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# Multiresolution Analysis of ECG Signals in Heart Rhythm Monitoring

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*The paper is devoted to multiresolution analysis of ECG signals in heart rhythm monitoring. The proposed method for R-wave detection in ECG signals is based on extracting detail coefficients from the wavelet decomposition of the ECG signal. It uses nonlinear transforms and the adaptive threshold algorithm. The suggested approach is compared to existing methods for R-wave detection in ECG signals used for processing clinical ECG records from the MIT Physionet database.*

## Introduction

Detection and processing of ECG signals are widely used in medical diagnosis. Progress in the development of cardiac monitoring systems based on the variability of cardiac rhythm parameters is increasing the demand for reliable methods of detection of the R-R intervals of the ECG signal under conditions of exposure to noise and artifacts of various origins [1, 2].

The variety of algorithms for detection of the R wave of the ECG signal used in current medical practice are mainly based on the calculation of the first and second derivatives, band-pass filtering, wavelet transform, matched filtering, syntactic methods, and neural networks, as well as various combinations of these methods [3-9].

The goal of this work was to describe a relatively simple method for detection of the R wave of the ECG signal providing high sensitivity and low error. This method includes three successive stages of digital processing of the ECG signal: large-scale wavelet transform, application of a set of nonlinear operators, and an adaptive detection algorithm.

## Materials and Methods

Signal decomposition based on discrete wavelet transform involves decomposition of the original signal into a series of approximation and detail coefficients [7]. The wavelet function type and the number of decomposition levels are the main decomposition parameters.

Numerous studies showed that the 6th-order Daubechies wavelets are the most effective wavelets for ECG signal processing [7, 10]. The time curves of the approximation and detail coefficients of the wavelet decomposition of a model ECG signal with LF, HF, and broadband noise are shown in Figs. 1 and 2, respectively. A simulation model suggested by P. E. McSharry et al. [11] was used to form biosignal fragments of required shape and with given amplitude and time parameters.

The coefficient of correlation between the model ECG signal containing only QRS complexes and the series of wavelet decomposition coefficients was determined in this work to select the optimum decomposition level and the wavelet coefficient type for detecting R waves. The numerical values of the correlation coefficient are given in Table 1.

Analysis of the obtained data showed that the sum of the detail coefficients of the 4th and 5th levels provided the best correlation with the model ECG signal containing only QRS complexes.

The following procedure for detection of R waves was suggested on the basis of preliminary studies:

1) large-scale wavelet transform of the original ECG signal for six decomposition levels;

2) summation of the detail coefficients of the 4th and 5th levels;

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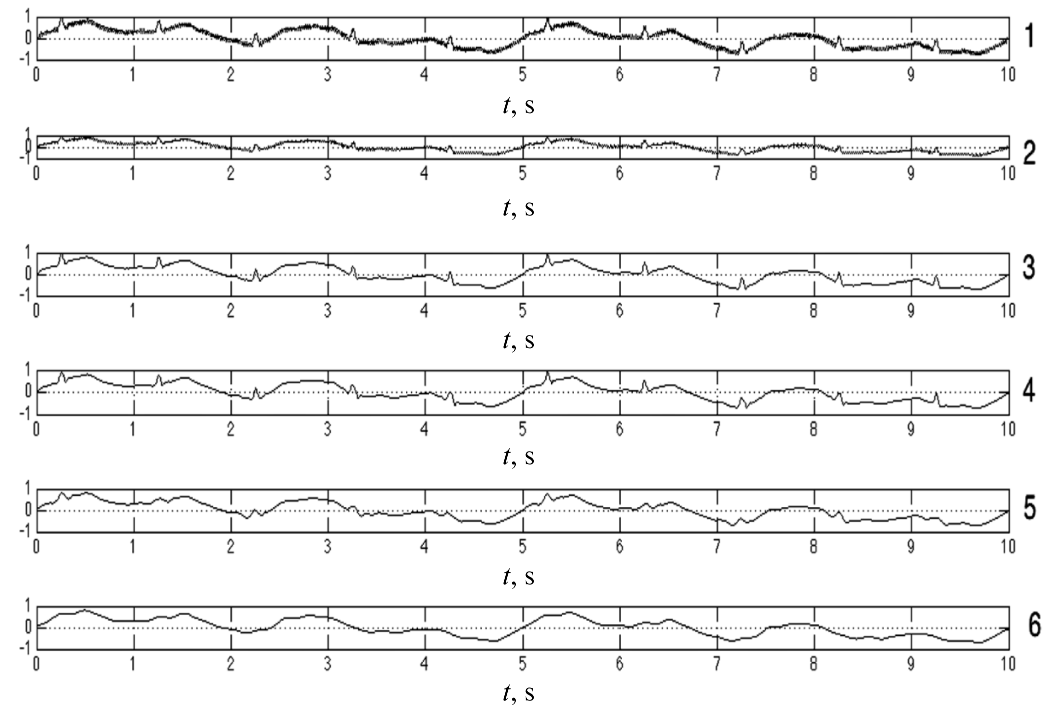


