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METHODS FOR DETECTION AND CLASSIFICATION IN ECG ANALYSIS

METODY DETEKCE A KLASIFIKACE V ANALÝZE EKG SIGNÁLU

DOCTORAL THESIS
TEZE DISERTAČNÍ PRÁCE

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Abstract

The first part of the presented work is focused on measuring of QT intervals. QT interval can be an indicator of the cardiovascular health of the patient and detect any potential abnormalities. The QT interval is measured from the onset of the QRS complex to the end of the T wave. However, measurements for the end of the T wave are often highly subjective and the corresponding verification is difficult. Here we propose two methods of QT interval measuring - wavelet based and template matching method. Methods are compared with each other and tested on standard QT Database.

The second part of the presented work is focused on modelling of arrhythmias using McSharry’s model followed with classification using an artificial neural network. The proposed method uses pre-processing of signals with Linear Approximation Distance Thresholding method and Line Segment Clustering method for establishing of initial parameters of McSharry’s model. The ECG data is taken from standard MIT/BIH Arrhythmia Database. The modelling was tested on the whole MIT Arrhythmia Database signals, lead MLII (modified limb lead II). All signals could be modelled with 10 Gaussians functions without significant distortion.

The third part of the presented work is focused on ECG classification. Premature Ventricular Contraction (PVC) beats are of crucial importance in evaluating and predicting life threatening ventricular arrhythmias. An algorithm is proposed for the identification of PVC beats. Signals modelled with 30 Gaussians parameters were supplied to the input of artificial neural network. Multilayer perceptron was used with classification accuracy of 93.10% for premature ventricular contractions (PVC) and 96.43% for normal beats.

Keywords

ECG, QT interval, wavelet transform, neural networks, McSharry’s model

Abstrakt

První část práce je zaměřena na měření QT intervalu. QT interval může být použit k hodnocení kardiovaskulárního zdraví pacientů a detekovat potenciální abnormality. QT interval je měřen od začátku QRS komplexu až po konec T vlny. Nicméně, měření konce T vlny je často vysoce subjektivní a jeho verifikace je obtížná. Představujeme dvě metody měření QT intervalu - vlnkovou a šablonovou metodu. Metody byly porovnány mezi sebou a testovány na QT databázi.

Druhá část práce je zaměřena na modelování arytmických signálů McSharryho modelem následována klasifikací s použitím umělých neuronových sítí. Metoda používá předzpracování signálů lineární aproximací a shlukování lineárních segmentů pro stanovení počátečních parametrů McSharryho modelu. Byly použity EKG signály standardní MIT/BIH Arrhythmia Databáze. Modelování bylo testováno na celé databázi a svodu MLII (modifikovaný svod II). Všechny signály mohou být modelovány 10 Gaussovými funkcemi bez významného zkreslení.

Třetí část práce představuje klasifikaci EKG do dvou tříd. Předčasné komorové kontrakce (PVC) mají vysoký význam při hodnocení a predikci život ohrožujících ventrikulárních arytmií. Představujeme algoritmus pro detekci předčasných komorových kontrakcí s použitím McSharryho modelu a neuronových sítí. Signály modelované 30 Gaussovými parametry byly předloženy na vstup umělé neuronové sítě. Použitý vícevrstvý perceptron dosáhl klasifikační úspěšnosti 93,10% pro předčasné komorové kontrakce (PVC) a 96,43% pro normální stahy.

Klíčová slova

EKG, QT interval, vlnková transformace, neuronové sítě, McSharryho model

Table of contents

1 INTRODUCTION

In the last ten years, huge part of the research has been focused on the processing of biomedical signals. Daily clinical practice generates any amount of biomedical signals during monitoring of patients and for diagnostic purposes. Therefore automatic processing systems are frequently used in medical data analysis. New methods can simplify and speed up the processing of large volumes of data. The physician very frequently has to decide a patient‘s diagnosis on the basis of a number of numerical values measured during examination. Orientation in this volume of data is not always easy and unambiguous. Therefore there exist consultation systems that help and minimise human errors.

Cardiac arrhythmias can affect electrical system of the heart muscles and cause abnormal heart rhythms, which can lead to insufficient pumping of blood and death risks. Conventional arrhythmia diagnosis is based on human observation. A lot of automatic arrhythmia detectors were developed in last ten years, because of requirements of intensive care units for permanent monitoring of the patients. These methods reach good results but provide only limited information about a signal and ignore its hidden nonlinear dynamics. Most of these techniques also need a lot of computational time for feature extraction and classification and are able to classify only a small number of arrhythmias (usually two or three types) [20], [21], [19], [3]. It is necessary to enlarge classification on more types of arrhythmias and enable implementation in real time [16]. Existing approaches generally suffer for high sensitivity to noise and unreliability in access to new or ambiguous patterns. For clinical practise we have to develop classifiers, which enable nonlinear discrimination between classes, uncompleted or unclear input patterns.

2 AIMS OF THE DISSERTATION

The main objective of the thesis is to design, realize and verify algorithms for analysis of electrocardiogram signals. The work is oriented on delineation in ECG signals and classification in analysis of arrhythmic signals. These two tasks are important in many situations from ambulant ECG examinations to intensive care monitoring.

Based on our previous experience and results, continuous wavelet transform, McSharry’s model, and artificial neural networks were used in the work. Their selection was not random - combination of methods results in high efficiency detections and classifications. Algorithms are to be implemented in Matlab and tested on standard libraries of ECG signals for objective comparison.

The proposed thesis framework sets the following research goals:

1. A comprehensive review of the state of the art of ECG detection and classification methodology.

2. R peak detection and QT interval measurement.

3. McSharry's modelling of ECG signals to provide discrimination parameters for arrhythmia analysis.

4. Classification of arrhythmias using artificial neural networks with McSharry's model parameters.

5. Realization and verification of the developed algorithms. Results evaluation.

3 ECG ANALYSIS

3.1 DETECTION OF QRS COMPLEX

For the detection of QRS complex [12], input data were transformed by continuous wavelet transform (CWT)

$$CWT(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} \psi^{*}\left(\frac{t-\tau}{s}\right) f(t)dt, \qquad 3.1.1$$

where s is a scale and τ is a time shift. Time-scale spectrum enables to measure time-frequency changes in the analysed signal with certain time and frequency resolution. Interpretation of a time-frequency resolution by CWT is following: CWT represents time-frequency decomposition realized by correlation of signal $f(t)$ with basic functions derived from the mother wavelet $\psi(t)$.

The transform is documented in Fig. 3.1.1 (b). Coiflet function was used as the mother wavelet ψ. QRS detector is not so sensitive to chosen type of the wavelet, but Coiflet function produced best results during testing. Scales were chosen within an interval of <1; 32>.

The image of $WT_{abs}(s, \tau)$ can be simplified by taking a z-axis slice for a chosen value $L \in$ <0; 1>. Thus, contour image C_L is created (Fig. 3.1.2 (b))

$$C_L(s,\tau) = \begin{cases} 1 & if \quad WT_{abs}(s,\tau) \in \langle L-\varepsilon; L+\varepsilon \rangle \\ 0 & if \quad otherwise \end{cases} \qquad 3.1.2$$

where ε is a small value.

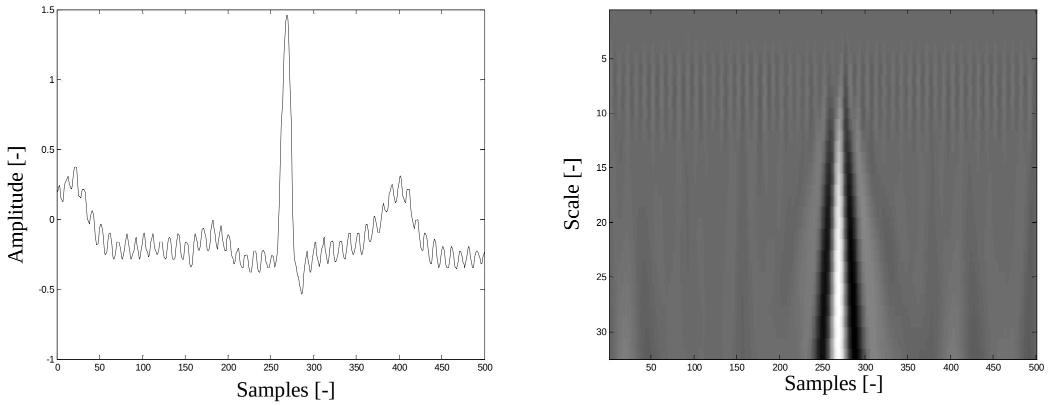

Fig. 3.1.1 Continuous wavelet transform of ECG.
(a) Raw ECG data, (b) CWT.

Only that part of the contour, which is the closest to the highest frequency, is considered. Such a contour is called a contour envelope *EC* and is defined as

$$EC(\tau) = \min_{s \in S,\, C_L(s,\tau) \neq 0} [s] \qquad 3.1.3$$

for all τ's.

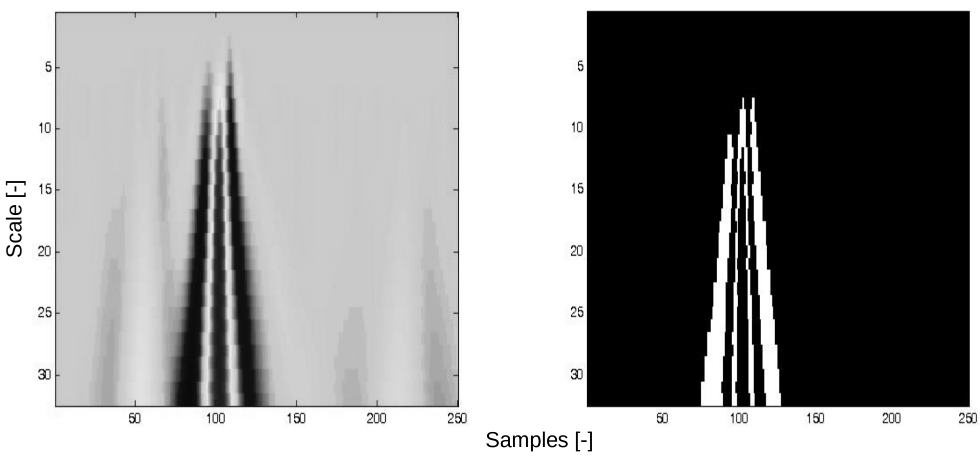

Fig. 3.1.2 Continuous wavelet contour image.
(a) CWT with Coiflet wavelet, (b) corresponding contour image C_L.

