

MEDICAL AND BIOLOGICAL MEASUREMENTS

COMPARATIVE ANALYSIS OF ALGORITHMS FOR ELIMINATION OF LOW-FREQUENCY NOISE IN ELECTROCARDIO-SIGNALS

A. A. Savostin, D. V. Ritter,
G. V. Savostina, and A. K. Koshekov

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The problem of suppressing the low-frequency component of the electrocardiogram signal during computerized electrocardiographic measurements is examined. The efficiency and possible realization of the main methods for eliminating low-frequency noise are compared and their applicability to different electrocardiographic measurements is examined. The results are confirmed by experimental studies of simulated and real electrocardiogram samples.

Keywords: *electrocardiogram, isoelectric line drift, digital filtering.*

In the course of medical electrocardiographic measurements, an entire range of noise of different origins shows up during the recording of electrocardio-signals (ECS). This noise makes the measurement and analysis of the parameters of the useful signal more difficult and can distort the resulting electrocardiograms (ECG). Here the main difficulty is choosing efficient and simple methods for filtering certain types of noise.

In modern computerized diagnostic systems the measured ECS after analog-to-digital conversion is a linear combination of the initial noise-free signal $\Sigma(kT)$ and some additive noise $\varepsilon(kT)$:

$$S(kT) = \Sigma(kT) + \varepsilon(kT), \quad (1)$$

where $k = 1, \dots, M$ are the numbers of the signal readouts, M is the total number of readouts, and T is the sampling period.

The noise $\varepsilon(kT)$ is a set of noise components (artefacts) of different kinds and intensities which must be eliminated. There is a special class of problem in which low-frequency (LF) noise in the form of a drift in the isoelectric line must be eliminated. The drift arises because of modulation in the amplitude of the ECS owing to breathing (the respiratory component), as well as artefacts from the biasing of the electrodes. This noise is caused by movements of the chest cavity of the patient with the attached electrodes owing to breathing and or movement of the limbs. Poor contact of an electrode with the skin or sweating by the patient can provoke a change in impedance that leads to LF oscillations of the isoelectric line. In addition, the effect of external destabilizing factors on the recorder amplifiers can produce LF drift of the ECS.

Correction of the isoelectric line drift of an electrocardiogram. The LF drift of the isoelectric line must be eliminated prior to any further signal analysis procedures. This requirement exists for the following reasons. To identify anomalies in cardiac activity during clinical measurements the shape and duration of the elements of the ECG [1, 2] are analyzed for deviations from the norm (Fig. 1). A shift in the isoelectric line makes these measurements much more difficult in either the manual or automatic modes owing to the distortion of the shapes of the elements of the ECG. For example, when analyzing the segment ST , a determination of its position relative to the isoelectric line is of special importance: norm, elevation (rise), or depression (drop). An LF drift makes it impossible to evaluate the shape (slope) of the segment ST in the ECG and, thereby,

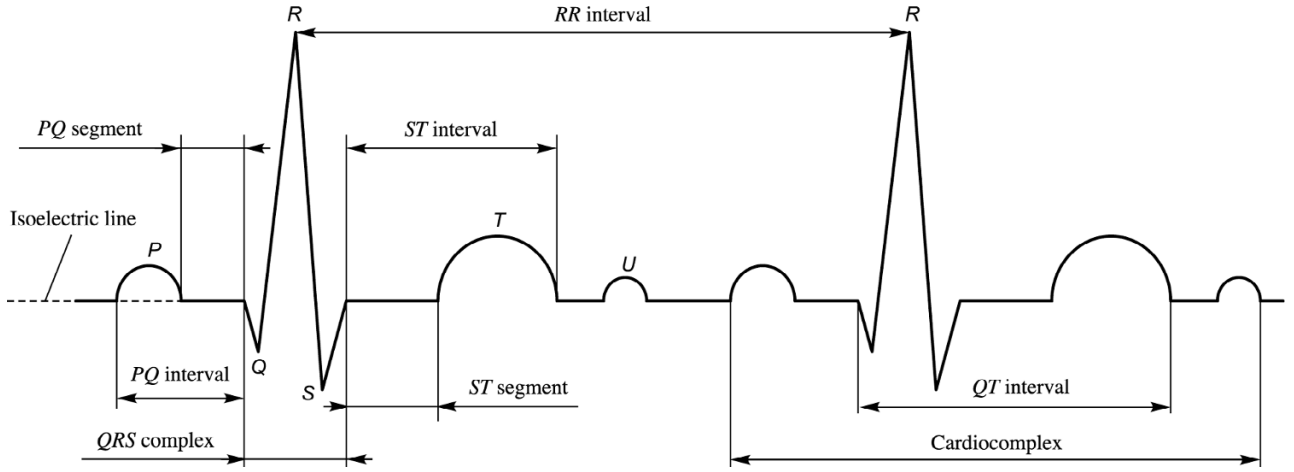


Fig. 1. Elements of a normal ECG.

