Using the Wavelet Transform for T-Wave Alternans Detection

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Abstract

This paper presents the T-wave alternans (TWA) detection applying the Wavelet Transform (WT) to electrocardiographic (ECG) synthetic signals. The TWA is generated with or without the sinusoidal addition of the wave with the required electrical level from 0.01 to 1 mV. The TWA is measured using the difference between the amplitude of the augmented T-waves and the normal ones.

Key words: , ECG signals, T-Wave Alternans, Wavelet Transform

1 Introduction and Preliminaries

Human beings have a heart with four cavities, two atria and two ventricles. The electrocardiogram (ECG) is the graphic, depending on the time, of the variations in electrical pulse generated by all cardiac cells. The different waves that comprise the ECG are P-waves, QRS complexes and T-waves.

The depolarization is a chemical process by means of which a cell changes its electrical potential, usually negative to a positive one by exchanging ions. The repolarization, by contrast, allows the cell's recovery of its negative charges.

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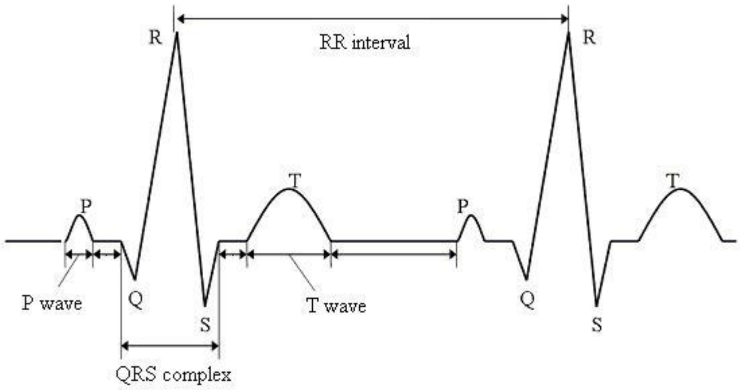

Fig. 1. A typical ECG.

The P-wave corresponds to the depolarization headset. The QRS complex corresponds to a power source that causes contraction of the right and left ventricles (ventricular depolarization). T-wave represents the ventricular re-polarization. It is positive in most of the ECG leads [1], although a T-wave inverted is normal in the leads V1 and V2. It is often asymmetrical: the branch upward is slow and the branch downward is fast. Moreover, when the QRS voltage is higher, it is also higher.

The most important part of any analysis system of the ECG signal is the detection of QRS complex; it gets the duration of the cardiac cycle, which it is possible to measure heart rate with (multiplicative inverse of the length of two complex QRS). Furthermore, once recognized, we can make a more precise analysis of the waves, segments and remaining intervals. The QRS is the set of larger waves and for this, it is also a best signal-to-noise in the ECG, which makes it easier to detect. The algorithms to detect QRS complexes filter, first, the signal to suppress P-wave and T-wave and noise, then they apply a transformation to the signal to highlight the QRS complexes and finally they use thresholds to determine the presence or absence of them.

T-wave alternans (TWA) are periodic beat-to-beat variations in the amplitude of the T-wave in a surface ECG. Since the early twentieth century, a large number of experimental and clinical studies checked the usefulness of T-wave morphological changes, as a parameter for evaluating risk of sudden death and malignant arrhythmia. There are evidences of TWA appearances: Long QT Syndrome, Myocardial Ischemia and Infarction, Cardiomyopathies, Heart Failure, Sudden Infant Death Syndrome, and so on.

For that, the aim of this paper is to detect TWA using the Wavelet Transform (WT).

[1] The signal ECG obtained depends on the location of the electrodes (lead). ECG leads calls unipolar (V1 to V6) are obtained with electrodes placed in the patient's chest.

