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Enhancing ECG Signal Quality Through Wavelet-Based Denoising

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Abstract – The electrocardiogram (ECG) is a fundamental tool for diagnosing heart disease. However, noise present during signal acquisition can alter signal quality and complicate clinical analysis. This article proposes an innovative noise suppression method based on the use of wavelets. After decomposing the signal into different frequency components, an evaluation technique was used to identify and retain only the significant elements of the signal. This approach effectively reduces interference while preserving essential information. The results show a significant improvement in the clarity of ECG signals, enabling more reliable analysis and diagnosis.

I. Introduction

An ECG captures the heart's electrical activity to assess cardiac health. However, it is often affected by various noises and artifacts (power line interference, baseline drift, motion-induced disturbances, muscle noise) caused by factors such as equipment, electrode contact, or breathing [1]. Removing these noises is essential for accurate diagnosis. Nonetheless, the denoising process is complex due to the ECG signals' non-stationary nature and the potential loss of critical information during filtering.

To address this, several techniques have been proposed in the literature, including adaptive filtering [2, 3], independent component analysis [4, 5], filter banks [6], discrete wavelet transform (DWT) [7–9], and empirical mode decomposition (EMD) [10–13]. Among these, DWT stands out for its multi-resolution decomposition approach, enabling hierarchical and structured signal analysis. This paper presents an innovative ECG noise suppression technique based on discrete wavelet transform.The proposed method is evaluated using various performance metrics to assess its effectiveness.

The remainder of this paper is organized as follows: Section 2 introduces the DWT method and outlines the methodology. Section 3 presents the results, followed by a discussion in Section 4. Finally, Section 5 concludes the study by summarizing the key findings.

II. Materials and Method

A. *Introduction of DWT*

The Discrete Wavelet Transform (DWT) [14][15] is a powerful method widely used in many fields to analyse signals. It allows a signal to be decomposed into different frequency components at several resolutions, offering simultaneous temporal and frequency representation. Unlike the Fourier Transform, which is limited to the analysis of stationary signals, DWT is particularly effective for non-stationary signals, where the characteristics change over time.

DWT relies on high-pass and low-pass filters to separate signals into two parts:

1. The approximations, representing the low-frequency components, containing the general trends of the signal.

2. The details, corresponding to the high-frequency components, highlighting rapid variations or fine details.

The number of decompositions, or levels, depends on the signal and the problem being addressed.

B. *The proposed DWT denoising methods*

The proposed DWT denoising method is presented in this study for its effectiveness in processing noisy ECG signals, with the Hurst exponent incorporated as a key criterion. The Hurst exponent, a measure of the long-term memory and self-similarity of a time series, quantifies the degree of correlation in a signal over time [16]. Its values vary from 0 to 1, where H<0.5 denotes an anti-persistent process, H=0.5 corresponds to a random (uncorrelated) process, and H>0.5 indicates a persistent process with long-range. In the DWT method, the signal is decomposed into approximations and details across four levels of decomposition, using an adapted mother wavelet.

Selecting an appropriate mother wavelet for ECG data is crucial, as it significantly influences the quality of the results. Empirical research and comparative analyses are necessary to identify the most suitable wavelet for a given application. In our study, after conducting thorough tests, we chose the Daubechies order 2 (db2) mother wavelet due to its effectiveness in capturing the characteristics of ECG signals. The Hurst exponent is employed to analyse the wavelet coefficients, identifying those that exhibit non-significant or predefined threshold values, which are then removed. The signal is subsequently reconstructed, retaining only the significant components.

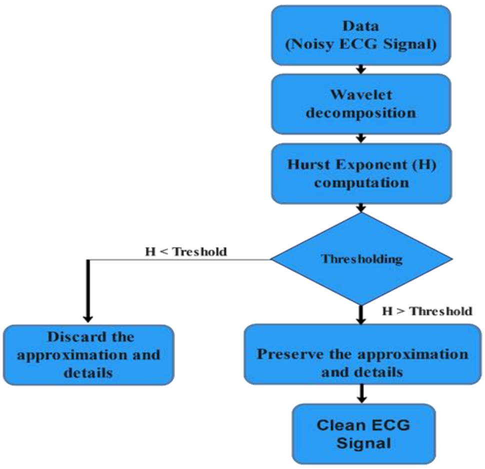

Fig. 1 DWT flowchart

III. RESULTS

The effectiveness of the proposed methods was evaluated using experimental tests on real and synthetic ECG signals. The real signals were collected from the MIT-BIH database [17] (Fig1), while the synthetic signals were generated using mathematical models [18] (Fig2). These two types of data offer a complementary perspective for assessing the robustness and accuracy of the techniques studied.

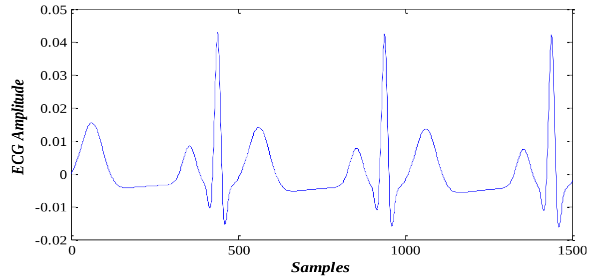

Fig. 2 Synthetic ECG Signal

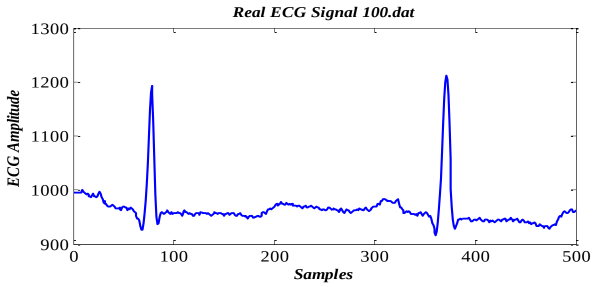

Fig. 3 Real ECG signal 100.dat

The results obtained for the DWT denoising methods is shown in the figures below. These graphs allow visual observation of this approach in terms of noise suppression and preservation of the main characteristics of the signal.

