An Alternative Decision Rule for Threshold Based T-Wave Measurement Algorithms Based on Second Derivative Extrema

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Abstract

QT interval is a surface ECG measure which has been the subject of great research interest. Usually, a prolongation of the QT interval beyond the normal value is associated with bad cardiac prognosis. In this paper we revisit the wavelet transform based method. Rather than using a threshold related or the highest inflection point of the derivative, we use the extreme on the second derivative which appears ahead of the inflexion point. This rule differs from the thresholds one in its simplicity of application and its potential for real time analysis. The algorithm detects the end of the T-wave by using the first and second derivative on the fifth scale. Results for the T wave obtained in simulations give a mean error of -6.73 +/- 14.5 ms (-7.80 +/- 21.04 ms when adding white noise in a SNR of approximately 4 dB) whereas results in Physionet's QTDB give (-1.22 +/- 38.85 ms) in the case of T end location. The results for the threshold method were (-1.6 +/- 18.1 ms).

1. Introduction

QT Interval is a time lapse comprised from the beginning of the ventricular depolarization (QRS complex) to the end of the ventricular repolarization (T-wave end). This is a difficult magnitude to measure mainly because the T-Wave is very smooth in its approach to the reference level.

Various methods have been proposed, but the lack of a gold standard (other than annotated databases)[1] makes it difficult to validate any of these methods. Another commonly found problem is the non-uniformity in cardiologist's criteria. They usually agree about the end of the T-wave when looking at a normalized ECG printed in paper, but when looking at digital signals, where more resolution is available, non-uniformity in criteria arises.

A suitable tool to use for this task would be the discrete wavelet transform (DWT)[2][3]. The DWT is a signal analysis tool which decomposes a signal into a set of sub-signals, each of them containing, non overlapping, frequency band's information[4][5] Because of its very nature it is easy to implement by means of a filter bank, which decompose the signal in a very fast way.

The signal we are going to work with, comes from a customizable simulator[6]. Amongst the parameters that can be customized we can find heart rate, it's standard deviation and noise level.

The algorithm used was the “Algorithme á trous” also called redundant wavelet transform. In this implementation, each scale is obtained by using filters interpolated from the filters used in the previous scale.

The main purpose of this study was to determine whether reliable measures could be obtained with an algorithm that doesn't need to rely on thresholds to determine wave boundaries.

2. Methods

The use of the DWT implies the choice of a suitable mother wavelet. The wavelet we chose for our specific problem was the quadratic spline since it has already been used with good results by Li [4], Bahoura[7] and Martinez[8].

Another important reason to choose this wavelet above any other is because the filter bank associated with it behaves like a signal differentiator that works only up to a frequency. That is to say, the quadratic spline wavelet allows the derivation of the signal components at a given scale while ignoring all the information contained in other scales. Besides, the filters are themselves very easy to implement and very fast, computationally speaking[8] [9].

Once a mother wavelet was chosen, the next step consisted in actually implementing the DWT by means of the "algorithme á trous" also called redundant transform.

Having done some tests, the adequate levels of decomposition needed in order to find the various events were assessed. For instance, the QRS complex is a 1st scale event whereas the T-wave lies in the 4th and 5th scale for its frequency range is around 4 Hz.

When the scale needed to study the T-wave was identified, a marking was made on its first local maximum or minimum, then it was differentiated again in order to obtain the second derivative of the ECG in the frequency band containing the T-wave.

Having obtained the second derivative, a search window is established in the search for the last modulus maxima (depending on the detected wave morphology). It was this point the one we identified as the ending of the T-wave, the logic behind this fact is similar to the one found in a work of Zhang[10] who in turn used a method based on mobile windows filtering which can be shown to be analogous to the double differentiation of the ECG signal.

