Evaluation of a Wavelet-Based ECG Waveform Detector on the QT Database

JP Martínez, S Olmos, P Laguna

Electronics Engineering and Communications Dpt., University of Zaragoza, Spain

Abstract

In this work we have evaluated a single-lead wavelet transform (WT) based detector of ECG significant points. A quadratic spline wavelet was used as prototype wavelet, and the first four scales of the Dyadic WT were analyzed. First of all, we detect QRS complexes. Then, the individual waves, the onset and the offset of the QRS complexes are identified, and finally P and T peaks and their onset and offset are detected. We have validated the algorithm with the manual annotations in the QT Database (QTDB), developed for validation purposes. QRS and other ECG waveform boundaries were independently evaluated. The mean and standard deviation of the differences between the manual and detector's wave boundary annotations were calculated. The standard deviations obtained with the WT approach are around the accepted tolerances between expert physicians, outperforming the results of a low-pass differentiator algorithm, which was used as a reference, especially in the T wave offset. The QRS detector obtained a sensitivity of Se=99.91 and a positive predictivity of P+=99.88%.

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. Some of the clinically useful information from the ECG is found in the intervals and amplitudes defined by its significant points (characteristic wave peaks and boundaries). Therefore, it is necessary to develop automatic systems to detect these significant points, specially for long recordings.

Different methods have been proposed in literature for detection of significant points in the ECG. Amongst these, we can highlight the approaches based on low-pass differentiation (LPD) [1] and the wavelet transform (WT) [2].

The wavelet transform provides a description of the signal in the time-scale domain, and permits the representation of the temporal characteristics of a signal at different resolutions, and therefore, it is a suitable tool to analyze the ECG signal, where we have a cyclic occurrence of patterns with different frequential content (QRS complexes, P and T waves), and moreover, the various noises and artifacts which affect the ECG signal also appear at different resolutions.

A multiscale QRS detector and a method for detecting monophasic P and T waves were proposed in [2], but only the QRS detector was validated with the MIT-BIH Arrhytmia Database. In this work, a generalization of the method proposed in [2] is presented and it is assessed with the manual annotations in the QT database, developed for validation purposes [3]. The performance is evaluated independently for QRS complexes and for waveform boundaries.

The paper is organized as follows: in Section 2, the basis essentials of the WT, the detection method and the validation process are described. Then we present the results of the validation in Section 3, and finally, we discuss the results and present our conclusions.

2. Materials and methods

2.1. Wavelet Transform (WT)

The wavelet transform is a decomposition of the signal as a combination of a set of basis functions, obtained by means of dilation (a) and translation (b) of a single prototype wavelet $\psi(t)$. Thus, the WT of a signal $x(t)$ is defined as

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

For discrete-time signals, the dyadic discrete wavelet transform (DWT) is used, where the scales a are integer powers of 2. It can be easily implemented with Mallat's algorithm, which is equivalent to an octave filterbank [4], as shown in Figure 1.

If we choose as the prototype wavelet the derivative of a low pass function, $W_a x[b]$ is proportional to the derivative of the signal once low pass filtered at scale a. Consequently the WT shows zeros at different scales in the positions where $x[n]$, approximated at a given scale, shows local maxima or minima. Whenever $x[n]$ has abrupt changes, $W_a x[b]$ will show positive maxima or negative minima through the scales.

In this work the selected prototype wavelet $\psi(t)$ was a

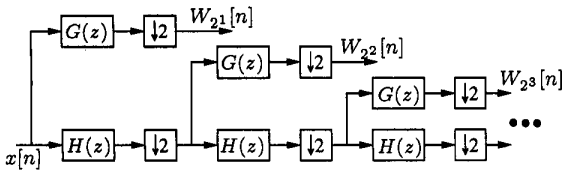

Figure 1. Filterbank implementation of DWT according to Mallat's algorithm.

quadratic spline whose continuous-time Fourier transform is

$$\Psi(\omega) = j\omega \left(\frac{\sin(\omega/4)}{\omega/4} \right)^4 \qquad (2)$$

which can be easily identified as the derivative of the convolution of four rectangular pulses, i. e. the derivative of a low-pass function.