The contour envelope *EC* is a 1D function, which is processed by classical time-domain processing algorithms. An example of the contour envelope is in Fig. 3.1.3 (b). QRS-complex is easy to distinguish from the T-wave and other components in *EC* as a local maximum of the contour envelope. *EC* is finally filtered by a low-pass Lynn's filter for the better performance.

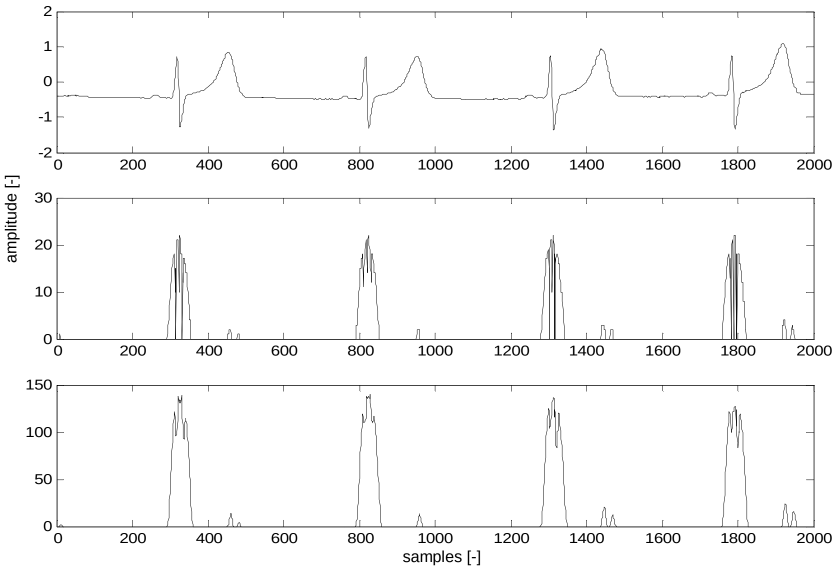

Fig. 3.1.4 Detection of QRS-complex.
(a) Raw ECG data, (b) contour envelope, (c) filtered contour envelope.

3.2 QT DELINEATION

QT interval is difficult to measure with sufficient precision. First, there is imperfection in the T-wave end identification because of lacking understanding of the recovery process and its projection on the body surface. The end of T-wave may not be recognizable at all due to missing inflexion point, insufficient change in slope of the curve, or any other reliably detectable point. Second, there are variations both in the onset of the QRS complex and the end of the T-wave among ECG leads and QT values depend on the leads selected for the measurement. Therefore, measurements for the end of the T-wave are often highly subjective and the corresponding objective verification is difficult. ECG signals can be labelled by experts and manually checked, but it is inappropriate for long-term studies. Many methods of QT interval detection have been published [17],[4]. Usually, results from more methods and more leads are used at the same time for verification. We present comparison of wavelet method and a template matching method.

In the first approach [11] the contour envelope *EC* (Eq. 3.1.3) is used for the detection of the R wave and Q by using time domain algorithms. The end of the T wave was found by searching for a local extremes in the ECG signal transformed by a single experimentally chosen scale - scale 20 and Mexican Hat wavelet, which is defined as second derivative of the Gaussian probability density function with following equation

$$\psi(t) = \left(\frac{2}{\sqrt{3}} \pi^{-1/4} \right) \left(1 - t^2 \right) e^{-t^2/2} . \qquad 3.2.1$$

Mexican Hat wavelet had the best results for T wave end detection in comparison with other wavelets and it has one of the best time-frequency resolution. Searching for a local extreme consists of searching for modulus maximum pairs and zero crossing in between. Searching for minima or maxima depends on the T wave morphology, it is documented in the following figures. Algorithm includes protection measures, based on time interval to reject anomalous deflections in ECG signal. Examples of different T wave morphologies and their wavelet transform at scale 20 with Mexican hat wavelet are in the Fig. 3.2.1 and Fig. 3.2.2.

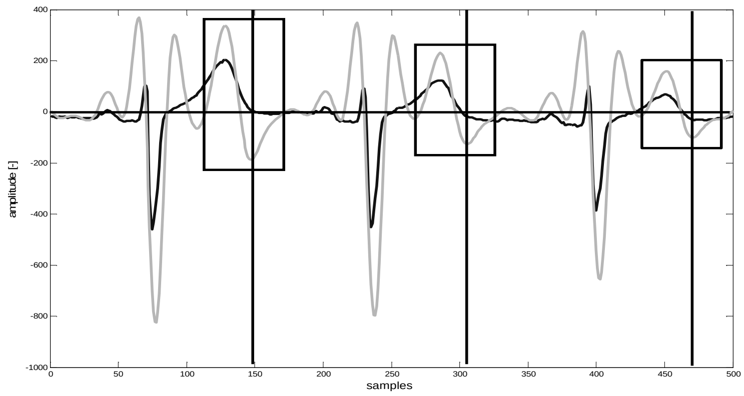

Fig. 3.2.1 Positive T wave

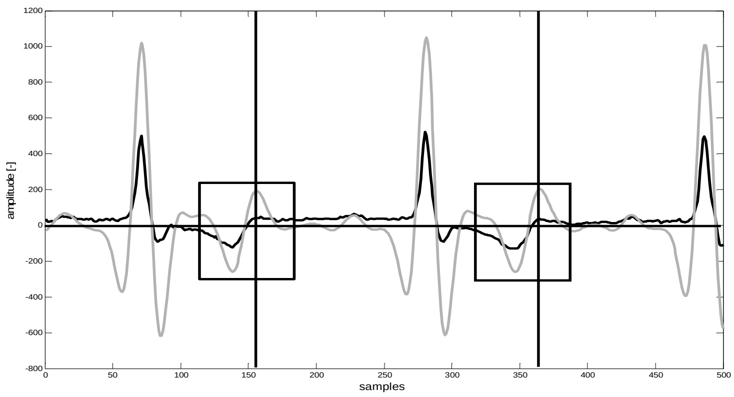

Fig. 3.2.2 Negative T wave

Black curve is ECG signal and grey curve is CWT. Long vertical lines show T end annotations while horizontal line is zero level and rectangles denote CWT modulus maximums pairs.

In the second template matching (TM) approach [1], the operator defines the template QT interval by selecting the beginning of the QRS complex and the end of the T wave in one heart cycle (Fig. 3.2.3 (a)).

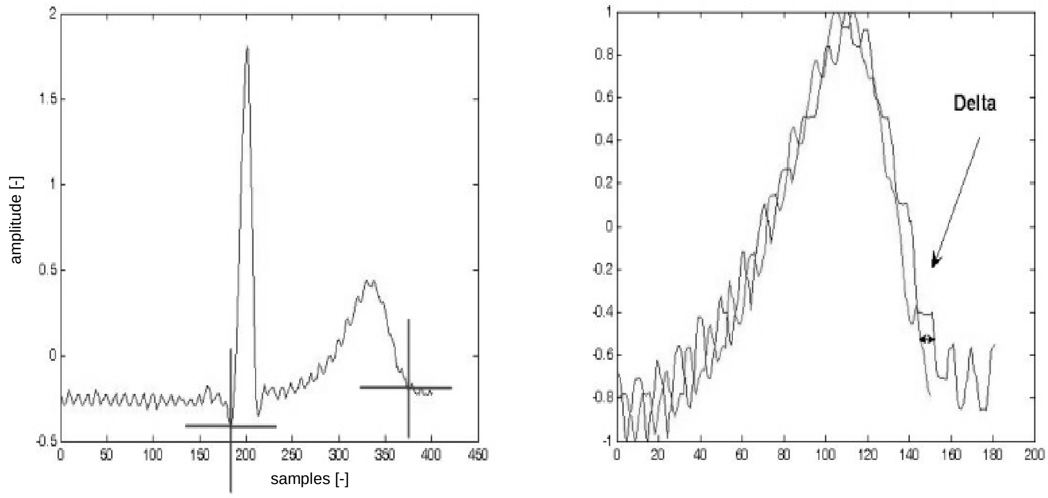

Fig. 3.2.3 Template matching.
(a) Selection of template boundaries by operator, (b) template matching.

The algorithm then determines the QT interval of all other beats by matching them to the template. It calculates the sum of squared differences between template and entire stretched or compressed T wave (Fig. 3.2.3 (b)). The algorithm uses only the ST segment and T wave. Blanking period behind R wave is 50 ms and signal amplitudes are normalized. Each R wave is detected with an automated peak detection algorithm (proposed wavelet method in Chapter 3.1). If the operator selects the end of the template T wave earlier or later after the true end, all computed QT intervals will have stable offset but the beat-to-beat variability will be relatively unaffected.

The third compared method developed by ASCR employs the least square optimized time shift of the regression model (RM) [11], see Fig. 3.2.4. The thick black curve $x(t)$ represents the regression model of T-wave (so called regression T-wave) computed as the average of selected segments $s(t)$ (light grey). The right limit of the regression model and the end of the regression T-wave at the same time is defined as the point of intersection of the descending regression T-wave tangent and the mean level of the foot - baseline line (end mark). The left limit is given by the maximum of the regression T-wave.

The end of each T-wave is computed as the least square optimized time shift

$$\varepsilon(i) = \sum \left[s(t) - x(t-i) \right]^2 \qquad 3.2.2$$

of the regression model (black rectangle A in Fig. 3.2.4.) in the region defined by the visible time window (black rectangle B in Fig. 3.2.4).

