SHORT REPORT

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# A brief analysis of the use of non-linear time-frequency filtering for processing ECG signals

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## Abstract

Some current trends of the use of non-linear time-frequency filtering approach to ECG signal processing are discussed herein. A brief review of an application potentiality of non-linear filtration is offered for long-term ECG signal processing. Possible problems of long-term monitoring, related to measurements interference and noise of ECG signal, are revealed. To eliminate the revealed problems, in further research, an implementation of a processing system using the non-linear-threshold time-frequency filtering method is planned. It is expected to improve an accuracy of cardiac data processing considering features of interference and measurement noise of different intensity.

## Keywords

ECG signal, Physiological noise, Time-frequency filtering, Threshold filtering, Empirical modes

## Imprint

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## Introduction

The analysis of long-term processing of electrocardiography signals (ECG) at the present time is an actual task in the area of modern technologies of data processing. A long-term study of ECG signal in practice is carried out on the basis of portable devices, which allow recording a diagnostic signal under physical activity of an individual [1-4]. A long-term recording of the ECG signals under the above conditions makes it possible to study and identify clinically relevant biomarkers of cardiovascular abnormalities, which cannot be detected during a short-term recording of the ECG signals at rest [1,3].

An ECG signal is a non-stationary multi-component, complexly structured, signal, which is individual for each biological object [6]. In practice, on the basis of the analysis of some multi-component (local) areas, the functional state of the cardiovascular system is assessed. The non-stationary of an ECG signal is determined with the variability of the local areas of the P, Q, R, S, T waves, that is attributed to the biological origin of the detectable signal [6]. Moreover, the local areas of the P, Q, R, S, T waves and their combinations, according to their diagnostic significance, are usually called the QRS complexes, the PQ, ST, TP segments and the RR, PQ, QT, ST intervals [6] (see Figure 1 herein).

## Features of ECG signal interference and ECG signal filtering

It is known that the procedure for ECG signal long-term recording is characterized by the presence of additive interference and noise of physiological and electrical nature, which may differ in their intensity, spectral characteristic and distribution [1-3]. The problems associated with intense interference of the ECG signals are very diverse [2.5]; their presence significantly reduces accuracy of the detection of amplitude and time parameters of the ECG bio-signal morphology [2.6] and produces an imitation of false heart arrhythmias (abnormalities) [7]. Increasing accuracy and effectiveness in the detection of the morphology ECG signals primarily depends on the decision on what filtration method should be used [2]. To date, for the long-term ECG signal recording, mainly employed are filtering algorithms by Wiener, Chebyshev and Butterworth, which are capable to exclude minor interference and noises and which were imported from the conventional short-term recording technologies, however, these conventional approaches [5,8] have some disadvantages as discussed below. Such approaches to the long-term processing analysis lead to the rejection of the diagnostic areas due to interference and distortions of the amplitude-time parameters of the ECG signals. In general, the percentage of the rejection of inacceptable long-term ECG recordings due to interference has increased from 3.7% to 12.7% [7]. Thus, to reduce the

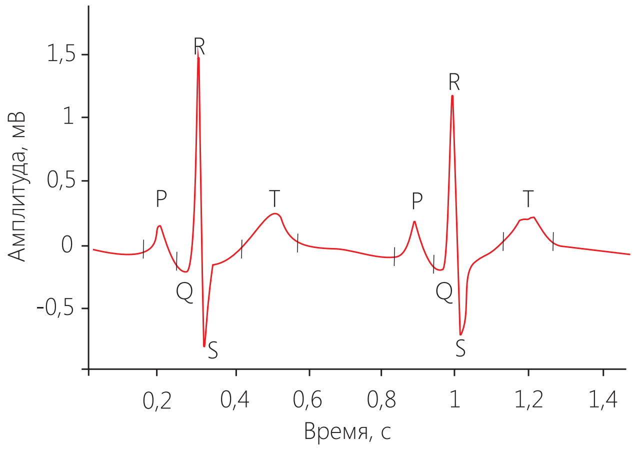

Figure 1. ECG signal components

rejection percentage rejection of the recorded cardiac cycles, it is a challenging issue to design and develop some fresh interference filtering algorithms, having considerable promise, which allowing increasing the accuracy of the detection of the morphologies under the lowest distortion of the ECG signals.