**Fig. 1.** Approximation coefficients for six levels of decomposition of noisy ECG signal (decomposition level increases from top to bottom).

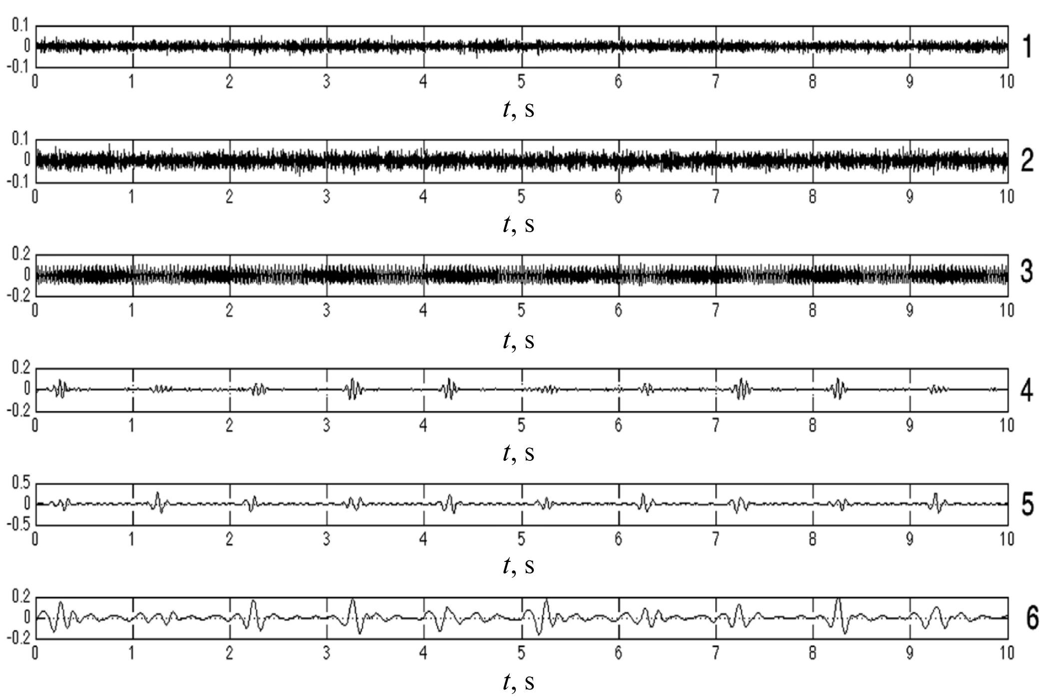


**Fig. 2.** Detail coefficients for six levels of decomposition of noisy ECG signal (decomposition level increases from top to bottom).

**TABLE 1.** Coefficient of Correlation between Model ECG Signal Containing only QRS Complexes and Series of Wavelet Decomposition Coefficients

| Decomposition level | Detail coefficients | Approximation coefficients |
|---|---|---|
| 1 | 0.08 | 0.46 |
| 2 | 0.13 | 0.51 |
| 3 | 0.17 | 0.48 |
| 4 | 0.6 | 0.32 |
| 5 | 0.71 | 0.35 |
| 6 | 0.6 | 0.2 |
| 4 + 5 | 0.8 | 0.33 |

3) substitution of zero values instead of negative readings;

4) squaring of the obtained result.