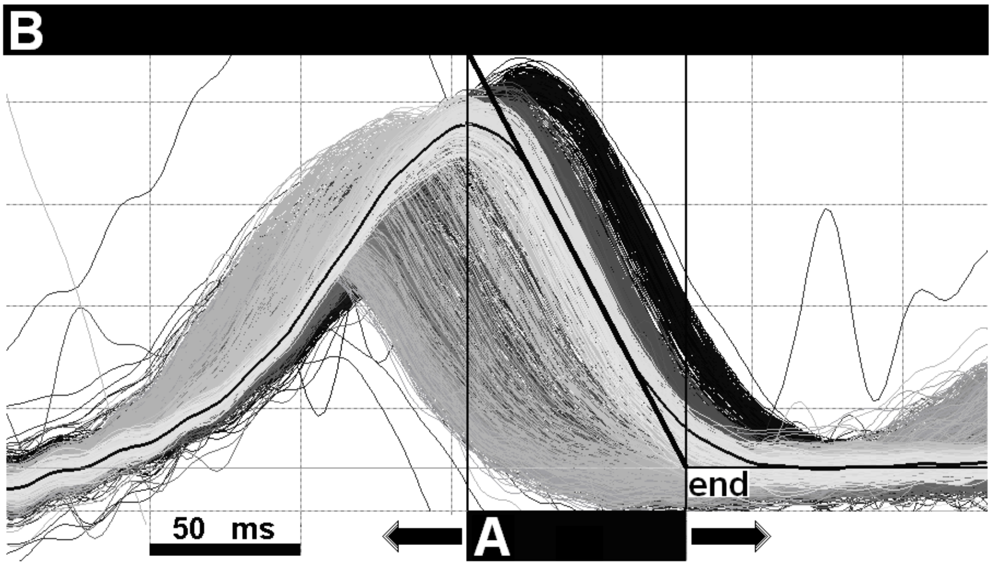

Fig. 3.2.4 T-wave end detection by the regression model method.
Two thousand heart beats drawn one over another.

4 ARRHYTHMIA CLASSIFICATION BY ARTIFICIAL NEURAL NETWORKS

4.1 MODEL OF ECG

We tested McSharry‘s model ability to model arrhythmic signals for the next approach of using model parameters for classification, because classification of the waveform in terms of the values of a_i, b_i, and θ_i of McSharry‘s model has not been explored in-depth. Input data were filtered before further analysis by Lynn’s filter, main goal of this filtration is subtracting of the baseline drift. We used general model [15], which was applied to ECG generation, blood pressure and respiratory waveforms; this model is characterized by Gaussian functions describing each ECG waveform (PQRST) by three parameters: an amplitude, width, and phase. Vertical deflection of the ECG, z, from the isoelectric line (at $z = 0$) is expressed by the following ordinary differential equation [15]

$$\dot{z}(a_i, b_i, \theta_i) = -\sum_{i\in\{P,Q,R,S,T\}} a_i \Delta\theta_i e^{\left(\frac{-\Delta\theta_i^2}{2b_i^2}\right)}, \qquad 4.1.1$$

where a_i is an amplitude, b_i width, phase $\theta_i=2\pi/t_i$, $\Delta\theta_i = (\theta - \theta_i)$ relative phase, (or relative position with respect to the R-peak). If we continue with numerical integration of the above-mentioned differential equation by the application of the parameters a_i, b_i and θ_i, the well-known ECG waveform appears. After analytical integration of the equation 4.1.1 we receive the following result

$$z(a_i, b_i, \theta_i) \;=\; \sum_{i \in \{P,Q,R,S,T\}} 2 a_i \Delta\theta_i e^{\left(\frac{-\Delta\theta_i^2}{2b_i^2}\right)} . \qquad 4.1.2$$

We intend to adjust this ECG model to the ECG signal *s(t)* by minimization of the squared error between *s* and *z*. Therefore, we seek minimal error

$$\min_{a_i, b_i, \theta_i} \;= \left\| s(t) - z(t) \right\|_2^2 , \qquad 4.1.3$$

over all ten *i*.

The solution to the equation 4.1.2 may be found using an 30-dimensional nonlinear gradient descent [6] on the parameter space (ten Gaussian three-parameter functions). Matlab function lsqnonlin.m was used for nonlinear least-squares optimization. We can average beats centred on their R-peaks to minimize the search space for fitting the parameters (a_i, b_i, and θ_i) and reduce the noise. The template window length is not important, as long as all the PQRST features remain in the window and does not expand into the next beat. Beats which are too far from the reference beat can be removed if the linear cross-correlation coefficient calculated between each beat and the template is less than 0.95. Initials positions θ_i and amplitudes a_i of the waveforms were obtained by using linear approximation and line segment clustering technique [18] described below.

Linear Approximation Distance Thresholding Method (LADT)

LADT method is an automatic clustering method [18], based on the distances between the approximating line and approximated signal points.

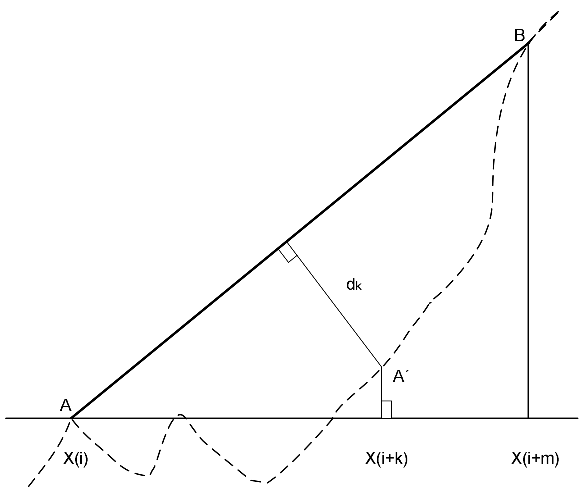

Fig. 4.1.1 The LADT method.
A is the start point and *B* is the end point of the signal segment. d_k is the maximum distance between the approximating *AB* line and the original signal (dashed line), *k* is the maximum distance position. If the maximum distance is below the threshold value, the original signal is replaced by the *AB* line.

The method is used as a noise reduction pre-processor. The results can provide input information for the line segment clustering. Distance threshold was set to 0.1. We used fixed length of the segment of 15 points (depending on the sampling rate). Procedure starts with the segment from the beginning of the ECG signal and determines start and end point of the segment and calculates linear equation between them (Fig. 4.1.1). Distance between segment of data and linear equation is calculated. Maximum of all distances is found. If maximum distance is larger than threshold, this segment is considered as significant, we save start point, end point and maximum distance point and ignore the other points. If maximum distance is smaller than threshold, this segment is not considered as important, we save only start point and end point and ignore other points. Whole algorithm is repeated until the end of the signal is reached.

Upon this procedure, the noise can be eliminated and most important message is extracted. This method was followed by line segment clustering technique described below.

Line Segment Clustering (LSC) technique

LSC technique is a clustering method [18], based on the line area of the signal. Clustering threshold which depends on how many important segments in signal we want to preserve was set to 11. Every 3 neighbouring LADT extracted points are linked and forms triangle. Area of those triangles is calculated and minimum is found. Middle point of minimum area is removed from data points set. These steps are repeated until the number of segments is smaller than threshold (see Fig. 4.1.2).

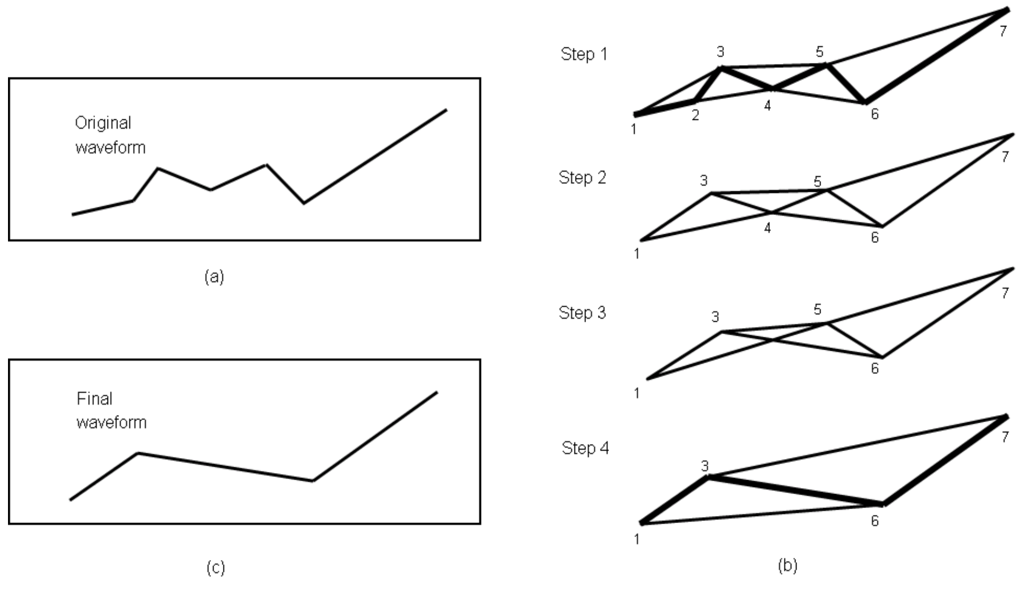

Fig. 4.1.2 The LSC method.
(a) The original wave form; (b) LSC technique steps; (c) the final waveform.

After preceding procedure the significant points of ECG signals, represented by line segments, are obtained. Number of segments was experimentally set to 11. Line points are used as initial positions (θ_i), amplitude of signal on these positions as a_i and width of triangles as b_i of the Gaussian functions of the model. Due to noise interference, the positions of the break points are not accurate. It is eliminated during nonlinear fitting of the model to real ECG. By combination of these known methods we will receive 30 input parameters for neural network classification.

4.2 COMPARISON OF TRAINING ALGORITHMS

It is not easy to choose which training algorithm will be faster for certain application. It depends on many factors and types of application. Some algorithms are suitable for recognition and another for approximation. Therefore we tested different algorithms for our application. We found as the best algorithm for our purpose Resilient Backpropagation RPROP algorithm followed with Scaled Conjugate Gradient Backpropagation (CGBP) or Powell-Beale (CGBP), because of speed of convergence. Fletcher-Powell (CGBP) and Variable Learning Rate algorithm did not converge during 6000 learning epochs.