In our study, we have been forced to generate synthetic ECG signals with TWA, due to the lack of databases containing ECG real signals with changes in the T-wave. Firstly, the ECG signal from the database MIT-BIH Arrhythmia DB is taken and the TWA beat-to-beat with the considered electrical level is added, in this case it is called augmented T-wave. It has been used to generate signals to software ECGLab [1], and TWA is generated with or without the addition of the sinusoidal wave with the required electrical level.

The difference between the amplitude of the augmented T-waves and the normal ones is called TWA-level. The TWA-level presented at a ECG signal has been verified by measuring the difference between the average amplitudes of the augmented T-waves (augmented level) and the normal ones (normal level). Several electrical levels: 1mV, 0.5mV, 0.2mV, 0.1mV, 0.05mV, 0.02mV and 0.01mV are used for the experiments presented below.

Next, we give some definitions and mathematical tools used along this paper.

Definition 1. [2] A function $\Psi(t) \in L^2(\mathbb{R})$ is said to be a wavelet if only if its Fourier transform $\widehat{\Psi}(\omega)$ satisfies

$$\int_{0}^{+\infty} \frac{\left|\widehat{\Psi}(\omega)\right|^2}{\omega} d\omega = \int_{-\infty}^{0} \frac{\left|\widehat{\Psi}(\omega)\right|^2}{|\omega|} d\omega = C_\Psi < +\infty.$$

This condition implies a zero average: $\int_{-\infty}^{+\infty} \Psi(t) dt = 0$.

This condition (called admissible condition) implies that a wavelet is compactly supported in both the time domain and the frequency domain [3].

In [4] it is showed the following definitions.

Definition 2. Given $\Psi(t) \in L^2(\mathbb{R})$ we denote $\Psi_a(t)$ the dilation of $\Psi(t)$ by a factor a (where a is a positive number)

$$\Psi_a(t) = \frac{1}{a}\Psi\left(\frac{t}{a}\right).$$

Definition 3. The convolution of two functions $f(t) \in L^2(\mathbb{R})$ and $g(t) \in L^2(\mathbb{R})$ is given by

$$f * g(t) = \int_{-\infty}^{+\infty} f(u)g(t-u)du.$$

Definition 4. A smoothing function is a function $\theta(t)$ whose integral is equal to 1 which converges to 0 at infinity and we assume also $\theta(t)$ to be differentiable.

Definition 5. The wavelet transform of a function f(t) at scale a is given by the convolution product

$$W_a f(t) = f * \Psi_a(t).$$

Remark 1. The dilation of a smoothing function is still smoothing function and the derivative of a smoothing function is a wavelet. A smoothing function can be viewed as the impulse response of a low-pass filter.

The convolution of a function $f(t)$ with a smoothing function attenuates part of its high frequencies without modifying the lowest frequencies and hence smooths $f(t)$ [5].

For practical applications the scale and the traslation parameters must be discretized. For a particular class of wavelets, the scale parameter can be sampled along the dyadic sequence $\{2^j\}_{j\in\mathbb{Z}}$ without modifying the overall properties of the transformation. Generally, the parameter j is known as level of decomposition.

In the following lines, the wavelet transform is written as a multiscale differential operator.

Theorem 1. [4] Let $\theta(t)$ be a smoothing function. Let $\Psi(t)$ be the first-order derivative of $\theta(t)$. Then

$$W_a f(t) = f * \left(a\frac{d\theta_a}{dt}\right)(t) = a\frac{d}{dt}\left(f * \theta_a\right)(t).$$

This relation tells that the wavelet transform of a function is proportional to the derivative of the smoothed function. By changing the scale a, we can obtain the derivatives of the smoothed function at different scales.

We refer to [4] for a complete treatment of the wavelet theory.

The paper will focus on Wavelet Transform (WT), which application is done in the next Section. In Section 3 the methods to detect R peaks and T peaks are analyzed. And 4 section, results and conclusions obtained are given.

