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Selection of Parameters of Bandpass Filtering of the ECG Signal for Heart Rhythm Monitoring Systems

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This work is devoted to the bandpass frequency filtering of the ECG signal in heart rhythm monitoring systems against the background of disturbances and noises of various origins. It was suggested to optimize the procedure for selection of the bandwidth and the type of bandpass filter using the criteria for minimization of uncertainty in the measurement of the R-R intervals. Two different approaches to the bandpass filtering were considered: use of a second-order analog active filter and of an eighth-order digital filter.

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].

The primary stage of processing of the ECG signal involves bandpass filtering reducing the baseline drift of the biological signal and the effect of motion artifacts and high-frequency noise. Correct selection of the frequency filter passband ensures adequate isolation of the high-frequency QRS complex of the ECG signal against the background of the low-frequency P and T waves of the signal, low-frequency noise, and 50-Hz power-line artifacts. The dependence of the spectral power of various components of the ECG signal on frequency (measured in relative units) is shown in Fig. 1 [2].

Analysis of the results demonstrates that isolation of the QRS complex of the ECG signal based on the principle of frequency selection can be very effective. The goal of this work was to substantiate the selection of the passband and the filter type for automated heart rhythm monitoring systems.

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Materials and Methods

The quantitative characteristics of the efficiency of the ECG signal frequency filtering were determined using model curves of a biological signal with disturbances.

The model of the ECG signal with disturbances and noises was assumed to be additive. The model curves were obtained using an imitation procedure for formation of ECG signal fragments with the required morphology and amplitude–time parameters of the biological signal suggested by P. E. McSharry et al. [3].

Mathematical modeling of disturbances can be based on *a priori* information about the origin of the disturbance or noise. The main types of ECG signal disturbances are power-line noise, noises in the analog tract used for detection of biological signals, and electrode polarization potential fluctuation, as well as physiological artifacts of respiration, patient mobility, and spontaneous myographic activity of peripheral muscles [4, 5].

The mathematical model of the effect of the power-line magnetic field can be described by the following equation:

$$L(k) = L_{\max} \sin\left(2\pi \frac{f_p}{f_s} k\right),$$

where $L_{\max}$ is the power-line disturbance amplitude, f_p is the power-line frequency, f_s is the disturbance sampling frequency, and k is the signal sequence number.

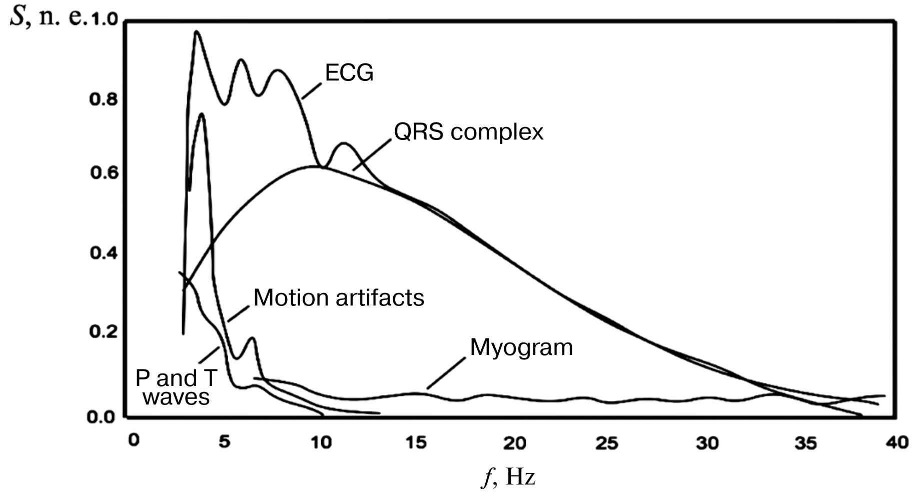

Fig. 1. Spectral power of various components of the ECG signal.

The disturbances caused by respiration and displacement of electrodes due to involuntary movements lead to distortions of the isoline and the ECG signal, as well as to isoline drift (a quasi-periodic signal of stochastic origin with the main frequency band below the mean frequency of cardiac contraction) [6].