After the two preliminary processing stages, the resulting signal is applied to the input of the adaptive circuit used for detection of the signal peaks serving as reference points of the QRS complex. The R wave is selected as the most distinct marker.

The essence of the adaptive algorithm for peak detection is the formation of a 2-s sliding window within which the peaks reaching above the given threshold level (*Lev*) are sought. The threshold level is determined individually for each sliding window based on the following threshold function:

$$Lev(i) = \begin{cases} 0.4 \cdot Max(i); & \Omega(i) \geq 0.2 \cdot Max(i) \ \& \ Max(i) < 2 \cdot Max(i-1); \\ 0.4 \cdot Max(i-1); & \Omega(i) \geq 0.2 \cdot Max(i) \ \& \ Max(i) \geq 2 \cdot Max(i-1); \\ 1.6 \cdot \Omega(i); & \Omega(i) < 0.2 \cdot Max(i), \end{cases}$$

where $\Omega(i)$ is the value of the mean square deviation of the signal amplitude readings within the limits of the $i$th sliding window; Max($i$) is the maximal value of the signal amplitude readings within the limits of the current sliding window; Max($i-1$) is the maximal value of the signal amplitude readings within the limits of the preceding sliding window.

The numerical values of the threshold function parameters were selected empirically based on the experimental data for the criterion of correct detection of QRS complexes and minimization of false detection and omission.

The peak detector determines the time position of the signal peak within the time interval of the search if the following conditions are observed simultaneously:

$$A(n) := Peak, \text{ if } A(n) > Lev \ \& \ A(n) >$$

$$> A(n+1) \ \& \ A(n) > A(n-1),$$

where $A$ is the signal at the input of the adaptive system (resulting signal at the 4th step of preliminary processing).

