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# ECG Signal Denoising with SciLab

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**Abstract:** This paper presents a study on de-noising electrocardiogram (ECG) signals using Scilab, an open-source software package known for its signal processing capabilities. ECG signals are often contaminated by various noise sources, which can reduce the accurate diagnosis and monitoring of heart health. In this work, digital signal processing methods such as Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters are used to effectively suppress noise while preserving the essential features of the ECG waveform. We explore main noise sources that commonly affect ECG recordings, such as baseline wandering noise, power-line interference, and muscle artifacts, and discuss their respective challenges. The de-noising methods has been extensively evaluated and demonstrated its ability to improve signal quality and diagnostic accuracy by eliminating noise artifacts. The results highlight Scilab's potential for de-noising ECG signals and its importance in improving patient care and biomedical signal processing applications. The efficacy of the de-noising methods is thoroughly evaluated through comparative analyses with other commonly used de-noising approaches. Experimental results demonstrate its superiority in preserving the QRS complex while efficiently eliminating noise artifacts, leading to more accurate and reliable diagnostic information. In conclusion, this paper presents a comprehensive study on de-noising ECG signals using Scilab, offering a valuable contribution to the field of biomedical signal processing. Researchers and practitioners in the domain of ECG signal processing can benefit from the insights and techniques presented herein to advance their studies and further applications.

***Keywords:*** *Baseline wander noise, breathing noise, denoising, power line interference, QRS detection, Scilab*

## 1. Introduction

Electrocardiogram (ECG) signal processing is an extensive research topic in the field of biomedical engineering, which aims to extract reliable information from the electrical activity of the heart to diagnose cardiovascular disorders and monitor various cardiac conditions of patients. However, ECG signals are susceptible to various noise sources and artifacts that can significantly affect their quality and accuracy. One of the major challenges in the clinical use of electrocardiogram (ECG) signals is the presence of various types of noise that adversely affect the diagnosis and interpretation of heart health. Therefore, de-noising ECG signals with high accuracy has become a vital step to increase the clinical utility of ECG analysis [3-5, 9]. These techniques aim to remove unwanted noise components while preserving the critical diagnostic features of the signal. Several studies have focused on developing and evaluating de-noising methods to improve the overall performance of ECG analysis systems. Unfortunately, de-noising ECG signals is a challenging task due to overlapping noise signals at both low and high frequencies [1]. Thanks to advances in ECG signal processing, an effective set of algorithms and processes is available to improve the quality of ECG signals and noise removal.

Some of the approaches proposed to address this problem includes adaptive filtering, wavelet methods, and empirical mode decomposition. W.Liuat al. [2] proposed an adaptive denoising technique using the Empirical Wavelet Transform. This technique can separate the non-linear and non-stationary components of ECG signals, which makes it effective for denoising. Other methods applied to denoise ECG signals include band-pass filters, adaptive filters, ensemble averaging techniques, extended Kalman filters and Wavelet Neural Networks. These methods aim to remove various types of noise from ECG signals, including white Gaussian noise. The work by Lastre-Domínguez et al. [3] focused on denoising ECG signals and extracting relevant features using unbiased Finite Impulse Response (FIR) smoothing, which proved to be promising in enhancing the signal quality and facilitating subsequent analysis. Their approach demonstrated promising results in effectively suppressing noise artifacts, contributing to more accurate diagnostic information.

In the context of medical advances and technological innovations, Lyon et al. [5] discussed the contribution of computational techniques in ECG analysis and interpretation. These techniques have paved the way for advancements in cardiac health monitoring and diagnosis, enabling more precise and timely interventions. In addition to conventional signal processing techniques, recent advancements in computational and machine learning methods have shown great potential to enhance ECG classification and identification of specific cardiac conditions. For instance, Kiranyaz et al. [4] employed 1-D convolutional neural networks for real-time patient-specific ECG classification, achieving impressive results in cardiac arrhythmia detection and highlighting the power of machine

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learning in accurate signal de-noising and classification. The significance of ECG de-noising goes beyond improving the accuracy of diagnostic algorithms. Wearable devices, such as smart phone-based platforms have been explored for real-time cardiovascular problem detection via ECG processing [10]. These devices leverage ECG signal processing techniques to enable early diagnosis and continuous monitoring, potentially revolutionizing personalized healthcare. Kannathal et al. [13] employed artificial neural networks for the classification of cardiac patient states, demonstrating the potential of machine learning algorithms in enhancing diagnostic capabilities.