to detect vitally important changes of state in the cardiac-vascular system. The lower frequency limit for the informative components of the ECG is not stationary and depends on the duration of the RR intervals; i.e., it is limited by the frequency of cardiac contractions. The frequency of cardiac compressions in 99% of people does not fall below 40 beats/min, or 0.67 Hz [3, 4]. The suppression of harmonics below 0.67 Hz then makes it possible to avoid LF noise to some extent. But in choosing methods for its suppression it is necessary to try to prevent a negative effect owing to the probability of partial overlap of the LF noise spectra and the informative part of the ECS, since the frequency components of the bump T lie above 1 Hz.

The use of analog filters in the receiver and amplifier circuit of an electrocardiographic system distorts the initial ECS (especially the ST segments, QT intervals, and the bump T ; see Fig. 1) because of the nonlinearity of the phase-frequency characteristics (PFC) [3]. In this situation, the drift of the isoelectric line is corrected by using digital signal processing algorithms: digital filtering by filters with finite and infinite pulse characteristics (FPC and IPC, respectively); filtering by time averaging; Kalman filters; and, spline interpolation. We now examine the effectiveness of these algorithms in electrocardiographic measurements.

Instruments and research methods. We shall test the workability of the algorithms on a model of an ECG that simulates an additive LF noise in the ECS. The initial parameters of the modeled noise can be used to determine the efficiency of the methods being studied. For this, we propose a model of the ECG which can reproduce different shapes of the ST segment, the T bump, and other elements of the ECG, as opposed to the models of Refs. 5–8. The initial data for the model are the coordinates of the characteristic points of the ECG in the form of the matrices $A = (a_{ij})$ which consists of the set of amplitudes of the elements of the ECG (the positions of the characteristic points relative to the isoelectric line) and $D = (d_{ij})$, which determines the position of the characteristic points in time. Here, $i = 1, 2, \dots, m$ is the sample number, and $j = 1, 2, \dots, n$ is the sequence number of the corresponding point of the element in the cardiological system.

Depending on its shape, each element of the ECG is made up of piecewise functions of the form

$$w_{ij}(t) = \begin{cases} 0 & \text{for } t \in (-\infty; 0); \\ G_{ij} \cos \omega_{ij} t + C_{ij} & \text{for } t \in [0; (d_{i(j+1)} - d_{ij})]; \\ 0 & \text{for } t \in [d_{i(j+1)}; +\infty), \end{cases} \quad (2)$$

where $G_{ij} = (a_{ij} - a_{i(j+1)})/2$; $C_{ij} = (a_{ij} + a_{i(j+1)})/2$; $\omega_{ij} = 2\pi f_{ij}$; $f_{ij} = [2(d_{i(j+1)} - d_{ij})]^{-1}$.

This produces a set of functions with the structure of Eq. (2). They can be written in the form of a matrix $w = (w_{ij})$, with $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n - 1$. Then, with the additive noise included, the model ECG can be written as

$$S_i(kT) = \sum_{r=1}^{N_{RR}} \sum_{j=1}^{n-1} w_{ij}(kT - d_{ij} - \tau_r) + \sum_l \varepsilon_l(kT), \quad (3)$$