In[10], a search is made for a maximum at a transformed signal of the ECG signal s(t) according to

$$A(t)=\int_{t-W}^{t}\left[s(\tau)-s(t)\right]d\tau \qquad (2.1)$$

By manipulating this expression, it can be shown that it es equivalent to

$$A(t)=s(t)*p\left(t-W/2\right)-W\delta(t)*s(t) \qquad (2.2)$$

Which in turn implies that it is a linear filter manipulation with impulse response equal to

$$h(t)=p\left(t-W/2\right)-W\delta(t) \qquad (2.3)$$

Resulting in a transfer function of

$$H(f)=W\frac{\sin(\pi fW)}{\pi fW}e^{-j\pi fW/2}-W \qquad (2.4)$$

And assuming f<< 1/W (if W=200 ms then f << 5 Hz which is the typical ECG wave contents) it can be approximate by

$$H(f)\approx -f^2\frac{\pi^2W^3}{3!} \qquad (2.5)$$

which is a second derivative filter and so the selection of the maximum of the moving window filtering is equivalent to choosing the maximum of the second derivative as proposed here in this paper. The selection of the window size is equivalent to the selection of the scale in the wavelet based method, since the window size determines the low pass filtering effect of the filtering.

This algorithm allows wave delineation without "a priori" knowledge of the studied wave morphology. This will come in handy shall this algorithm ever be implemented in real time[5] for we are avoiding a series of calculations.

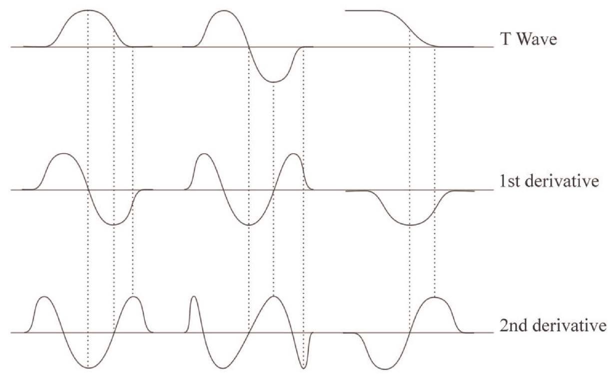

Fig. 1 Outline showing some T-wave morphologies and their derivatives.

3. Results

Once the algorithm was implemented, we proceeded to apply it on a synthetic signal generated with the script "ecgsyn"[6], from the physionet's website. The script was set to generate signals sampled at 250Hz with added white noise with various SNR (5.46, 7.96, 11.48 and 17.5 dB), mean heart rate was also varied (70, 100 and 130 beats per minute) and the standard deviation of heart rate was set to 15 bpm. Also, monophasic and biphasic waves were studied.

Figure 2 shows 3 heart beats with the detections made for the ending of the T-wave.

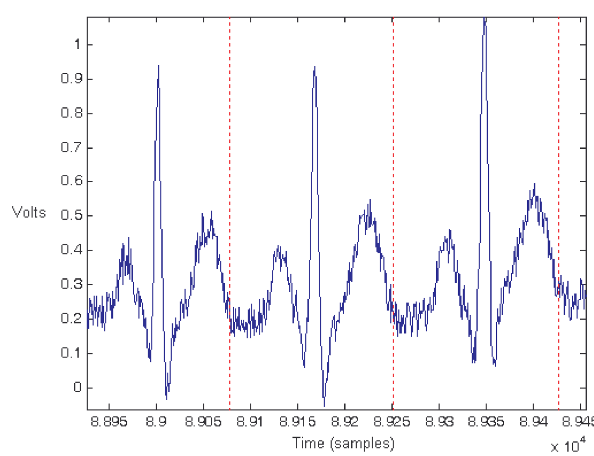

Fig. 2 Sample signal with red lines showing the detected points.

Since we don't have a gold standard for measuring the T-wave's end, we had to resort to another method of detection in order to perform the comparation. In this paper we resorted to a well-validated method, such as the threshold method in Martinez et al.[8]. We can see in figure 3 three sample beats with the T wave delineation provided by both algorithms to see how they compare.

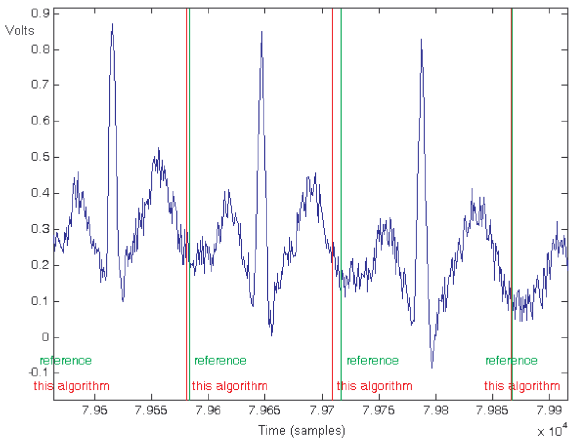

Fig. 3 Sample signal with annotations made by both algorithms (Martinez [8] in green and this work in red).