Filtering methods have been extensively explored to effectively suppress noise components in ECG signals. The digital three-pole Butterworth filter, as introduced by Alarcon et al. [14], offers a simple yet efficient solution for arbitrary cut-off frequency applications in digital electroencephalography. In addition, the digital filter proposed by Gaydecki for biomedical signal enhancement [15] includes a high-level design interface for versatile applications, works in real-time and programmable. The removal of electromyogram (EMG) artifacts from ECG signals has been addressed by Christov and Daskalov [16], who introduced a dedicated filtering method to improve the reliability of ECG analysis. Baseline wandering (BLW) noise and muscle artifact reduction in the ECG signals have been studied by De Pinto [19], who presented filtering techniques tailored to minimize these unwanted components. Various approaches for addressing power-line interference in ECG signals have been investigated, with Cramer et al. [21] providing a comparative analysis of digital filtering methods to estimate and remove power-line noise. The significance of ECG signal de-noising and feature extraction has been further highlighted by McManus et al. [18], who compared digital filtering methods to characterize and eliminate AC noise in electrocardiograms. Efforts have been made to develop real-time microprocessor-based notch filters, such as the 50 Hz notch filter introduced by Choy and Leung [20], specifically designed for ECG signal processing to reduce interference from power-line noise. To ensure the safety and reliability of medical electrical equipment, including electrocardiographs, standards such as IEC 60601-2-51 [15] and IEC 60601-1 [17] have been established, specifying requirements for safety and essential performance.

While numerous de-noising and ECG analysis techniques have been proposed, there remains a need to explore and evaluate additional methodologies for further improvements in signal quality and accuracy. Scilab provides a suitable platform to implement these de-noising techniques with its signal processing functions and libraries.

In this paper, we will review the existing techniques on ECG de-noising, including digital filters such as IIR and FIR filters [12], as well as advanced machine learning-based approaches [6] [7]. Additionally, we will investigate the applicability of unbiased FIR smoothing, as presented by Lastre-Domínguez et al. [1], in the context of Scilab-based ECG signal processing. This research aims to investigate the noise of ECG signals and contribute to existing knowledge using Scilab, a powerful open-source software package well suited for scientific computing and signal processing applications, and with this feature a free alternative to MATLAB. It provides a suitable platform to implement de-noising techniques due to its high computational capabilities and can be used for pre-processing and post-processing of ECG signals. Researchers and practitioners can easily implement de-noising algorithms for ECG signals using Scilab's signal processing functions and libraries. Furthermore, the software has a user-friendly interface and a wide range of signal processing functions, making it highly preferable for both experts and beginners in signal processing applications. By evaluating the effectiveness of Scilab-based filtering techniques in suppressing noise and preserving relevant diagnostic features, this work aims to advance the understanding of ECG signal processing and contribute to improved diagnostic accuracy, ultimately contributing to the field of biomedical signal processing and its impact on cardiovascular healthcare. The contributions of this work are expected to advance the field of ECG signal de-noising and provide valuable information for researchers, clinicians and developers in improving the accuracy and reliability of ECG-based diagnostic and monitoring systems. Ultimately, these studies could lead to better patient care, early diagnosis of cardiac disorders, and the development of more efficient wearable and portable ECG monitoring devices.

This section provides a comprehensive review of ECG de-noising methods, highlighting their advantages and limitations. The rest of this article is organized as follows: Section 2 describes the implementation of various denoising techniques using Scilab and Section 3 discusses the experimental results. Finally, Section 4 concludes the paper and outlines potential future research directions in the field of ECG signal processing.

## 2. Methodology

During ECG recording, noisy signals are typically affected in the form of noise due to patient electrode movement, power line interference, baseline entanglement noise, respiratory noise, and high frequency noise, respectively. Movement caused by the movement of patient electrodes leads to changes in the contact resistance between the electrodes and the skin, resulting in baseline entanglement noise. On the other hand, electrical power lines act as a source of electromagnetic interference at power frequencies, and ECG electrodes can act as antennas to capture and record this interference. Another source of noise is high frequency noise that can occur during recording due to moving tower signals, pump operations, motor commutation, etc. In addition, electromagnetic interference noise due to the range of ECG signals from 0.05 to 106 Hz is also considered as a factor. These artifacts strongly affect the signal quality of the ST segment and reduce the frequency resolution. This produces signals of large amplitude that can also resemble PQRST waveforms on the ECG and mask small features important for clinical diagnosis. Elimination of these artifacts in ECG signals is important for better diagnosis.

