Application of the Wavelet Transform Modulus Maxima method to T-wave detection in cardiac signals

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Preface

In order to obtain my master degree at Maastricht University, I wrote a thesis concerning electrocardiogram analysis. I chose this discipline after considering various other subjects. The things that convinced me, was the ability to work at the Instrument Development Engineering & Evaluation (IDEE) institute and the ability to research a subject that is closely related to a real life application.

I would like to thank everybody at IDEE, especially my supervisor Iwan De Jong. Also many thanks go to the people of the Cardiology institute of the UM, especially Dr. Paul Volders and Roel Spätjens. A special thanks also goes out to my family and friends for providing me with the necessary distractions in order to complete this thesis. Last but not least I would like to thank my promoters Ronald Westra, Joel Karel and Ralf Peeters for their great guidance and patience.

It was an informative and interesting experience.

Abstract

The method described in this report 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 and therefore a method based on this concept was developed. A QRS-complex detection method was customised by revising the scales and adjusting and polishing the decision rules. 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.

Contents

Chapter 1

General Introduction

Complex patterns and signals can be efficiently represented by decomposing them in different frequencies. The conventional method for this approach is the Fourier analysis. However, a certain instance may vary in time and space over the frequencies. In such cases it is more appropriate to decompose the signal using another approach, which allows for spatial variation in the spectral composition of the signal. Examples of such approaches are the Windowed Fourier Approach[1] and the multiresolution analysis approach[2], based on so called wavelets. 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. 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 analysing 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 heartsignals 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 their 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 this study, the WTMM-based method is applied to detect the T-wave, an important but weakly pronounced aspect of the ECG. First, an introduction behind the wavelet analysis and the WTMM-method will be discussed. Next, the method based upon the WTMM applied to the more significant QRS-complex will be introduced alongside the adjustments necessary for detecting T-waves. The last two chapters present the results and the major conclusions.

Chapter 2

Wavelets Analysis

2.1 Introduction

Wavelet analysis is a relatively recent development in the world of mathematics. In this chapter, the origin and history of wavelets will be briefly discussed. Next, the strong links between the wavelet and Fourier analysis will be explained. This will be followed by an explanation of wavelets and the wavelet transform. The last part will provide the basic ideas behind multi-resolution analysis.

2.2 Wavelets

2.2.1 Fourier Analysis

The two main domains for analysing a signal are the time and the frequency domain. Finding small fluctuations in large datasets in the time-domain is rather hard. These difficulties can be easily overcome by searching in the frequency domain. The most common method used for converting a signal to the frequency domain is called the Fourier transform. This method was invented by a French mathematician J. Fourier in 1822. He showed that any periodic function can be expressed as an infinite sum of cosine and sine functions, also called the Fourier series:

$$f(x) = \frac{1}{2}a_0 + \sum_{k=1}^{\infty} a_k \cos(kx) + \sum_{l=1}^{\infty} b_l \sin(lx)$$

Where

$$a_0 = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)dx$$

$$a_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)\cos(kx)dx$$

$$b_l = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)\sin(lx)dx$$

Since sine and cosine functions can be expressed in terms of complex notations by using the Euler's formula ($e^{ix} = \cos(x) + i\sin(x)$), one often uses the more compact notation:

$$f(x) = \int_{-\infty}^{\infty} F(\omega)e^{2\pi i\omega x}d\omega$$

One disadvantage concerning the Fourier transform is the disability to provide information about a simple discontinuity shown in the following figure:

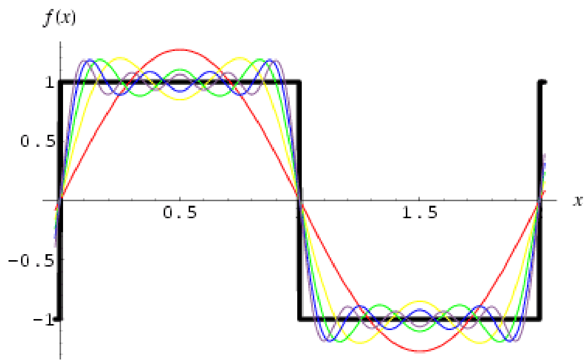

Figure 2.1: Gibbs phenomenon

Another disadvantage is that the lack of time-localization. A method to achieve time-localization is the windowed Fourier transform. As the name suggests, we multiply the signal f with a window function $b(t - t_0)$, where $b(t)$ is nonzero only in a finite region around t_0. Then the windowed Fourier transform of f is:

$$\hat{f}(\omega, t_0) = \int_{-\infty}^{\infty} f(t)b(t - t_0)e^{-i\omega t}dt$$

Obviously only the region where $t_0 - \epsilon < t < t_0 + \epsilon$ contributes to the transform, since this is the window of width 2ϵ that is moving along the time axis. Although this method is also vulnerable for the Gibbs phenomenon.

2.2.2 Origin and History

Wavelet analysis is a relatively new technique mostly used in signal processing. The foundation of the wavelet was a method that Joseph Fourier used in 1807. His approach for frequency analysis is the basis for the Fourier Transform, today the most commonly used technique of measuring the frequency content of a signal. However this transform has one large disadvantage: It provides information about how much of each frequency exists in a signal, but it does not indicate when in time these frequency components occur.

