Wavelet Transform Based ECG QRS Detector

Yuliyan S. Velchev[1], Ognian L. Boumbarov[2]

Abstract – **In this paper an ECG QRS detection algorithm is described, based on continuous wavelet transform. It involves a significant improvement of the method with zero-crossing of the wavelet coefficients for edge localization in the QRS complexes. The characteristic points in QRS complexes are computed trough different scale wavelet decompositions. The QRS identification uses feature vectors composed of modulus maxima values, computed using continuous wavelet transform with the first derivative of the Gaussian function. The QRS classification method is based on K-nearest neighbors algorithm (K-NN).**

Keywords – **QRS detection, ECG analysis, ECG delineation, wavelet transform**

I. INTRODUCTION

Although the electrocardiogram (ECG) is one of the oldest diagnostic tools in cardiology, its clinical significance remains undoubted. The development of the portable ECG recorders (Holters) gives the possibility for more accurate diagnosis of cardiac diseases at early stage. Also, manual analysis for more than 24h long ECG recordings is hard and impractical. For these reasons, researches in the field of automatic ECG analysis are still challenging.

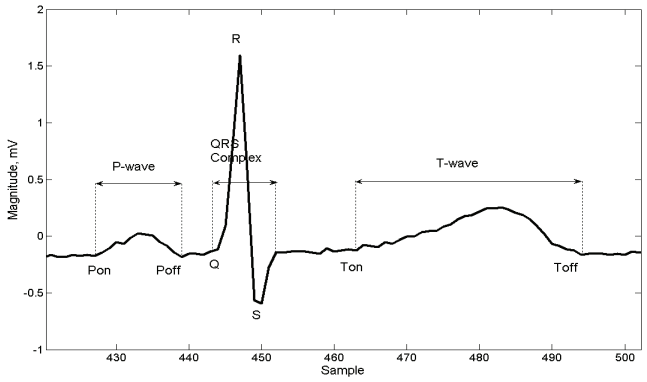

Fig. 1. Normal ECG

The ECG is a record of the electrical activity of the heart muscle. The ECG signal is considered to be a non-stationery random process with outstanding cyclic recurrence. Significant ECG-information is found in the amplitude and time intervals between defined characteristic points. The following points shown on Fig. 1, determine the standard waves in human ECG: P-wave, QRS complex, T-wave and sometimes U-wave. The portion of ECG between two neighbor R points forms a full cardiac cycle.

Boundary determination and classification of ECG waves and complexes (ECG delineation) is the main entry for automatic ECG analysis. The most significant approach in ECG analysis is to implement a probabilistic model in order to deal with non-stationery properties of the signal. Recently, the research it these probabilistic models is concentrated mainly in Hidden Markov Model (HMM) and Hidden Semi-Markov Model (HSMM). Very appealing results have been achieved by combining HMM and HSMM with wavelet transforms [7], which can be used as features of the signal [4], or can be used for edge localization and characterization [1].

The QRS complexes are the most distinct part in the ECG. On the other hand, T and P-waves detection without any prior knowledge can be difficult due to their low sharpness and possible baseline drift. This is why QRS detection is used as a starting point in wide range of methods and algorithms for automatic ECG analysis. In addition, the information about shape and time of occurrence of the QRS complexes (cardiac cycle duration) can provide enough information for automatic diagnosis of some cardiac diseases such as sinus tachycardia, sinus bradycardia, sinus arrhythmia etc [10].

According to mentioned concept a QRS detector is present in this paper. As result from QRS detection is clustered ECG signal into cardiac cycles, which can be used to detect some cardiac diseases and to make an entry for full ECG delineation (determination of onset and offset of each standard ECG component).

The remainder of this paper is structured as follows. In section II the different morphologies of the QRS complexes are discussed and grouped according to definite rules. Section III continues the work with detection of the characteristic points and boundaries of the QRS complexes, using wavelet transforms. Also, in this section, the features for QRS complexes identification are selected. In Section IV a QRS identifier is described, based on *K*-nearest neighborhood method. Section V shows experimental results and brief discussion.

