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T-Wave Detection Based on an Adjusted Wavelet Transform Modulus Maxima

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Abstract**—**The method described in this paper deals with the problems of T-wave detection in an ECG. Determining the position of a T-wave is complicated due to the low amplitude, the ambiguous and changing form of the complex. A wavelet transform approach handles these complications therefore a method based on this concept was developed. In this way we developed a detection method that is able to detect T-waves with a sensitivity of 93% and a correct-detection ratio of 93% even with a serious amount of baseline drift and noise.

Keywords**—**ECG, Modulus Maxima Wavelet Transform, Performance, T-wave detection

I. Introduction

THE heart is a hollow muscular organ which through a coordinated muscle contraction generates the force to circulate blood throughout the body. Each beat of our heart is triggered by an electrical impulse from special sinus node cells in the right upper heart chamber. The electrical impulse travels to other parts of the heart and causes the heart to contract. An ECG records these electrical signals.

The T-wave that is the focus of this study is one of the five main waveforms in an electrocardiogram (ECG) and corresponds to the repolarization phase of the heartbeat [1]. In some pathological conditions the morphology of the T-wave may change from beat to beat, the simplest and most easily recognizable change being an amplitude change of the wave. Manual detection was used to provide a known reference for the exploration, so these ECG's were first annotated completely by an experienced cardiologist. In the procedure of manual detection a cardiologist reads each ECG and marks the beginning and end of every T-wave [1].

Wavelet analysis provides important information about the mathematical morphology of a signal. An important method based on wavelet analysis is the Wavelet Transform Modulus Maxima (WTMM)-method [2]. Using this method it is possible to describe the characteristic elements of a complex quasi-periodic signal. This description can then be used to recognize these elements in new signals. The WTMM-formalism is also suitable for analyzing multi-dimensional patterns, but the complexity increases fast when dimensions are added. A number of publications describe the application of the WTMM [3] [4] for characterizing and identifying the behaviour of heart signals as recorded on an electrocardiogram (ECG). A normal ECG can be decomposed in characteristic components, named the P, Q, R, S and T-wave. Each of these components has its own typical form and behaviour. The relative shape and position of these components relate to the actual condition of the heart such as in a state of stress or pathology.

In Section II, an algorithm based on the WTMM will be presented. This algorithm has proven to be very successful in detecting T-waves in an ECG-recording. Section III describes three parameters on which we are based when we are interested in ECG waves detection especially in T-wave detection. In Section VI, we explain the adjustments made to the algorithm so it can also detect the difficult T-waves. We discuss the WTMM method performance in section V. Finally, Section VI presents the conclusion.

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II. Wavelet Transform Modulus Maxima Method

Most of the information in a signal is carried by its irregular structures and its transient phenomena, called singularities. A method that excels in finding and identifying these singularities is the Wavelet Transform; because of its capability of decomposing a signal into elementary building blocks that are well localized in both time and frequency. Because of this capability, the Wavelet Transform is capable of defining the local regularity of a signal. The local regularity of a function is often measured with the Lipschitz exponents [5], also called the Hölder exponent.

We define what we mean by a local maximum of the wavelet transform modulus [6].

Let $Wf(x)$ is the wavelet transform of a function *f(x)*

•We call a local extremum any point x_0 such that $\frac{d(Wf(x))}{dx}$ has a zero crossing at $x = x_0$, when x varies.

•We call a modulus maximum; any point x_0 such that $|Wf(x)| < |Wf(x_0)|$ when x belongs to either a right or left neighbourhood of x_0, and $|Wf(x)| \leq |Wf(x_0)|$ when x belongs to the other side of the neighbourhood of x_0.

•We call maxima line, any connected curve in the scale space x along which all points are modulus maxima.

III. T-WAVE DETECTION

The T-wave which corresponds to the ventricular repolarization of the heart has a remarkable behaviour in some situations. This makes this phenomenon hard to detect. The figure bellow illustrates some typical behaviour.
The first situation is a typical T-wave. The wave displayed here has a rather large amplitude, so it will not be hard to detect, however this amplitude can decline to very small magnitude. In this case the standard methods will have a very hard time pointing out the exact location of the T-wave. The second situation has the same problems as the first but here the T-wave has inverted itself. This makes detection hard for some methods that do not use the modulus of the signal. In the third situation, we present an ascending or descending T- wave. Another problem that can occur with all these situations is a bad positioning of the T-wave. Sometimes it is situated to the close to the QRS-complex or the P-wave. This makes it difficult to separate these two complexes.