The analysis of the factors affecting the ECG signal isoline drift demonstrated that this type of disturbance could be considered as a sum of deterministic and random components:

$$W(k) = W_{\max} \cdot \left[\sum_{i=1}^{4} \sin 2\pi f_i \frac{k}{f_s} + \psi(k) \right],$$

where $W_{\max}$ is the amplitude of the isoline drift model signal, $\psi(k)$ is the random component obtained by filtering of the white Gaussian noise using a low-frequency filter (cut-off frequency, 1 Hz), and f_i is the additive frequency set of harmonic signals (deterministic component). In modeling the ECG signal isoline drift the following frequency values were used: f_1 = 0.1 Hz; f_2 = 0.2 Hz; f_3 = 0.4 Hz; f_4 = 0.8 Hz.

Measurements with an accelerometer attached to a patient's extremity with subsequent spectral analysis of the detected motion signals demonstrated that the frequency range depended on the activity types and ranged from 0 to 4 Hz [7]. The low-frequency component of the motion artifacts (frequency <1 Hz) produced isoline drift of the ECG signal.

The effect of the high-frequency motion artifacts (frequency >1 Hz) on the ECG signal shape was described using an additive set of three harmonic signals with frequencies 1, 2, and 4 Hz, respectively:

$$D(k) = D_{\max} \cdot \left(\sum_{j=1}^{3} \frac{1}{e^{j-1}} \cdot \sin 2\pi F_j \frac{k}{f_s} \right),$$

where $D_{\max}$ is the amplitude of the motion artifact model signal and F_j is the frequency set of the signal harmonics.

The interference caused by peripheral muscles located in the ECG electrode projection is a random broadband signal. The mathematical model of the myographic activity is represented by a normal process with zero mean and mean square deviation σ_1 [6]. The additive component of the disturbance with normal distribution also simulates the effect of the internal noise of the ECG signal detection unit and random origin of the motion artifacts.

The absolute error (Δ) of the R-R interval measurement in the presence of noise in the ECG signal subjected to bandpass filtering was considered in this work as the criterion of the efficiency of filtering of the ECG signal.

The error of the R-R interval measurement was estimated using the quantile characteristics, at which the error measured with a given confidence interval P falls within the interval of uncertainty. At the confidence factor $P = 0.9$ for the most widespread probability distribution laws there is a one-to-one relation between the error and the mean square deviation regardless of the distribution law [8]. At $P = 0.9$ the absolute error is:

$$\Delta_i = 1.6 \cdot \sigma_{R\text{-}R},$$

where Δ_i is the absolute error in the R-R interval value and $\sigma_{R\text{-}R}$ is the mean square deviation of the R-R interval size from the true value determined as:

$$\sigma_{R-R} = \sqrt{\frac{\sum_{i=1}^{N}\left[RR'(i) - RR(i)\right]^2}{N}},$$

where $RR(i)$ is the R-R interval size for the model ECG signal in the absence of distortions, $RR'(i)$ is the measured R-R interval size for the processed noise-contaminated ECG signal, and N is the total number of R-R intervals in the biological signal fragment under consideration.

In this work, accurate estimates of the R-R interval size were obtained using a noise-free method of detection of the QRS complexes based on sequential bandpass filtering, the Hilbert transform, and an adaptive procedure for detection of maximums [9].

Recursive filters with an infinite pulse characteristic are most frequently used for biological signal processing. These filters have such advantages as simple implementation, high operation speed of digital filters, and the possibility of analog implementation.

The ECG signal filtering parameters were selected for the standard Butterworth filter (A), Butterworth filter with correction of the phase curve nonlinearity (B), Bessel filter (C), and Chebyshev type II filter (D).

The phase curve nonlinearity of the Butterworth filter was corrected by transmitting the filtered output signal through the filter again in the inverse order. In this case the order of the filter was doubled [4]. The Chebyshev type I filter and the Cauer filter (elliptic filter) were not considered in this work because of the frequency response pulsation in their frequency bands leading to significant distortions of the ECG signal.

The results given below were obtained using the MATLAB computing environment and standard Signal Processing Toolbox functions for digital filter design.

Results

The optimal passband of the filter was selected with regard to the most difficult conditions: the lower cut-off frequency was selected for the minimal rate of cardiac contraction within the physiological range, and the upper cut-off frequency, for the maximal contraction rate. This approach ensures selection of the optimal passband with regard to the variability of cardiac rhythm under actual conditions.

The dependence of the R-R interval measurement error Δ on the lower cut-off frequency F_L of the bandpass filter is shown in Fig. 2. These curves were obtained for the following model parameters: filter order – 8; cardiac contraction rate – 30 beats/min; QRS complex duration – 100 ms; QRS complex amplitude – 1; $L_{max} = 0.5$; $f_p = 50$ Hz; $f_s = 500$ Hz; $W_{\max} = 0.5$; $\sigma_1 = 0.1$; $D_{\max} = 0.5$.