2 Applying Wavelet Transform (WT)

The ECG signal is a not stationary signal, that is, its statistical properties change over time. That is the cause why WT is convenient for analysis. WT indicates the precise moment in time when the transients (ruptures, rapid changes in time of the frequency components, and so on) appear, whereas the Fourier Transform does not do this. The WT is able to decompose a signal in different frequency components and to study each one of them with a different resolution, allowing for example the elements' identification of different resolution, as ECG waves, noise and artifacts. At small scales, the WT reflects the high frequency components of the signal and, at large scales it reflects the low frequency components of the signal. For example, T-waves have different frequency content and could be detected at higher scales of decomposition.

The WT depends on two parameters: scale and translation. Scale corresponds to the intuitive notion of the term used in the maps scale; low levels correspond to detailed information and high levels offer a global information. By decomposing signals into elementary building blocks, the WT can characterize the local regularity of signals [2]. Signal singularities often show the most important information.

The WT modulus' local maxima at different scales can be used to locate the sharp variation points of ECG signals [6]. In [4] is showed that if the wavelet is the first derivative of a smoothed function, the maximum local of dyadic WT indicates the abrupt signal changes, while the minimum local indicates slow variations. Besides, the WT submits zeros at different scales in the positions where signal is maximum local or minimum local.

3 R peaks and T peaks detection

On the time–frequency plane of the wavelet transform, the wave rising edge of the QRS complex corresponds to a negative minimum, and the dropping edge corresponds to a positive maximum at different scales. The zero-crossing points of these positive maximum-negative minimum pairs are found to give the location of R peaks [6].

Usually, the onset of the QRS complex contains the high-frequency components, which are detected at finer scales, here we use the level of decomposition $j = 1$ because the modulus maxima detected at large scale may also include those induced by P-waves and T-waves, as well as the baseline drift. Using a small scale can also eliminate their effects.

A similar procedure has been used in the detection of T-waves, using $j = 9$ as the level of decomposition because T-waves have different frequency content and could be detected at higher scales of decomposition.

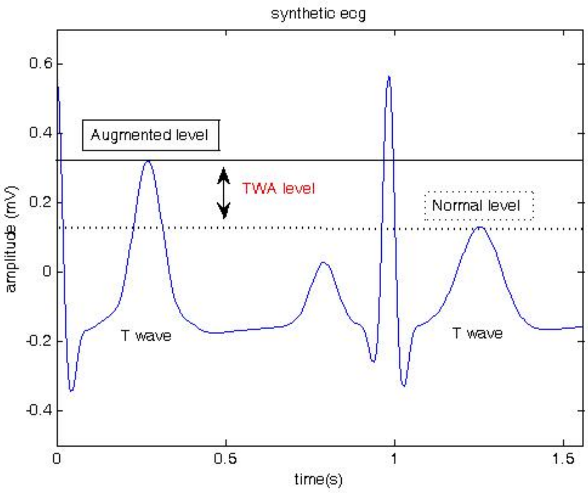

Fig. 2. TWA-level is the difference between the augmented level and normal level.

The mother wavelet used is 'rbio3.1' (reverse biorthogonal spline wavelet), a real wavelet.

We describe below the process followed in the experiments.