II. QRS MORPHOLOGY

The proposed QRS detector is intended to detect only normal QRS complexes. Any abnormal QRS morphology should not be marked by the algorithm thus the abnormality can be detected in the next stage of ECG analysis, using the information from separated full cardiac cycles.

The normal QRS complexes can be very different in their morphology (number of waves, dominant wave, etc).

Any positive deflected wave is labeled as *R*, if the wave is dominant or *r* if its size is relatively small. Any negative wave that appears prior to R wave is labeled as *Q* or *q*, respectively. Any negative wave coming after R wave is labeled *S* or *s* according to the abovementioned rule. If there is more than

[1]Yuliyan S. Velchev is with the Faculty of Telecommunications, Technical University of Sofia, Address: 8, Kliment Ohridski St. Sofia-1000, BULGARIA, E-mail: julian_velchev@abv.bg

[2]Ognian L. Boumbarov is with the Faculty of Telecommunications, Technical University of Sofia, Address: 8, Kliment Ohridski St. Sofia-1000, BULGARIA, E-mail: olb@tu-sofia.bg

one wave from a given type, the remaining waves are labeled with "prime" ('), additionally. For example QRS, qRS, qR, Qr, rSRS', etc.

Obviously, it is hard to build universal QRS identifier. So, the QRS complexes are grouped in several classes according to following rules: number of waves that form the QRS complex and dominant wave (waves) in the QRS complex.

For each of these classes a set of separate QRS identifiers is built and trained with training set constructed from annotated ECG signals with the same QRS morphology.

III. QRS Boundary Detection

Most of the characteristic points in the QRS complexes can be associated with local extrema of the ECG in given time interval. Many methods for QRS detection are based on signal derivatives [2]. A significant drawback is the insufficient robustness when high frequency noise is present.

Wavelet transforms (WT) are widely used in automatic ECG analysis [1,3,5,6]. As can be seen below, they are closely related to signal derivatives, but the transform is less sensitive to high frequency noise.

The wavelet analysis of the signal *s(t)* means decomposition of the signal using translated and scaled single prototype wavelet function ψ. This function has unit energy and zero average. The translation *b* and scaling *a* of the wavelet function is expressed by (3.1).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3.1}$$

The WT of the signal *s(t)* is defined by:

$$Ws(a,b) = \left\langle s,\psi_{a,b}\right\rangle = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} s(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{3.2}$$

For a fixed scale *a* the WT can be rewritten as convolution:

$$Ws(a,b) = \int_{-\infty}^{\infty} s(t)\psi_a(t-b)\,dt = s \otimes \overline{\psi}_a(b) \tag{3.3}$$

Where $\overline{\psi}_a(b) = \psi_a(-b)$

In terms of edge localization of the components forming the QRS complexes, the chosen wavelet function $\psi^1(t)$ is the first derivative of a single Gaussian function: $\psi^1(t) = \frac{d\theta(t)}{dt}$, where $\theta(t) = \frac{1}{\sqrt{2\pi}}e^{-t^2/2}$ is the Gaussian function with unit width and zero position of the center of the peak.

In this case the wavelet transform $W^1s(a,b)$ can be expressed as proportional to smoothed first derivative of the signal *s(t)* by scaled version of Gaussian function $\overline{\theta_a}(b)$:

$$W^1s(a,b) \propto \frac{d}{db}\left[s \otimes \overline{\theta_a}(b)\right] \tag{3.5}$$

The onset and offset of a rising or falling edge in particular wave in ECG is derived from the zero-crossing of $W^1s(a,b)$ around each modulus maxima (MM) [8]. The MM is at any point b_0, where $|Ws(b)| < |Ws(b_0)|$ when *b* belongs to either a right or the left neighborhood of b_0, and $|Ws(b)| \le |Ws(b_0)|$ when *b* belongs to the other side of the neighborhood of b_0.

The scale of the wavelet transform *a* gives the resolution of the edges, which can be detected. The small values of *a* give a better time resolution, and thus the onset and offset of the wave can be precisely determined, but the transform becomes sensitive to noise. So, achieving the good time resolution for QRS boundary detection with good noise robustness, a combination of wavelet transforms from different scales is applied.

The algorithm uses wavelet transforms for boundary localization starting from higher scale and précising the currently determined point by lowering the scale before next iteration.