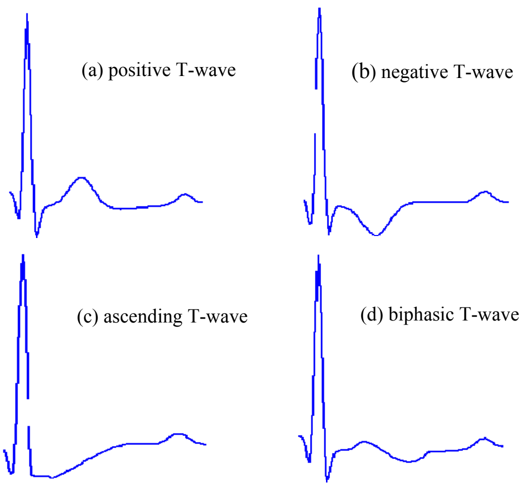

Fig. 1 various T-waves

A. Choice and implementation of the mother wavelet:

The mother wavelet used in this study is the first derivative of the Gaussian function. Other possibilities, like the second derivative (Mexican Hat) were examined but did not offer any advantages. In most studies concerning ECG detection [3][4], the wavelet transform is implemented using a composition of a low pass and a high pass filter.

This study however, used an implementation based on the continuous wavelet transform of a discrete-time signal, as discussed in the article of Provaznik [7].

B. Onset/Offset detection:

The T-wave is hard to detect in some cases because of its low amplitude and its changeable state. By using the WTMM, it is possible to detect certain characteristic points in the wavelet transform. These points can then be used to develop decision rules that help detect the T-wave. Applying this method to detect onsets gives certain problems. The biggest problem is the influence of the QRS-complex.

When looking at a wavelet transform of a PQRST-complex at higher scales it is obvious that the effect of the QRS-complex has not sufficiently faded in the environment of the T-wave onset. This makes searching for characteristic points concerning the onset very hard. Using low scale transforms does not really improve the reliability, as the amplitude of the onset is not sufficiently larger than the amplitude of frequently appearing noise.
The problem with the QRS-complex does not concern the offset and therefore it is detectable with a good reliability when there is not a high amount of noise. The onset/offset are normally characterised by a modulus maximum that occurs before/after the T-wave that exceeds a certain threshold.

C. Choice of scales

The use of non-dyadic scales can be useful for detecting low amplitude complexes. In this paper we use scale 10 for T-wave detection. This scale appeared to give better results that 2^3 or 2^4. This choice was made because $2^3$was too sensitive to noise. 2^4 on the other hand, did not divide the complexes in the transformation and therefore restricts good detection.

IV. ADJUSTMENTS OF THE WTMM FOR T-WAVE DETECTION

The method described in the previous section and in the article by Li et al. [3] is also suitable for detecting T-waves after making some adjustments.
A normal T-wave and its transform clearly display a modulus maxima pair with opposite signs. The T-wave is found at the zero-crossing between the two modulus maxima.

Figure 3 shows an alternative T-waves, it indicates that not all T-waves can be detected by searching for a modulus maxima pair. In some cases, there is an only one modulus maximum available. By using the method described below, it is possible to detect most T-wave variations.

Although this method has a lot in common with the standard WTMM method, the modifications will be described step by step:

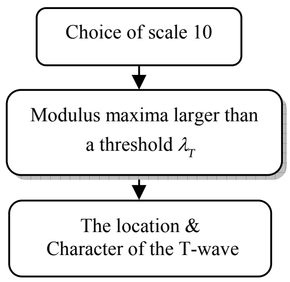

Fig. 2 Adjustments made for T-wave detection

The T-wave's energy is mainly preserved between the scales 2^3 and 2^4. Therefore it was more appropriate to turn away from the dyadic scales and to choose the scale 10 for the WT. The next step consists of the search for modulus maxima. At scale 10 we analyzer a signal and search for modulus maxima larger than a threshold λ_T .

This threshold is determined by using the root mean square (RMS) of the signal between two R-peaks. J.P Martinez [4] found that $\lambda_T = 0.25RMS$ is suitable for detecting most of the T-peaks. When there are two or more modulus maxima with the same sign, the largest one is selected. After finding one or more modulus maxima, it is possible to determine the location and character of the T-wave. The first situation occurs when there is a modulus maxima pair with opposite signs. This indicates a small hill when the signs are +/- and a small inverted hill when the signs are -/+. When there is only one modulus maxima present, the + sign indicates a T-wave that consists only in a ascending. When the sign is -, we see a T-wave formed by an descending.

V. The WTMM Method Performance

We will discuss certain parts of signals chosen from MIT-BIH Arrhythmia Database that will regularly lead to failure of a correct detection due to frequently appearing difficulties in T-wave detection.

1) *Low amplitude:* Most methods require frequently adapted thresholds in order to detect a low amplitude T-wave. In most cases these thresholds are used to distinguish the wave from the noise. Figure 3 shows the capability of the WTMM based method. By using scales that contain most part of the energy of the T-wave it is possible to acquire a precise detection.