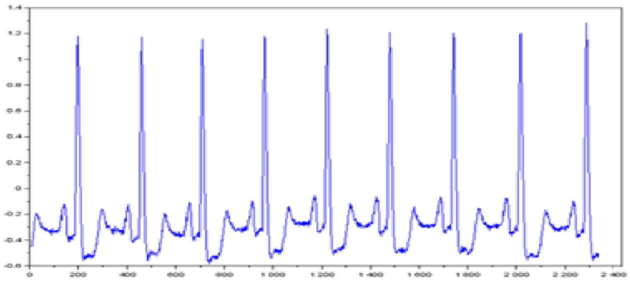

**Fig. 1**. ECG signal MITBIH105 from Physionet

The ECG signals used in this study were taken from the physio-net database. Fig.-1 shows an example from this database. Various filtering techniques were used to reduce the effect of noise artefacts. High-pass filters with cut-off frequencies of 2 Hz and 6 Hz have been used to remove the basic navigation noise and respiratory noise, respectively [8, 9]. In addition, a high-pass filter was used to remove the ringing effect caused by unwanted attenuation at frequencies close to the center frequency (50 Hz). The ringing effect can affect the right side of the QRS complex and lead to loss of information in the S-T region [18, 20, 21].

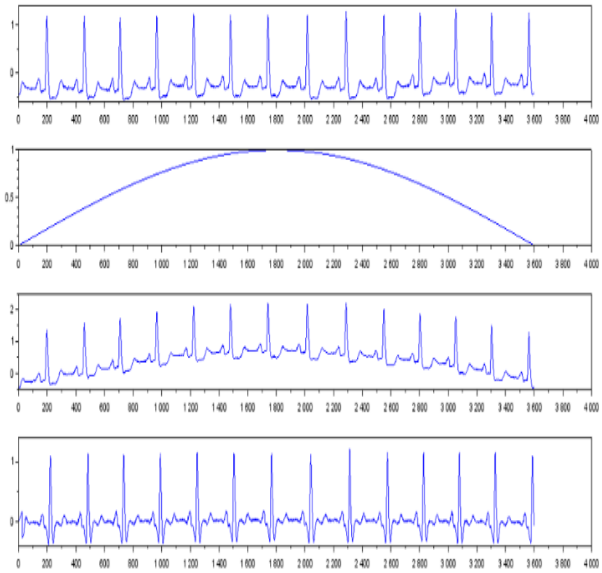

**Fig. 2.** 1st plot is pure ECG,2nd plot is BLW noise, 3rd plot is ECG with BLW noise and 4th plot is the filtered ECG

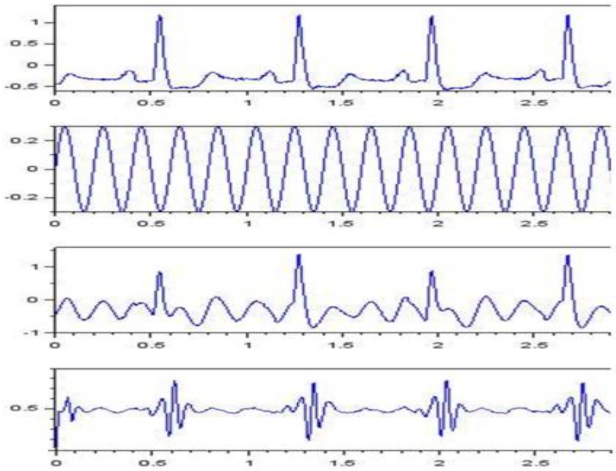

**Fig. 3.** 1st plot is pure ECG,2nd plot is breathing noise, 3rd plot is ECG with Breathing noise and 4th plot is the filtered ECG

ECG measurements can be distorted due to a lot of noise. Major areas of interest include: PLI noise, base line wander noise, respiratory noise, and high-frequency noise. These artifacts strongly affect the ST segment and degrade the frequency resolution. It also produces large amplitude signals that may resemble PQRST waveforms on the ECG due to the proximity in the frequency values. The proximity of noise and original signal frequencies leads to distortion of PQRST waveforms and masking of small features that are important for clinical monitoring and diagnosis. Filtering out these artifacts and noises in ECG signals increases frequency resolution and makes an important contribution to better diagnosis while preserving important clinical features [12, 16].