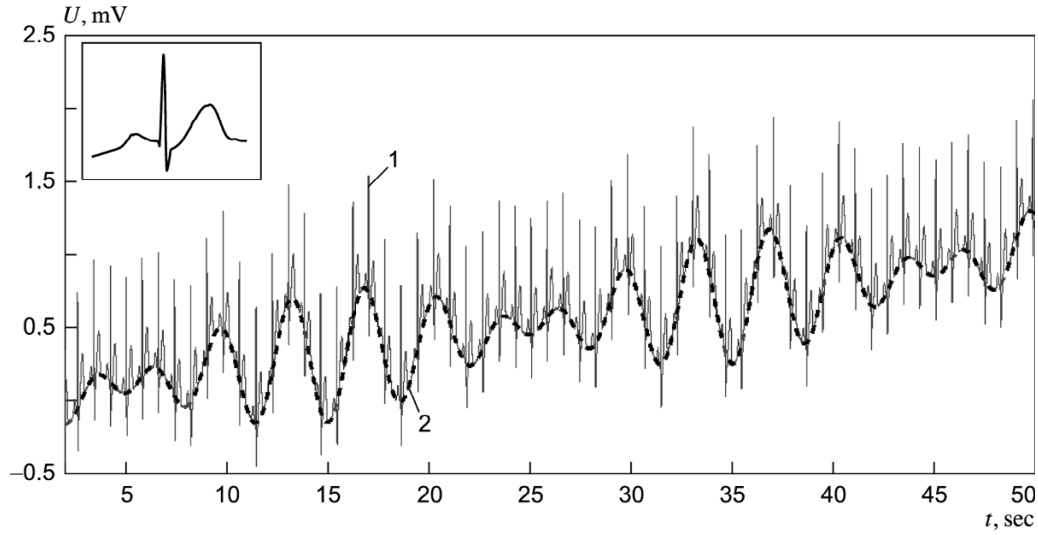


Fig. 2. The ECG model; the inset shows a single cardiocomplex on an enlarged time scale: 1 and 2 denote the models for the ECG and the LF drift, respectively.

where $S_i(kT)$ is the ECG model in the i th sample; N_{RR} is the number of cardiac compressions; $w_{ij}(kT)$ is a function of discrete time of form (2); $T = 1/f_S$ is the sampling period; f_S is the sampling rate; d_{ij} is the corresponding element of the matrix $D_{m \times n}$; τ_r is the model series of values based on the duration of the RR intervals between successively recorded cardiac cycles and determines the time at which a regular cardio-complex occurs; and $\varepsilon_i(kT)$ is the form of the noise.

The model additive LF noise ε_{LF} is specified as

$$\varepsilon_{LF} = a(kT) + U_1 \sin(\omega_1 kT) + U_2 \cos(\omega_2 kT), \quad (4)$$

where $a(kT)$ is a component that models the variation in the impedance of the electrodes with $a = \text{const}$; $U_1 \sin(\omega_1) + U_2 \sin(\omega_2)$ models the respiration component with $\omega = 2\pi f$.

In Eq. (4), we can take $f_1 = 0.25$ Hz, $f_2 = 0.3$ Hz [9], and $a = 20$ μ V, along with typical amplitudes $U_1 = 200$ μ V and $U_2 = 250$ μ V. A model calculation based on Eqs. (2)–(4) with $f_S = 1$ kHz is shown in Fig. 2. The variability of the cardiac rhythm is taken into account in the model by generating corresponding values of τ_r , while the electrophysiological noise is modeled as a bandwidth limited additive white gaussian noise with a signal-to-noise ratio of 25 dB.

We evaluate the operating efficiency of the algorithms using the calculated values of the root mean square error

$$RMSE = \sqrt{\frac{1}{M} \sum_{k=1}^M (\hat{y}_k - y_k)^2},$$

where $\hat{y}_k$ are the components of the vector of the values of the model noise ε_{LF} (see Eq. (4)), and y_k are the components of the vector of the observed values owing to filtering.

The relative error is defined as

$$RRSE = (RMSE/\sigma_\varepsilon) \cdot 100,$$

where σ_ε is the standard (mean square) deviation of the noise model ε_{LF} from Eq. (4).

The algorithms for testing were chosen on the basis of the following considerations. To ensure the required steepness of the amplitude-frequency characteristic it is necessary to use high order FPC filters with a linear PFC. For example, an FPC filter for high frequencies with a suppression frequency limit of $f_{\text{sup}} = 0.5$ Hz, a transmission frequency $f_{\text{tr}} = 1$ Hz, maximum damping in the suppression bands of $A_{\text{sub}} = 80$ dB, and transmission $A_{\text{tr}} = 1$ dB should have a minimal order of 5490. Here, the use of IPC filters with a nonlinear PFC leads to critical distortions in the initial ECS, as shown in Fig. 3 for an eighth order