The dependence of the R-R interval measurement error Δ on the upper cut-off frequency F_H of the bandpass filter is shown in Fig. 3. These curves were obtained for the same model parameters as in the previous case, except for the following: cardiac contraction rate – 240 beats/min; QRS complex duration – 60 ms.

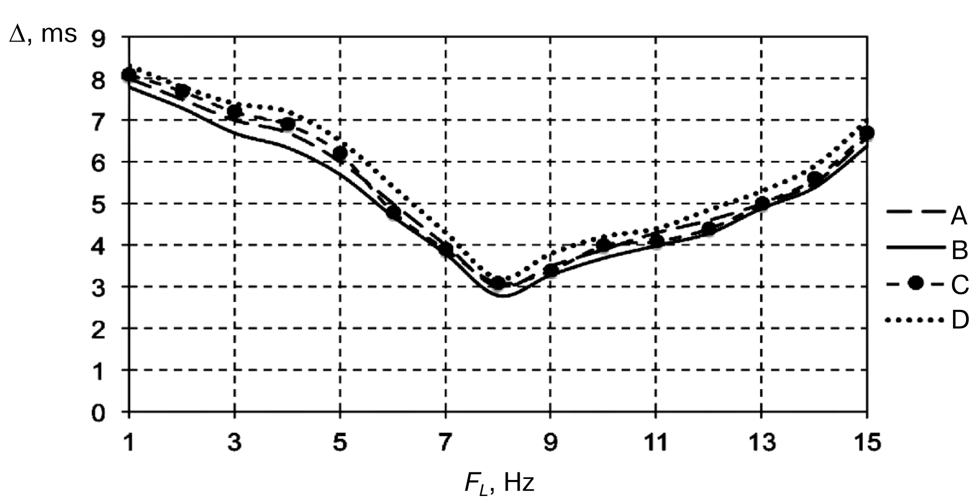

Fig. 2. Dependence of the R-R interval measurement error on the lower cut-off frequency of the bandpass filter: A) Butterworth filter; B) Butterworth filter with correction of the phase curve nonlinearity; C) Bessel filter; D) Chebyshev type II filter.

The results of processing of a noisy ECG signal with an eighth-order digital Butterworth filter (passband, 8-20 Hz) are shown in Fig. 4: a) ECG signal corrupted by motion artifacts and isoline drift; b) results of processing of the noisy ECG signal (R waves of the ECG signal are indicated by crosses).

The analysis of the results obtained in this work shows that the digital Butterworth filter improves significantly the signal-to-noise ratio and facilitates the detection of the R waves of the ECG signal in the presence of noise.

The simulation of the ECG signal filtering with active analog filters requires the filter order to be changed, because in the majority of ECG detection systems bandpass filters are implemented using sequential cascades of upper and lower frequency filters of the first

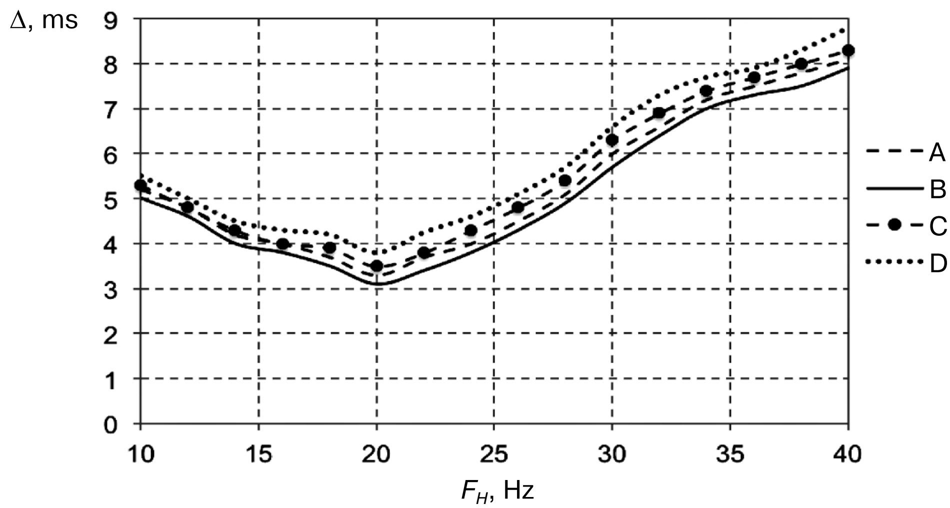

Fig. 3. Dependence of the R-R interval measurement error on the upper cut-off frequency of the bandpass filter: A) Butterworth filter; B) Butterworth filter with correction of the phase curve nonlinearity; C) Bessel filter; D) Chebyshev type II filter.