As can be seen from Fig. 2, the boundaries of the QRS complexes can't be detected precisely or even can be missed. The method with zero-crossing of $W^1s(a,b)$ is usually applied to detect the boundaries of "subclasses" in the ECG, formed by some parts of neighboring standard "waves", such as the part between points P_{off} and *R*, *R* and T_{on} etc (Fig. 1). After "subclasses" classification, the boundaries of the standard waves are determined by rule, according to given ECG morphology.

The proposed algorithm for QRS boundary detection is based on zero-crossing of $W^1s(a,b)$, applied not only on original ECG signal, but also on its appropriate wavelet decomposition and composition (Fig. 2).

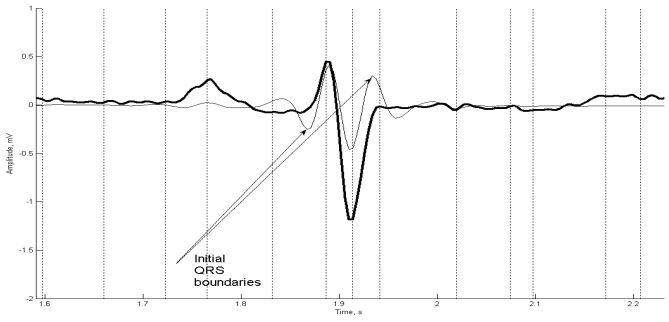

Fig. 2. QRS characteristic points detection: original ECG (thick line), wavelet transformed ECG with Coiflet-5, level 3 (thin line), detected characteristic points (dashed vertical lines)

After determination of the internal characteristic points and successful QRS identification, the ECG signal is decomposed with WT to 8 levels of decomposition. At first iteration stage, the signal is composed back only from 3rd level. The approximated onset and offset of the QRS complexes are found by applying the same method with zero-crossing of $W^1s(a,b)$ on composed signal, before and after first and last

modulus maxima in QRS complexes. Iteratively the zero-crossing method is applied on ECG composed from higher levels, thus précising the current onset and offset, until maximum accuracy for QRS boundaries detection is achieved.

IV. QRS IDENTIFICATION

As mentioned above, the QRS complexes occupy higher frequency regions in ECG spectrum. Thus, the unique combination from modulus maxima values for each edge in the QRS complexes gives well enough discriminative information in order to make a robust identification.

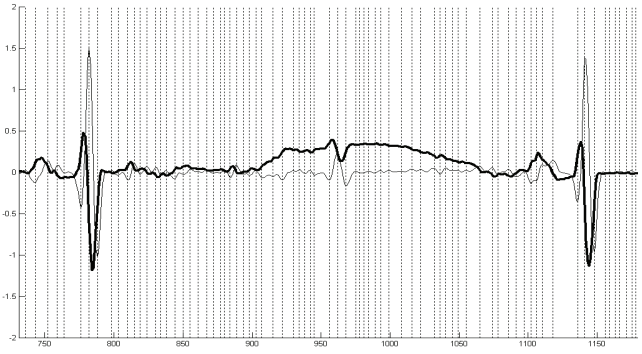

Fig.3. Features extraction from ECG signal with *rS* morphology of the QRS complexes: ECG (solid line), wavelet coefficients from wavelet transform with first derivative of Gaussian function at scale $a = 2$ (thin line), modulus maxima positions at scale $a = 2$ (dashed vertical lines)

The modulus maxima in determined from wavelet transform with first derivative of the Gaussian function at scale $a = 2$. This value is chosen to achieve good description for given edge, along with acceptable noise robustness (Fig. 3).

The feature vectors $\boldsymbol{M}$ are built from consecutive normalized modulus maxima values m_i with size according to particular QRS morphology (4.1).

$$\boldsymbol{M} = [m_1, m_2, ..., m_n]^t, 2 \le n \le 5 \qquad (4.1)$$

Fig. 4 shows the feature space diagram for ECG record with *rS* morphology of the QRS complexes by combination of the features - m_1 , m_2 and m_3 .