In the 1930's, a physicist named Paul Levy was investigating a type of random signal by using a scale-varying basis function called the Haar basis function. He found that this function was better for studying small variations in the motion of the signal. This became a key concept in the development of wavelets because here a transformation was computed separately for different segments of the time-domain signal.

Fifty years later, a physicist and engineer by the names of Morlet and Grossman, respectively, defined wavelets in the context of quantum physics. Morlet introduced the theoretical form in a paper about the analysis of seismic data [5]. Grossman followed by publishing a paper about the mathematical foundations.

In 1985, Stephane Mallat and Yves Meyer made a huge leap in the field of wavelet analysis by introducing the idea behind multiresolution analysis [2]. Inspired by this I. Daubechies constructed families of orthonormal wavelets with compact support [6]. Nowadays wavelets are used in many fields of research and have been used in many applications ranging from fingerprint detection to seismology.

2.2.3 Wavelet Transform

The disadvantages of the Fourier Transform mentioned before can be overcome using wavelets. The Wavelet transform is a method based on expressing functions or signals as sums of 'little waves'. These waves are used like the sines and cosines in a Fourier series. In contrary to the Fourier transform, the wavelet transform is localized both in time and frequency and it has compact support. Therefore it is perfectly suitable for displaying small fluctuations in signals.

A family of wavelets can be constructed from a function, sometimes called the "mother wavelet," which is ideally confined in a finite interval. In practice however, also not-compact supported wavelets are used such as Gaussian or Morlet. "Daughter wavelets" are formed by translation (b) and dilation (a) of the mother wavelet. An individual wavelet can be defined by:

$$\psi^{a,b}(x) = |a|^{-\frac{1}{2}}\psi\Big(\frac{x-b}{a}\Big)$$

Then the transformation is performed by an inner product of this "Daughter wavelet" $\psi_{a,b}$ and a function f:

$$W_\psi(f)(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\psi\Big(\frac{t-b}{a}\Big)dt$$

This method has much in common with the windowed Fourier transform. The difference lies in the behaviour of the analysing functions $b(t-t_0)e^{-i\omega t}$ and the wavelet ψ. The function $b(t-t_0)e^{-i\omega t}$ stays unchanged throughout the whole transformation, while the wavelet adapts its width to the frequency. Therefore high energy wavelets are very narrow while low frequency wavelets are much broader. This lets the wavelet transform "zoom in" on high frequency phenomena.

2.2.4 Multiresolution Analysis with Wavelets

Multiresolution analysis [7], as implied by its name, analyses the signal at different frequencies with different resolutions. Take a given resolution, a signal is approximated by ignoring all fluctuations below that scale. As we increase the resolution, finer details are added to the description, providing a better approximation of the signal. Eventually we recover the exact signal with the information contained in all scales.

This method is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations.

2.3 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 [8], also called the Hölder exponent.
Definition:

- Let n be a positive integer and $n \leq \alpha \leq n+1$. A function $f(x)$ is said to be Lipschitz α, at x_0, if and only if there exists two constants A and $h_0 > 0$, and a polynomial of order n, $P_n(x)$, such that for $h < h_0$

$$|f(x_0 + h) - P_n(h)| \leq A\,|h|^{\alpha}$$

  [9]

- The function $f(x)$ is uniformly Lipschitz α over the interval $[a, b]$, if and only if there exists a constant A and for any $x_0 \in [a, b]$ there exists a polynomial of order n, $P_n(h)$, such that the equation from the previous point is satisfied if $x_0 + h \in [a, b]$

- We call Lipschitz regularity of $f(x)$ and x_0, the superior bound of all values α such that $f(x)$ is Lipschitz α at x_0.

- We say that a function is singular at x_0, if it is not Lipschitz 1 at x_0.

When a function is continuously differentiable at a point, its Lipschitz exponent is 1 at this point and so there is no singularity present at that location. The Lipschitz exponent α gives an indication of differentiability but it is more precise. If the Lipschitz exponent α of a function at x_0 satisfies $n < \alpha < n+1$ we know that the function is n times differentiable at x_0 but it also indicates that the n'th derivative is singular at x_0 and α characterizes this singularity.

Now, let us precisely define what we mean by a local maxima of the wavelet transform modulus:

Let $Wf(x)$ be 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 $\mid Wf(x) \mid < \mid Wf(x_0) \mid$ when x belongs to either a right or left neighbourhood of x_0, and $\mid Wf(x) \mid \leq \mid Wf(x_0) \mid$ 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.

In [10] was proven that when a wavelet transform has no modulus maximum at fine scales in a given interval, the function is uniformly Lipschitz α, where α is close to 1, in this interval. This means that a function is not singular in any neighbourhood where its wavelet transform has no modulus maxima at fine scales.

Chapter 3

Wavelet-based ECG-complex detection

3.1 Introduction

In this chapter the application of the methods discussed in the previous chapter will be explained. Here these methods will be used in the context of the identification of the T-wave in an ECG-complex. The first section will give a small introduction in the world of electrocardiography. Second, an algorithm based on the WTMM will be presented. This algorithm has proven to be very successful in detecting different complexes in an ECG-recording. Not only the process will be described, also the advantages and disadvantages of this method. The last two sections will explain the adjustments made to the algorithm so it can also detect the difficult T-waves.

3.2 Electrocardiogram

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 your heart is triggered by an electrical impulse from special sinus node cells in the right upper chamber of your heart. The electrical impulse travels to other parts of the heart and causes the heart to contract. An ECG records these electrical signals.