The equivalent frequency responses for the first 5 scales of the DWT with a sampling rate of 250 Hz are shown in Figure 2. It is noteworthy that the characteristics of the responses are those of low-pass differentiators.

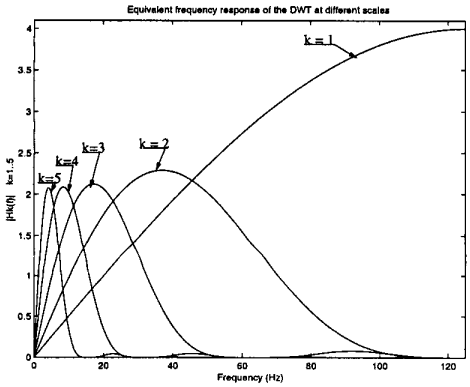

Figure 2. Equivalent frequency responses of the DWT at scales 2^k, $k = 1 \cdots 5$, for 250 Hz sampling rate.

2.2. Detection of ECG significant points

Most of the energy of the ECG signal lies at scales 2^2, 2^3 y 2^4. For scales higher than 2^4, the energy of the QRS is very low. Only P and T waves have significant components at scale 2^5, but at this scale the influence of baseline wandering is very important. Consequently, we only use the first four scales $W_{2^k}x[b]$, $k = 1, 2, 3, 4$. The reason for including scale 2^1 in this work is that it supplies the best time-domain resolution.

Simulated waves similar to those appearing in the ECG, and its WT at the first four scales are shown in Figure 3. To monophasic waves, as exemplified in (a) or (b), corresponds a positive maximum—negative minimum pair along the scales, with a zero crossing in between. A sharp change in the signal is associated to a line of maxima or minima across the scales. In the wave (c), which simulates a QRS complex, it can be observed that the small Q and S wave peaks have zero crossings associated in the WT, mainly at scales 2^1 and 2^2. P or T-like waves (d) have their major component at scale 2^4, whereas artifacts like (e) produce isolated maximum or minimum lines, which can be easily discarded. If the signal is contaminated with high-frequency noise, like EMG noise (f), the most affected scales are 2^1 and 2^2, but higher scales are hardly affected by this kind of noise. Baseline wander (g) only affects slightly to scale 2^4.

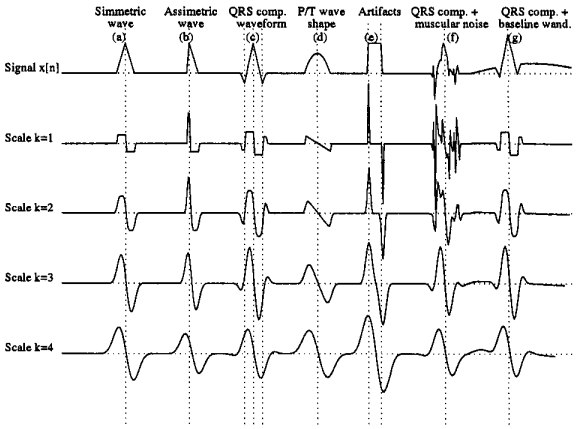

Figure 3. DWT at the first four scales of ECG-like simulated waves.

Using the information of local maxima, minima and zero crossings at different scales, the algorithm identifies the significant points in four steps: 1) Detection of QRS complexes. 2) Detection and identification of QRS individual waves (Q,R,R',S), onset and offset. 3) T wave peak, onset and offset and 4) peak and limits of P wave.

First of all, QRS complexes are detected using an algorithm based on the multiscale method proposed in [2], which we have done more robust searching for the more significant wave of the QRS complex, not necessarily the R wave. Li's algorithm searches across the scales for "maximum modulus lines" which exceed some thresholds. Then the regularity exponent is tested to distinguish QRS lines from lines produced by noise, artifacts or other waves. After eliminating all isolated and redundant maximum lines, the zero crossing of the WT at scale 2^1 between a positive maximum–negative minimum pair are marked as a QRS. Other protection measures are taken, like a refractory period or a search back if a significant time has passed without detecting any QRS.