4.3 ANN CLASSIFICATION OF TIME SERIES

ECG signals from MIT/BIH Arrhythmia Database were filtered by Lynn’s filter and extracted 200 ms (72 samples) before R peak and 355 ms (128 samples) behind R peak which presents 200 samples for 360 Hz sampling frequency. We used known multilayer perceptron network (MLP) mostly used for classification purposes for distinguishing of normal beat and premature ventricular contraction. A MLP network has been adapted for the classification procedure and trained by the Scaled Conjugate Gradient Backpropagation algorithm [7] due to fast convergence. It was designed with four layers: an input layer, two hidden layers, and an output layer.

Neurons in the input layer act as buffers for distributing the input signals to neurons in the hidden layer. The backpropagation algorithm was performed for 200-dimensional input vectors and one output for two feature sets. Desired output (e.g. normal beat, premature ventricular contraction) is represented by the binary-coded desired values 0, 1. The MLP was trained several times using different number of hidden neurons until getting the best accuracy. The results of changing the number of hidden neurons on the performance were evaluated on the basis of a performance improvement that was obtained when the number of hidden neurons was increased to 50. However, no significant increase in the performance was observed for the higher number of hidden neurons. Thus, the number of hidden neurons was set to 50 in both layers both in training and testing procedures.

Training set had 1000 N (normal) beats and 666 V (premature ventricular contraction) beats, 20 beats from nearly each signal and 60 beats from few of complicated signals as 105, 108, 203 and 233. Testing results are summarized in Chapter 5.5

4.4 ANN CLASSIFICATION OF MCSHARRY'S MODEL PARAMETERS

After McSharry's modelling (Chapter 4.1) we obtained input parameters for neural network training and classification. ECG time series from MIT/BIH Arrhythmia Database were first filtered by Lynn's filter, extracted as 100 samples before R peak and 150 behind R peak and after that modelled by Gaussian functions.

We used 10 Gaussian functions which are enough to model different ECG morphology. They are described by 3 parameters - position, width and amplitude, therefore we obtained 30 input parameters. We used known multilayer perceptron mostly used for classification purposes. We classified two types of beats - normal beats and premature ventricular contractions. Training Resilient Backpropagation algorithm (RPROP) was chosen due to fast convergence of training (Chapter 4.2). It was designed with three layers: an input layer, one hidden layer, and an output layer contrary to raw time series. The number of hidden neurons was set to 200 both in training and testing procedures.

Training set had 3996 N beats and 2079 V beats, 100 beats from nearly each signal and less beats from signals with smaller number of beats in particular category. Testing results are summarized in Chapter 5.6.

5 EXPERIMENTS AND RESULTS

5.1 DETECTION OF QRS COMPLEX

The method was implemented in MATLAB with Wavelet and Signal Processing toolboxes. The algorithm was tested on 48 signals (100-234) from MIT-BIH Arrhythmia library in full length (each approximately 30 minutes). In total, 24 hours of signals were analyzed with 99555 QRS-complexes. The average detection ratio was 99.45%. The lowest ratio was found in signal No. 207 (88.63%) with large periods of ventricular fibrillation, where it was difficult to determine individual QRS-complexes from chaotic signal. 24 signals were analyzed with detection ratio higher than 99.9%. In 43 of 48 signals, detection ration exceed 99.0%.

This algorithm is relatively noise-resistant and robust as it is documented in Fig. 5.1.1. On the upper panel, a signal No. 105 processed by the proposed algorithm is depicted with stars marking detected QRS-complexes. The lower panel shows the same signal with original QRS-complex notation from MIT-BIH database.

The detection and delineation of QRS-complexes showed high independence of the algorithm on the type of the used wavelet. However, the best performance for signals with noise and artefacts was obtained for Coiflet4 wavelet. We tested most of common wavelets: Haar wave, Symlet, Daubechies, Morlet, Biorthogonal waves but with Coiflet wavelet we received the best detection accuracy and contour envelope which was easily analysed in time domain. The detection accuracy is comparable to the recently published results.

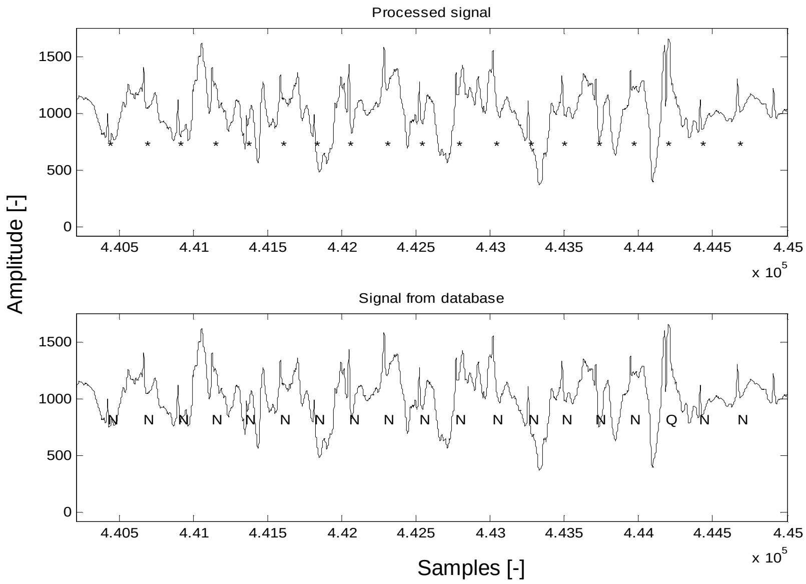

Fig. 5.1.1 Detection of QRS-complexes - signal no. 105.
(a) The signal with the algorithm output, (b) the same signal with MIT-BIH notation.

5.2 QT DELINEATION

The CWT and TM methods were implemented in MATLAB environment with Wavelet and Signal Processing toolboxes. The methods were tested on 19 signals from healthy probands with following parameters (500 Hz, a 16-bit AD converter, 5 minutes in supine position, 15 minutes in 75 degree tilt, 5 minutes in supine, paced breathing 6 per minute (0.1 Hz)). Data were collected at the 1st Internal Department, Saint Anne’s University Hospital, Brno, Czech Republic [11].

5.2.1 Comparison of CWT versus TM

The comparison of these methods had similar results; it is documented in Fig. 5.2.1 for different patients from testing set. The upper signal (black line) was processed by the proposed wavelet algorithm and the lower signal (grey line) with the template matching method. The wavelet method showed the same progress but slightly longer QT interval. The progress of template matching method was less smooth and had higher dispersion for less quality data (Fig. 5.2.1 right panel), but in comparison with wavelet algorithm it does not incline to high escaped values. Wavelet method is fully automatic whereas template matching method requires operator’s input.

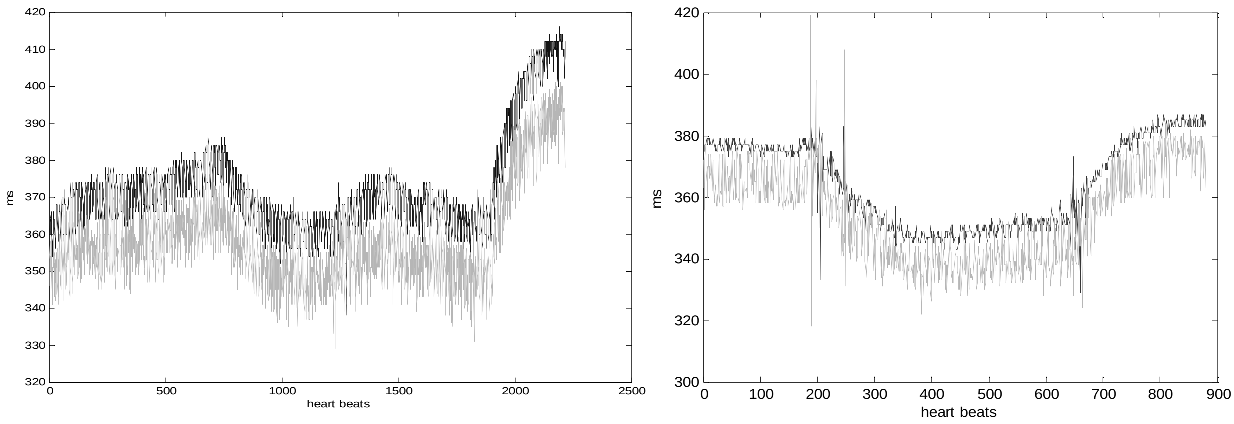

Fig. 5.2.1 Comparison of QT trends between CWT and TM.
Upper curve - CWT method, lower curve - template matching method.

5.2.2 Comparison of CWT versus RM

The CWT algorithm for the detection of the QT interval has been developed in the MATLAB environment using Wavelet Toolbox. Data were digitized and methods compared by ScopeWin ANNAlab ANS software developed at Institute of Scientific Instruments, Brno, Czech Republic with their results [11].

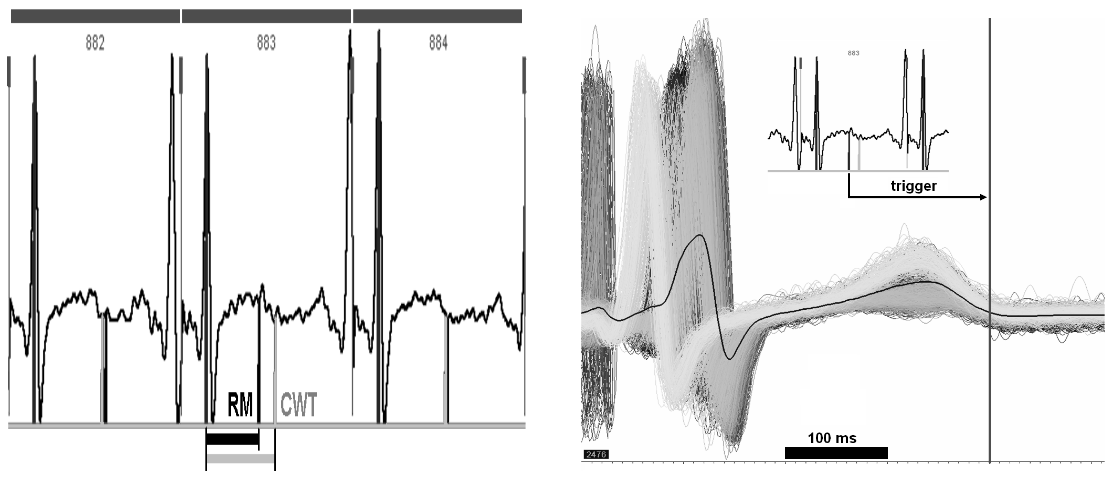

Fig. 5.2.2 On the left panel: example of graphical inspection of detected T- wave ends in a segmented ECG signal (R wave as trigger). Black marks define T-wave end detected by the RM method, grey mark T-wave end detected by the CWT method. On the right panel: ECG re-segmentation, trigger: T-wave end detected by RM method without undesirable deflection.