A typical ECG is displayed in figure 3.1. Looking at the picture you can see that there is a recurrent pattern in this ECG. Every characteristic of this pattern has certain features and a certain physiological meaning. The

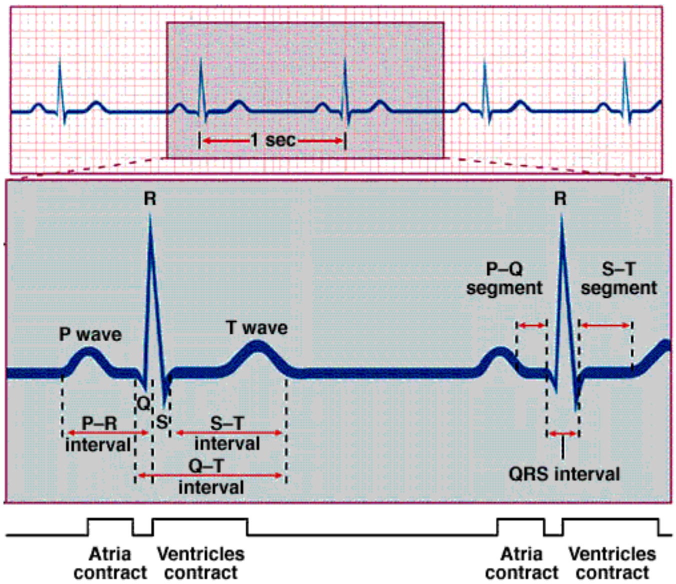

Figure 3.1: typical ECG signal

first deflection, termed the P-wave is due to the depolarization of the atria. None of the detection methods described in this report are applied to this wave so this will not be considered here.

The large QRS-complex is due to the depolarization of the ventricles. This is the complex with the highest amplitude. The detection methods discussed in the next two sections were developed for detecting this QRS-complex.

The last and most significant part for this report is the T-wave. It corresponds to the ventricular repolarization of the heart. The T-wave has a remarkable behaviour in some situations. This makes this phenomenon hard to detect. The next figure illustrates some typical behaviours.

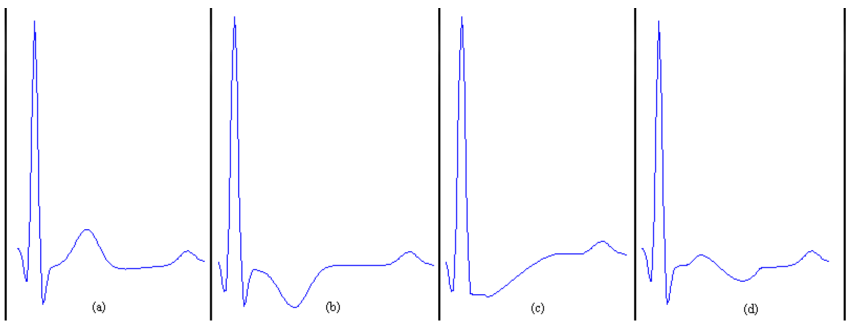

Figure 3.2: Various T-waves

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 the wave is constructed only of a descend or an ascend. The last situation displays a bi-phasic T-wave, but this type will not be discussed in this report. Another problem that can occur with al 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.

3.3 Standard methods for the detection of the QRS-complex

There is a large variation of QRS-detection methods. Almost all QRS-detection algorithms use a filter stage prior to the actual detection in order to attenuate other signal components and artifacts, such as P-wave, T-wave, baseline drift, and incoupling noise. The main difference between different methods lie in the filtering method they employ. Some are derivative-based, other filter-based, there are also some that use learning methods like Neural networks or adapting filters.

The method that will be discussed here, is the derivative-based method. It is mainly used in online applications because it offers good performance on clean signals and is easy to implement.

This method uses a differentiator as high-pass filter. This makes use of the characteristic steep slope of the QRS-complex for its detection. Difference equations of possible differentiator filters are [11][12]:

$$y(n) = x(n+1) - x(n-1)$$

$$y(n) = 2x(n+2) + x(n+1) - x(n-1) - 2x(n-2)$$

$$y(n) = x(n) - x(n-1)$$

Some algorithms also compute the second derivative and use a linear combination of the magnitudes of the first and the second derivative.

The detection of a QRS-complex is accomplished by comparing the differentiator against a threshold. Usually the threshold levels are computed signal dependent such that an adaptation to changing signal characteristics is possible. A frequently used threshold is:

$\Theta = \delta \cdot max[X]$ where $\delta \in [0.3, 0.4]$ and X is the signal between two R-peaks.

Where the maximum is determined online or from the current signal segment. Most QRS detectors use this or a similar method to determine the threshold.

The peak detection logic is frequently completed by further decision rules that are applied in order to reduce the number of false-positive detections. Such rules usually put heuristically found constraints on the timing and the sign of the features or introduce secondary thresholds to exclude non-QRS segments of the ECG with QRS-like feature values.

3.4 Detection of the QRS-complex using WTMM

Here, we describe an algorithm based on wavelet transforms for detecting the characteristic points in an ECG. By using a multiscale approach this method is capable of distinguishing the QRS-complex from high P or T waves. The method explained in the next section has been described by Li et al.[3] and Almeida et al.[4] for detection of the QRS complex with the wavelet transform.

