Вестник РУДН. Серия: Инженерные исследования
RUDN Journal of Engineering Research

2025;26(4):447–456

ISSN 2312-8143 (Print); ISSN 2312-8151 (Online)
journals.rudn.ru/engineering-researches

DOI: 10.22363/2312-8143-2025-26-4-447-456
EDN: BLXPCY

Research article / Научная статья

Digital Modelling of Low-Frequency ECG Signals Denoising

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Article history

Received: June 4, 2025
Revised: September 12, 2025
Accepted: September 25, 2025

Conflicts of interest

The authors declare that there is no conflict of interest.

Abstract. The problem of low-frequency noise (baseline wander) in long-duration digital electrocardiogram (ECG) signals, which can distort critical diagnostic features such as the ST-segment and T-wave morphology, is considered. Digital filtering methods are studied with an emphasis on low-frequency noise extraction and correction using Chebyshev type II and Butterworth filters synthesized in Python. The results show that a 7th-order high-pass filter with a cutoff frequency of 1 Hz effectively isolates the zero-potential line, whereas the filtfilt function is essential to avoid phase distortions. The success of the filtering method depends on the rate of change of the zero-potential line, and further work is required to develop quantitative criteria for evaluating and correcting filter-induced distortions. The proposed approach aims to improve automated ECG analysis and reduce false alarms in cardiac-monitoring systems.

Keywords: ECG filtering, Butterworth filter, Chebyshev filter, cardiac signals, QRS complex

Authors' contribution

Kurbanov S.V. — mathematical modeling, visualization, writing; *Andrikov D.A.* — research concept; *Agasieva S.V.* — general guidance, validation; *Iaroshenko A.V.* — conducting hardware experiments. All authors read and approved the final version of the article.

For citation

Kurbanov SV, Andrikov DA., Agasieva SV, Iaroshenko AV. Digital modelling of low-frequency ECG signals denoising. *RUDN Journal of Engineering Research.* 2025;26(4):447–456. http://doi.org/10.22363/2312-8143-2025-26-4-447-456

Цифровое моделирование снижения шума низкочастотных сигналов ЭКГ

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История статьи

Поступила в редакцию: 4 июня 2025 г.
Доработана: 12 сентября 2025 г.
Принята к публикации: 25 сентября 2025 г.

Аннотация. Рассмотрена проблема низкочастотного шума — дрейфа базовой линии — в сигналах цифровой электрокардиограммы (ЭКГ) большой длительности, который может искажать критические диагностические признаки, такие как морфология ST-сегмента и T-зубца. Изучены методы цифровой фильтрации с упором на извлечение и коррекцию

Заявление о конфликте интересов

Авторы заявляют об отсутствии конфликта интересов.

низкочастотных помех с использованием фильтров Чебышева II типа и Баттерворта, синтезированных на Python. Результаты исследования продемонстрировали, что фильтр верхних частот 7-го порядка с частотой среза 1 Гц эффективно изолирует линию нулевого потенциала, тогда как функция filtfilt необходима для предотвращения фазовых искажений. Успех метода фильтрации зависит от скорости изменения линии нулевого потенциала, и требуется дальнейшая разработка количественных критериев оценки и коррекции искажений, вызванных фильтром. Предлагаемый подход направлен на улучшение автоматизированного анализа ЭКГ и снижение ложных тревог в системах мониторинга сердца.

Ключевые слова: ЭКГ-фильтрация, фильтр Баттерворта, фильтр Чебышева, кардиосигналы, QRS-комплекс

Вклад авторов

Курбанов С.В.— математическое моделирование, визуализация, написание текста; *Андриков Д.А.* — концепция исследования; *Агасиева С.В.* — общее руководство, валидация; *Ярошенко А.В.* — проведение аппаратных экспериментов. Все авторы ознакомлены с окончательной версией статьи и одобрили ее.

Для цитирования

Курбанов С.В., Андриков Д.А., Агасиева С.В., Ярошенко А.В. Цифровое моделирование снижения шума низкочастотных сигналов ЭКГ // Вестник Российского университета дружбы народов. Серия: Инженерные исследования. 2025. Т. 26. № 4. С. 447–456. http://doi.org/10.22363/2312-8143-2025-26-4-447-456

Introduction

The process of making a correct diagnosis has always been complex and challenging. Advances in medical technology have significantly improved this process. However, the increased flow of information has necessitated the introduction of automated diagnostic data processing tools into clinical practice. Cardiogram recordings can last tens of hours, and the number of heartbeats in such recordings can reach tens of thousands. Therefore, automated diagnostics, which harmoniously combines medical expertise with the machine-like precision of biological signal processing, is becoming increasingly important. At the same time, the need to extract diagnostically significant components from biological signals, i.e., filter these signals, is also growing.

