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Noise Modeling and Removal from Electrocardiogram Signals: A Study Using Wavelet Transform with Graphical User Interface

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Abstract

The electrocardiogram (ECG) is the recording of the electrical potential of the heart versus time. The analysis of ECG signals has been widely used in cardiac pathology to detect heart disease. The ECGs are non-stationary signals which are often contaminated by different types of noises from different sources. In this study, simulated noise models were proposed for the power-line interference (PLI), electromyogram (EMG) noise, base line wander (BW), white Gaussian noise (WGN) and composite noise. For suppressing noises and extracting the efficient morphology of an ECG signal, various processing techniques have been recently proposed. In this paper, wavelet transform (WT) is performed for noisy ECG signals. The graphical user interface (GUI) system is developed for visual representation and adaptive enhancement on noise modeling in ECG-based signal processing. Percentage root mean square difference (PRD) was measured between the modeled noisy signals and the samples of the original ECG. Moreover, cross correlation ($XCorr$) and root mean square error ($RMSE$) were performed between the noisy ECG signals and the denoised ones which resulted from WT denoising technique initially to evaluate the effectiveness of the WT denoising technique. The results show that the WT was successfully removed different types of proposed models of noises. The PRD was reasonable and are within the acceptable range, which is less than 50%, with 17% for BW and 47% for PLI indicating that the models and methods used for prediction are ideal for high precision signal applications. This study will help medical doctors, clinicians, physicians, and technicians to eliminate different types of noise.

Moreover, the project could be crucial for the process of automatic diagnosis of different heart diseases.

1. Introduction

The heart is a muscular organ the size of a fist right behind and slightly left from the breast bone. The cardiovascular system is a network of arteries and veins that the heart pumps blood through. ECG signals are widely used in clinical researches for the diagnosis of heart disorders [2]. It assists in the diagnosis of chest pain etiology, and early intervention for myocardial infarction is dependent upon it. It can also assist in determining the cause of dizziness, syncope and dyspnea. This test is used to detect and record the heart's electrical activity [1,3,4]. But ECG signals are usually corrupted with noise like electrode motion artifacts (EM), power-line interference (PLI), and baseline wander (BW) apart from electromyogram (EMG) noise; white Gaussian noise WGN and composite noise. The current conventional filteration process shows unsatisfactory results for the removal of ECG noise because associated non-stationary sources have spectral overlaps with desired signals [5]. There is a high false alarm rate for current ECG abnormality detection methods because these techniques do not to classify artifacts from real ECG signals, particularly when the artifact looks similar both in shape and frequency of the normal. These consequences include increased detection for physicians and a high risk of misinterpretation in non-specialists. Therefore, it is essential to determine the type of noises in ECG recordings that allow selecting signal processing techniques suitable for noise types.

The removal of noise from the electrocardiogram (ECG) signal is essential to ensure the accuracy and reliability of the ECG data, and realizes a wide range of applications e.g., if clean ECG signals are required for clinical diagnosis it is perfect for heart conditions. By removing noise from the ECG signal, healthcare professionals can more closely examine the electrical activity of the heart and detect abnormalities or abnormalities, such as palpitations detection, heart rate variability analysis, and other cardiac tests to provide more accurate results and actionable insights. Furthermore, in telemedicine and remote patient monitoring applications, ECG denoising is essential to ensure the quality of intermediate ECG signals Noise removal can improve the accuracy of the remote diagnostic process, and improve health professionals have been able to monitor patients' cardiac health remotely and intervene when necessary -Help extract relevant information from signals, thereby improving understanding of cardiac function and identifying new diagnostic markers ECG noise eliminating methods AI systems effectiveness and reliability of tasks such as ECG classification, anomaly detection and risk prediction help improve [6,7].

Overall, ECG noise removal is an important aspect in various applications where accurate, reliable, and high-quality ECG signals are important for clinical diagnosis, diagnosis, remote sensing, indication applications, and advanced healthcare technology by improving the quality of ECG data Noise cancellation techniques help lead to improved patient care, better heart health insights, and improvements in cardiac awareness.