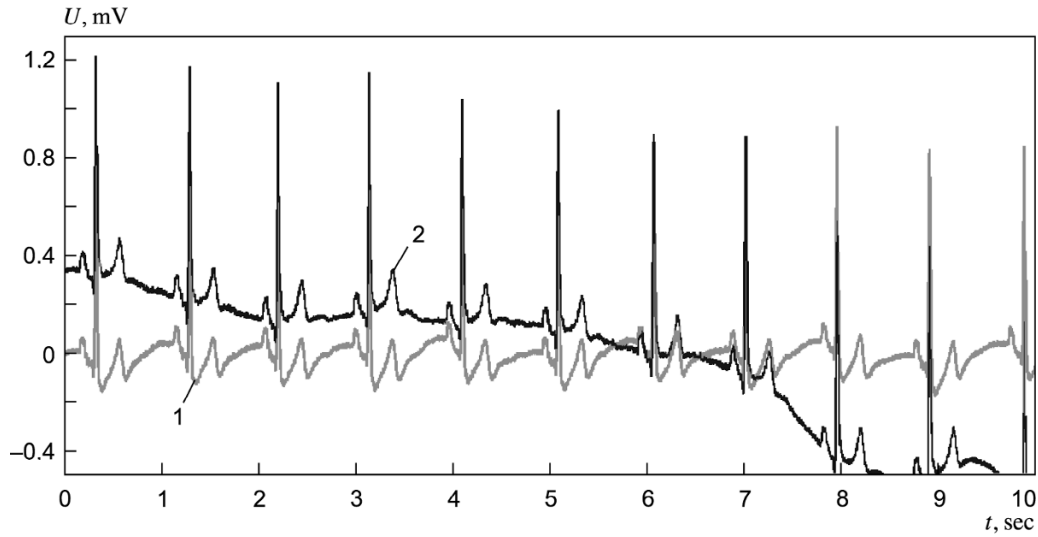


Fig. 3. Distortions of the *ST* segments, *QT* intervals, and *T* bumps of an initial electrocardio-signal after processing with an eighth order Butterworth IPC filter: 1 and 2 denote the processed and initial signals, respectively.

high-frequency Butterworth filter with a cutoff frequency of 0.67 Hz. Given these considerations, the following algorithms for processing ECS have been chosen as alternatives to IPC and FPC.

1, An IPC filter of the first kind [10] with a transfer function of the form

$$H_1(z) = \left(\frac{1 - z^{-1}}{1 - 0.995z^{-1}} \right). \quad (5)$$

The transfer function (5) provides a filter gain coefficient close to unity at frequencies beginning roughly with 0.5–1 Hz. The group delay time for the filter is zero at 95% of the frequency range.

2. A zero-phase filter with exponential averaging, defined as

$$H_2(z) = \alpha / [1 - (1 - \alpha)z^{-1}].$$

For a cutoff frequency of 0.67 Hz, the weighting coefficient is $\alpha = 0.006$. The transfer function for a zero-phase filter is calculated using the expression $H_2'(z)H_2(z)H_2(z^{-1})$ [11], which provides compensation for the phase shift.

3. Filtering in the time domain using a sliding average filter with a window size of $L = 0.67f_s$. Signal readouts to the left and right of the current discrete sequence number are averaged:

$$H_3(z) = \frac{1}{L} \sum_{k=1}^L z^{k-L/2}.$$

4. Filtering in the time domain using a sliding average filter analogous to that in item 3, but the signal is processed in two steps with different window sizes: $L = 0.3f_s$ and $0.67f_s$ in the first and second stages, respectively.

5. Filtering the ECS in the time domain analogous to item 4, in two stages using a median filter.

6. An effective recursion filter (Kalman filter) [12].

7. Interpolation with cubic splines—a special form of multi-interval interpolation that ensures continuity at the points of the approximation function, as well as continuity of its derivatives. The spline for modeling the drift of the isoelectric line is calculated using readings corresponding to the isoelectric segments of the cardiocomplex at the level of the segment *PQ* (see Fig. 1).

When filters (algorithms) 2–7 are used, the noise component $\varepsilon_{LF}(kT)$ is isolated from the ECS (see Eq. (1)). The result of the filtering is the difference between the original signal and the filtered component of the noise: $\Sigma(kT) = S(kT) - \varepsilon_{LF}(kT)$.

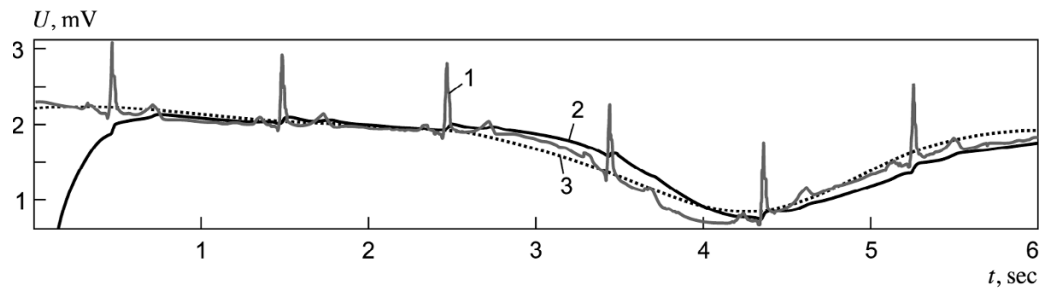


Fig. 4. Effects of filtering on a real ECG (I) using an IPC filter of the first kind (2) and cubic spline interpolation (3).