Electrocardiogram (ECG) signals are often distorted by low-frequency fluctuations (baseline drift) caused by respiration (0.1–0.5 Hz), patient movement (motion artifacts), and poor electrode contact (skin impedance changes). These distortion disturbances can be critical for assessing ST-segment and T-wave morphology, which are important for diagnosing ST depression/elevation or certain arrhythmias (QT prolongation). A comprehensive review and comparison of various digital filters for ECG noise reduction is presented below [1].

In medical practice, some filtering methods are often used, such as baseline removal without distorting ST/T waves and preserving ultra-low-frequency components for heart rate variability analysis. There are many low-frequency noise reduction methods: wavelet methods [2; 3], Kalman filtering [4; 5], and other methods [6; 7; 8].

In modern conditions, digital signal processing (DSP) is becoming increasingly widespread. In addition to the traditional fields of signal processing (television, radar, communications), new areas of application are emerging — speech analysis and telephony, medicine, image processing, and the analysis of various physical phenomena [9].

The development of computing technology has enabled the creation of reliable and inexpensive digital signal processing devices with high speed and quality. However, the expansion of the scope of application of digital signal processing to phenomena in the material world inevitably leads to the complexity of both the useful signal and the interference. The complication of the useful signal can be expressed, for example, in the instability of the time period, in the presence of short pulses of significant amplitude, instability of the envelope shape and modulation frequency, and in other similar manifestations. Interference can be caused by a non-random process, the signal spectrum of which overlaps with the spectrum of the useful signal over a relatively wide frequency range [10]; interference can also be non-stationary, having a spectrum that varies over time; the interference spectrum can differ significantly from the well-studied spectra of widespread noise.

Therefore, the solution to one of the main problems of signal processing — the filtering problem — for natural, in particular biological, non-stationary signals of complex shape is non-trivial and requires the development of specific methods and corresponding digital filters.

1. Methods and Materials

1.1. Problem Statement

In this paper, the filtering problem is addressed for a long-duration digital cardiac signal (ECG), ranging from tens to tens of thousands of heartbeats. The objective is to maximize the ECG's adaptability to subsequent computer processing. Long-duration ECG signals contain unique information about the dynamics of cardiac activity during a person's daily activities. However, this information is distorted, for example, by electrode displacement due to movement or the appearance of potentials unrelated to cardiovascular activity at the electrode sites. Such extraneous influences on the ECG manifest themselves as noise and low-frequency oscillations in the zero potential line of the digital ECG. Examples of such interference in a single signal from a single ECG from the Russian Society of Holter Monitoring and Noninvasive Electrophysiology database (data availability: http://rohmine.org/baza-dannykh-rokhmine/) are shown in Figures 1–3.

Figure 1 shows a nearly constant shift of the zero potential line. Figures 2 and 3 show fairly slow oscillations of the zero potential line, lasting at least three heartbeats. The amplitude of these oscillations, as seen in Figure 3, can be several times greater than the QRS complex amplitude.

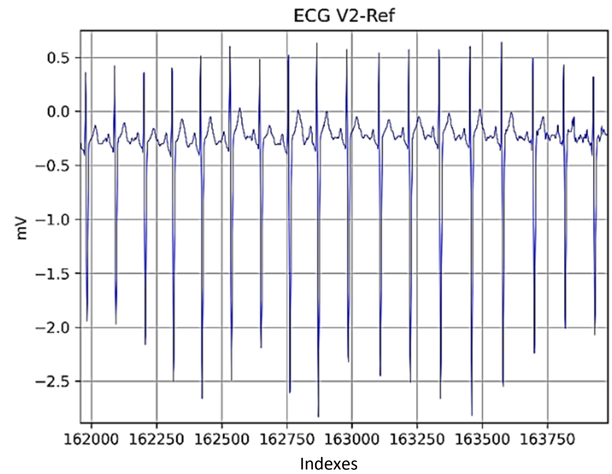

Figure 1. The zero-potential line offset
Source: by S.V. Kurbanov in the Python software