To our knowledge, no systematic framework exists for the automatic identification and classification of noise and artifacts present in the ECG signal. These limitations are critical design considerations for real-time ECG signal analysis and detection systems under resting, ambulatory and exercise recordings. This paper has four main objectives, firstly, to develop different noise sources that are artificially modelled including power-line interference (PLI), electromyogram (EMG) noise, baseline wander (BW), white Gaussian noise (WGN) and composite noise models that are able to synthesized noisy ECG signals by adding the noises models to the normal ECG signal. Secondly, to reconstruct the clean ECG signal from the generated noisy ECG signals using the wavelet (WT) denoising method. Thirdly, to build a graphical user interface (GUI) system for visual representation and adaptive enhancement on noise modeling in ECG-based signal processing. Finally, to evaluate the effectiveness of the WT denoising technique, percentage root mean square difference (PRD) was measured between the modeled noisy signals and the samples of the original ECG and cross-correlation ($XCorr$) with root mean square error ($RMSE$) was performed between the noisy ECG signals and the denoised ones which resulted from WT denoising techniques initially.

2. Methodology

To handle the problem of high false alarm rate from ECG signals that help in developing a valuable system for ECG abnormality detection, the ECG dataset needs successive signal processing stages. Figure 1 illustrates the schematic block diagram of this study.

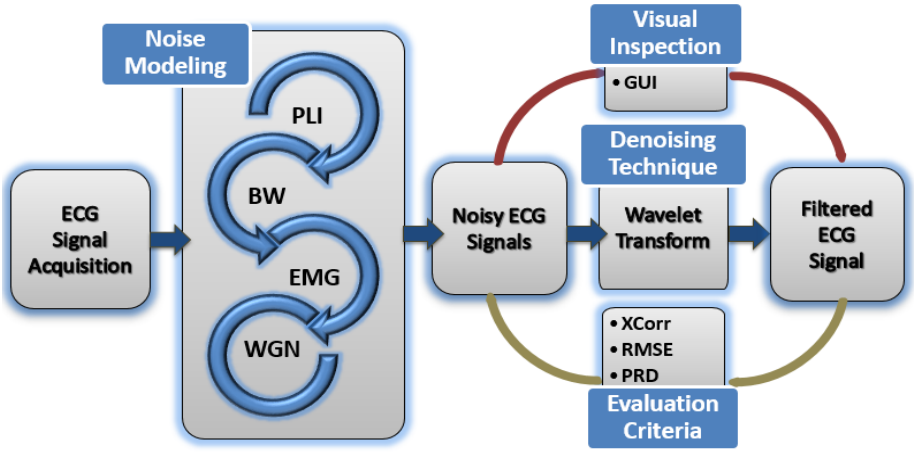

Fig. 1 *Schematic block diagram of this study*

2.1 ECG Dataset and Noise Modeling

The normal ECG signals have been downloaded from (ftp://ftp.ieee.org/uploads/press/rangayyan/) which is a noise-free signal. The ECG signal has been sampled at a rate of 200 Hz.
In this section, the mathematical model of PLI, BW, EMG and WGN noises will be illustrated and computed.

- Power Line Interference noise (PLI)

The PLI noise is modeled by the following sinusoidal wave:

$$PLI = A(t)\, sin\,(2\pi \times f_0/f_s) \tag{1}$$

where $A(t)$ is the time-varying peak value of the interference; f_0 is the fundamental frequency, which could be 50 Hz or 60 Hz; fs is the sampling frequency [2].

- Baseline wandering noise (BW)

The mathematical model of the BW noise is defined as follows:

$$BW = C(1 + A\,(t) sin\,(2\pi t \times \Delta f) cos(2\pi t \times K) \tag{2}$$

where $A(t)$ is the time-varying peak value of the interference; f_s is the sampling frequency. The scaling factor C is a random number from the uniform distribution [0;1], it was used to increase the total power of the artifact. $\Delta f = fs/N = 0.02$ Hz where N is the total number of samples in the signal. Additionally, $K = f_c/f_s$ is the number of sinusoidal functions that could be placed within the chosen spectrum and $K = 0.25$ [3].