One of the novelties with respect to Li's algorithm is the detection and identification of the QRS individual waves.

For this purpose, we look in the environs of the QRS position for all the maximum moduli of the WT which surpass a threshold at scales 2^1 and 2^2. The zero crossings between them will be assigned to wave peaks, and they are labelled depending of the polarity and the distribution of the waves. We consider any possible QRS morphology with 3 or less waves (QRS, RSR', QR, RS, R and QS complexes).

The onset (offset) of the QRS is before (after) the first (last) slope of the QRS, which will be associated with a maximum of $|W_{2^k}x[n]|$. So, we first identify the first and last peaks associated with the QRS in $W_{2^2}x[n]$, say n_{peakon} and n_{peakoff}. To determine the onset and offset, we apply two criteria: the first one searches for the sample where $|W_{2^2}x[n]|$ is below a threshold relative to the amplitude of the peak ($|W_{2^2}x[n_{\text{peakon}}]|$ or $|W_{2^2}x[n_{\text{peakoff}}]|$); the second criterion searches for a local minimum of $|W_{2^2}x[n]|$ before n_{peakon} or after n_{peakoff}. In both cases the criterion selected finally is the one that supplies the nearest sample to the QRS. The same procedure is also applied at scale 2^1.

As for the T and P waves, the process is as follows: first of all, we define a search window for each wave, relative to the QRS position and depending on the RR interval. Within the window we look for maxima of $|W_{2^4}x[n]|$ whose amplitude surpasses a threshold, and the zero crossings in between. Depending of the number and polarity of these peaks, we distinguish different morphologies (positive, negative, biphasic, only upwards and only downwards). The criteria to identify the limits of these waves were the same as for QRS onset and offset, but applied to scale 2^4.

2.3. Validation

For validation purposes, we have used the QT database (QTDB) [3] which includes annotations carried out by cardiologists. The database has 105 fifteen-minute excerpts of two-lead digitized ECG's. For each of its 105 records, in a minimum of 30 consecutive beats, the waveform peaks and boundaries have been manually annotated by cardiologists. Moreover, the QRS complexes have been annotated in 79 complete recordings.

To evaluate the QRS detector we have used the percentages of misdetections defined as Sensitivity $Se = \frac{TP}{TP+FN}$ and Positive Predictivity $P+ = \frac{TP}{TP+FP}$, where TP are the number of true positive detections, FN stands for the number of false negative and FP for the number of false positive misdetections.

For the rest of the points, we have calculated the Se and the mean (m) and the mean standard deviation (σ) of the differences between cardiologists' and automated annotations. Given the format of the QT database, it was not possible to quantify the $P+$, as it was noted in [5].

The first recorded channel was used in the assessment of the QRS detector. As for the other points, we chose for each beat the best channel, coherently with the fact that the experts had in sight both leads when they annotated the recordings.

3. Results and discussion

The values of Se and $P+$ obtained by the QRS detector are shown in Table 1. These results are compared with those obtained by the commercial software ARISTOTLE [6] (in single-lead mode), which is based on a matched filter approach.

Table 1. Performance of the WT-based QRS detector, compared with ARISTOTLE.

Detector	*N*	*FP*	*FN*	*Se %*	*P+ %*
DWT	82991	103	72	**99.91**	**99.88**
Aristotle	82991	203	2336	**97.18**	**99.75**

The results of Se, m and σ at some wave boundaries are presented in Table 2. We have also applied an LPD-based method [1] to the same database, and its results are also included in the table. The LPD algorithm was also validated with the QTDB in [7]. In the last row, we include the accepted standard deviation tolerances from the measurements made by different experts on the CSE database [8].

Table 2. Table: Performance of the detector for other significant points, and acceptable tolerance between experts.

