INTERNATIONAL CONGRESS ON COMPUTATIONAL BIOENGINEERING
M. Doblaré , M. Cerrolaza and H. Rodrigues (Eds.)

AUTOMATIC DELINEATION OF T AND P WAVES USING A WAVELET-BASED MULTISCALE APPROACH

R. Almeida[1], J. P. Martínez[2], S. Olmos[2], A.P. Rocha[1], P. Laguna[2]

[1]*Departamento de Matemática Aplicada, Faculdade de Ciências, Universidade do Porto, Portugal.*

[2] *Communications Technology Group, Aragon Institute of Engineering Research, University of Zaragoza, Spain.*

ABSTRACT

In this work we present an extension of a previously developed single-lead Wavelet Transform based ECG delineation system. A multiscale methodology is applied to detect and delineate P and T waves for a wide range of morphologies, taking advantage of the time-scale domain description provided by the Wavelet Transform. The performance was assessed using the QT database in which the algorithm presents a high sensitivity, both in P (98.87%) and T waves (99.77%). The waves are detected and delineated with mean errors smaller than or around 1 sample (4 ms) and standard deviation of the errors are comparable with the accepted differences between the cardiologists. The results obtained outperform other algorithms, in particular in the T wave end.

1. INTRODUCTION

The analysis of the ECG is extensively used as a diagnostic tool to provide information on the heart function. The delineation of ECG characteristic waves (by detecting their peaks and boundaries) supplies fundamental features for extracting clinically useful information: namely durations of physiological phenomena, expressed in the time intervals like PR and QT. Determination of these time intervals requires delineation of P and T waves, which is a particularly challenging task due to the low SNR and the lack of universally accepted criteria. Therefore, developing accurate and robust methods for automatic ECG delineation is a topic of main interest, in particular for the analysis of long records.

The Wavelet Transform (WT) provides a description of the signal in the time-scale domain, allowing the representation of the temporal features at different resolutions, according to their frequency content. Noise and artefacts can be avoided considering their different contribution at various scales. A WT based QRS detector including single scale delineation of monophasic P and T waves was first proposed although not evaluated, in [1]. This approach was generalized in [2] to account (among other novelties) for different T wave morphologies. In this work we present an extension of [2] applying a multiscale methodology to detect and delineate P and T waves for a wide range of morphologies, integrated with the previously developed single-lead WT based ECG delineation system.

2. METHODOLOGY

2.1. Wavelet Transform

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

$$W_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt, a > 0.$$

The greater is the scale factor a, the wider is the basis function, and consequently, the corresponding coefficient gives information about lower-frequency components of the signal, and vice versa. In this way, the temporal resolution is higher at high frequencies than at low frequencies, achieving the property that the analysis window comprises the same number of periods for any central frequency.

The scale factor a and/or the translation parameter b can be discretized. The usual choice is to follow a dyadic grid on the time-scale plane: $a=2^k$ *and* $b=2^k l$. The transform is then called dyadic wavelet transform, with basis functions

$$\psi_{k,l}(t) = 2^{-k/2}\psi\left(2^{-k}t - l\right); k, l \in Z^+.$$

For discrete-time signals, the dyadic discrete wavelet transform (DWT) is equivalent, according to Mallat's algorithm, to an octave filter bank [3], and can be implemented as a cascade of identical cells (low-pass and high-pass FIR filters). This algorithm includes downsamplers after each filter to remove the redundancy of the signal representation, but as side effects they make the signal representation time-variant, and reduce the temporal resolution of the wavelet coefficients for increasing scales. To keep the time-invariance and the temporal resolution at different scales, we use the same sampling rate in all scales, what is achieved by removing the decimation stages and interpolating the filter impulse responses of the previous scale. This algorithm, called *algorithme à trous* [4], is shown in Figure 1.