- Electromyogram (EMG) noise

Equation 3 shows a simple model of the EMG signal:

$$EMG = A(t) \sin\,((2\pi t \times f_c) + C cos(2\pi t \times f_e) \tag{3}$$

where $A(t)$ is the time-varying peak value of the interference; the frequency of the carrier is $f_c = 375\,Hz$, the frequency of the envelope is $f_e = 50\,Hz$, the modulation index $C = 125$ with randomly varying amplitude, sampled with a sampling rate of 1000 Hz [8].

- White Gaussian noise (WGN).

Gaussian noise is generated with the mean (μ), standard deviation (σ) and variance (σ^2) as given by the following Equation [2,3]:

$$WGN = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \quad (4)$$

In this study, four noise models can be developed from the previous stage to get the noisy ECG signals. Therefore, by visual examination of real ECG signals and the different noise models, a specific model depending on the changes that are observed in the signal can be developed. The model concerns the PLI, BW, EMG and WGN noises [9]. The ECG and these noise models can be approximated and represented with additive functions as given in the following Equation:

$$\mathrm{ECG}_n = ECG + Noise\ model \quad (5)$$

2.2 Wavelet Denoising Technique

One of the well-known denoising techniques is the Wavelet Transform (WT) used to process nonstationary signals, e.g., noisy ECG [10,11]. analysis and application on a broad scope of subjects, mainly signal compression. To date, the issues in ECG are solved by different applications of WT like data compression, ventricular late potentials analysis and finally characteristic waves. WT splits the input signal into a series of levels depending on the frequency components present in this signal and analyzes each level with a specific resolution [12,13].
The time-frequency windows of $\psi_{m,n}$ are overlapped each other, which means there is information redundancy in CWT from m to n sample. The discrete wavelet transforms (DWT) provide a perfect reconstruction of the signal upon inversion [14,15].

The DWT is a rapid non-repeatable transform used in practice to analyzed both the low and high frequency of ECG signals, as it takes less time than CWT. Getting the discrete values of parameters and, as in Equation 6, allows for processing DWT. It can be found a set of these decomposition functions, relating to the signal-correlation and shifting or stretching by location parameter (b) on one specific function called mother wavelet function $\psi(t)$. In Equation 7, MWT is shifted by the location parameter and dilated or contracted by frequency scaling parameter a [10,11,12,13].

$$DWT_{m,n}(f) = a_0^{-m/2} \int f(t)\,\psi(a_0^{-m}t - nb_0)dt \quad (6)$$

a_0 and b_0 values are set to 2 and 1, respectively.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a\epsilon\mathbb{R}^+, b\epsilon\mathbb{R} \quad (7)$$

2.3 Threshold Technique

SURE threshold is based on an adaptive soft approach whereby the limit of each level value only depends upon Stein's unbiased risk estimation [15].
To decrease the thresholding risk in rigrsure, it is common to choose a lower threshold hold than that of universal setting. Donoho and Johnstone showed that the SURE threshold is unbiased [16]. Equation 8 can be used for its calculation.

$$th_j = \sigma_j\sqrt{\omega_b} \quad (8)$$

Where ω_b is the b^{th} squared wavelet coefficient at minimum risk is taken from the vector $W = [\omega_1, \omega_2, \dots\dots, \omega_N]$. σ denotes standard deviation of noisy signal. But as the signal-to-noise ratio is excessively low, SURE becomes close to true risk and its variance can lead errors when signaling energy does not exceed noise. In this case, the heursure thresholding method may improve the denoising process, which is a combination of both universal threshold SURE threshold and rigrsure methods [16].