The results of T-wave detection by the CWT and RM methods were compared by QT time series analysis and by the multiple segmentation technique (Fig. 5.2.2). Time series comparison of RM and CWT method showed almost identical results. Time progress (trend) of the series and their dynamics were same. Slight amplitude offset was systematic and stable. It can be easily eliminated by setting of the methods - subtraction of the offset.

There are only sporadic artefacts in all experiments using both detection methods. The artefacts were analysed in more detail by visual inspection of critical heart cycles (see Fig. 5.2.2). It leads to typical findings: the RM method is more sensitive to the distorted end of the T-wave than the CWT method. It is most probably caused by more robust analysis in time-frequency domain in CWT method rather than time measurements in RM. Further, the CWT method provides a longer QT interval than RM. However, the prolongation is constant and thus removable.

5.3 COMPARISON OF QT DELINEATION WITH QT DATABASE

5.3.1 Template method versus QT Database

The template method (TM) results were compared to manually and automatically annotated QT intervals from QT Database from www.physionet.org. Seventy-three representative signals were used with total 2255 beats. We present mean values and standard deviations of T end difference between template method and manual annotations (file .q1c - manually determined waveform boundary measurements for selected beats (annotator 1 only -- second pass)). Mean error is relatively low (offset depends on operator) while standard deviation is high in a number of cases. Detailed manual studies have shown that the template method produced significantly more stable results comparing to the manual annotations in QT Database. In other word, T ends in QT Database express significantly higher beat-by-beat variability possibly due to low quality annotations by experts. This fact is documented below in text and Fig. 5.3.1 - Fig. 5.3.4.

Following Fig. 5.3.1 presents examples of differences in manual annotations positions, as a consequence of high difference between semi-automatic template method and database. Manual annotations often provide higher variability.

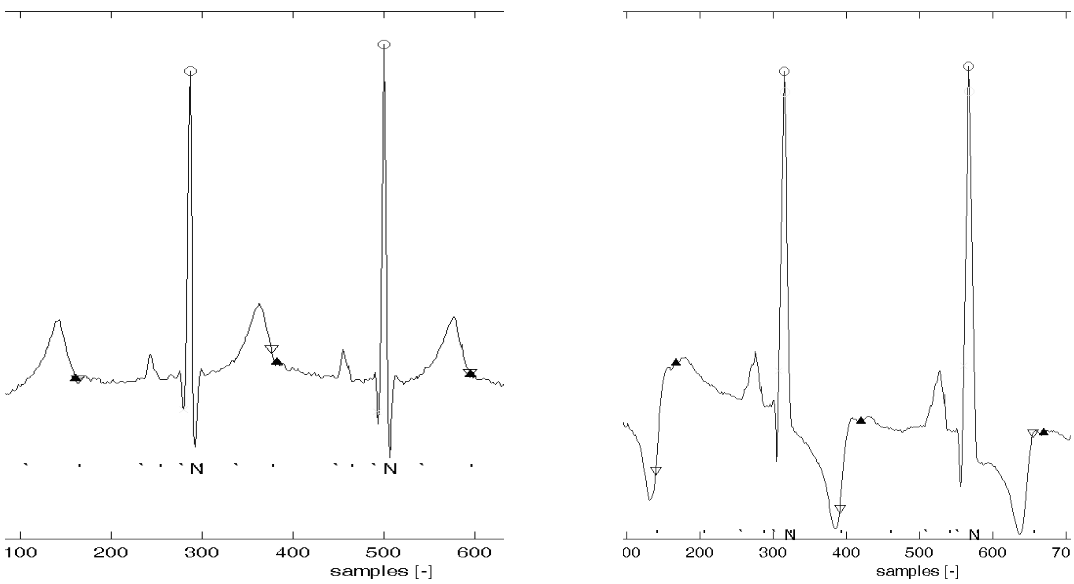

Fig. 5.3.1 Comparison between TM detection and manual database annotations on signal sel16539 and signal sel808. Filled triangle mark is TM detection point, unfilled triangle is a manual mark from QT Database.

Template method marks have much more stable position within T wave ends and marks from database are more fluctuating. It is visible also from QT trends which are smoother for TM method (Fig. 5.3.2). Offset difference is determined by operator's initial template selection.

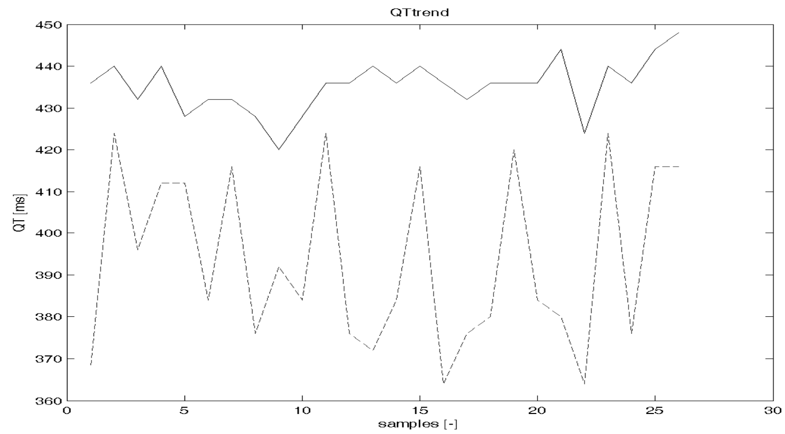

Fig. 5.3.2 Comparison between TM QT trends and database on signal sel808.
Solid line represents our detection points, dashed line represents manually marked points from QT Database.

In comparison with automatic annotations from database (files .pu0 with automatically determined waveform boundary measurements for all beats based on signal 0 only), we also received smoother results (Fig. 5.3.3 - Fig. 5.3.4).

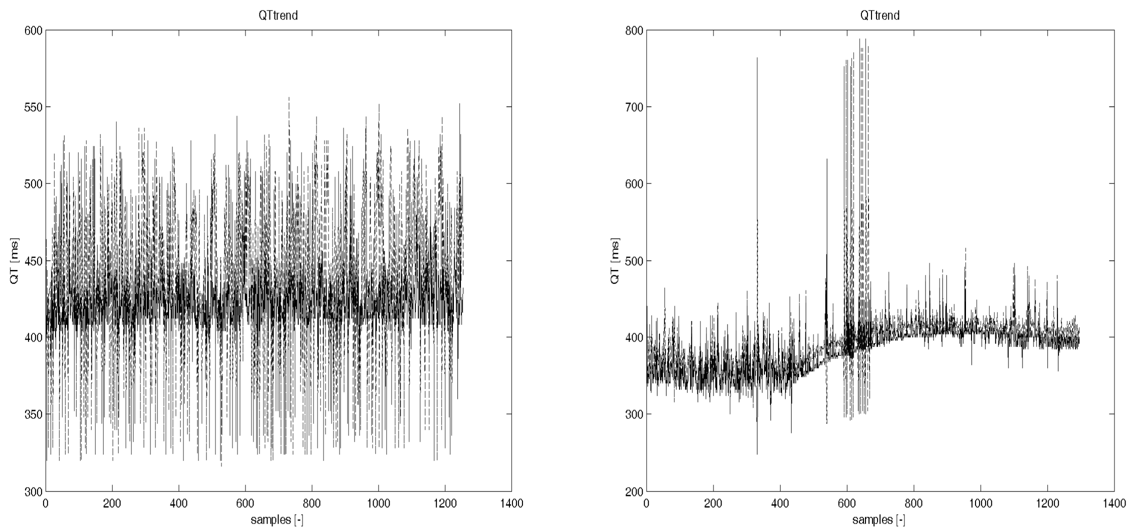

Fig. 5.3.3 Comparison between TM QT trends and database on signals sel891 and sel308. Black solid line represents our detections, dashed grey line represents automatic QT detections from database.

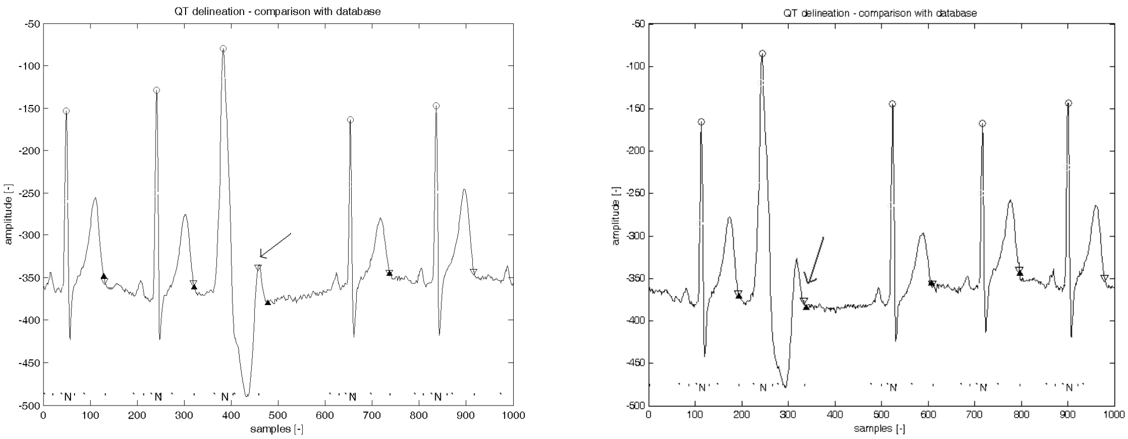

Fig. 5.3.4 Comparison between TM detection and automatic database annotations on signal sele0411. Filled triangle mark is our detection point, unfilled triangle is an automatic mark from QT Database.