In the tables 1 and 2 below we can see a summary of the obtained results. Results are reported by taking Martinez's algorithm, a positive result means that this algorithm annotates after Martinez's reference while a negative result means that it annotates before the reference algorithm. This translates in results being reported as the mean and the standard deviation of the difference between marks made by each algorithm.

Monophasic T-wave (synthetic)		Heart rate					
		70		100		130	
		Mean (ms)	SD (ms)	Mean (ms)	SD (ms)	Mean (ms)	SD (ms)
SNR (dB)	17.5	17.68	21.20	-1.24	11.80	-11.92	12.92
	11.4	21.52	23.04	5.92	15.72	-13.52	15.48
	7.96	14.16	23.96	11.44	18.80	-11.72	16.00
	5.46	8.88	22.32	10.24	19.56	-8.80	15.36

Table 1 T-wave end results for the monophasic wave (Using [8] as a reference)

Biphasic T-wave (synthetic)		Heart rate					
		70		100		130	
		Mean (ms)	SD (ms)	Mean (ms)	SD (ms)	Mean (ms)	SD (ms)
SNR (dB)	17.5	-5.24	17.12	-2.80	3.84	-10.24	8.68
	11.48	-9.80	22.20	-3.44	6.96	-10.12	8.64
	7.96	-12.48	23.52	-2.88	5.36	-9.44	8.76
	5.46	-8.56	19.60	-4.04	8.40	-9.96	8.88

Table 2 T-wave end results for the biphasic wave (Using [8] as a refference)

In table 1 (monophasic T-wave) we can observe how the marks tend to shift themselves to the right with increased heart rate, yet standard deviation decreases. Not only that, but the mean values tend to look more accurate with increased added white noise.

On the other hand, in table 2, results were always shifted to the right by as much as three samples but dispersion was significantly lower in this case compared to the monophasic wave.

The second validation for this algorithm was made with the help of physionet's QTDB. The QTDB is a database of heart beats manually annotated by one or two cardiologists. This database is freely and publicly available at physionet's web site[1]. This database has become the standard against which tests are made because of the lack of a gold standard in ECG wave detection.

When comparing this algorithm to threshold methods directly over physionet's QTDB[1] we can observe that results are as good as Zhang's[10](in fact, dispersion is one sample smaller in spite of being equivalent algorithms) but continue to have dispersions significantly greater than threshold methods (see table 3)

Author	Mean (ms)	SD (ms)
Martínez [8]	-1.6	18.1
Zhang [10]	1.72	41.27
Chen [6]	-7.8	18.8
This work	-1.22	38.85

Table 3 T-wave end results for the QTDB

The results generated from the QTDB are really promising since we actually achieve the smallest bias of all the tested algorithms. The downside being that dispersion increases. The higher dispersion of this method compared with the threshold ones may be seen as a trade off for the added simplicity of the algorithm, which rejects any kind of ad-hoc rule needed for threshold methods.

4. Discussion and conclusions

T-wave delineation is an open problem in the field of biomedical signal analysis, and as such, different solutions and algorithms are often developed. We have presented and validated a wavelet-based T-wave end detector. The approach taken in this paper hopes to be of a certain innovation because of it's two main premises: The lack of any ad-hoc rule to determine the T-wave ending and the lack of needing to preprocess the signal to be analyzed.

The results have been compared with those of other authors and have shown a good accuracy with respect to the annotated values, as well as an acceptable dispersion value.

Results are promising because they depend exclusively on the wave morphology and not on calibrations or heuristic rules that could be used to tweak results. The problem with calibrations is that they are heavily dependent on the calibrator.

Being a wavelet based detector which implies low-pass filtering, noise effect is attenuated. For instance, EMG associated noise shall, after applying the DWT, be found mostly on the 1st level of decomposition. While baseline wander will make its appearance in the 5th level, leaving the 4th level almost noise free in most of the cases.

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