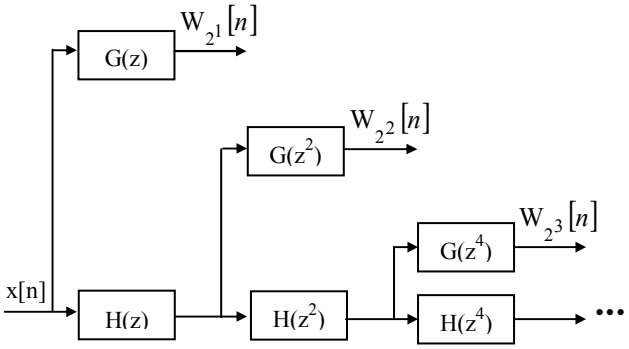

Figure 1. Filter-bank implementation of DWT without decimation (algorithme à trous).

2.2. Prototype wavelet

We used as prototype wavelet a quadratic spline originally proposed in [5] that was already applied to ECG signals in [1] and [6]. The quadratic spline Fourier transform

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

easily allows to identify this wavelet as the derivative of the convolution of four rectangular pulses, i.e. the derivative of a low-pass function. It can be shown [5] that if the prototype wavelet $\psi(t)$ is the derivative of a smoothing function $\theta(t)$, the wavelet transform of a signal $x(t)$ at scale *a* is proportional to the derivative of the filtered version of the signal with a smoothing impulse response at scale *a*.

Therefore, the zero-crossings of the WT correspond to the local maxima or minima of the smoothed signal at different scales, and the maximum absolute values of the wavelet transform are associated with maximum slopes in the filtered signal. Regarding our application, such type of prototype wavelet is very convenient as we are interested in detecting ECG waves, which are composed of slopes and local maxima (or minima).

For the selected prototype wavelet, the filters H(z) and G(z) to implement the DWT as in Figure 1 are [1, 7]

$$H(e^{j\omega}) = e^{j\omega/2}\left(\cos\frac{\omega}{2}\right)^3$$

$$G(e^{j\omega}) = 4je^{j\omega/2}\left(\sin\frac{\omega}{2}\right),$$

which are FIR filters with impulse responses

$$h[n] = 1/8\{\delta[n+2] + 3\delta[n+1] + 3\delta[n] + \delta[n-1]\}$$

$$g[n] = 2\{\delta[n+1] - \delta[n]\}.$$

Using the *algorithme à trous* and the filters *H(z)* and *G(z)* the equivalent frequency responses are those represented in Figure 2. According to the spectrum of the ECG signal waves [10], most of the energy of the ECG signal lies within the scales 2^1 to 2^5 with P and T waves having significant components at scales 2^4 and 2^5. Since the influence of baseline wandering is important at scale 2^5, this scale must be used carefully.

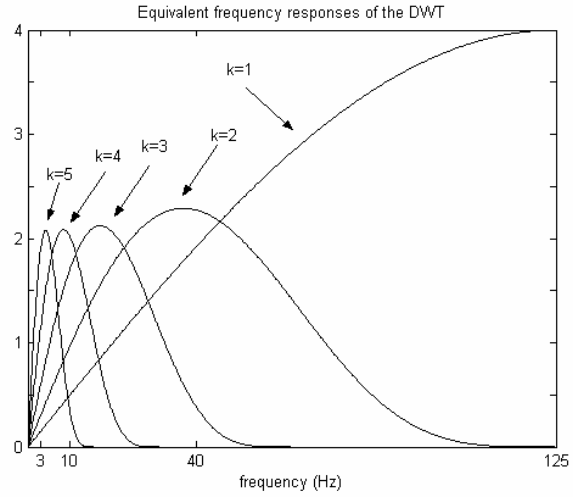

Figure 2. Equivalent Frequency responses of the DWT at scales 2^k, k=1,...,5 for 250 Hz sampling rate.