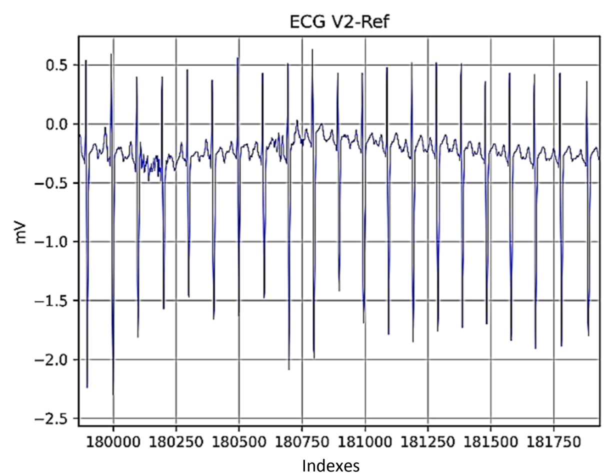

Figure 2. The zero-potential line small oscillations
Source: by S.V. Kurbanov in the Python software

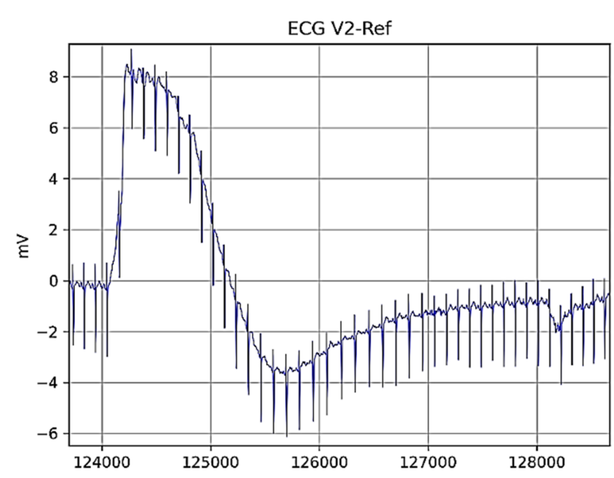

Figure 3. The zero-potential line large oscillations
Source: by S. V. Kurbanov in the Python software

Figure 2 also shows areas of high-frequency bursts with a period comparable to the duration of the QRS complex but significantly shorter than the duration of the P- and T-waves. However, there is insufficient evidence to unambiguously identify these high-frequency bursts as interference; it is possible that this noise characterizes processes occurring in the heart.

Furthermore, the powerful high-frequency spectrum of the short-duration QRS complex is a potential problem in ECG signal filtering. Since the QRS complex has unconditional diagnostic value, it must be preserved with minimal distortion throughout all ECG manipulations.

Due to the described ECG characteristics, the task of filtering the digital ECG signal can be reduced to finding a sequence of applying digital filters of certain types, with the aim of:

- identifying the deviation of the ECG zero potential line,
- numerically estimating the magnitude of this deviation,
- correcting the ECG zero potential line if the deviation magnitude allows such correction,
- removing an ECG section if the deviation magnitude does not allow its correction,
- identifying areas of high-frequency bursts, preserving the original ECG shape, in particular the QRS complex, during ECG manipulations.

1.2. Types of Digital Filters and Methods of Their Synthesis

Decomposing the ECG filtering problem suggests that low-frequency interference itself is a valuable information resource. Therefore, the proposed study applies a non-standard approach to filtering a digital biological signal, which involves explicitly and precisely identifying the interference, followed by correcting the useful signal by subtracting the identified interference. This approach is similar to adaptive filtering and is characterized by a virtually perfect tuning of the filter weighting coefficients. To achieve this tuning, the actual magnitude of the interference is subtracted from the processed signal with high accuracy at each sampling step, which should result in the isolation of a virtually noise-free useful signal. If the interference is so significant that the isolation of the useful signal cannot be guaranteed, then the time interval during which the "bad" signal exists can be precisely defined, thereby eliminating it from further processing. The disadvantage of the proposed method is its limited applicability for signal processing in real time, due to the significant delay in isolating the interference and obtaining the filtered signal [11].

The theory of digital filters and the methods for their synthesis are well developed and described. The simplest method is to synthesize a digital filter based on an analog prototype, such a filter is stable provided the prototype is stable. The prototype is selected based on the required amplitude-frequency response (AFR) of the filter. Thus, to isolate the low-frequency component from the signal with maximum accuracy, the filter's AFR in the passband must be as flat as possible. Of the main types of analog filters, the Butterworth filter and the inverse Chebyshev filter (also called the Chebyshev type 2 filter) have this property. The remaining filters have a slight unevenness in the passband, expressed as frequency response fluctuations of several decibels (AFR unevenness). Typically, in theory, an AFR of about 3 dB is allowed, which corresponds to a 30% signal attenuation; such attenuation is clearly unacceptable in the proposed filtering model.

