2: Recapitulate results QRS detection using MITDB (not including MIT 207)..

Ref	***Annot***	***Detecte***	***FN***	***FP***	***TP***	***Se (%)***	***Spp (%)***	***FDR (%)***
Total	107634	107595	190	151	107444	99,82	99,86	0,32

For this database recordings, the Sensitivity and the Positive Predictivity of our automatic annotations were computed and give 99.85 % and 99.81 % respectively. The False Discovery Rate has varied between 0 % and 2.81 %.
For the MIT-BIH Polysomnographic Database, the results of the identification process for different ECG by applying proposed detection algorithm are shown in Table 3.

Tableau 3: Results of detection for MIT-BIH Polysomnographic Database.

Record	***Annot beats***	***Detect Beats.***	***FN Beats.***	***FP Beats.***	***Samples. .10³***	***Duration. .hh:mn***
Slp01a	7806	7803	5	2	1800	2:00
Slp01b	11467	11466	7	6	2700	3:00
Slp02a	16145	16080	202	137	2700	3:00
Slp02b	11314	11378	104	168	2025	2:15
Slp03	24917	25127	41	251	5400	6:00
Slp04	27029	26986	107	64	5400	6:00
Slp14	22920	23063	9	152	5400	6:00
Slp16	27604	27439	305	140	5400	6:00
Total	149202	149342	780	920	30825	34:15

The total performances are evaluated as FDR(%)=1.19, Se(%) = 99.48 and Spp(%)= 99.38.
The analysis of the simulations result confirms that the present method can identify the R peak position with reasonable accuracy.
Exhaustive comparisons with the literature algorithms are made with the purpose of evaluate the performance of the proposed detection algorithm of QRS complexes. The main result is shown in table 4.
This preliminary study demonstrates that the actual algorithm presents some advantages. It reduces for the most cases the Fault Detection Rate in comparison with other algorithms in the same topic and it is fast time execution.

(Insert Here the Table 4 of the end of the paper)

5. Conclusion

Much work has been carried out in the field of QRS complex and specifically R-Peak detection. Performance is generally good, but each method has situations where it fails. This paper was presented a new QRS complex detection algorithm based on the saturation of all R-peaks values in order to equalize approximately the maxima as one. So, the detection by the threshold becomes easier. Otherwise, the relative low amplitudes of P or T waves are attenuated by an appropriate function. The insensitivity of the algorithm on the threshold is also demonstrated. The proposed detector has been tested in two phases. First, the QRS detection in ECG registrations from the MIT-BIH database has been performed experimentally, which led to an average detection ratio of 99.5%. Secondly, the MIT-BIH Polysomnographic Database is tested; The FDR reaches 0.32% for the QRS detector. The Sensitivity is evaluated at 99,82% and the positive predictivity is 99,86%. Then, the performances have been compared with

some algorithms cited in literatures. The results were shown that our approach gives best average detection.