The identifier for QRS complexes uses *K*-nearest neighbor algorithm (*K-NN*). It is based on closest training examples from the training set in the feature space. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its *K* nearest neighbors. In this particular case (binary classification), *K* is chosen to be an odd number (K= 3).

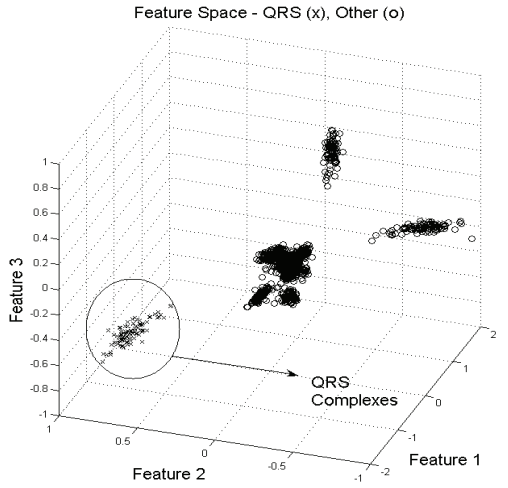

Fig. 4. Feature space diagram for the ECG signal from Fig. 3. Features: Feature 1 - m_1, Feature 2 – m_2, Feature 3 – m_3

Let $T_{XY} = \{(\boldsymbol{x}_1, y_1), ..., (\boldsymbol{x}_l, y_l)\}$ be a set from prototype vectors $\boldsymbol{x}_i \in X \subseteq \mathbf{R}^n$ and corresponding hidden states $y_i \in Y = \{1, ..., c\}$. Let $\mathbf{R}^n(\boldsymbol{x}) = \{\boldsymbol{x}' : \|\boldsymbol{x} - \boldsymbol{x}'\| \le r^2\}$ be a ball centered in the vector $\boldsymbol{x}$ in which lie K prototype vectors $\boldsymbol{x}_i$ $i \in \{1, ..., l\}$ i.e. $\left|\{\boldsymbol{x}_i : \boldsymbol{x}_i \in \mathbf{R}^n(\boldsymbol{x})\}\right| = K$. The *K-NN* classification rule $q : X \to Y$ is defined as:

$$q(\boldsymbol{x}) = \arg\max v(\boldsymbol{x}, y), y \in Y \qquad (4.2)$$

Where $v(\boldsymbol{x}, y)$ is number of prototype vectors $\boldsymbol{x}_i$ with hidden states $y_i = y$ which lie in the ball $\boldsymbol{x}_i \in \mathbf{R}^n(\boldsymbol{x})$

V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

The performance of the described algorithm for QRS complexes detection is evaluated according to (5.1) and (5.2) and the results are shown in Table I.

$$Se = \frac{TP}{TP + FN} \qquad (5.1)$$

$$+P = \frac{TP}{TP + FP} \qquad (5.2)$$

Where *Se* denotes sensitivity, $+P$ denotes positive predictivity, *TP* is number of true positive detections, *FN* is number of false negatives and *FP* is number of false positives.

For performance evaluation the following ECG databases are used: MIT-BIH Normal Sinus Rhythm Database, MIT-BIH Long-Term ECG Database, QT Database and others.

The analyzed signals have been resampled to standard sampling rate of 256 Hz. Each signal is 60 s long and consists about 60-100 QRS complexes.

TABLE I
PERFORMANCE EVALUATION OF THE QRS DETECTION

ECG Signal	Se, %	+P, %
16265 sig 0	96.9	100
16265 sig 1	100	100
16272 sig 0	98.4	100
16272 sig 1	93.7	95.2
16273 sig 0	98.8	100
16273 sig 1	98.9	100

The classifier is made under Statistical Pattern Recognition Toolbox for Matlab [9].

The performance of the described algorithm for detection of QRS characteristic points has been evaluated using mean value m and standard deviation σ of the absolute error. The reference for absolute error is expert annotated QRS characteristic points of real ECG signals.