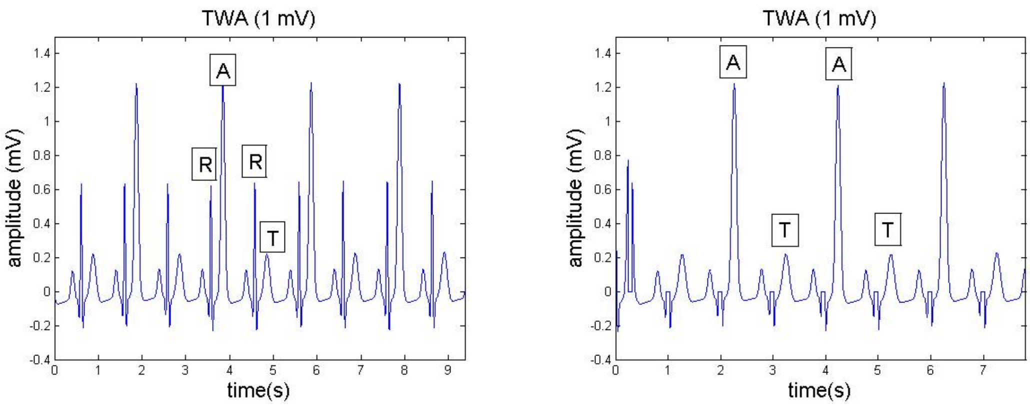

Fig. 3. (Left) The R-peaks are detected . The augmented T-waves (TWA-level=1 mV) are labeled as A and normal T-waves are labeled as T. (Right) The resulting signal once the R-peaks have been deleted.

1). Firstly, QRS complexes are detected and removed from the signal x.

In the overall process, the detection of QRS interval is very important. The R peaks has been detected using a algorithm which is inspired in work [7].

To detect QRS complex, the signal is taken and it is passed through filter passband FIR (order 100), between 1 and 20 Hz and the 100 first samples

(400 ms) are removed. Next, the first 5 seconds of this signal are subdivided in intervals of 200 ms since this period is considered as a refractory period. In this period, once detected a R peak, the appearance of another one is not expected. In each interval, the local maxima of the $|WT|$ are obtained. And between these maxima values that exceed a threshold, are selected and they are labelled x_i. The considered threshold is $u1 = 0.8$ times the mean($|WT|$) of the total signal.

We consider the Wavelet Transform ($WT(x)$) and we take windows from 0.16 s, beginning from a point $i/|WT(i)|$ exceed a second threshold: $u2 = 0.8$ times the mean($|WT(x_i)|$). If in that window exists the zero-crossing of the WT, we will consider the intervals $[a-i, a+i]$, where $a = 0.12$ s. The maximum of signal x in this interval is founded and this one will be a possible R peak. The maxima founded such that they exceed a threshold $u3$ times the maximum amplitude of the signal x, are the R peaks. We take $u3 = 0.3$.

We apply the detector at level of decomposition $j = 1$ creating a vector x_1 which contains positions corresponding to R peaks of the signal. Let x_2 be a cardiologists' detections vector. Next, we compare the vectors x_1 and x_2 and we accept an error of 5 samples (20 ms). This error is smaller than the method of validating the assessment criteria recommended by the AAMI (Association for the Advancement of Medical Instrumentation). Once detected R peaks of the ECG signal, they are eliminated and we call to the new signal g.

2). Secondly, T-waves are detected (both augmented as normal).

We return to apply to signal g the same filter and the 100 first samples are eliminated.

We apply the detector at level of decomposition $j = 9$. The procedure is similar to that described above.

We consider the wavelet transform $WT(g)$ and we take windows from 0.16 s, beginning from a point $i/|WT(i)| >$ mean$|WT(g)|$. If in that window exists the zero-crossing of the WT, we will consider the intervals $[a-i, a+i]$, where $a = 0.12$ s.

The maximum of function g in this interval is founded and this one will be a possible T peak. The maxima founded such that they exceed a threshold u times the maximum amplitude of the signal g, are the T peaks. We take $u = 0.11$ for the level-TWA $= \{1, 0.5\}$ mV; $u = 0.16$ for the level-TWA $= \{0.2\}$ mV and $u = 0.2$ for level-TWA $= \{0.1, 0.05, 0.02, 0.01\}$ mV.

The range of variation allowed in error is 5 samples.