Template method QT interval trends are smoother than trends from QT Database. Stable offset is determined by operator during template selection. This method works perfectly for signals with low variability. Changeable morphology is not detected so precisely.

5.3.2 CWT method versus QT Database

The CWT method results were compared to manually and automatically annotated QT intervals from QT Database from www.physionet.org. Seventy-three representative signals were used with total 2198 beats. We present mean values and standard deviations of T end difference between CWT method and manual annotations (file .q1c - manually determined waveform boundary measurements for selected beats (annotator 1 only -- second pass)). As it can be seen from the table, mean error is relatively low while standard deviation is high in a number of cases. 81% of signals fulfils criteria from [14] and had standard deviation lower than 30.6 msec. Detailed manual studies have shown that the CWT method produced significantly more stable results comparing to the manual annotations in QT Database. In other word, T ends in QT Database express significantly higher beat-by-beat variability possibly due to low quality annotations by experts. This fact is documented below in text and figures.

High values for signal sel102, sel213, sel223, sel33, sel39 and sel45 are caused by different T wave end position definition as we documented in Fig. 5.3.5, where we can compare opposite behaviour of CWT detection and manual annotations.

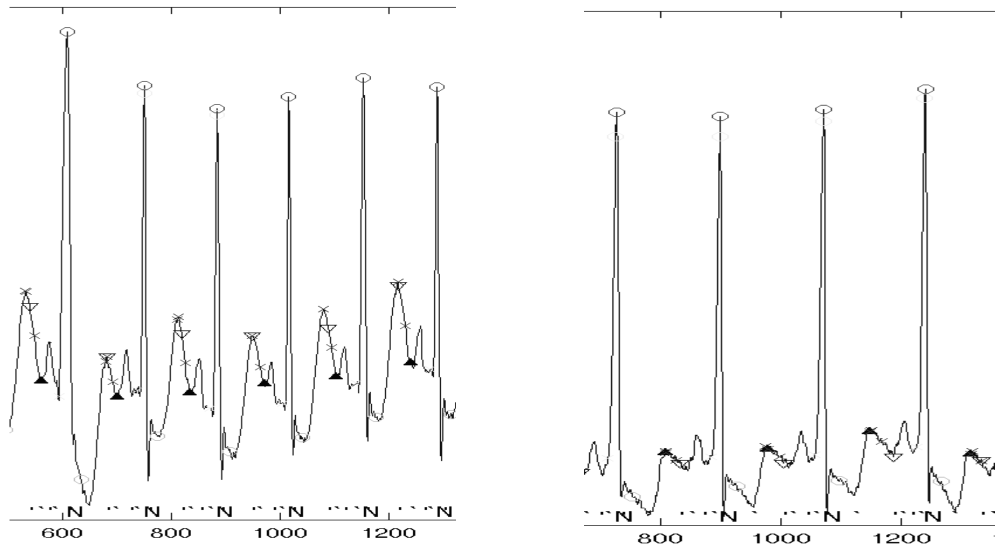

Fig. 5.3.5 Comparison between CWT detection and manual database annotations on signal sel213 on the left panel and signal sel223 on the right panel. Filled triangle mark is our detection point, unfilled triangle is a manual mark from QT Database.

High values for signal sel104, sel307, sel31, sel50 are caused by fluctuation of manual T wave end annotations as we documented in Fig. 5.3.6 (left panel). High value for signal sel14172 is caused by difficultly defined end of T wave (right panel). Amplitude of T wave is low and signal is noisy.

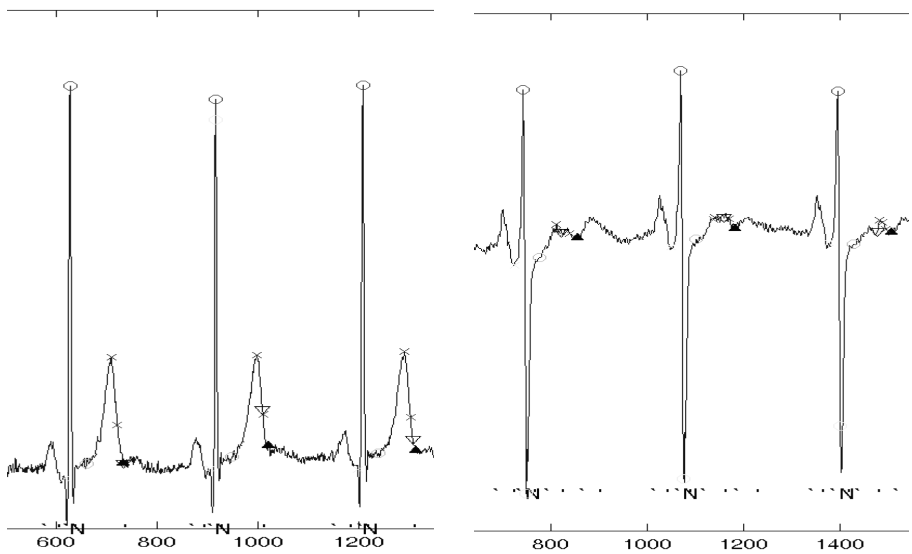

Fig. 5.3.6 Comparison between CWT detection and manual database annotations on signal sel307 on the left panel and signal sel14172 on the right panel. Filled triangle mark is our detection point, unfilled triangle is a manual mark from QT Database.

In Fig. 5.3.7 we compare QT interval trend with manually annotated trend from database. Wavelet method has smoother progress of QT intervals than manual annotations, because of their high dispersion.

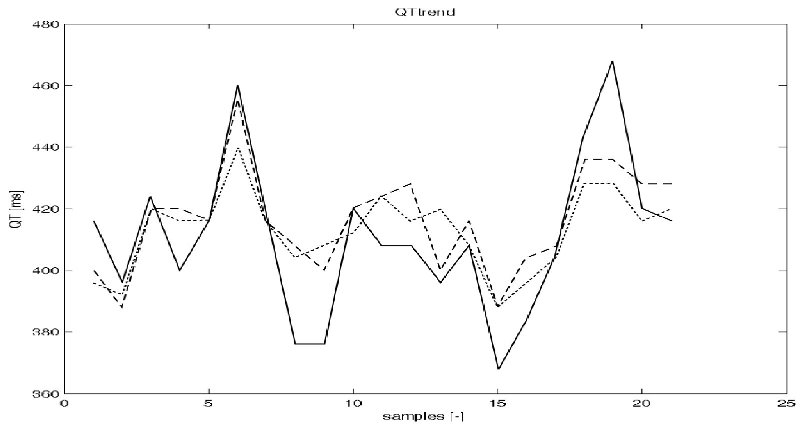

Fig. 5.3.7 Comparison between CWT QT trends and database on signal sel103. Dotted line represents our QT detection, dashed line represents our T end detection and manually annotated Q wave from QT Database, solid line represents manually marked points from QT Database.

If we compare our detection with automatic database annotations (files .pu0 with automatically determined waveform boundary measurements for all beats based on signal 0 only), we also receive smoother result, but wavelet method has different stable offset for different T wave morphologies.

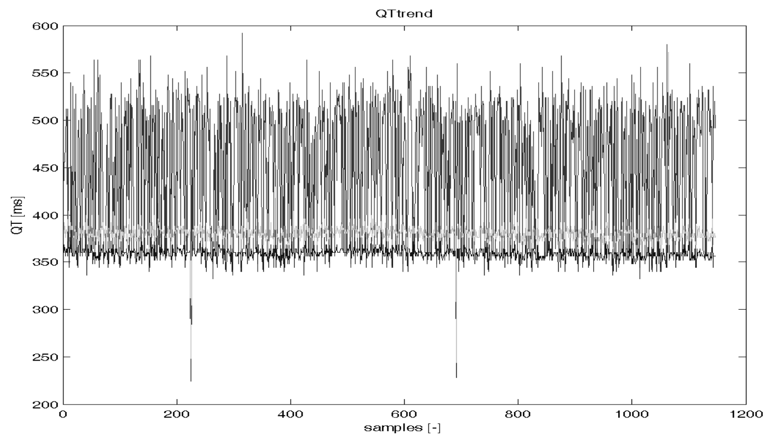

Fig. 5.3.8 Comparison between CWT QT trends and database on signal sel820. Black line represents our QT detection, light grey line represents our T end detection and automatically annotated Q wave from QT Database, dark grey line represents automatic QT detection from database.

In the figures Fig. 5.3.8 and Fig. 5.3.9 we show that our T wave ends are detected permanently on the same T end positions contrary to automatic and manual marks from QT Database, therefore our QT trend has smaller dispersion.

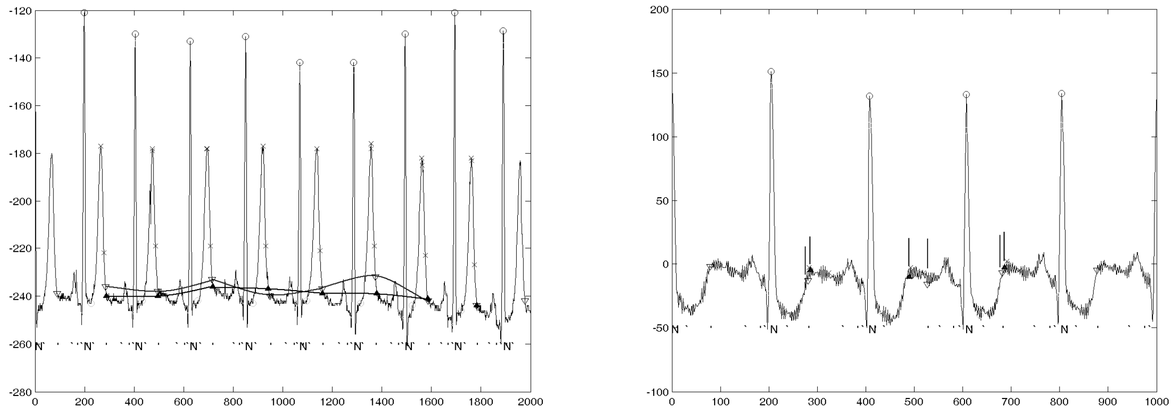

Fig. 5.3.9 Comparison between CWT detection and manual database annotations on the left panel (signal sele0210, approximated T ends show higher dispersion of manual T end annotations than our annotations). Comparison between CWT detection and automatic database annotations on the right panel (signal sel820, filled triangle mark is our detection point, unfilled triangle is a manual mark from QT Database).