3.4.1 Application of the WTMM method for QRS-detection

As the name WTMM indicates, we use the wavelet transform (WT) to retrieve useful information from the signal.

$$W_s f(x) = f(x) * \psi_s(x) = \frac{1}{s} \int_{-\infty}^{\infty} f(t) \psi\Big(\frac{x-t}{s}\Big) dt$$

Where s is the scale factor. $\psi_s(x) = \frac{1}{s}\psi(\frac{x}{s})$ is the dilation of a basic wavelet $\psi(x)$ by the scale factor$s$. Let $s = 2^j$ ($j \in \mathbf{Z}$,$\mathbf{Z}$ is the integral set), then the WT is called a dyadic WT. The mother wavelet used here is the derivative of a Gaussian smoothing function [6][10].

Figure 3.2 displays the result of such a dyadic wavelet transform. Complex (c) displays a wave that has a large resemblance with a QRS-complex. The WT's across the scales show that the peak of the complex corresponds to the zero crossing between two modulus maxima of the WT at all the scales.

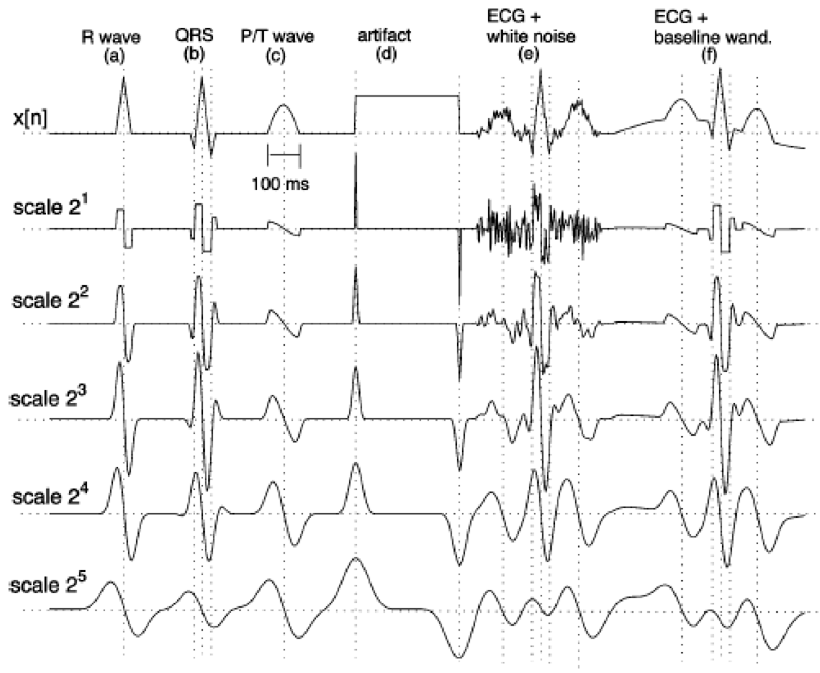

Figure 3.3: Dyadic wavelet transform of a signal adapted from [4]

The method explained here uses this property to find the QRS-complexes in large ECG-recordings.

The method consists of the following steps:

1. The first step of this method is the WT. An example for determining the appropriate scales is shown in figure 3.4. It can be seen that the WT at small scales reflects the high frequency components of the signal and, at large scales, the low frequency components. The energy contained at certain scales depends on the center frequency of the used wavelet. In this case the Gaussian wavelet. The article of Thakor et al.[13] states that most energies of a typical QRS-complex are at scales 2^3 and 2^4, and the energy at scale 2^3 is the largest. From scale 2^3 to smaller or lager scales, the energy of the QRS-complex decreases gradually. According to Li et al.[3], for QRS-complex with high frequency components, the energy at scale 2^2 is larger than that at scale 2^3. Therefore scales 2^3 to 2^4 are used.

2. In the second step, a method for the detection of modulus maxima lines corresponding to R-waves is applied. As seen in figure 3.3, we can see that the QRS-complex corresponds to two modulus maxima

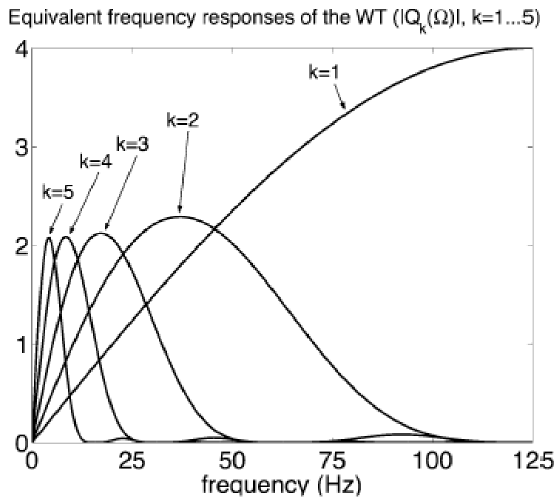

Figure 3.4: Frequency responses at different scales

lines with opposite signs. A method to select these modulus maxima from large to small scale is as follows:

- Find all of the modulus maxima larger than a threshold ϵ_4 at scale 2^4 to obtain the location set of modulus maxima $\{n_k^4 | k = 1...N\}$;
- Find a modulus maximum larger than the threshold ϵ_3 in the neighbourhood of n_k^4 at scale 2^3 and define its location as n_k^3. If several modulus maxima exist, then the largest one is selected. But, the modulus maxima closest to n_k^4 will be selected if the largest one is not larger than 1.2 times the others. If no modulus maximum exists, then set n_k^3,n_k^2 and n_k^1 to zero. So, the location set $\{n_k^3 | k = 1...N\}$ can be found.
- Similar to the previous step, the locations of the modulus maxima at scales 2^2 and 2^1 are found. Then, the location sets $\{n_k^2 | k = 1...N\}$ and $\{n_k^3 | k = 1...N\}$ will be obtained.