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References

[1] Addison P.S, 2005, Wavelet transforms and the ECG: a review, Physiol. Meas. Vol 26, R155–R199.
[2] Afonso V.X, Tompkins W.J, Nguyen T.Q, and Luo S, 1999, ECG beat detection using filter banks, IEEE Trans. Biomed. Eng., vol. 46, 192–201.
[3] Arzeno N.M, Poon C.S, and Deng Z.D, 2006, Quantitative Analysis of QRS Detection Algorithms Based on the First Derivative of the ECG, Proc. of the 28th IEEE EMBS Ann. Int. Conf., New York City, USA.
[4] Augustyniak P, 2003, Time–frequency Modelling and Discrimination of Noise in the Electrocardiogram, Physiol.Meas., vol 24, 753-767.
[5] Christov I.I, 2004, Real time electrocardiogram QRS detection using combined adaptive threshold, BioMedical Engineering OnLine, vol3, no28.
[6] Dinh H.A.N, Kumar D.K; Pah N.D and Burton P, 2001, Wavelets for QRS detection., Proceedings of 23th IEEE Int. Conf. of the Eng. in Med. and Biology Society, Vol.2, 1883 – 1887.
[7] Duverney D, Gaspoz J.M, Pichot V, Roche F, Brion R, Antoniadis R and Barthelemy J.C, 2002, High Accuracy of Automatic Detection of Atrial Fibrillation Using Wavelet Transform of Heart Rate Intervals, Pacing Clin Electrophysiol, 25(4 Pt 1), 457-462.
[8] Friesen G.M et al., 1990, A comparison of the noise sensitivity of nine QRS detection algorithms, IEEE Trans. Biomed. Eng., vol. 37, 85–98.
[9] Gao D., Madden M., Chambers D. and Lyons G. , 2005, Bayesian ANN Classifier for ECG Arrhythmia Diagnostic System: A Comparison Study, Proc. of Int. Joint Conf. on Neural Networks, Montreal, Canada, July 31 - August 4, 2005.
[10] Hadjileontiadis L.J, Panoulas K.I, Penzel T. and Panas S.M, Performance of Three QRS DetectionAlgorithms During Sleep: A comparative Study, Proc. 23rd Ann. EMBS, October 25-28,2001, Turkey.
[11] Hamilton P.S and. Tompkins W.J, 1986, Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database, IEEE Trans Biomed. Eng., vol. BME-33, 1157–1165.
[12] Kestler H.A, Haschka M, Kratz W, Schwenker F, Palm G, Hombach V and Hoher M, 1998, Denoising of High-resolution ECG Signals by Combining the Discrete Wavelet Transform with the Wiener Filter. Computers in Cardiology, Vol25, 233-236.
[13] Kohler B.U, Hennig C, Orglmeister R, 2002, The principles of software QRS detection, IEEE Engineering in Medicine and Biology Magazine, Vol. 21, Issue 1, 42 – 57.
[14] Martínez J.P, Almeida R, Olmos S, Rocha A.P and Laguna P, 2004, A Wavelet-Based ECG Delineator: Evaluation on Standard Databases, IEEE Transactions on Biomedical Engineering, vol. 51, no. 4.
[15] Meyer C, Gavela J.F, and Harris M, 2006, Combining Algorithms in Automatic Detection of QRS Complexes in ECG Signals, IEEE Transactions on Information Technology in Biomedicine, vol. 10, no. 3.
[16] Moraes J.C, Freitas M.M.; Vilani F.N, Costa E.V, 2002, A QRS complex detection algorithm using electrocardiogram leads, Computers in Cardiology, 205 – 208.
[17] Pan J and Tompkins W.J, 1985, A real-time QRS detection algorithm, IEEE Trans. Biomed. Eng., vol. 32, no.3, 230-236.
[18] Sahambi J.S, Tandon S, and Bhatt R.K, 1997, Using wavelet transform for ECG characterization, IEEE Eng. Med. Biol., vol. 16, no. 1, 77–83.
[19] Shyu L.Y, Wu Y.H and Hu W, 2004, Using Wavelet Transform and Fuzzy Neural Network for VPC Detection From the Holter ECG, IEEE Transactions On Biomedical Engineering, Vol.51,No.7.
[20] Yimman S, Hinjit W, Desyoo P, Bholsithi W and Dejhan K, 2004, Wavelet packet transform applications on QRS detection, , Proc. of the Fourth IEEE Intern. Symp. on Signal Processing and Information Technology, 445 – 448.
[21] http://www.physionet.org/physiobank/database/mitdb/
[22] http://www.physionet.org/physiobank/database/slpdb/

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Tableau 4: Comparison results of proposed QRS detection and literatures.

	Nber of beats	***Detected Beats***	***FP***	***FN***	***TP***	***Se (%)***	***Spp (%)***	***FDR (%)***	***Method***	***Notice MITDB***
Dinh et al. 2001 [6]								0,75	Cubic Spline method	5 mn
Proposed algorithm								0,34	Equalize the maxima	5 mn
Sahambi 1997 [18]	14481		93	84				1,22		100 to 107
Martínez et all 2004 [14]	14481		43	23				0,46	WT based	100 to 107
Proposed algorithm	13210		39	10				0,37	Equalize the maxima	100 to 107
Christov I.I, 2004 [5]	110050	109548	215	294	109254	99,73	99,80	0,46		
Moraes et al. 2002 [16]						99,22	99,73			24 hours
Pan and Tompkins [17]	116137		507	277		99,76	99,56	0,68		24 hours
Proposed algorithm	107634	107595	151	190	107444	99,82	99,86	0,32	Equalize the maxima	Excluding 207