	P_{on}	P_{off}	QRS_{on}	QRS_{off}	T	T_{off}
nbeats	3101	3101	3621	3621	3540	3540
DWT DETECTOR						
Se (%)	83.8	83.8	97.8	99.2	98.1	97.0
m (ms)	8.2	4.2	4.6	0.8	-7.4	-0.6
σ (ms)	12.0	10.8	7.8	9.0	13.8	22.6
LPD DETECTOR						
Se (%)	98.5	98.5	93.4	94.8	99.1	97.4
m (ms)	10.4	-3.7	-4.1	-1.0	-8.0	11.6
σ (ms)	12.5	11.4	9.0	8.4	15.0	28.2
TOL	10.2	12.7	6.5	11.6	-	30.6

A new T-U complex detector (TU) has been recently proposed and also validated on the QT database [5]. The detection results for the T wave peak and T_{off} are given in Table 3 for comparison purposes.

Table 3. Some of the validation results of TU detector [5].

	nbeats	*Se* (%)	$m \pm \sigma$ (ms)
T	3528	92.6	-12.0±23.4
T_{off}	3528	92.6	0.8±30.3

On the whole database the best performance for T peak and T wave offset was achieved by the WT detector. In contrast, the P wave detection performance was better with LPD. With respect to algorithm complexity, the TU detector seems to be the most complex method, but it is the only one which can detect U waves. Moreover, the WT detector is a bit more complex than LPD only at the QRS complex, due to its multiscale procedure, but the performance of QRS detection was larger for DWT than for LPD.

We also performed a record by record analysis in order to observe in which records there was an accurate detection, as it was proposed in [7] and more recently used in [5]. In order to facilitate comparison with previous works with chose the same threshold than in [5], i.e. 15 ms for the bias and 30.6 ms for the standard deviation. Thus, the records are classified into four groups, according to:
Group I: bias<15 ms and σ<30.6 ms.
Group II: bias>15 ms and σ<30.6 ms.
Group III: bias<15 ms and σ>30.6 ms.
Group IV: bias>15 ms and σ>30.6 ms.
The recording stratification results for the T wave peak and T offset on the three algorithms are given in Table 4. The percentage of records and also the mean value of bias and σ in each group is shown. The stratification performance is quite similar for all three methods, but the TU detector seems to give a larger population of well-detected recordings in the T offset.

Table 4. Stratification according to detection accuracy.

		T			T_{off}		
Gr		LPD	DWT	TU	LPD	DWT	TU
I	%	84	82	82	55	64	72
	bias	3	3	4	5	5	7
	σ	8	7	9	13	13	16
II	%	2	5	8	9	12	16
	bias	45	39	36	57	35	31
	σ	13	15	15	20	18	18
III	%	1	4	4	10	11	4
	bias	8	7	9	4	1	9
	σ	35	41	38	45	42	35
IV	%	13	9	6	26	13	8
	bias	57	72	32	50	56	49
	σ	62	55	40	58	52	45

4. Conclusions

A WT-based ECG significant point detector has been developed and validated with more than 3500 beats (more than 80000 in the case of QRS detection) manually annotated by physicians at the QTDB. From the results of the validation, we can conclude that:

In QRS detection, the method attains very good results (Se = 99.91 % and $P+$ = 99.88 %) at the validation database. The WT-based system has a Sensitivity greater than the software ARISTOTLE by 2%, maintaining a similar Positive Predictivity. The clue to this improvement is, to our understanding, the multiscale approach, which permits to avoid noise at rough scales, and then to fine-tune the precision of the QRS position with the help of the lower scales.

The detection of waveform boundaries (P_{on}, P_{off}, QRS_{on}, QRS_{off}, T and T_{off}) was sufficiently precise. The differences between automatic annotations and the manual ones are within the accepted tolerances between human experts, outperforming the low-pass derivative method [1]. The point with the most significant improvement are the T peak and the T wave offset. Thus, we can state that the performance of the WT approach in detecting significant points in the ECG is comparable to the experts' at least on the QT database

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Address for correspondence:
Juan Pablo Martínez
Dep. Ingeniería Electrónica y Comunicaciones
Maria de Luna, 3. 50015-Zaragoza (SPAIN)
E-mail: juanpabl@tsc1.cps.unizar.es