By searching the modulus maxima at characteristic scales, the location set of modulus maximum lines $\{n_k^4 n_k^3 n_k^2 n_k^1 | k = 1...N\}$ is obtained. By eliminating those modulus maximum lines with $n_k^1 = 0$, the location set of remaining modulus maximum lines $\{n_k^4 n_k^3 n_k^2 n_k^1 | k = 1...N_1\}$. Searching from large to small scales has two advantages. The first is the decrease of the calculation time. The second advantage is that by using this method, the noise will be minimized at large scales, so it will not give false modulus maxima.

3. The third step, as described by Li et al.[3] is the calculation of the singular degree. This degree and the decay of the wavelet transform

over different scales is illustrated by the Lipschitz exponent. By using this exponent it is easy to spot singularities that are caused by noise. However, this step is not discriminative in most cases and does not really contribute to the detection of T-waves. Therefore the extensive explanation will be skipped in this report.

4. This step removes isolated or redundant modulus maxima. The removal of isolation lines is obtained by deriving a threshold that approximates the maximum length between two consecutive R peaks. Next, it is possible to search for modulus maxima lines that are not contained in a certain interval provided by the threshold.

   The removal of redundant modulus maxima is obtained by using certain decision rules. Because an R-peak is indicated by only two modulus maxima lines, the rules are applied to remove the redundant ones when there are more than 2 of these present. Scale 2^3 is used because the largest part of the energy of the QRS-complex is maintained here. Now take a situation with 2 minima's named Min1 and Min2, their absolute values are A_1 and A_2 respectively. The intervals between the minima's and the maximum are called L_1 and L_2. Using these parameters, the following rules will search for redundant lines:

   Rule1: If $A_1/L_1 > 1.2A_2/L_2$, Min2 is redundant.

   Rule2: If $A_2/L_2 > 1.2A_1/L_1$, Min1 is redundant.

   Rule3: Otherwise, if Min1 and Min2 are on the same side of the maximum, the minimum that is farthest away is redundant. If they are on opposite sides, the minimum following the maximum is redundant.

5. The last step detects the R-peak. As seen at the start of this chapter, the R-peak corresponds to the zero-crossing of two modulus maxima's of the WT. All the previous steps have outlined every pair of these modulus maxima, so the last step only searches the zero-crossing.

3.4.2 Advantages and disadvantages of the WTMM-based method

The main advantage of the WTMM method is the resistance against noise. The noise degrades consistently over the scales. At scale 2^3, the scale that is most suitable for QRS-complex detection, the WT signal is almost completely cleared of any low level interference caused by external activities. Another large advantage is the capability of removing the redundant modulus maxima lines using decision rules. However, these rules are not suitable for every situation. The adaptation of each rule according to the circumstances is a very ambiguous and time-consuming work. Another complication is the acquisition of certain thresholds used by the method. Here the same problems as with the decision rules occur.

The last disadvantage is the complexity of this method. As alternative algorithms are capable of performing their duties online, this method uses an advanced, time consuming transformation and boosts complexity with optimizations that use numerous iterations. This results in a method that is only capable of performing its services offline, given no special optimizations are made. Of course this also results in a performance and reliability that lies far above the ones achieved by the alternative methods.

3.5 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. The method described here analyses the region between two R-peaks. These R-peaks are detected using a QRS-complex detection algorithm.

The first modification to involves the WT. The difference between the QRS-complex and the T-wave is not only visible in the original signal, their transforms also have marked differences.

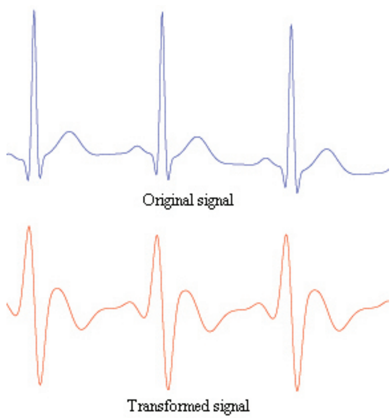

Figure 3.5: Transform at scale 2^3

Using the figure, it is easy to determine the similarities and the differences. Here we have a normal T-wave and its transform clearly displays a modulus maxima pair with opposite signs. Just like the WTMM-method for detecting R-peaks, the T-wave is found at the zero-crossing between the two modulus maxima. However not all T-waves are like the one displayed in the figure. The next figure shows an alternative T-waves as discussed in section 3.2 with its corresponding WT.

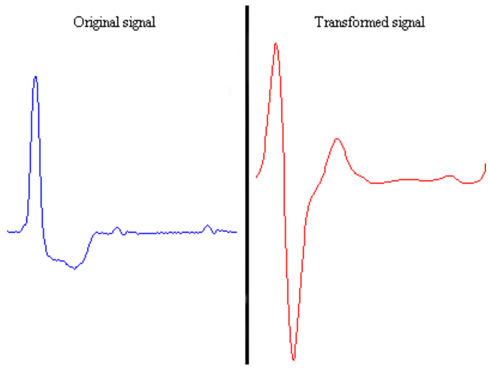

Figure 3.6: Transform of an atypical T-wave at scale 10

The figure indicates that not all T-waves can be detected by searching for a modulus maxima pair. In some cases, there is only one modulus maxima 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:

1. 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.