2.3. P and T waves detection and delineation

The multiscale detection and delineation the P and T waves are performed without any prefiltering and assuming a previous QRS detection. Search windows relative to the QRS position are defined for each beat taking into account the cardiac frequency. Within these windows, we look for local maxima of the $|W_{2^4}x[n]|$ and a P or T wave is considered to be present if at least two of the found maxima exceed a threshold proportional to the root mean square (RMS) of WT measured between two consecutive QRS. A local maximum is considered as a significant slope of the wave if its amplitude exceeds a threshold relative to the maximum of $|W_{2^4}x[n]|$ within the search window. Depending on the number and polarity of the found

maxima, one out of four possible P wave morphologies is assigned: positive (+), negative (-) and biphasic (+/- or -/+). For the T wave two additional morphologies are admitted: only upwards and only downwards. If a wave is not found at scale 2^4, we repeat the above process over the scale 2^5 on the correspondent search window. Attending to the loss of time resolution in the growing scales, the peak(s) of the P and T waves are taken as the zero crossing(s) at scale 2^3, if they exist, or at the scale 2^k in which the wave was found.

The onset (end) of the waves lies before (after) the first (last) significant slope. Candidates to onset and end are determined in the scale 2^k by applying two criteria:

i) searching for the sample where $\left| W_{2^k} x[n] \right|$ is below a threshold ξ_{Ton} (ξ_{Tend}) relative to the amplitude of the first (last) maximum modulus;

ii) searching for a local minimum of $\left| W_{2^k} x[n] \right|$ before (after) the first (last) maximum modulus.

Finally the onset and end are selected as the candidates that supply the nearest sample to the P or T wave.

2.4. Validation

The validation was carried out using the QT database [8], which was developed for wave limits validation purposes. This database includes 105 ECG recordings (2-lead) at 250 Hz and it provides cardiologist annotations for at least 30 beats per recording (ref1), with marks including P and T waves peaks, onsets and ends. For 11 out of its 105 records, an additional annotation performed by a second cardiologist (ref2) is also provided.

The wavelet-based delineator works on a single-channel basis, while the manual annotation process was performed having in sight all available leads. Therefore, to compare, in a reasonable way, the manual annotations on the database with the two single-channel annotation sets produced by the delineator, we chose for each point the channel with less error.

To assess the detection performance we calculated the Sensitivity $Se = \frac{TP}{TP + FN}$ where TP is the number of true positive detections and FN stands for the number of false negative misdetections. It is worthwhile to remark that given the format of this database, it was not possible to evaluate the performance in terms of the false positive misdetections, as it was already noted in [11]. As a matter of fact, when there is not an annotation, we do not know either if the cardiologist considered that no wave was present or if he simply believed that he could not confidently annotate the point (e.g. because of the noise).

Regarding wave delineation, we calculated the errors as the time differences between automatic and cardiologist annotations, and calculated *m* as the average and *s* as the average standard deviation of the error, computed by averaging the intra-recording standard deviations.

3. RESULTS

The results obtained on the QT database with the WT-based delineator (this work) are presented in Table 1. For comparison purposes we also included the results of a low-pass-differentiator-based method (LPD) [9] (for which a previous version had already been validated on the QT database in [12]), and the results for T peak and T end of the T-U complex detector recently proposed in [11]. In the last row, we include the accepted two-standard-deviation tolerances given by the CSE working party from measurements made by different experts [13, Table 2].

Within the subset of the QTDB with double reference annotations, we compare the delineation errors with respect to both referees (ref1 and ref2) and the inter-cardiologist differences, obtaining the results presented in Table 2. Since the second cardiologist did not annotate any P wave, no results are given for this wave.