Different offset for different T wave morphologies is explained in the following Fig. 5.3.10. Wavelet method mostly provide longer QT interval because it detects T wave end on the T wave end minimum. However, the prolongation is constant and thus removable.

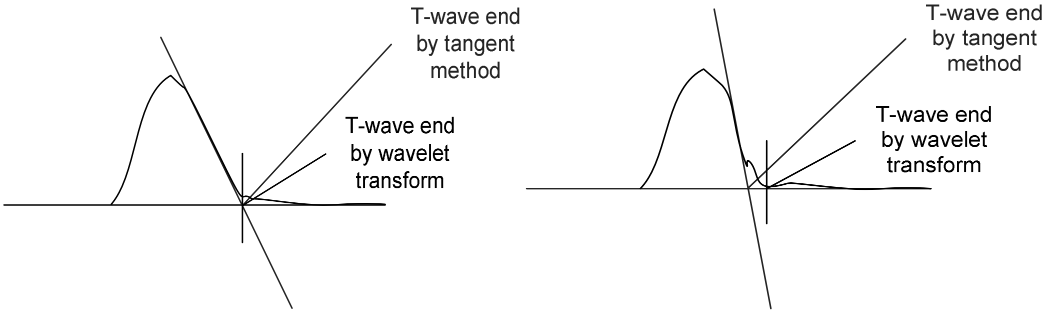

Fig. 5.3.10 Explanation of the offset difference in T end detection by classical method and by our wavelet method.

In order to quantify and compare TM and CWT method by numbers and classify correctness of T end location (with manual annotations), we divided signal results into following groups:

- **Group 1:** well detected signals with reasonable mean and standard deviation (mean<40 ms, standard deviation<50 ms),
- **Group 2:** signals with morphology identification errors - systematic errors (mean>40 ms, standard deviation <50 ms),
- **Group 3:** signals with noise or too small T wave amplitude (mean<40 ms, standard deviation>50 ms),
- **Group 4:** combination of groups 2 and 3 (mean>40 ms, standard deviation>50 ms). Usually morphology identification error together with poor SNR and high variability of signal.

Classification results are summarized in table below.

Comparison results show that performance of both methods is similar. **96%** (TM) and **95%** (CWT) of signals belong into group 1 or 2. CWT method has more systematic errors and is fully automated, whereas TM is semi-automatic and systematic errors are eliminated by operator during template selection. Most of systematic errors could be eliminated with deeper cardiologic experience. Majority of systematic errors for CWT method is caused by biphasic T wave morphology.

Tab. 5.1 TM and CWT method results classification

TM

Group	Number of signals	Percentage
1	69	94,52%
2	1	1,37%
Subtotal	**70**	**95,89%**
3	2	2,74%
4	1	1,37%
Subtotal	**3**	**4,11%**
Total	**73**	**100,00%**

CWT

Group	Number of signals	Percentage
1	60	82,19%
2	9	12,33%
Subtotal	**69**	**94,52%**
3	1	1,37%
4	3	4,11%
Subtotal	**4**	**5,48%**
Total	**73**	**100,00%**

We verified annotations variability for several signals also on Physionet website automatic graphical outputs.

In case of well detected morphology, progress of CWT QT detection is smoother that TM progress. We obtained 81% of records (CWT) with variance in T end location within manual referees variance (standard deviation 30.6 ms [8]). This is minimal value that could be requested to any automatic algorithm.

For further improvement of CWT algorithm cooperation with cardiologists is necessary. Contrary to template method the algorithm does not know any reference input and does not have any prior knowledge about morphology. With deeper medical knowledge most of systematic errors can be eliminated.

Main objective of CWT method was to test if T end measurement using only one scale of wavelet transform is suitable for continuing in analysis. Processing time of 15 minutes long ECG signals was in average 8 minutes without any optimization and with a lot of graphical outputs for visual inspection. This method is suitable for online processing.

5.4 MCSHARRY'S MODELLING

We have applied this method to ECG records from the MIT/BIH Arrhythmia Database, which include several types of beats: normal sinus, depression of ST segment, multiform PVCs and fusion beats, left bundle blocks, right bundle blocks, etc. These signals were sampled at f_s = 360 Hz. Fig. 5.4.1 illustrates the results of the fitting model to a segment of arrhythmic signals. The locations of the P, Q, R, S and T peaks match the underlying signal. The error around the isoelectric point and ST-level are insignificant in a clinical sense (< 0.1 mV, or about 5% to 10% of the QRS amplitude).

We tested our approach on the whole MIT/BIH Arrhythmia Database on the lead MLII and we can model all signals with 10 Gaussians functions without significant distortion. Average time for processing of one beat is 7s. Note that the error around the ST-segment is extremely small. The application of the method to ECG signals from MIT/BIH Arrhythmia Database has shown performance of MSE_{rel}=(0.49±1.06)%. The majority of authors use the MSE error as an objective method to analyze the performance of data modelling methods. But in this way the impact on cardiological diagnosis is not evaluated. We propose the analysis in main points of ECG obtained by LADT and LSC.

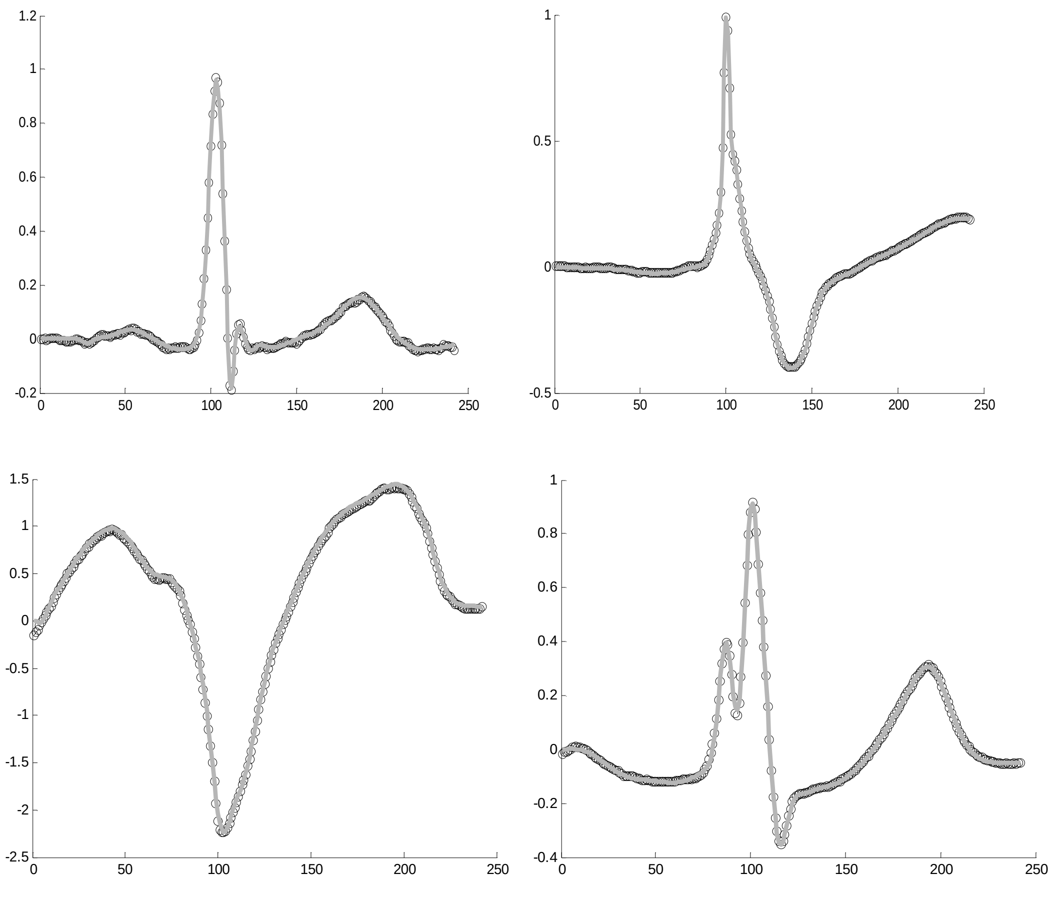

Fig. 5.4.1 Fitting of model to a segment of ECG taken from the MIT-BIH Arrhythmia Database. Solid grey line represents modelled ECG and black circles are real averaged ECG. It is visible that modelled signal replaced original signal.

By fitting a set of ten Gaussians (each defined by three parameters) in an ordinary differential equation, we verified that we can model arrhythmic ECG signals with mathematically tractable compact representation. As a result, it can be used as a generalized technique for processing of any semi-periodic signal. This model was successfully verified on arrhythmic signals of MIT-BIH Arrhythmia Database. We also mentioned possibilities of evaluating of the models and we suggest computing of local error in area of significant points, obtained by Line

Segment Clustering method. Our further intention was to test parameters of McSharry‘s models for classification, because classification of the waveform parameters a_i, b_i, and θ_i of McSharry‘s model has not been explored in-depth.