Python was used to synthesize the digital filters, so the study and comparison of the frequency responses of the filters planned for use were performed using Python tools, using the numpy, scipy, and math libraries. The mathematical description is presented in sufficient detail in the literature, for example, [12]. Both prototype filters were synthesized as filters with an infinite impulse response (IIR filters) using the iirfilter function, which returns the numerator ***b*** and the denominator ***a*** of the filter transfer function:

```
b, a = iirfilter(Nf, wsr, rs = 40, btype =
'lowpass',analog = True,ftype = 'cheby2')
```

according to specified parameters: **Nf** — the order of the filter, which determines the steepness of the drop in its frequency response in the mid-frequency region between the pass and stop bands; **wsr** — circular cutoff frequency of the filter (ω), determined through the normal cutoff frequency according to the formula [2*np.pi*fsr]; **rs = 40** — minimum attenuation in the stopband in dB, attenuation of 40 dB corresponds to attenuation by a factor of 100 times; **btype = 'lowpass'** — filter type (low pass, high pass, band pass, etc.), here the low pass filter is specified; **analog = True** — a logical constant that determines the type of filter being synthesized; True corresponds to an analog filter, False to a digital filter; **ftype = 'cheby2'** — filter type: Chebyshev Type II filter is specified here.

The comparison result between Chebyshev Type II and Butterworth filters is shown in Figure 4.

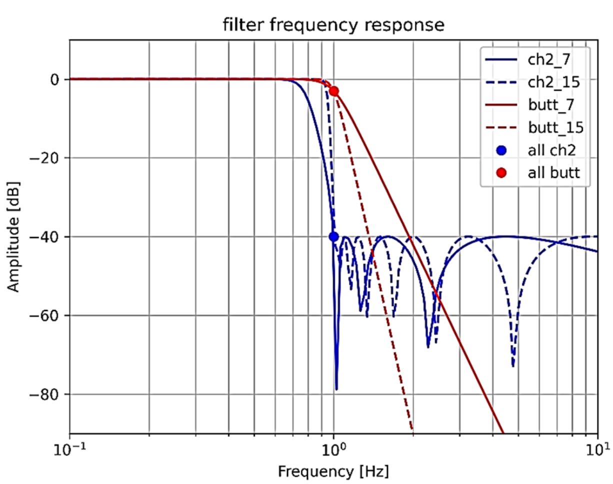

Figure 4. Comparison of Chebyshev type II and Butterworth filters
S o u r c e: by S.V. Kurbanov in the Python software

Frequency responses of both types of 7th and 15th order filters were constructed. Filter features are listed below:

1) The specified cutoff frequency for Butterworth filters characterizes the highest passband frequency, while for Type II Chebyshev filters it characterizes the lowest stopband frequency;

2) Butterworth filters are characterized by a smooth frequency response drop compared to Type II Chebyshev filters (confirming the theoretical conclusions); for a 7th-order filter, the specified attenuation of 40 dB is achieved at a frequency of almost 2 Hz, and for a 15th-order filter, at a frequency of approximately 1.4 Hz, i.e., the spectrum of the filtered signal will contain a significant number of frequencies above the specified cutoff frequency;

3) Type II Chebyshev filters have a steeply falling frequency response; for a 7th-order filter, distortion will appear at a frequency of 0.7 Hz, and for a 15th-order filter, at a frequency of 0.9 Hz, i.e. In the filtered signal spectrum, a small number of frequencies below the specified cutoff frequency will be suppressed.

Thus, it can be concluded that it is advisable to use a Type II Chebyshev filter to isolate low-frequency interference from a cardiac signal. Only such filters will be considered below [13].

1.3. Study of Digital Filters Applied to the Problem of Filtering ECG Signals

Solving a filtering problem usually comes down to selecting filter parameters, which involves determining the cutoff frequency and filter order.