The ECG signal may include BLW noise due to the improper electrodes or breathing of around 0.5 to 0.6 Hz, respiratory noise (5 Hz), sinusoidal power-line interference from main supply (50 or 60 Hz), EMG muscle noise (above 100 Hz), or Electrode artifact noise caused by possible movement of the Patient. Due to the fact that the range of the ECG signal is between 0.05-106 Hz, during recording, the ECG electrodes capture the electrical frequency of the power source by acting as antennas and leading to its recording together with the ECG. In this study, Scilab has been used to perform signal processing functions in the elimination of the aforementioned noises in the ECG signal. A zero-phase high-pass filter can be used to eliminate BLW noise with a cut-off frequency of 0.5 to 0.6 Hz and to eliminate breathing noise with a cut-off frequency of 6 Hz. A band stop (notch) filter of 50Hz cut-off frequency can be used to remove power-line interference (50/60 Hz). After the noise cleaning functions, the differentiation method can be done for QRS detection.

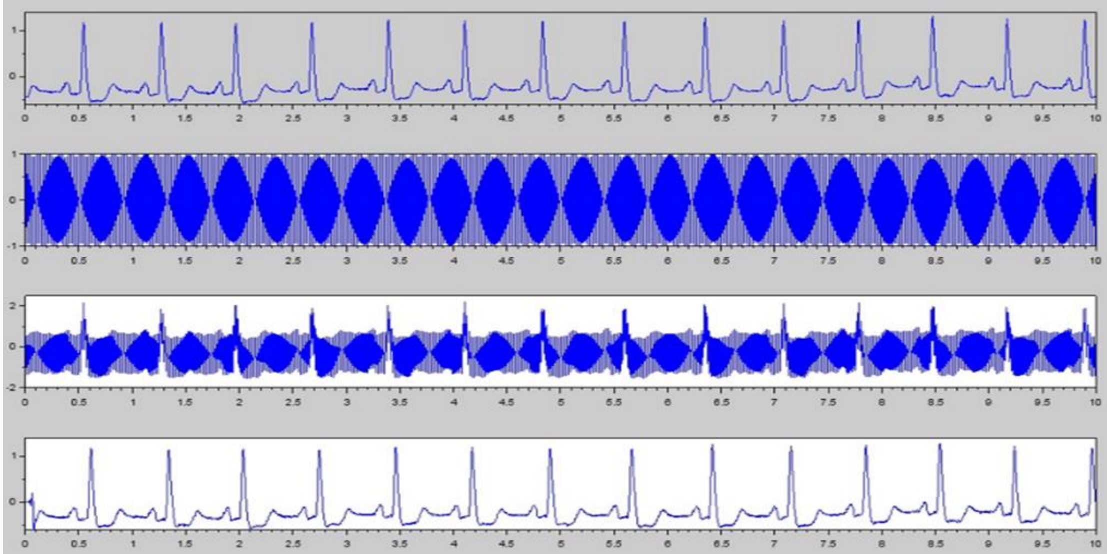

**Fig. 4.** 1st plot is pure ECG,2nd plot is PLI noise, 3rd plot is ECG with PLI noise and 4th plot is the filtered ECG

De-noising and filtering techniques were implemented using Scilab, which facilitates data manipulation and analysis by providing direct access to Microsoft Office Excel Worksheet (.xlsx) files in scilab formal web site. Thus, to the ECG signal above, BLW noise at a frequency of 0.5 Hz was added [8,9]. A high-pass filter with a cut-off frequency of 2 Hz was used to remove BLW noise as in Fig.-2 and respiratory noise was eliminated by using a high-pass filter with fc=6 Hz as can be seen in Fig.-3. When an ECG signal is processed, a ringing effect occurs on the right side of the QRS complex, causing information loss in the S-T region. The ringing effect causes unwanted attenuation at frequencies close to the center frequency (50Hz). [18,20,21]. QRS detection was performed using first and second derivative methods. The first derivative method calculates $y_0(n)$ as the difference between the current sample ($x(n)$) and the sample two positions behind ($x(n-2)$) as in Eq.1. The second derivative method calculates $y_1(n)$ as the difference between the current sample ($x(n)$), the sample two locations behind ($2.x(n-2)$) and the sample four locations behind ($x(n-4)$) (Eq.2). Then $y_2(n)$ is calculated as 1.3 times $y_0(n)$ plus 1.1 times $y_1(n)$ (Eq.3). Finally, $y_3(n)$ is obtained as the sum of eight samples of $y_2(n)$ with appropriate weights as in Eq.4 [16].