2.4 Graphical User Interface (GUI) Systems

In this study, the graphical user interface (GUI) system was built for the visual representation of our proposed approaches. For the implementation and representation of the original, noisy ECG signal with different noise models and WT denoising method, GUI system was developed for adaptive enhancement on noise modeling in ECG-based signal processing as in Figure (2).

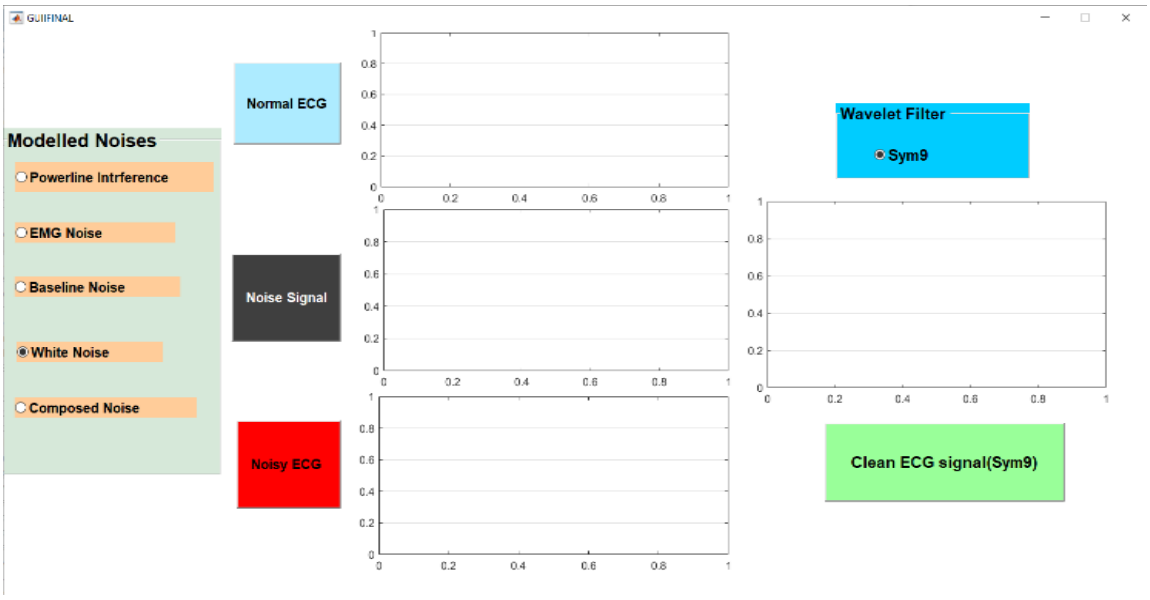

Fig. 2 *GUI system for adaptive enhancement on noise modelling in ECG-based signal processing*.

2.5 Denoising Techniques Performance Evaluation

In this work, the quality measurement of the modeled signals is obtained computed the percentage root mean square difference (PRD) between the samples of the original ECG(x) and the samples of the model signal(X). The PRD can be calculated using Equation 9 [9]:

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}\sum_{i=1}^{N}(X-x)^2}{\sum_{i=1}^{N}(X)^2}} \tag{9}$$

Moreover, to conduct a comparison, cross-correlation $(XCorr)$ and root-mean-square error $(RMSE)$ were performed between the ECG corrupted with the proposed noisy models and the denoised ECG using WT. The correlation $XCorr$ presented in Equation 10 [17,18,19].

$$XCorr(X,\mathrm{Y}) = \frac{\sum(X-x)\,(Y-y)}{\sqrt{\sum(X-x)^2\,(Y-y)^2}} \tag{10}$$

The root-mean-square error $(RMSE)$ for a leng th of N to the selected window can be calculated using Equation 11:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x-y)^2} \tag{11}$$

3. Results And Discussion

3.1 ECG Dataset and Noise Modeling Results

The ECG signal have been obtained from a healthy subject, this signal has a sampling rate of 200 Hz as shown in the following figure:

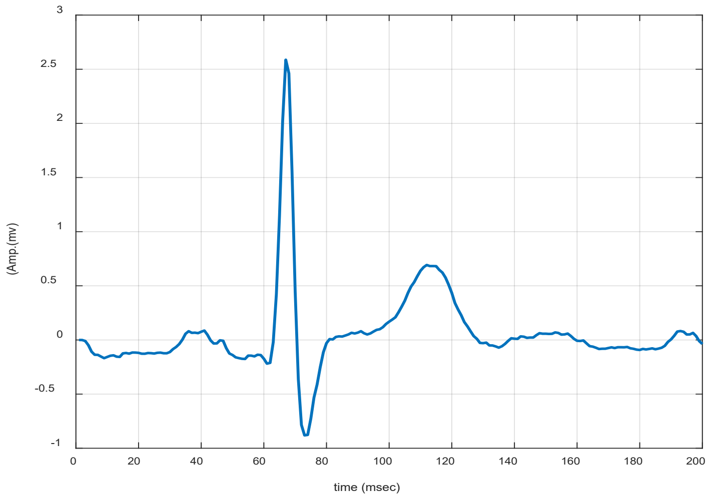

Fig. 3 *ECG signal from healthy subject*

In this section, the mathematical model of PLI, BW, EMG and WGN noises will be illustrated and denoised as in the following sections:

3.1.1 Power Line Interference noise (PLI)

This the PLI noise was modeled using a frequency of 50 Hz and a sampling rate of 200 Hz (the black signal) then added in time domain into the original normal ECG signal to represent noisy ECG with PLI noise (the red signal). Then, the ECG signal was denoised by the WT denoising method using sym9 mother WT as shown in the Figure 4. It can watch the suspension of the PLI noise when contrasted with the raw noisy ECG signal (the blue signal).

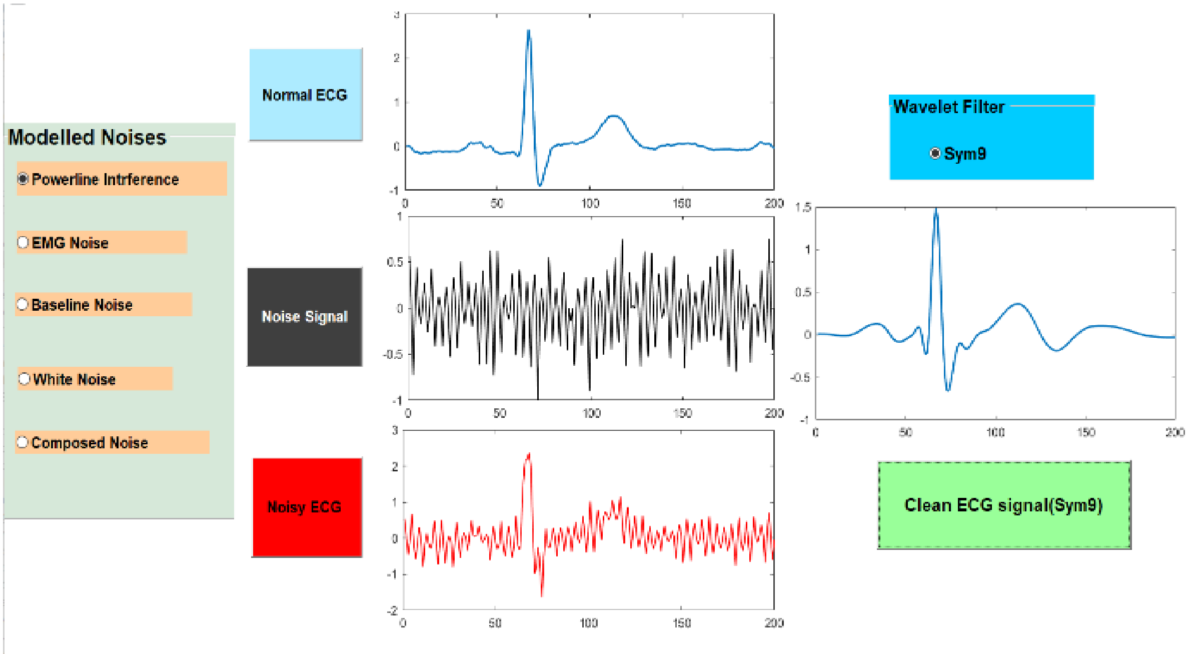

Fig. 4 *GUI systems for the visual implementation of normal ECG, PLI noise and clean ECG signal using WT de-noising method*