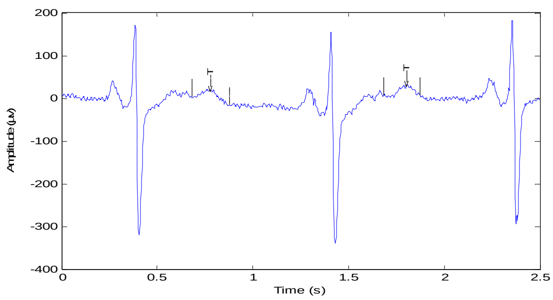

Fig. 3 Low amplitude (220.dat)

2) *Noise:* The WTMM approach used in this paper uses the Gaussian wavelet as mother wavelet. A large advantage of this choice is the "smoothing" property this wavelet offers. The higher the scale, the smoother the transformation. This results in a method that is very robust to noise.

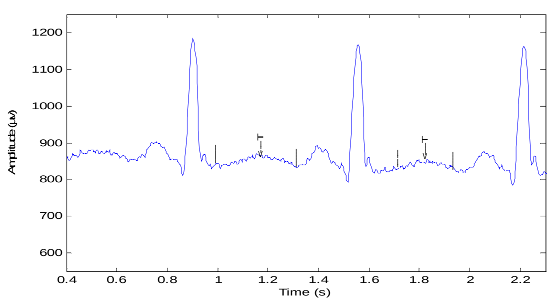

Fig. 4 Noise (122.dat)

3) *Baseline drift:* The WTMM-based method only considers variations of the signal that has a certain resemblance with the T-wave. Therefore, it is insensitive to baseline drift.

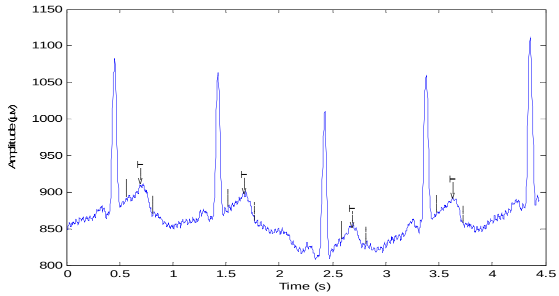

Fig. 5 Baseline drift (121.dat)

4) *Ambiguous waves:* As most standard methods, the WTMM-based method uses certain decision rules to distinguish different kinds of T-waves. The difference with the other methods lies in the fact that the rules are applied to the transformation instead of to the pure signal. The transformation gives a clearer view of the signals information and therefore it is better suited for decision rules.

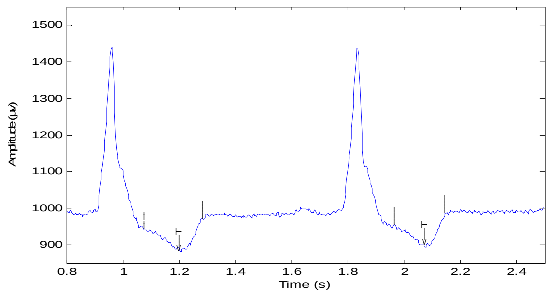

Fig. 6 Ambiguous waves (214.dat)

The datasets are signals coming from the MIT-BIH Arrhythmia Database [8]. However not every long signal contains large amounts of useful information. When there is no change in a wave through-out the whole signal, it is not useful to analyse every peak. Therefore, only the parts which define the ECG will be discussed. The performance of the methods will be tested by using several cases with certain difficulties. Every case will be described first; next the performance will be measured by certain parameters:

- Number of True Positive detections (TP)
- Number of False Positive detections (FP)
- Number of True Negative detections (TN)
- Number of False Negative detections (FN)
- Total number of peaks (Total Peak)
- Percentage of detected T-waves (Se)
- Percentage of detected non visible T-waves (Sp)
- Ratio of correct detections (RCD)

1) *Case 1:* This case contains a signal with a clear T-wave. The noise consists of some small artifacts. The behaviour is rather unstable as the signal tends to climb for a while and to descend at the end. This short signal offers easy to detect T-waves at the start (first 10 beats). At the end of the signal, the alternative method is confused because of the climb and therefore detects some incorrect T-waves. The WTMM based method only misses one and therefore is better suited for this kind of unstable signal.