2. 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 ϵ. This threshold is determined by using the root mean square (RMS) of the signal between two R-peaks. J.P Martinez [4] found that $\epsilon = 0.25 \cdot \text{RMS}$ 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.

3. 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 of a descend. When the sign is -, we see a T-wave formed by an ascend.

3.6 Research concerning T-wave detection

This chapter contains a review of additional research that has been done concerning T-wave detection. Different points and their results will be discussed briefly.

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 lowpass and a highpass 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 [14].

Onset/Offset detection:

As discussed in previous section, 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 problems 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. The threshold used in this research are the ones discussed in [4].

Choice of scales:

The use of non-dyadic scales can be useful for detecting low amplitude complexes. In this report 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 to sensitive for noise. 2^4 on the other hand, did not divide the complexes in the transformation and therefore restricts good detection.

Chapter 4

Experimentation and Results

4.1 Experimentation

In order to avoid the problems of the standard methods, we will discuss frequently appearing difficulties. In this section we will discuss certain parts of signals that will regularly lead to failure of a correct detection.

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 4.1a 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.

Noise:

The WTMM approach used in this report 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. (figure 4.2b)

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. (figure 4.1b)

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. (figure 4.1d)

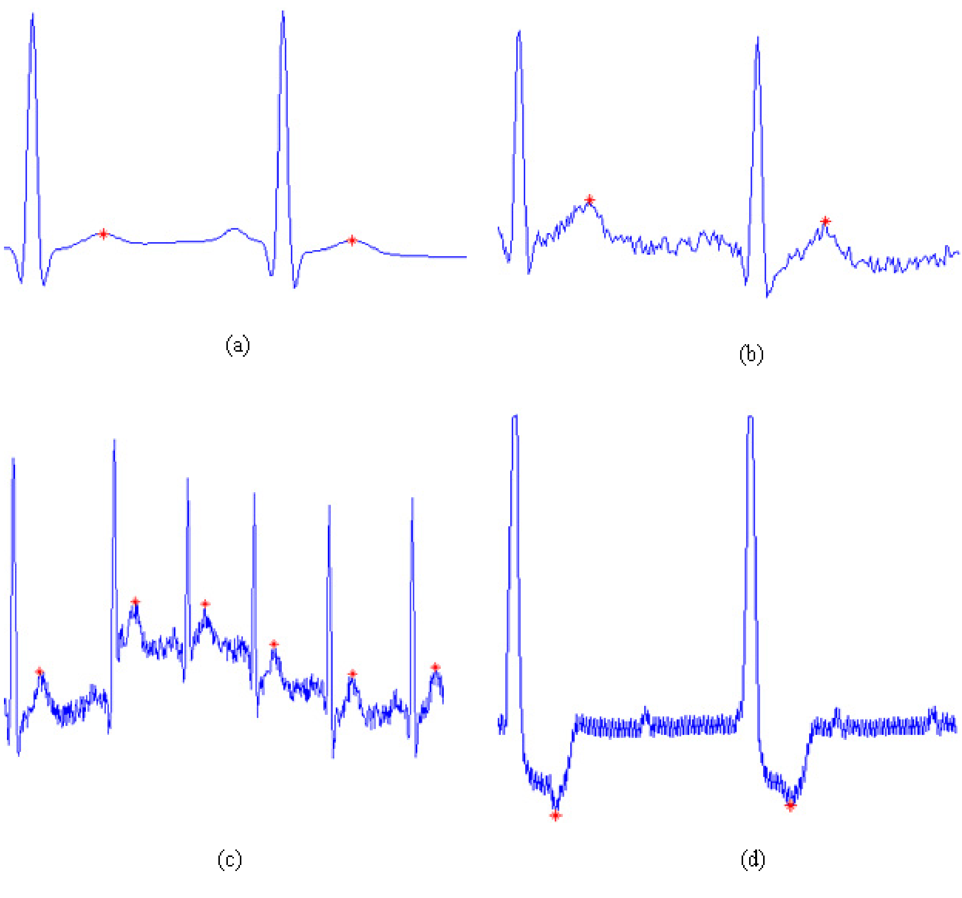

Figure 4.1: Experimentation results

4.2 Results

This section contains a review of the performance of the WTMM method and the standard method. The datasets are signals coming from the MIT-BIH Arrhythmia Database [15] (www.physionet.org) and also include recordings made at cardiology department of University Maastricht.

The performance of the methods will be tested by using several testcases with certain difficulties. In this section, the every testcase will be described first. Next, the performance will be measured by certain parameters:

- Number of True Positive detections (TruePos)
- Number of False Positive detections (FalsePos)
- Number of True Negative detections (TrueNeg)
- Number of False Negative detections (FalseNeg)
- Total number of peaks (TotalPeak)
- Percentage of detected T-waves (Sensitivity)
- Percentage of detected nonvisible T-waves (Specificity)
- Ratio of correct detections (CorrRatio)

Some of the testcases are derived from long ECG-recordings and therefore contain lots of peaks. However not every long signal contains large amounts of useful information. When there is no change in a wave throughout the whole signal, it is not useful to analyse every peak. Therefore, only the parts which define the ECG will be discussed in this results section.