Using filter 1 yields a noise-free signal $\Sigma(kT)$ at the output. Thus, to analyze the quality of this filter's operation it is necessary to calculate $\varepsilon_{LF}(kT) = S(kT) - \Sigma(kT)$.

The results of the analysis of the effectiveness of the different filters are shown in the table for a standard deviation of $\sigma_\varepsilon = 363.5594 \mu\text{V}$ for the additive low-frequency noise model. The values of $RMSE$ and $RRSE$ are calculated from the results of 30 simulations. The simulations and calculations were done in the 32 bit MATLAB7 program. The computation times t are for a computer with the following characteristics: Intel Core i3 2.96 GHz CPU, 2 Gb operational memory, and NVIDIA GeForce GT220. A fragment of the result of filtering a real one-minute signal from an open base of ECG traces [13,14] is shown in Fig. 4.

Discussion of results. According to the data in the table, algorithm 7 (cubic spline interpolation) was the most efficient. It corresponds to curve 3 in Fig. 4. Algorithm 7, however, is difficult to realize because it is in multiple stages and the intermediate results have to be accurate. To obtain reference points in the PQ intervals it is necessary to detect the peaks of the R -bumps. The Pan–Tompkins algorithm [15], in which the sampling rate is fixed (200 Hz), is often used for this. For signals at another frequency this algorithm must be modified. Spline interpolation requires special measures for processing boundary segments of the function to be interpolated; without these it was not possible to obtain values of $RRSE$ less than 7%.

Algorithms 3 and 4 (sliding average) are simple to realize (but with significant time consumption) and are only slightly less accurate than algorithm 7, especially for filtering in two passes. The error for exponential averaging $RRSE \approx 7\%$, but only if the phase shift is compensated. Otherwise, $RRSE$ goes to 20%. These algorithms do not require a large amount of memory and computing power.

Algorithm 5 (median filter) has a high resource volume and an error of about 11%.

The error $RRSE$ for algorithm 6 (Kalman filter) is 20% since it is represented in the form of white noise, which does not match the nature of the process being analyzed. The advantages of algorithm 6 include the ability of a Kalman filter to process signals in real time.

The IPC filter of the first kind has the highest error ($RRSE \approx 22\%$) since its PFC is nonlinear at low frequencies (algorithm 1). The operational quality of this filter is well illustrated by curve 1 (Fig. 4). When the phase shift is compensated, $RRSE \leq 8\%$. This filter is the fastest of those considered here.

Note that the use of modeled signals cannot ensure complete objectivity of the analysis. For the artificial low-frequency noise in real ECS from the data base of traces [13,14] recorded with minimal drift of the isoelectric line, the ratio of the errors for the different filters (algorithms) agreed with those described above when these errors were increased by roughly a factor of two.

Conclusion. The filtering algorithms studied here are far from a complete collection of currently available methods for elimination of LF noise, but these results are indicative and yield the following conclusions. It is quite difficult to eliminate the low-frequency component thoroughly from the electrocardio-signal by simple methods in real time. The way to deal with this problem is to use sectioned processing of the signal, but then it is necessary to account for the distortions at the boundaries of the processed segments.

The sliding average filter and spline interpolation (algorithms 3, 4, and 7) yield similar results, but differ in their complexity and time expenditure. The latter may not be critical for delayed processing. These filtering algorithms can be

TABLE 1. Results of an Analysis of the Effectiveness of the Filtering Algorithms

Algorithm No.	Filtering algorithm	RMSE, μV	RRSE, %	t, sec
1	IPC filter of the first kind	79.8522	21.96	0.413988
2	Zero-phase filter with exponential averaging	25.7231	7.08	0.016270
3	Sliding average filter with a single pass	20.2646	5.57	1.241701
4	Sliding average filter with two passes	17.8187	4.90	2.052019
5	Median filter	38.2155	10.51	4.076837
6	Kalman filter	72.2696	19.89	6.649407
7	Cubic spline interpolation	16.5919	4.56	0.031845

recommended for analyzing high-resolution ECG. For measuring the qualitative indices of variability of the heart rhythm, an IPC filter should suffice, since these studies assume detection of R-bumps without analyzing other elements of the ECG. In clinical measurements of ECG, besides filters that have minimal error it is also possible to use a zero-phase exponential averaging filter.

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