5.5 ANN CLASSIFICATION USING TIME SERIES

We tested the ANN classification system using time series on whole MIT/BIH Arrhythmia Database. We distinguished between two classes: normal beats N and premature ventricular contractions V. Classification process was performed in three stages: 1. pre-processing (Lynn’s filter for baseline drift removing), 2. data extraction, and 3. non-linear classification (MLP). Topology of the used network contained 200 input neurons (corresponding to samples of the filtered ECG), 50 neurons in the first hidden layer, 50 neurons in the second hidden layer, and a single output neuron (200-50-50-1 topology). Hyperbolic tangent (tansig, which maps output into the range of -1,1) was used as an activation function in the input layer while a sigmoid function (logsig, which maps output into the range of 0,1 required for binary classification) was used in the hidden and the output layers. Training goal of the mean squared error was set 0.001, which was selected experimentally as sufficient for successful training while keeping low computational costs. The network was trained with Scaled (CGBP) algorithm described in Chapter 4.2 on 1000 normal beats (N) and 666 ventricular premature beats (V). Testing set had 74054 N beats and 6444 V beats.

The used ANN was implemented in Matlab 7.1 environment and tested on a common PC Pentium 4, 2.6GHz with 512MB RAM. Training phase took about 120 sec, testing took about 320 sec for the above described dataset and the mean squared error. We obtained overall accuracy for whole testing dataset **98.82%**, accuracy for normal beats **98.89%** and accuracy for premature ventricular contractions **97.94%**.

5.6 ANN CLASSIFICATION USING MCSHARRY’S MODEL

We tested the ANN classification system using McSharry’s model on whole MIT/BIH Arrhythmia Database. We distinguished between two classes: normal beats N and premature ventricular contractions V. Classification process was performed in four phases: 1. pre-processing (Lynn’s filter for baseline drift removing), 2. data extraction, 3. feature selection (McSharry’s model), and 4. nonlinear classification (MLP). Each phase was carefully chosen to enhance the performance of the system.

We tested different network topologies, different number of neurons in one hidden layer and also 2 hidden layers. We chose topology 30-200-1 which had the highest accuracy for normal beats and the second highest accuracy for premature ventricular contractions. Second alternative could be topology 30-180-1 which had the highest accuracy for premature ventricular contractions and the third highest accuracy for normal beats.

Topology of the network contained 30 input neurons (corresponding to 30 McSharry’s input parameters), 200 neurons in a hidden layer, and a single output neuron (topology 30-200-1).

Hyperbolic tangent (tansig) was used as an activation function in the input layer while a sigmoid function (logsig) was used in the hidden and the output layers. Training goal of the mean squared error was set to 0.01, which was set experimentally as sufficient for successful training while keeping low computational costs. The network was trained with RPROP algorithm (see Chapter 4.2) on 3996 normal beats and 2079 ventricular premature beats (approximately 100 beats from each signal in each category). Testing set had 70707 N beats and 4930 V beats. The used ANN was implemented in Matlab 7.1 environment and tested on a common PC Pentium 4, 2.6GHz with 512MB RAM. Training phase took about 266 sec, testing took about 199 sec for the above described dataset and the mean squared error.

We obtained overall accuracy for whole tested beats **96.21%**, accuracy for normal beats **96.43%** and accuracy for premature ventricular contractions **93.10%**. Although comparison of our system with other systems given in the literature is really difficult due to the varieties in the classification techniques and data properties (e.g. different number of beat types belonging to different patients), it can be seen that our proposed novel system based on McSharry's model parameters and MLP enables PVC and normal beats classification. The performance of our system is comparable with the results reported in the literature.

6 DISCUSSION AND CONCLUSIONS

We have presented ECG signal processing that uses wavelet transform for ECG delineation and McSharry's model with artificial neural network for classification. Wavelet transform has been extensively used in many different fields such as image processing, etc. Regarding classification of biological signal, the concept and use of McSharry's model for classification is quite new.

In Chapter 1 of full version we compiled the comprehensive state of art and looked at different classification methods. We have found that the classification with McSharry's model parameters has not been fully explored yet and neural network as classifier is successfully used in many applications. Pre-processing delineation phase is almost a prerequisite of standard ECG analysis. We use wavelet transform which is suited very well for biological signals analysis.

In Chapter 2 we declare aims of dissertation. First we describe methods for QT interval measuring and QRS detection (Chapter 3) then we continue with methods of ANN classification and McSharry's modelling in Chapter 4 . Results of all methods are summarized in Chapter 5 .

Regarding QRS complex detection we implemented wavelet contour envelope technique with comparable results tested on MIT-BIH Arrhythmia Database (Chapter 5.1). Concerning QT interval measurement, we proposed an automatic method using one scale of wavelet transform. The method with other scales is able to detect all characteristic points in ECG signal [14]. We concluded that the proposed approach can work sufficiently (Chapter 5.2 and 5.3) and has mostly smoother results of QT trends than manual and automatic marks from standard QT database. We also implemented semi-automatic template method, which has less smooth results than wavelet method for less quality data and variable morphology. Wavelet method provides mostly longer QT interval than database, this offset is stable for whole signal and can be subtracted.

The main advantages of the classification method are modelling capabilities of McSharry's model enabling automatic simulation of different arrhythmia beats as we could see in Chapter 5.4. Furthermore, we coped with the difficult task of correct number of Gaussian functions to model different types of arrhythmias without significant distortion.

We classified ECG beats from MIT/BIH Arrhythmia Database (Chapter 5.5 and 5.6). We were focused on two class classification of normal beats and premature ventricular contractions which are life threatening arrhythmias. The average rate of classification accuracy for raw time series and normal beats was 98.89% and for premature ventricular contractions 97.94%. The average rate of classification accuracy for McSharry's model and normal beats was 96.43% and premature ventricular contractions 93.10%. We believe that the achieved performance of McSharry's model is very reasonable. Results of McSharry's model with ANN are lower than for raw time series but they show ability of classification and they still leave place for improvement.

Classification of normal beats for raw time series had worst results for signals 105 and 203. Signal 105 has uniform PVCs but the predominant feature of this tape is high-grade noise and presence of artefacts. Signal 203 has multiform PVCs, there are QRS morphology changes in the upper channel due to axis shifts, there is considerable noise in both channels, including muscle artefacts and baseline shifts. This is a very difficult record, even for humans! Without these two signals classification accuracy for normal beats is 99.45%.

Classification of premature ventricular contractions for raw time series had worst results for signals 105, 108 and 215. Signal 108 has multiform PVCs, the lower channel exhibits considerable noise and baseline shifts. Signal 215 has also multiform PVCs. There are two very short occurrences of tape slippage. Classification accuracy without these three signals for premature ventricular contractions is 98.13%.

Classification of normal beats for McSharry's model had worst results for signals 108, 114 and 203. Signal 108 and 203 are described above. Signal No. 114 has similar shape to normal morphology. Without these three signals classification accuracy for normal beats is 97.96%.

Classification of premature ventricular contractions for McSharry's model had worst results for signals 215, 223 and 228. All three signals have multiform PVCs. Signal 223 has episodes of ventricular tachycardia. Signal 228 has short occurrences of tape slippage. Without these three signals classification accuracy for premature ventricular contractions is 94.98%.

The performance of our system is comparable to the results reported in the literature. The main drawback of the used McSharry's modelling method is its computational costs because used initialization steps (LADT and LSC). On the other hand, the fact of high computational cost is compensated by some enhancement capacities of McSharry's modelling.

Notwithstanding, we did not consider the performance speed measures in the thesis, we rather preferred to focus on the theoretical issues development and consequently their implementation in most convenient software tools from the point of view of saving programming effort. Yet this suggestion might be pursued as a future direction.

6.1 ACHIEVEMENT OF GOALS

In the previous paragraphs, the achieved results have been described. We shall now discuss how our research goals set in Chapter 2 have been accomplished.

1. **State of the Art.** A comprehensive review of the state of the art of classification methodology will be carried out. We have covered wide range of used classification techniques. Thus we have achieved the goal.

2. **R peak detection and QT interval measurement**. This goal consists of the two proposed QT-interval measurement methods. We have applied wavelet transform on the problem of QRS detection and QT interval measuring in Chapter 3.1 and 3.2. We have concluded that the operator semi-automatic is more sensitive to less quality data and changeable morphologies of the T wave. Therefore, we have preferred the method based on wavelet transform described in Chapter 3.2. Thus we have achieved the goal.

3. **Electrocardiogram Modelling**. We have illustrated the usefulness of McSharry's model in context of ECG modelling. We have shown in Chapter 5.4 that McSharry's framework is able to model different arrhythmic electrocardiogram signal without significant distortion. The modelling approach has been based on a careful initialization techniques (Chapter 4.1) using pre-processing of ECG signal by Linear Approximation Distance Thresholding Method and Line Segment Clustering Technique. To sum up, we have accomplished the goal.

4. **Electrocardiogram Classification**. We have shown that the McSharry's model ANN framework is able to solve the classification task. Indeed, in Chapter 5.6 we have concluded the usefulness of this approach on the basis of classification test on MIT/BIH Arrhythmia Database. Thus we have achieved the goal of electrocardiogram classification.

5. **Application of developed algorithms and results evaluation**. Algorithms were tested and results evaluated in Chapter 5 . Thus we have achieved the goal.

6.2 CONTRIBUTION OF THE THESIS

Recently, a lot of aspects about ECG classification have been developed ([5],[13],[1], etc.), but most of the suggested methods still leave room for improvement and next research. Big amount of cardiologic signals still miss reliable classification algorithms. We think that the major contribution of the thesis to the actual state is novel classification framework and QT interval measuring. Mainly:

• We have developed important pre-processing framework using wavelet transform for electrocardiogram characteristic points detection.

• Especially, QT interval measuring method without need of any pre-processing and with ability of real time operation.

• Furthermore, we have focused our attention on the question which wavelet is the most appropriate for our T wave end detection and tested ability of its detection using only one scale of CWT.

• We tested ability of McSharry's model to model different arrhythmic signals.

• Furthermore, we have focused our attention on the question how many Gaussian functions of McSharry's model are enough for arrhythmias modelling without significant distortion.

• We tested ability of McSharry's model parameters to classify arrhythmic signals.

• Moreover, raw time series ANN classification has been also applied for comparison purposes with novel McSharry's model parameters ANN framework. In both cases: raw filtered data ANN classification and McSharry's model ANN classification were tested on MIT/BIH arrhythmia beats with results comparable to results reported in literature.

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Available from: <http://www.physionet.org/physiobank/database/>.