Our analysis revealing the specific feature of the interference enables one to improve the decision-making on the selection of the best method of filtering interference in ECG signal processing. During the long-term recording of ECG signals, following types of interference can be identified: power line interference, muscle noise, movement artifacts and baseline wander. All these types of the interference (except for the power line interference) have an a priori unknown wide frequency spectrum overlapping with the frequency spectrum of the ECG signal. Especially susceptible to overlapping is the spectral characteristics of the ECG signal during long-term recording. Intensity of the overlapping varies depending on physical activity. Intensity of the physiological interference during the recording changes depending on physical load, age of a person, movements of the recording electrodes and movements of a biological object. In addition, the spectral density shows a non-Gaussian distribution in the frequency range of this interference type [2].

The use of linear filters under overlapping frequency spectra does not allow filtering out the ECG signal without distortion. A non-linear filter makes possible to process the signals under the conditions of overlapping of the frequency spectra of the interference with a signal [9]. One of the promising approaches to the processing of ESG signals is an application of non-linear threshold filters based on the time-frequency representation of the signal [2.10]. The peculiarity of this method consists in a decomposition of a signal to empirical modes (frequency components), the filtration of individual components (interference, noise) and the subsequent reconstruction of the analyzed signal in the time-frequency domain. In doing so, it is assumed that when using such methods for long-term processing, gain in the accuracy in detecting the morphology of the ECG signals under minimized distortion of the amplitude and time parameters is obtained.

Empirical modes are multi-component constituents of a signal, which are amplitude- and frequency-modulated, varying with time [11]. For the long-term processing of the ECG signals, in some papers first proposed has been an application of a non-linear threshold filter by Nonnegative-Garrote type, based on the time-frequency representation of the signal [1,2,10]. This method is designed for sequential extraction of diagnostic information from the TP segment of the ECG signals. But at the same time, it is known that because of the physiological and clinical specific features during the long-term recording, the reference points of the TP segment on the ECG signal morphology are not always detectable. In some situations this segment is generally missing at all, for example, under the ventricular extra systole and other arrhythmias [4]. In such cases, the application of this approach for the purpose of the long-term monitoring of the cardiovascular conditions leads to difficulties in identifying the ECG signal morphology due to the missing TP segment.

In order to overcome this drawback, based on the Nonnegative-Garrote approach, we have selected the most promising types of adaptive threshold filters, which are based on Hard Threshold (1), Soft Threshold (2), and Non-linear Exponential Sigmoid Function (3) [12,13]. The formulas (1), (2), (3) show the equations of

$$d_j(k) = \left\{ \begin{matrix} d_j(k), \text{if} \left|d_j(k)\right| > T \\ 0, \text{if} \left|d_j(k)\right| \le T \end{matrix} \right\} \quad (1)$$

$$d_j(k) = \left\{ \begin{matrix} \text{sign}(d_j(k)) \times (\left|d_j(k)\right| - T), \text{if} \left|d_j(k)\right| > T \\ 0, \text{if} \left|d_j(k)\right| \le T \end{matrix} \right\} \quad (2)$$

$$\hat{d}_{j,k} = \left\{ \begin{matrix} (d_{j,k} - T) - \left[ \dfrac{2}{1 + e^{k^{\left(\frac{d_{j,k}-T}{T}\right)}}} - 1 \right] T, d_{j,k} \ge T \\ 0, \left|d_{j,k}\right| < T \\ (d_{j,k} + T) - \left[ \dfrac{2}{1 + e^{k^{\left(\frac{d_{j,k}+T}{T}\right)}}} - 1 \right] T, d_{j,k} \le -T \end{matrix} \right\} \quad (3)$$

the selected non-linear threshold filters, namely, a hard threshold filter, a soft threshold filter (2) and a threshold filter based on the exponential sigmoid function (3). where $d_{j,k}$ are the processed threshold level coefficients j, T – a threshold, which determines the level of interference.

As to the above listed types of the threshold filters, at present they are widely used in wavelet filtration of the ECG signal. A peculiarity of the combination of the selected types of the threshold filters according to the method of empirical modes allows processing of the ECG signals on adaptive a posteriori basis, that is always justified for the purpose of the processing and the analysis of diagnostic signals and that requires less computing resources. In this case, there is no need to use a priori information of the maternal wavelet functions.

## Conclusion

Thus, based on the topical issues on the ECG signal processing, in the future it is planned to implement the method of the non-linear time-frequency filtering to improve the accuracy of the signal morphology detection during the cardiac data processing and thereby improve the accuracy of diagnosing diseases of the cardiovascular system in the time-frequency plane.

## Statement on ethical issues

Research involving people and/or animals is in full compliance with current national and international ethical standards.

## Conflict of interest

None declared.

## Author contributions

All the authors read the ICMJE criteria for authorship and approved the final manuscript.

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