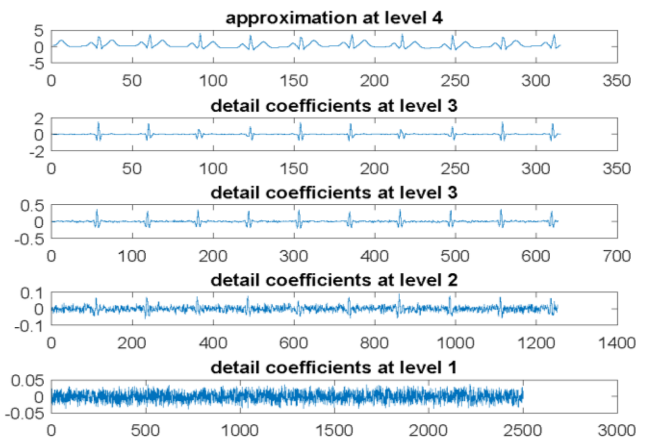

Fig. 4 DWT decomposition of noisy synthetic ECG signal.

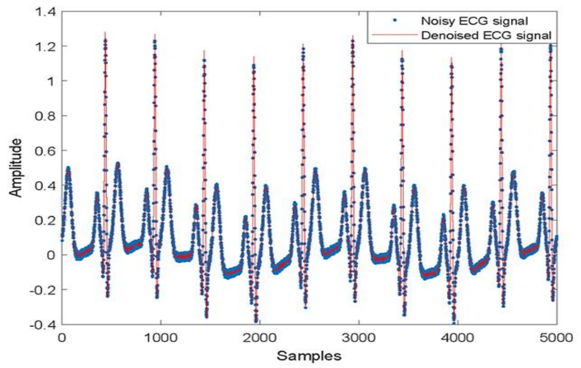

Fig. 5 DWT-based denoising of noisy synthetic ECG signal

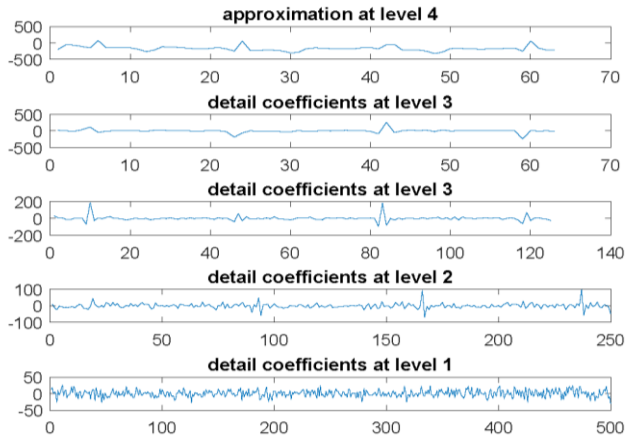

Fig.6 DWT decomposition of noisy real ECG signal.

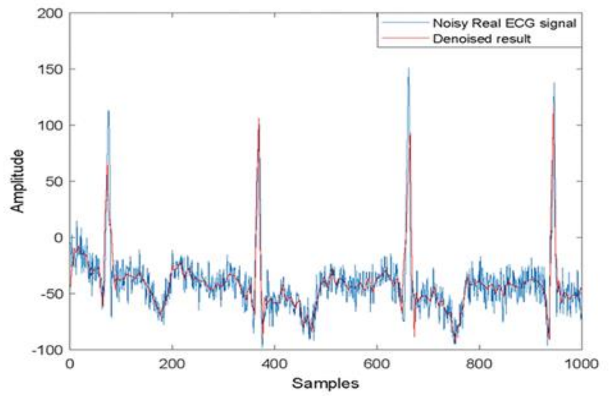

Fig. 7 DWT-based denoising of noisy real ECG signal

To objectively assess the performance of this methods, several quantitative evaluation metrics were used, including signal-to-noise ratio (SNR), mean absolute error (MAE) and mean square error (MSE).

The SNR is utilized to measure the overall quality of a signal in the presence of noise, while MAE and MSE quantify the discrepancies between predicted and actual values, thus providing a comprehensive assessment of our method's accuracy. The following table summarises the performance:

Table 1. DWT performance across different noise intensities.

Noise intensity	***MSE***	***MAE***	SNR_{output}
$5dB$	0.016769	0.103217	7dB
$10dB$	0.004391	0.052856	12dB
$15dB$	0.001467	0.0330502	16Db

IV. DISCUSSION

From these results, it is clear that the DWT method provides effective noise suppression, achieving satisfactory performance in terms of SNR, MSE, and MAE. These observations demonstrate the capability of DWT to process non-stationary signals such as ECG, thanks to its structured decomposition and the ability to isolate significant components. While the method may face certain limitations due to the rigidity of the filters used in wavelet decomposition, the results confirm its potential for high-performance denoising of non-stationary biological signals.

V. CONCLUSION

This study explored the application of the Discrete Wavelet Transform (DWT) for ECG signal denoising, incorporating the Hurst exponent as key criteria for identifying and eliminating noisy components. Experimental results demonstrated that DWT effectively suppressed noise while preserving the main characteristics of the ECG signal.

These findings highlight the importance of using a structured decomposition method like DWT, which is well-suited for processing complex and non-stationary signals such as ECG, ensuring a balance between noise reduction and signal integrity.

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