TABLE II
EVALUATION OF THE ABSOLUTE ERROR OF QRS CHARACTERISTIC POINTS DETECTION

ECG Signal	QRS on m, σ (ms)	QRS off m, σ (ms)	Q m, σ (ms)	R m, σ (ms)	S m, σ (ms)
16265 sig 0	3.5, 3.2	3.0, 8.8	-0.2, 1.8	0.8, 1.9	0.5, 5.8
16265 sig 1	2.6, 12.7	-0.9, 2.3	0.4, 2.0	0.1, 1.6	0.2, 2.3
16272 sig 0	-1.2, 8,8	0.5, 4.6	-1.2, 8,8	0.5, 1.3	-1.5, 2.1
16272 sig 1	-0.8, 5.3	0.5, 4.9	-0.8, 5.3	0.1, 0.6	0.1, 1.1
16273 sig 0	2.6, 2.5	-0.4, 7.5	0.3, 2.9	0.8, 1.6	-0.4, 7.5
16273 sig 1	-2.3, 6.6	-2.1, 4.1	1.5, 2.9	-1.4, 2.3	-2.1, 4.1

Table II shows the experimental results for several signals from MIT-BIH Normal Sinus Rhythm Database with different QRS morphologies (qR, rSRS', Rs, rS). As can be seen, the mean value and standard deviation of the absolute error are comparable with the sampling interval for the analyzed ECG signals.

VI. CONCLUSION

In this paper a robust QRS detector have been present. Detection of the characteristic points in the QRS complexes is based on wavelet transform with first derivative of the Gaussian function. The onset and offset of the QRS complexes are determined with the same algorithm, but applied on wavelet composed signal from different scales, using Coiflet-5 as prototype function. This prototype function is chosen because the transformation uses digital filters with phase response linearity considerably better than other wavelets.

The QRS identifier employs *K*-nearest neighborhood method for QRS complex identification. Its features are normalized consecutive modulus maxima values, determined with wavelet transform with first derivative of Gaussian function at scale $a = 2$, thus the detector is insensitive to baseline drift of the signal.

The further analysis of the ECG is planned to be at full cardiac cycle level and finally to make detection of the remaining waves (T-wave, P-wave and U-wave).

VII. ACKNOWLEDGEMENT

This work was supported by National Ministry of Education and Science of Bulgaria under contract BY-TH-202/2006 "Multimodal biometric analysis: methods and algorithms"

REFERENCES

[1] Cuiwei Li, Chongxun Zheng, and Changfeng Tai., "Detection of ECG Characteristic Points using Wavelet Transforms", IEEE Trans. on Biomedical Engineering, vol. 42 (1), pp. 21–28, 1995.

[2] J. Pan, W. J. Tompkins, "A Real-time QRS Detection Algorithm", IEEE Transactions on Biomedical Engineering, vol. 32 (3), pp. 230-236, 1985.

[3] M. Nasor M. J. Burke, "Wavelet based Analysis and Characterization of the ECG Signal", Journal of Medical Engineering and Technology, vol. 28 (2), pp. 47–55, 2004.

[4] N. P. Hughes, L. Tarassenko, S. J. Roberts," Markov Models for Automated ECG Interval Analysis", In Advances in Neural Information Processing Systems, Number 16, pp. 611-618, 2004.

[5] J. P. Martínez, R. Almeida, S. Olmos, A. P. Rocha, "A Wavelet-based ECG Delineator: Evaluation on Standard Datbases", IEEE Transactions on Biomedical Engineering, vol. 51 (4), pp. 570-58, 2004.

[6] P. S. Addison, "Wavelet Transforms and the ECG: a Review", Physiological Measurement, vol. 26, pp. R155-R199, August 2005.

[7] R. Andreão, J. Boudy, "Combining Wavelet Transform and Hidden Markov Models for ECG Segmentation", EURASIP Journal on Advances in Signal Processing, vol. 2007, pp. 95-95, 2007.

[8] S. Mallat, W. L. Hwang, "Singularity Detection and Processing with Wavelets", IEEE Transactions on Information Theory, Vol. 38, No. 2, pp. 617-643, March 1992.

[9] V. Franc, V. Hlavac, "Statistical Pattern Recognition Toolbox for Matlab", June, 2004, http://cmp.felk.cvut.cz/cmp/software/stprtool/index.html

[10] G. Clifford, P. McSharry, "Advanced Methods and Tools in ECG Analysis", Publisher: Artech House, Incorporated, October 2006.