The filter cutoff frequency was determined based on well-known time and frequency characteristics of periodic processes occurring in the human body. The closest approximation to the heart rate is the respiratory rate, which normally is approximately 20 breaths per minute, corresponding to a frequency of 0.3 Hz. In adults, the heart rate ranges from 60 to 80 beats per minute, and a decrease in this rate below 60 beats per minute is considered to be bradycardia. However, trained individuals can normally have a lower heart rate (up to 45 to 50 beats per minute). Thus, the lower limit of the heart rate spectrum is located near a frequency of 0.75 Hz, and the expected frequency of the low-pass filter passband lies in the range of 0.3 to 0.7 Hz. Taking into account the nature of the frequency response of the Chebyshev filter of the 2nd type (Figure 4), the cutoff frequency of the low-pass filter for the proposed filtering method should be in the range of 0.2...0.8 Hz.

The limits for changing the filter order were determined primarily by means of a computational experiment, the design of which took into account that the digital filter order determines the number of terms in the difference equation. On the one hand, increasing the filter order leads to a more accurate separation of the signal by frequency due to an increase in the slope of the characteristic. On the other hand, this increases the volume of calculations and the length of the data array required to solve the difference equation. Based on the fact that the number of data for one heart period at a sampling frequency of 200 Hz is approximately 100, it seems reasonable to limit the filter order to 15. An attempt to synthesize such filters in Python revealed the phenomenon of frequency response distortion in the passband depending on the filter order. Figure 5 shows the undistorted frequency response of a 5th-order filter with a cutoff frequency of 0.2 Hz, and Figure 6 shows the distorted frequency response of a 7th order filter with the same cutoff frequency.

This effect is evident at a cutoff frequency of 0.3 Hz above the 6th order; at cutoff frequencies of 0.4 Hz and 0.5 Hz, also above the 6th order; and at cutoff frequencies of 0.6–0.8 Hz, above the 7th order.

The filtering efficiency criterion for diagnostic purposes should characterize the conditions under which the filter application does not introduce significant distortions to the ECG at frequencies above f0 = 0.7 Hz, as this frequency range is important for diagnostics. It follows that for significant distortions to occur in the diagnostic spectrum, the rise or fall time of the low-frequency component of the ECG must be approximately 1/f0 ≈ 1.4 seconds. The increase in electrical potential during this time should be of the same order of magnitude as the average peak-to-peak amplitude of the QRS complex, i.e., approximately 4 mV. In other words, for the effective filter to be successfully implemented, the rise and fall slopes of the low-frequency component of the ECG must be no more than 3 mV/s. Refining this criterion requires significant additional research.

The results of the filter parameter study are summarized in the Table.

Thus, the maximum order of a low-pass filter in the 0.2–0.8 Hz range is 5, when implemented using Python without developing special functions. For high-pass filters processing signals with frequencies of 300 oscillations per minute (5 Hz), no restrictions were found for filters of order no higher than 15. For example, the same methods are available in [3] only for wavelets.