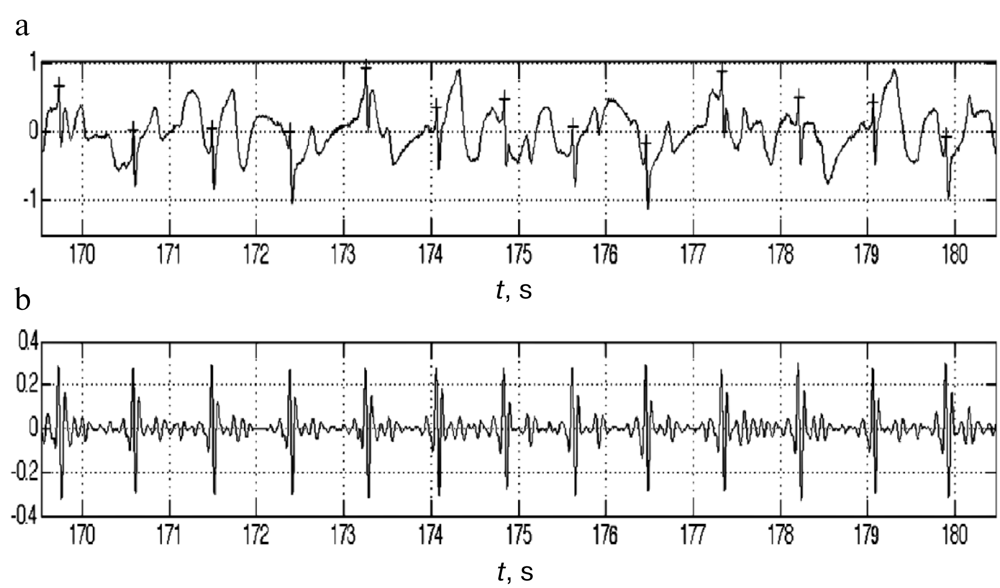

Fig. 4. ECG signal processing using bandpass filter: a) initial noisy ECG signal; b) ECG signal after bandpass filtering.

and second orders. Research showed that for filters of the second order the optimal passband was within the range 5-30 Hz. The error of the R-R interval measurement using a hardware Butterworth filter with this passband was 4.3 ms; if the Bessel filter was used, 4.4 ms; for the Chebyshev type II filter, 4.7 ms.

Conclusion

The results obtained in this work showed that the optimal filter passband for ECG processing and minimization of the error of the R-R interval measurement against the background of disturbances of various intensities for higher order filters was 8-20 Hz. The value of the R-R interval measurement error in the case of the use of the digital filters and the Hilbert transform, as well as an adaptive procedure of search for maximums, was 3 ms. Within the frequency band 8-20 Hz these filters provide approximately equal values of accuracy of the R-R interval measurement. The minimal measurement error was provided by the Butterworth filter with correction of the phase curve nonlinearity.

In the case of digital processing of the ECG signal, any of the filters considered above can be used. In the case of analog filtering, the Butterworth filter is recommended because of the simple implementation of the filtering procedure. The slope angles of the frequency response curves of the Butterworth filters are rather sharp in the transition frequency band and maximally flat in the passband, which minimizes corruption of the biological signals and provides effective suppression of signal disturbances beyond the passband. These filters are effective and rather simple in their implementation. Their analog versions are available in the Rauch and Sallen–Key topologies. The software filters can be implemented with linear phase characteristics, which makes it possible to include them into software for modern systems of portable ECG detection and processing.

It should be noted that the majority of disturbances accompanying ECG signal detection are broadband random signals with spectral characteristics overlapping with the spectrum of the main ECG signal, which makes it difficult to use linear frequency filtering for effective suppression of disturbances.

Nevertheless, the stage-by-stage use of bandpass filtering became *de facto* a standard procedure for primary processing of biomedical signals, including ECG signal processing. Thus, correct selection of the optimal passband and the filter type became especially important for minimizing the error of R-R interval measurement.

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