Method	Parameters	P begin	P peak	Pend	T peak	T end
	# annotations	3194	3194	3194	3542	3542
This work	Se (%)	98.87	98.87	98.75	99.77	99.77
	m ± s (ms)	2.0±14.8	3.6±13.2	1.9±12.8	0.2±13.9	-1.6±18.1
LPD	Se (%)	97.7	97.7	97.7	99.0	99.0
	m ± s (ms)	14.0±13.3	4.8±10.6	-0.1±12.3	-7.2±14.3	13.5±27.0
TU [11]	Se (%)	N/A	N/A	N/A	92.6	92.6
	m ± s (ms)	N/A	N/A	N/A	-12.0±23.4	0.8±30.3
Tolerances	$2s_{CSE}$ (ms)	10.2	-	12.7	-	30.6

Table 1. Delineation performance in the QT database. N/A: not applicable

Method	Parameters	T peak	T end
WT vs ref 1 all records	# annotations	3542	3542
	m ± s (ms)	0.2±13.9	-1.6±18.1
WT vs ref 1 11 records	# annotations	487	487
	m ± s (ms)	-0.6±8.9	-9.7±18.1
WT vs ref 2 11 records	# annotations	402	402
	m ± s (ms)	0.3±12.5	-10.8±20
inter-expert 11 records	# annotations	402	402
	m ± s (ms)	5.1±15.9	2.1±22.4

Table 2. Delineation performance in the QT database considering both referees.

4. DISCUSSION

It is difficult to find in the published approaches explicit results for P and T waves delineation, despite the WT-based detector allows to take advantage of the same wavelet analysis stage for ECG wave delineation. In [1] and [6], the possibility of detecting monophasic P and T wave peaks was stated, but not evaluated. Only in [14], an algorithm for detecting the peaks, onsets and ends of monophasic P and T waves was validated using the CSE multilead measurement database. A previous version of the delineation system here presented [2] was validated on QT database taking into account different T wave morphologies. The current version applies a multiscale methodology to detect and delineate P and T waves for a wide range of morphologies and presents improved results.

According to the performance results our WT algorithm can detect annotated P and T waves with high sensitivity (Se=98.87% for the P waves and 99.77% for the T waves) with mean errors which are in all cases smaller than or around 1 sample (4 ms). The standard deviations are around 3 samples for the P wave and 3-4 samples for the T peak and the T end. The comparison of our results with those of the LPD approach and the TU detector on the QT database show that our algorithm outperforms them clearly, particularly in the T wave end, which shows, in general, the greatest difficulty.

Considering the values given by the CSE Working Party in [13, Table 2] as a reference for delineation error tolerances, WT an LPD detectors accomplish these criteria in QT database for P end and T end. Although, as this CSE tolerances were computed from a very different set of signals (number of channels, resolution, sampling frequency, quality and rhythms) the comparison with QT database results are not so straightforward. From the 11 recordings annotated by a second cardiologist we estimated the differences between the two annotations. It can be observed from the results presented in Table 2 that for T peak the error between the WT-based delineation system and each of the referees is lower or similar to the inter-cardiologist differences, while in the T end an appreciable bias is obtained for this 11 records, becoming insignificant when we take into account the whole database. Having annotation of more than one cardiologist in the whole QTDB is essential to improve the reliability of the validation.

5. CONCLUSIONS

In this work we present an extension of the previously developed single-lead WT based ECG delineation system by applying a multiscale methodology to detect and delineate P and T waves for a wide range of morphologies.

Performance results show that our WT algorithm can detect annotated P and T waves with high sensitivity and can delineate them with errors comparable to the inter-expert variation, outperforming other approaches. This is particularly important in T wave end detection, which, in general, shows increased difficulty.

According to our understanding, this performance improvement outcome from the multiscale approach, allowing to attenuate noise at rough scales, and then to refine the precision of the positions with the help of finer scales.

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Acknowledgments

This work was supported by the by the projects TIC2001-2167-C02-02 from MCyT and FEDER, P075/2001 from DGA and the integrated action HP2001-0031 / CRUP-E26/02. The first author acknowledges the grant SFRH / BD / 5484 / 2001 supported by FCT and ESF (III CSF).