$$y_0(n) = [x(n) - x(n-2)] \tag{1}$$

$$y_1(n) = [x(n) - 2x(n-2) + x(n+4)] \tag{2}$$

$$y_2(n) = 1.3y_0(n) + 1.1y_1(n) \tag{3}$$

$$y_3(n) = \frac{1}{8}\sum_{k=0}^{7} y_2(n-k) \tag{4}$$

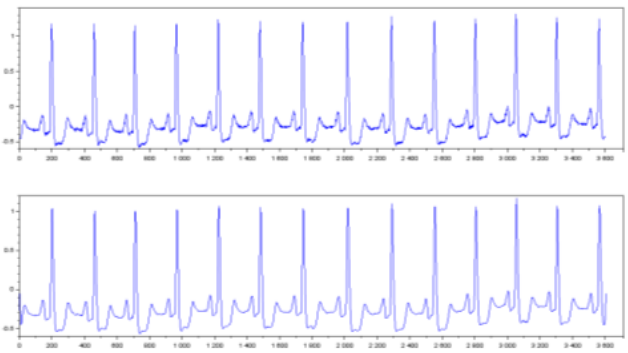

**Fig. 5.** 1st plot is pure ECG contaminated with EMG noise EMG muscle noise or Electrode artifact noise caused by possible movement of the Patient and 2nd plot is the filtered ECG using 8th order moving average filter

### 3. Discussion

The observations from the conducted experiments reveal the effectiveness of the de-noising and filtering techniques employed in this study for eliminating various types of noise artifacts from the ECG signal. Base line wander noise (0.5Hz), seen in Fig. 2, was successfully eliminated using an FIR high-pass filter with an order of 51 and a cutoff frequency of 2 Hz. The application of this filter resulted in the removal of low-frequency noise, enhancing the overall quality of the ECG signal. As a consequence, the baseline fluctuations that could obscure important diagnostic features were effectively mitigated, improving the accuracy of subsequent analyses.

Furthermore, breathing noise (5 Hz), depicted in Fig. 3, was efficiently suppressed using an FIR high-pass filter with an order of 51 and a cutoff frequency of 6 Hz. This filtering process removed the undesirable frequency components associated with breathing artifacts, which could otherwise lead to misinterpretation of ECG features. By eliminating breathing noise, the signal clarity and fidelity were enhanced, facilitating more precise cardiac monitoring and diagnosis.

The interference caused by power line noise (PLI), as evident in Fig. 4, was addressed using an FIR band-stop filter with an order of 51. The band-stop filter was designed with a lower cutoff frequency (Flc) of 20 Hz and an upper cutoff frequency (Fhc) of 80 Hz, effectively attenuating the PLI frequency of 50 Hz. The EMG noise was reduced using moving average filter and it is shown in Fig. 5.

QRS detection was carried out using the differentiation method having a band-pass filter with a bandwidth of 5-15 Hz. The first and second derivative filters, both with an FIR high-pass filter order of 5, played a pivotal role in extracting the QRS pulses accurately. The combined output of these filters revealed distinct QRS pulses, providing crucial information about the electrical activity of the heart. To smooth the QRS pulses, a moving average filter was used.

The successful application of these de-noising and filtering techniques resulted in an improved ECG signal quality, with enhanced feature extraction and reduced noise interference. The results obtained from this study demonstrate the potential of these filtering techniques in enhancing the utility of ECG signals in clinical applications. From the results in Table-1, we can see that output signal SNR and MSE are improved as compared to input.