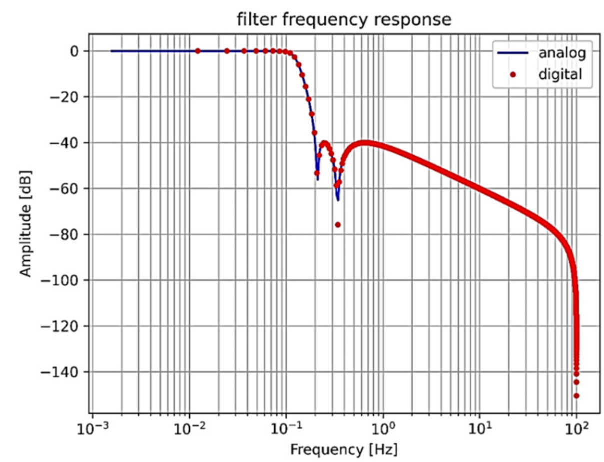

Figure 5. AFC of 5th order filter with cutoff frequency 0.2 Hz

Source: by S.V. Kurbanov in the Python software

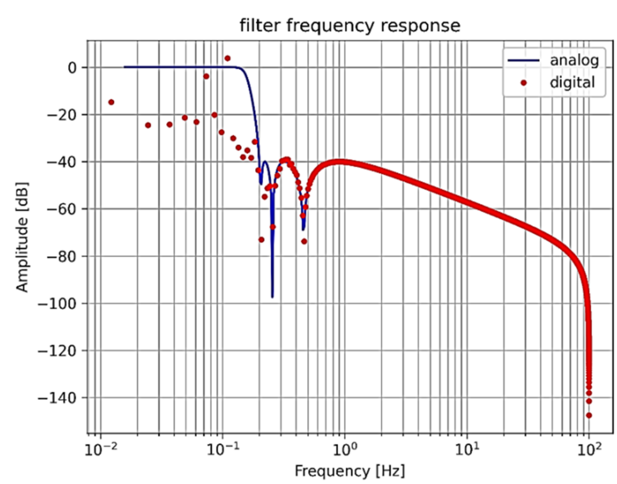

Figure 6. AFC of 7th order filter with cutoff frequency 0.2 Hz

Source: by S.V. Kurbanov in the Python software

The Effect of the Cutoff Frequency of Chebyshev Filters of the Second Kind on the Allowable Filter Order

Cutoff frequency, Hz	The maximum filter order	Efficiency criterion for the front or decline of the low-frequency component, mV/s
0.2	5	3
0.3	5	3
0.4...0.5	5	3
0.6...0.8	6	3

Source: by S.V. Kurbanov

2. Results of Applying Synthesized Filters to Real ECG Signals

Filtering and detrending ECG time series have their advantages, such as simplifying the process of ECG recognition and analysis. Typically, the obtained data is either analyzed immediately or subjected to further processing. However, such methods have limitations: for example, baseline shifts can cause changes in the amplitude of the waves and segments of the ECG, as well as the appearance of false elements that can be mistakenly interpreted as pathology. Everything depends on how much the potential of the ECG readings changes compared to the original data, since it can be one value at the peak line and another at the zero level line, which also affects diagnostics [14].

The result of applying a 5th-order filter to a real cardiac signal (one branch of V2) is shown in Figure 7; a fragment of the cardiogram is shown. Two algorithms from the **scipy.signal** library implemented in Python were tested: 1) **lfilter**, which implements filtering from beginning to end, with the filtered signal having a phase shift; 2) **filtfilt**, which implements filtering with start-end-start return, which corrects phase shifts. For the proposed filtering method, the phase shift is a critical parameter. Without compensation for this shift, the method is fundamentally ineffective. In this case, the phase shift was equal to five heartbeat periods, which for the pattern in Figure 7 corresponds to approximately a quarter of the period of slow oscillations.

Clearly, only filtering with phase shift compensation merits further study. The result of subtracting the extracted low-frequency component from the original cardiac signal is shown in Figures 8, 9, and 10.

Figure 8 shows the zero potential line correction for small and slow changes. It is evident that these changes are successfully compensated, with the ECG remaining in the positive potential region, except for the Q and S waves.

Figure 9 shows the zero potential line correction for significant and rapid changes. In this case correction is unachievable near areas of abrupt changes, such as near index 124200 in Figure 9.

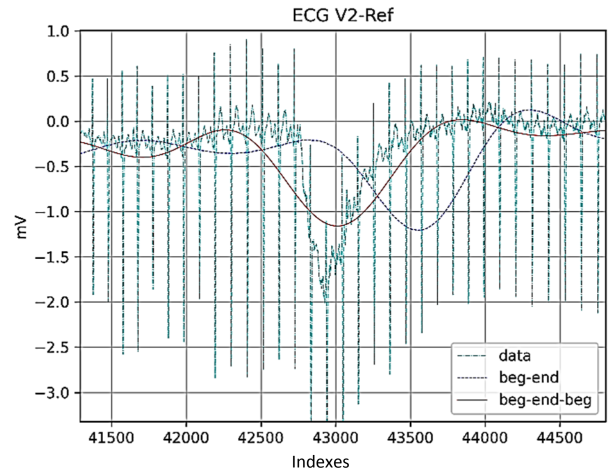

Figure 7. The result of filtering a real cardiogram
S o u r c e: by S.V. Kurbanov in the Python software

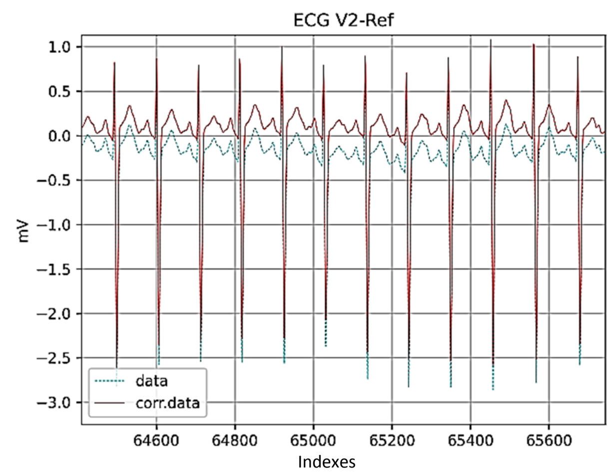

Figure 8. Correction of small slow changes
S o u r c e: by S.V. Kurbanov in the Python software