Testcase 1

Description:

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.

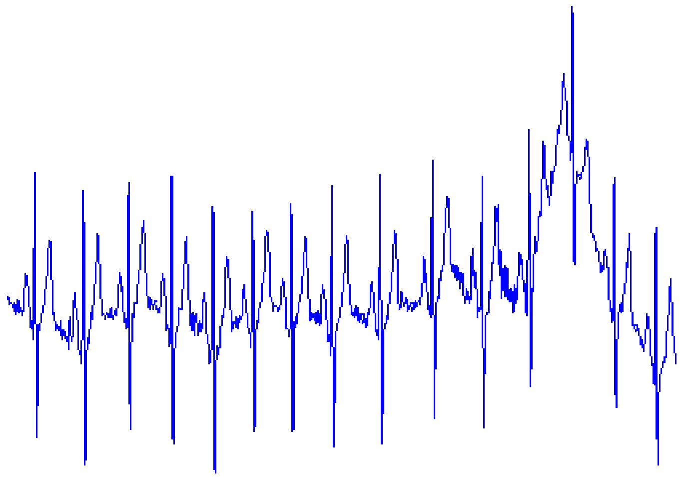

Figure 4.2: Testcase 1

Performance:

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.

Table 4.1: Testcase1

	WTMM	Alternative
TruePos	14	11
FalsePos	0	0
TrueNeg	0	0
FalseNeg	1	4
TotalPeak	15	15
Sensitivity	93%	73%
Specificity	/%	/%
CorrRatio	93%	73%

Testcase 2

Description:

This testcase has two kinds of T-waves. The first hours of the ECG show negative T-wave that consists only of a descend and this makes this signal hard to process. 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.

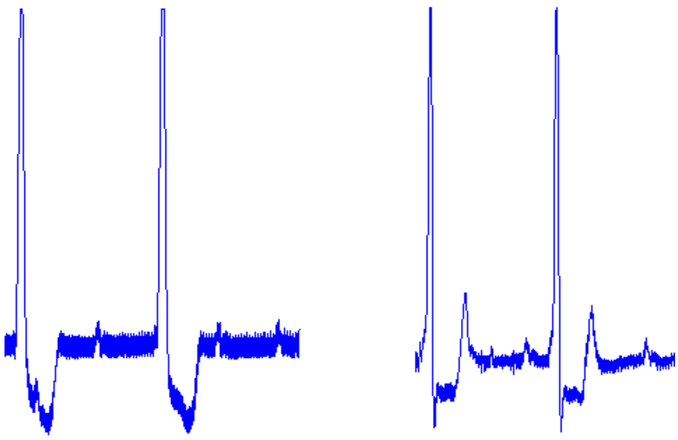

Figure 4.3: Testcase 2 Part I and Part II

Performance:

As most of the detection methods [9], the alternative method searches for a T-wave that consists of an ascend and a descend. 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.

Table 4.2: Testcase2 - Part I

	WTMM	Alternative
TruePos	90	0
FalsePos	1	6
TrueNeg	5	0
FalseNeg	6	94
TotalPeak	100	100
Sensitivity	93.75%	0%
Specificity	83.3%	0%
CorrRatio	95%	0%

Table 4.3: Testcase2 - Part II

	WTMM	Alternative
TruePos	99	73
FalsePos	0	0
TrueNeg	1	0
FalseNeg	0	27
TotalPeak	100	100
Sensitivity	99%	73%
Specificity	100%	100%
CorrRatio	99%	73%

Testcase 3

Description:

This case offers a signal with a clear T-wave and no noise.

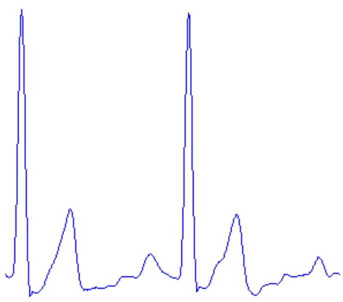

Figure 4.4: Testcase 3

Performance:

This is the most successful testcase that was tested because of the pureness of this testcase. The part that is used for analysis only has some small artifacts that is not able to disrupt the WTMM-based method. The alternative method is more sensitive to these artifacts, but is still very reliable.

Table 4.4: Testcase3

	WTMM	Alternative
TruePos	297	273
FalsePos	0	0
TrueNeg	0	0
FalseNeg	3	27
TotalPeak	300	300
Sensitivity	99%	91%
Specificity	/%	/%
CorrRatio	99%	91%

Testcase 4

Description:

The last testcase consists of a signal with a high amplitude S-wave and an ambiguous T-wave. The noise is limited to some high frequency disturbance.