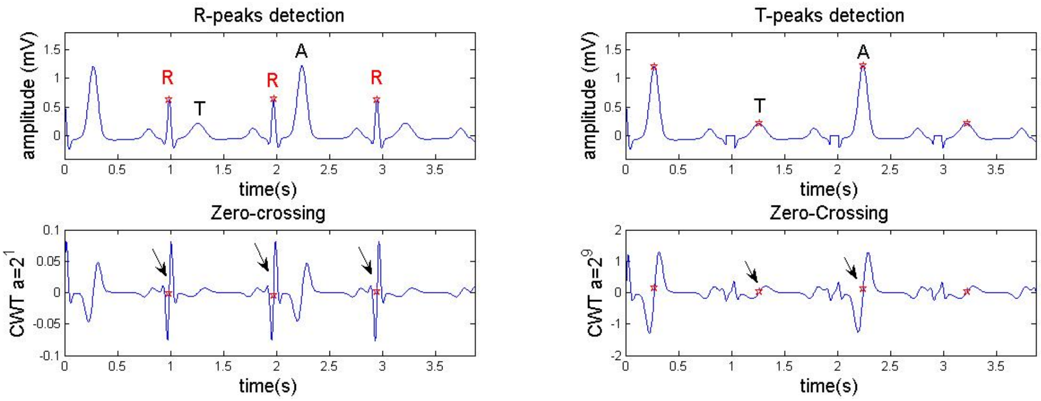

Fig. 4. (Left) Detection R-peaks using WT. (Right) Detection the augmented T-waves (TWA-level=1 mV) (A) and normal T-waves (T) using WT.

4 Results and conclusions

We use the following notations: TP (true positive): peaks detected correctly; FP (false positive): peaks that algorithm marks incorrectly; FN (false negative): peaks not detected. Other statistics as the positive prediction index (+P), sensibility (Se) and error (E) are presented too.

$$+P = \frac{TP}{TP + FP}100 \quad Se = \frac{TP}{TP + FN}100 \quad E = \frac{FP + FN}{TP + FN}100 \qquad (1)$$

In this work we have used the maximum modulus pair of the WT for TWA detection. Firstly, we have detected the R peaks, being the average error from 0.06%. Next, the R peaks have been removed from the signal. Secondly, we have detected T peaks (both normal and augmented T-waves). In the T peaks detection, we can see in the table 2 that it has reached an average of 99.68% and 99.96% in $+P$ and Se respectively, which give us an average error of 0.36%.

The TWA-level present at the ECG signal has been verified by measuring the difference between the average amplitudes of the augmented T-waves and the normal ones.

We think that the results are quite satisfactory. However, we must bear in mind that they have been obtained in synthetic ECG signals, and to verify the proper detector's operation, it would have to be tested in real ECG signals.

TWA-level	R Det.	TP	FP	FN	+P(%)	Se(%)	E(%)
1 mV	2049	2048	1	1	99.95	99.95	0.10
0.5 mV	2048	2048	0	1	100	99.95	0.05
0.2 mV	2048	2048	0	1	100	99.95	0.05
0.1 mV	2048	2048	0	1	100	99.95	0.05
0.05 mV	2048	2048	0	1	100	99.95	0.05
0.02 mV	2048	2048	0	1	100	99.95	0.05
0.01 mV	2048	2048	0	1	100	99.95	0.05
Mean					99.99	99.95	0.06

Table 1
Detection of R peaks. The number of detected peaks is shown in R Det.

TWA-level	T Det.	TP	FP	FN	+P(%)	Se(%)	E(%)
1 mV	2054	2048	6	1	99.71	99.95	0.34
0.5 mV	2052	2049	3	0	99.85	100	0.15
0.2 mV	2054	2048	6	1	99.71	99.95	0.34
0.1 mV	2057	2048	9	1	99.56	99.95	0.49
0.05 mV	2057	2048	9	1	99.56	99.95	0.49
0.02 mV	2051	2048	3	1	99.85	99.95	0.20
0.01 mV	2058	2048	10	1	99.51	99.95	0.54
Mean					99.68	99.96	0.36

Table 2
Detection of augmented T-waves and normal T-waves. The number of detected peaks is shown in T Det.

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