**Table 1.** SNR & MSE results of different type of errors

| *Input Signal with* | *Input SNR (dB)* | *Output SNR (dB)* | *MSE* |
|---|---|---|---|
| Base line wander noise | -1.692 | -1.496 | 1.38e-04 |
| Breathing noise | -0.2357 | -0.0320 | 17.92e-02 |
| PLI noise | -5.308 | -1.1450 | 0.1e-06 |
| EMG noise | -5.233 | -4.8741 | 13.93e-02 |

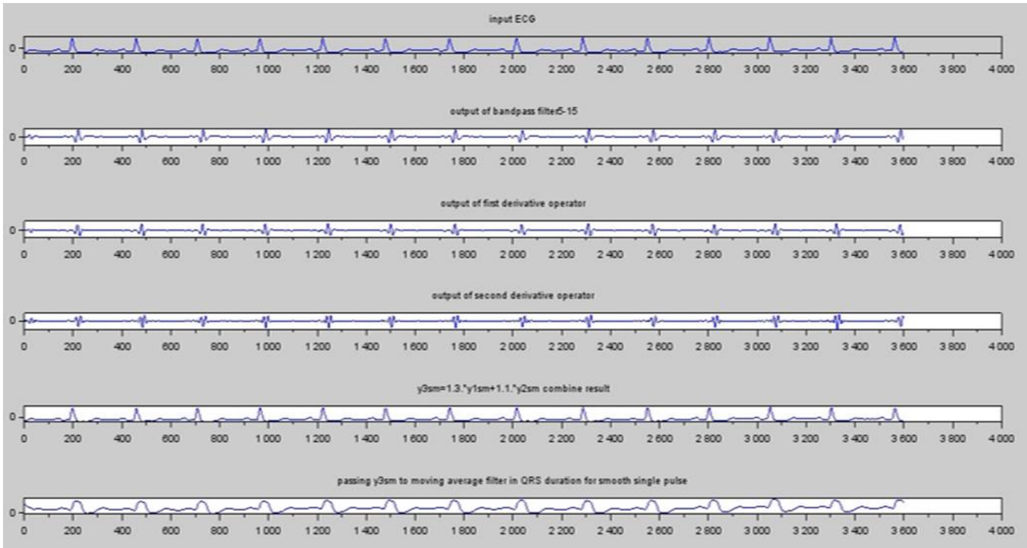


**Fig.6.** 1st plot is pure ECG,2nd plot is output of band-pass filter, 3rd plot is output of first derivative and 4th plot is the output of second derivative, 5th plot is combined output of first and second derivative, 6th plot is the output of moving average filter for smooth single pulses of QRS duration

## 4. Conclusion

In this paper, we presented a comprehensive study on de-noising and signal processing techniques for electrocardiogram (ECG) signals using Scilab. ECG signals are frequently corrupted by various types of noise, such as base line wander, breathing, and PLI, which can significantly affect the accuracy and reliability of diagnostic analyses. Our goal was to effectively eliminate these noise artifacts while preserving the essential features of the ECG waveform. To address the common noise sources in ECG signals, we employed high-pass and band-stop filters. Base line wander noise, characterized by a frequency of 0.5 Hz, was successfully removed using an FIR high-pass filter with a cutoff frequency of 2 Hz. Breathing noise, with a frequency of 5 Hz, was eliminated using another FIR high-pass filter with a cutoff frequency of 6 Hz. Additionally, PLI noise at 50 Hz was effectively attenuated using an FIR band-stop filter with 20 Hz lower cutoff frequency (Flc) and an upper cutoff frequency (Fhc) of 80 Hz. The EMG noise was reduced using moving average filter.

The de-noising and signal processing techniques presented in this study yielded de-noised ECG signals of improved quality. By eliminating noise artifacts and enhancing signal fidelity, these techniques have the potential to significantly improve the accuracy of ECG-based diagnostic procedures. Our signal processing approach leveraged Scilab, an open-source software package, to facilitate data manipulation and analysis. QRS detection, a crucial step in ECG analysis, was achieved using the differentiation method, which effectively acted as a high-pass filter. Single QRS pulses are obtained after moving average filtering. Differentiation is basically high pass filtering and moving averaging is low pass filtering.

In conclusion, this paper contributes valuable insights into de-noising and signal processing techniques for ECG analysis using Scilab. The successful elimination of common noise sources, such as base line wander, breathing, and PLI noises, paves the way for more accurate and reliable diagnosis of cardiac disorders. The combination of differentiation and moving averaging methods effectively facilitated QRS detection and feature extraction, leading to the isolation of single QRS pulses for detailed analysis. The findings of this study highlight the significance of robust de-noising and signal processing techniques in enhancing the clinical utility of ECG signals. These methods can play a crucial role in improving patient care, facilitating early diagnosis, and monitoring the cardiac health of individuals. The proposed approaches hold great promise for advancing the field of biomedical signal processing and contributing to the development of more efficient and reliable cardiac healthcare systems.

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