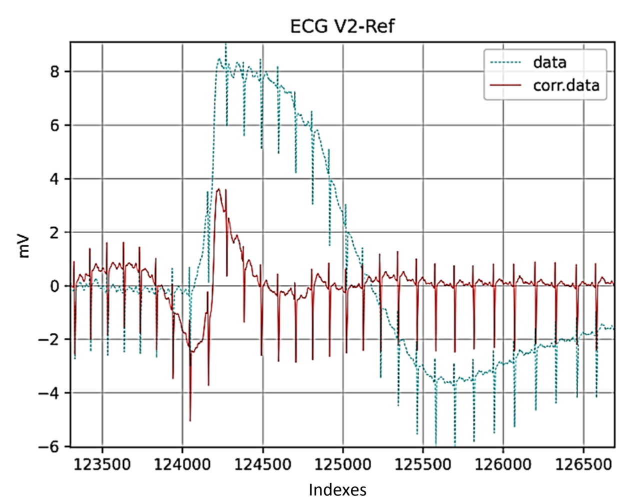

Figure 9. Correction of large rapid changes
S o u r c e: by S.V. Kurbanov in the Python software

A visual comparison of the original and filtered ECG data allows us to formulate a hypothesis that the factor determining the success of the proposed filtering method is the rate of change of the original signal. This is indicated by the successful correction of a large deviation in the range of 125,500...126,500 indices, whereas no correction is observed at the steep front of the change in the zero potential line at 124,200 indices. On the contrary, the filter introduces additional distortions into the zero potential line. A visual signal enhancement method based on the digital wavelet transform can provide an accurate result [15], but in the case of a wavelet, we urgently need to find the best wavelet mother function and determine the correct scale to make the figure suitable for study. Therefore, the proposed method, compared to the digital wavelet transform, appears to be a significantly simpler means of improving the cardiac signal. To eliminate distortions, studies were conducted to modify the proposed digital filtering method. Due to the distortion of the zero potential line, an attempt was made to extract this line in a form as close as possible to that observed in the original signal. To achieve this, a seventh-order high-pass filter with a cutoff frequency of 1 Hz was applied to the original cardiac signal, followed by calculating the difference between the original and filtered signals. The result is shown in Figure 10.

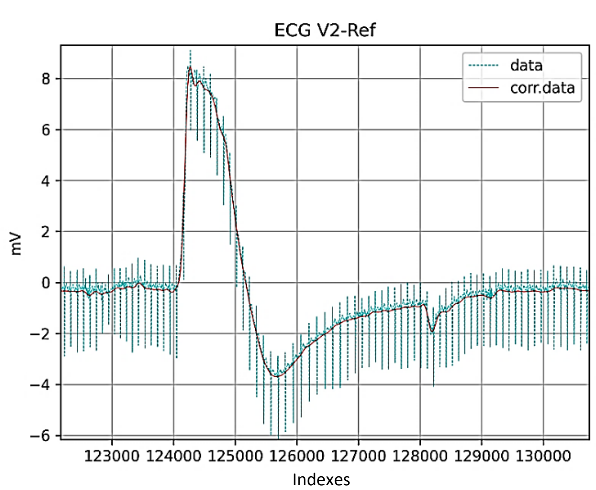

Figure 10. The result of the selection of a low-frequency component by a high-frequency filter
S o u r c e: by S.V. Kurbanov in the Python software

Here, the distortion of the useful signal at the steep leading edge at indices 124100–124250 is also observed, which confirms the previously proposed hypothesis.

Both studies aim to remove noise and baseline drift from ECG signals while preserving diagnostically important features (QRS complex, ST segment, T-wave).