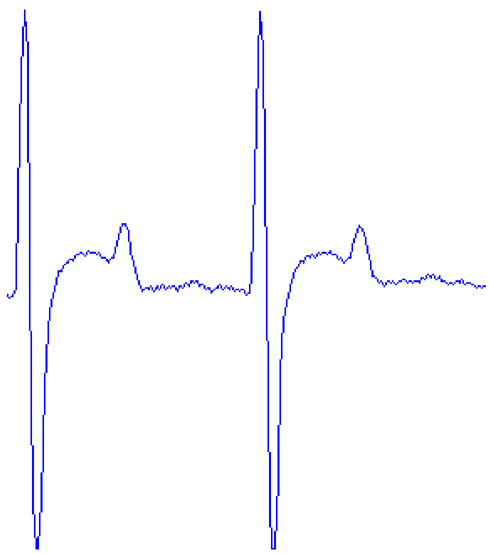

Figure 4.5: Testcase 4

Performance:

This testcase offers a T-wave that manifests itself on an other wave, which confuses the alternative method and therefore it sometimes registers a false detection. The wavelet transform of this irregular complex does not always offer a clear modulus maxima pair. This explains the drop of reliability in this case.

Table 4.5: Testcase4

	WTMM	Alternative
TruePos	83	64
FalsePos	1	3
TrueNeg	2	0
FalseNeg	14	33
TotalPeak	100	100
Sensitivity	85.5%	64.6%
Specificity	66.6%	100%
CorrRatio	85%	67%

Chapter 5

Conclusions

5.1 Discussion

When looking at the results, it is clear that the reliability of the algorithm is high in most cases. However, not every ECG-recording is processed without difficulties. Although the method is robust to noise and baseline-drift it also has its limitations. An ECG with a low amplitude T-wave and high amounts of noise and baseline drift will certainly give a detection with a lower reliability.

An instance with a small ST-interval (time between the S and T-wave) will also yield detection problems. The problems are caused by the high scale used for T-wave detection. This high scale tends to give a transformation where the transform of the QRS and the T-wave are not sufficiently separated. This results in the same problems that occur with the onset detection that is discussed before.

Another problem is the diversity of the mathematical morphology of the T-wave. This forces a method to contain well defined decision rules for every possible instance in order to get good results in all situations. For example, the method discussed in this report is unable to detect bi-phasic T-waves because of the absence of decision rules adapted to the bi-phasic situation.

5.2 Recommendations

A solution to the problem of high noise and baseline-drift is an automatic scale adjuster. If a method is able to find the scale with the optimal mixture of high T-wave energy and low noise energy, it can use that scale to detect the T-wave complex. This would make detection more reliable.

There is also room for improvement by studying the wavelet transform of an instance and developing or implementing decision rules for that specific variation. An opportunity would be the potential to detect biphasic T-waves, as these are frequently observed. The study regarding decision rules, could also be useful for an other purpose. Namely, by storing and processing many of the characteristic attributes of different T-wave variations, it could be possible to automate the development of decision rules for deviating T-waves by using some kind of learning method using these stored attributes.

An other improvement that can be made, concerns the position of every characteristic wave in an ECG-complex. The QRS-detection methods used in this report only indicated the R-position. The exact position of the S and P-wave can improve the T-wave detection by decreasing the window in which the T-wave is searched.

5.3 Conclusions

We have presented and validated in this thesis 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. Some of these testcases contained easily detectable T-waves, other were more complex due to the amount of noise or baseline-drift. Testcases with a simple T-wave and a limited amount of noise result in errorless detection. None of the more complex testcases result in a correct-detection ratio below 93% or a sensitivity under 93%, except for the last testcase 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 an 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. 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.

Bibliography

[1] Peter Bloomfield. Fourier analysis of time series, an introduction. 1999.

[2] S. Mallat. Multiresolution approximations and wavelet orthonomal bases of L2. 1989.

[3] C. Li, C. Zheng, and C. Tai. Detection of ECG characteristic points using wavelet transform. *IEEE Transactions on Biomedical Engineering, vol.52, no.1*, 1995.

[4] R. Almeida, J.P. Martnez, S. Olmos, A.P. Rocha, and P. Laguna. A wavelet-based ECG delineator: Evaluation on standard databases. *IEEE Transactions on Biomedical Engineering, vol.51, no.4*, 2004.

[5] A. Grossman and J. Morlet. Decomposition of hardy functions into square integrable wavelets of constant shape. *SIAM J. Math. Anal. 15*, 1984.

[6] I. Daubechies. Ten lectures on wavelets. *CBMS-NSF Regional Conference Series in Applied Mathematics*, 1992.

[7] S. Mallat and S. Zhong. Characterization of signals form multiscale edges. *IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.14, no.7*, 1992.

[8] S. Mallat. Zero-crossings of a wavelet transform. *IEEE Transactions on Information Theory, vol.37*, 1991.

[9] B.U. Kohler, C. Hennig, and R. Orglmeister. The principles of software QRS detection. *IEEE Eng Med Biol Mag. , vol.21, no.1*, 2002.

[10] S. Mallat and W.L. Hwang. Singularity detection and processing with wavelets. *IEEE Transactions on Information Theory, vol.38, no.2*, 1992.

[11] R.A. Balda. Trends in computer-processed electrocardiograms. 1977.

[12] J. Fraden and M.R. Neumann. Qrs wave detection. *Med. Biol. Eng. Comput., vol. 18*, 1980.

[13] N.V. Thakor, J.G. Webster, and W.J Tompkins. Estimation of QRS complex power spectra for design of a QRS filter. *IEEE Trans Biomed Eng.,vol.31*, 1984.

[14] I. Provaznik. Wavelet analysis for signal detection - application to experimental cardiology research. 2001.

[15] G.B. Moody and R.G. Mark. The impact of the mit-bih arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3*, 2001.