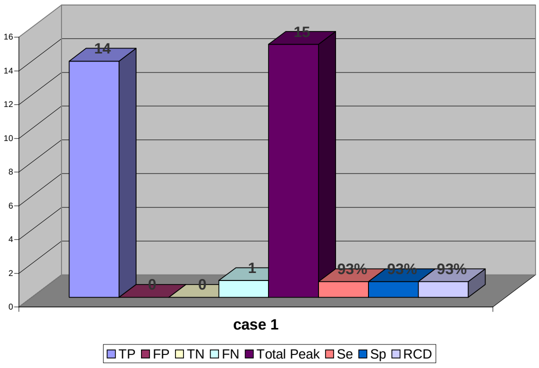

Fig. 7 case 1 performance

2) In the last hour, the T-wave starts manifesting itself and becomes positive.
There is also some high frequency noise between every two consecutive R-peaks. As most of the detection methods [9], the alternative method searches for a T-wave that consists in an ascending and a descending. Therefore this method was unable to detect any wave in the first part. The second part was more suited and so the method proclaimed a high detection ratio. The WTMM- based method has no problem with detecting the T-waves in the first or second part.

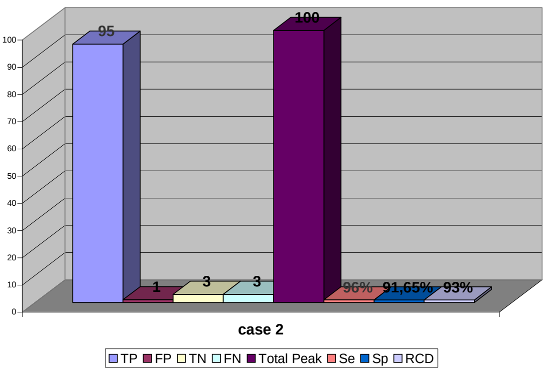

Fig. 8 case 2 performance

3) *Case 3:* This case offers a signal with a clear T-wave and no noise. This is the most successful case that was tested because of the pureness of this case. The part that is used for analysis only has some small artifacts that are not able to disrupt the WTMM-based method. The alternative method is more sensitive to these artifacts, but is still very reliable.

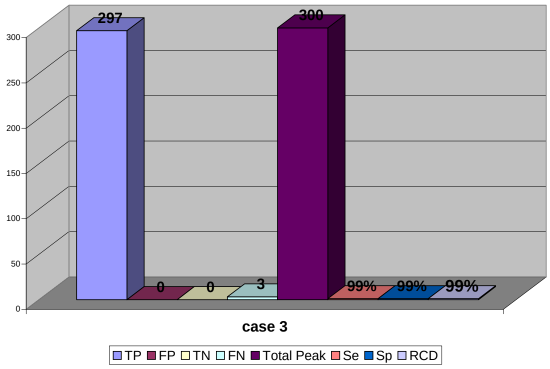

Fig. 9 case 3 performance

4) *Case 4:* The last case consists of a signal with a high amplitude S-wave and an ambiguous T-wave. The noise is limited to some high frequency disturbance. This case offers a T-wave that manifests itself on an other wave, which confuses the alternative method and therefore it sometimes registers.

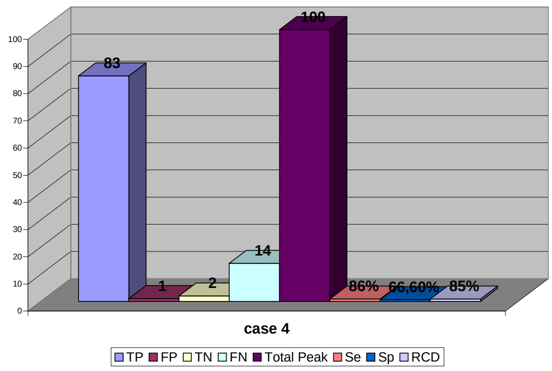

Fig. 9 case 4 performance

VI. Conclusion

We have presented and validated in this paper an ECG-detection method which detects T-waves using the WTMM approach and a collection of decision rules. The method has been validated using several ECG-recordings with a wide variety of T-wave morphologies from MIT-BIH arrhythmia database. Some of these cases contained easily detectable T-waves, other were more complex due to the amount of noise or baseline-drift. Cases with a simple T-wave and a limited amount of noise result in errorless detection.

None of the more complex cases result in a correct-detection ratio below 93% or sensitivity under 93%, except for the last case that is specifically designed to test the weaknesses of this method. These results have been compared with one conventional derivative-based approach and have shown that the developed method provides a reliable and accurate detection of the T-wave complex, which is able to outperform the reference algorithm and has a fault-detection percentage well within the acceptable range.

The superior performance is a result of the WTMM approach, which is able to decrease the effect of noise without reducing the T-wave information. It is robust to measurement noise, to T-wave morphological variations and to baseline wander. This WTMM based method also gives the opportunity to study low amplitude complexes by using different scales, and therefore, it is suited for T-wave detection.

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