This study evaluates the performance of Chebyshev II (inverse Chebyshev) and Butterworth filters for baseline drift correction, with an emphasis on minimizing phase distortion through zero-phase filtering. The results are compared with the work of Chavan [16] and Kaur [17], who analyzed Chebyshev I and II filters for ECG noise reduction. In this study, Chebyshev Type II filters (7th order, 1 Hz cutoff) and Butterworth filters implementing zero-phase filtering were tested using Python's **scipy.signal.filtfilt** to remove time-domain artifacts. The Chebyshev Type II filter demonstrated superior performance in baseline correction due to a sharper stopband rolloff, while Butterworth filters exhibited a slower rolloff, resulting in ST segment distortion. Phase alignment was found to be critical, with zero-phase filtering reducing time-shift artifacts to less than five heartbeat periods.

The curve obtained as the result of the filtering process almost exactly replicates the zero-potential line for a locally selected heartbeat period. Clearly, the corrected useful signal, possibly with minor distortions, is obtained immediately as a result of filtering (Figure 11).

Chavan [16] compared Chebyshev Type I (flat passband) and Type II (flat stopband) filters, measuring performance through improved signal-to-noise ratio (SNR) and QRS complex preservation. The Chebyshev Type II filter outperformed Type I filters in noise removal and QRS energy preservation, consistent with the results of the present study. Both studies highlight the limitations of Butterworth filters in preserving diagnostic features.

The computational complexity of the proposed algorithm can be estimated as follows. The difference equation for each point of the original signal is solved in a fixed number of operations, with a solution complexity of O(1). For filtering a digital ECG with a length of n samples, the algorithm has a linear complexity of O(n). Compared to neural network algorithms, they have a minimum quadratic complexity of O(n2), as shown in [17]. The proposed method requires significantly fewer computational resources than neural network algorithms.

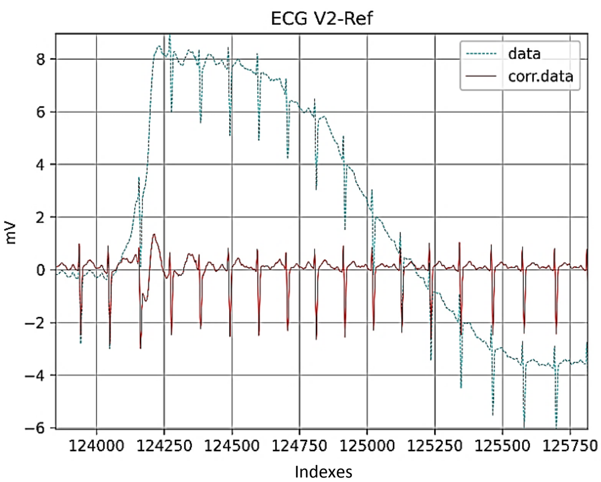

Figure 11. The result of the selection of a useful signal by a high-frequency filter
Source: by S.V. Kurbanov in the Python software

The results show that Chebyshev Type II filters are optimal for ECG noise reduction, providinga balance between effective noise suppression and minimal distortion of critical signal components. Zero-phase filtering is essential for maintaining signal integrity, especially for automated diagnostics and long-term monitoring. Future work may explore hybrid methods, such as combining wavelet transforms with Chebyshev filters, to remove non-stationary noise and further improve real-time processing.

Conclusion

On balance, this study confirms the advantage of Chebyshev type II filters for ECG signal noise reduction, consistent with previous studies. The emphasis on zero-phase implementation provides practical insights for clinical applications, ensuring accurate interpretation of ECG data. Limitations on the filter order are determined depending on the cutoff frequency: for cutoff frequencies of 0.2–0.8 Hz, it is recommended to use a filter of no higher than 5th order, and for higher cutoff frequencies, no higher than 7th order.

To minimize distortion, the absence of phase distortion is critical, so in Python, the filtfilt function from the scipy.signal library should be used, which implements two forward and reverse passes through the signal value array.

Comparison of the results of using high-pass and low-pass filters to extract the zero-potential line allows a clear choice in favor of using a 7th-order high-pass filter with a cutoff frequency of 1 Hz. The filtered signal represents an ECG signal with a zero-potential line correction, and the difference between the original and filtered signals represents the zero-potential line itself. A hypothesis was formulated and tested that the factor determining the success of the proposed filtering method is the rate of change of the zero-potential line of the original signal. To numerically estimate the magnitude of distortions introduced by the filter and correct these distortions, it is necessary to develop a distortion assessment criterion and an algorithm for calculating this criterion.

Future work: classification of drift sources (respiration, movement, and pathology) and integration with clinical ECG software without the need for manual adjustments. This will improve automated diagnostics (e.g., AI-based ECG interpretation) and reduce the number of false alarms in cardiac monitoring systems.

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