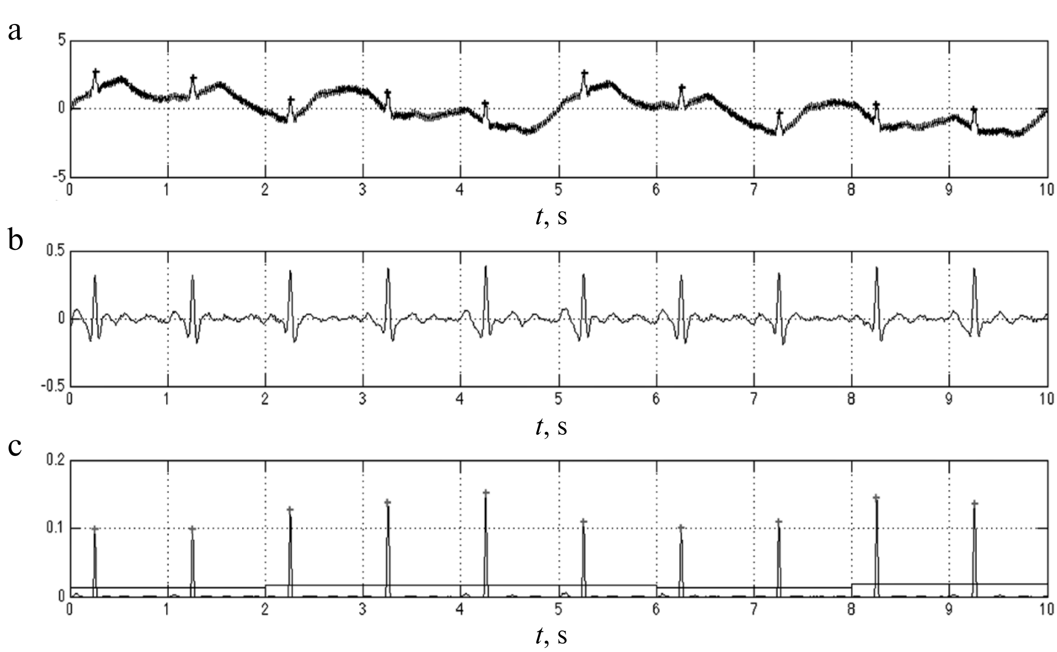


**Fig. 3.** Model noisy ECG signal curves at different stages of processing.

**TABLE 2.** Efficiency of Detection of R Waves of the ECG Signal

| Signal fragment | 100 | | | 104 | | | 105 | | | Mean value averaged over 48 fragments | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_T$, % | $P_F$, % | $P_{er}$, % | $P_T$, % | $P_F$, % | $P_{er}$, % | $P_T$, % | $P_F$, % | $P_{er}$, % | $P_T$, % | $P_F$, % | $P_{er}$, % |
| 1 | **100** | **0** | **0** | 99.2 | 0.1 | 0.9 | 99.7 | 0.03 | 0.33 | 99.8 | **0.02** | 0.22 |
| 2 | **100** | 0.04 | 0.04 | 99.7 | 0.08 | 0.38 | 99.5 | 0.04 | 0.54 | 99.6 | 0.05 | 0.45 |
| 3 | 99.9 | 0.09 | 0.19 | 99.8 | 0.07 | 0.27 | 98.2 | 0.12 | 1.92 | 98.9 | 0.08 | 1.18 |
| 4 | **100** | **0** | **0** | 99.9 | 0.04 | 0.14 | **99.89** | **0.02** | **0.13** | **99.9** | **0.02** | **0.12** |

Model ECG signal curves at different stages of processing by the method suggested in this work are shown in Fig. 3. The original model signal containing motion artifacts, baseline drift, and broadband noise is shown in Fig. 3a; the sum of the detail coefficients of the 4th and 5th levels, in Fig. 3b; the input signal of adaptive circuit for peak detection using sliding windows, in Fig. 3c. The adaptive threshold is indicated with a straight line; the detected R waves are marked with crosses.

## Results

The detector suggested in this work was verified using the PhysioNet ECG signal database of the Massachusetts Institute of Technology (http://physionet.org). The efficiency of detection of QRS complexes was estimated using the following statistical parameters:

1) probability of detection of reference points $P_T$:

$$P_T = (N_T/N)\cdot 100\%;$$

2) probability of detection of false reference points $P_F$:

$$P_F = (N_F/N)\cdot 100\%;$$

3) parameter of the detection error level $P_{er}$:

$$P_{er} = ([N_m + N_F]/N)\cdot 100\%,$$

where $N_T$ is the number of correctly detected R waves, $N_F$ is the number of falsely detected R waves, $N$ is the total number of R waves, and $N_m$ is the number of omitted R waves.

ECG signal samples available from the MIT-BIH Arrhythmia Database were used in the tests. The database contains 48 fragments of actual ECG signals (30 min each); one sample with low noise (record 100) and two samples with high-amplitude noise (records 104 and 105) were specially selected for the tests [12]. Comparative analysis of the QRS complex detection efficiency was carried out using the following detectors: 1) the detector based on multiresolution analysis of ECG signals suggested in this work; 2) detector based on a matched filter [9]; 3) Pan—Tompkins detector [8]; 4) detector based on neural network [6].

The results of quantitative evaluation of the efficiency of the detector suggested in this work as compared with currently used approaches to processing of actual ECG signals are presented in Table 2.

## Conclusion

It follows from the results obtained in this work that the detection of R waves of the ECG signal based on wavelet decomposition is an effective method for processing ECG signals measured under actual clinical conditions. The method suggested in this work made it possible to achieve 100% error-free detection in a low-noise 30-min-long ECG signal sample. In a noisy ECG signal, the detection error level was no more than 0.9%.

The advantages of the method for R wave detection described in this work are easy implementation, high speed, high rate of correct detection of QRS complexes, and low incidence of errors caused by false detection and omission. The suggested method is slightly less effective that the detection technique based on neural network. However, the latter method is considerably more complicated and labor-consuming; in addition, it requires preliminary neural network training using considerable arrays of experimental data.

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