3.1.2 Base Line Wandering Noise (BW)

BW noise was modeled with a sampling rate of 200 Hz (the black signal) then added in time domain into the original normal ECG signal to represent noisy ECG with BW noise (the red signal). Then, the ECG signal was denoised by the WT denoising method using sym9 mother WT as shown in the Figure 5. It can watch the suspension of the BW noise when contrasted with the raw noisy ECG signal (the blue signal).

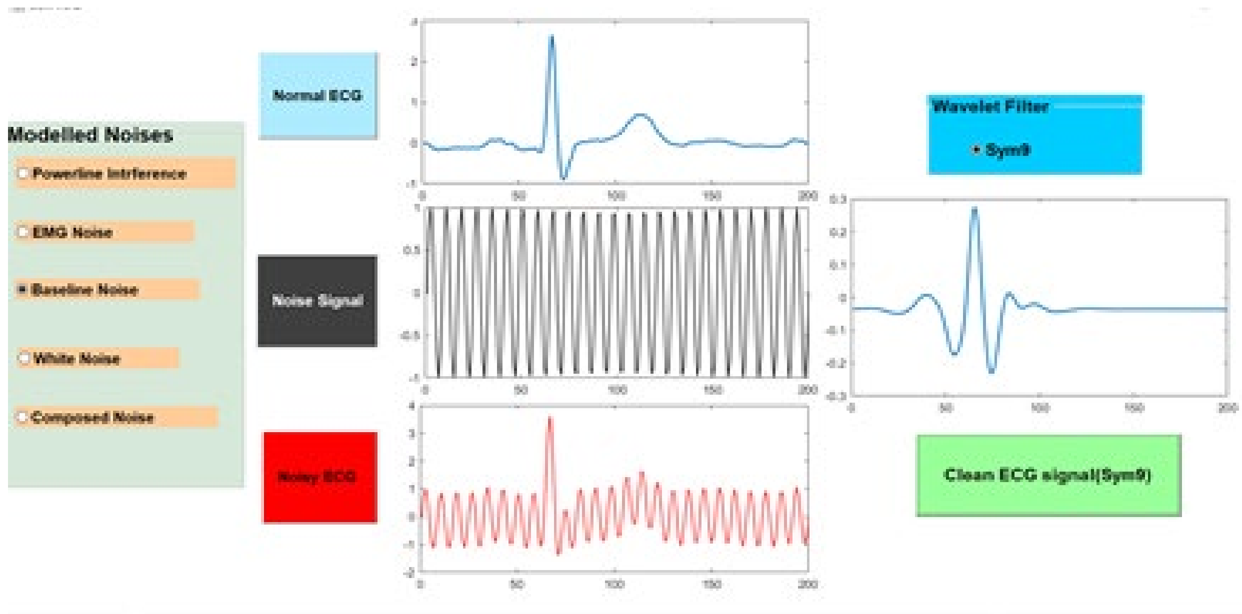

Fig. 5 *GUI systems for the visual implementation of normal ECG, BW noise and clean ECG signal using WT denoising method*

3.1.3 Electromyogram (EMG) Noise

The EMG signal was modeled with a sampling rate of 1000 Hz. The EMG signal has down sampled (dEMG) to 200 Hz (the black signal) to be compatible to be added to the original ECG signal to represent noisy ECG with EMG noise (the red signal). Then, the ECG signal was denoised by the WT denoising method using sym9 mother WT as shown in the Figure 6. It can watch the suspension of the EMG noise when contrasted with the raw noisy ECG signal (the blue signal).

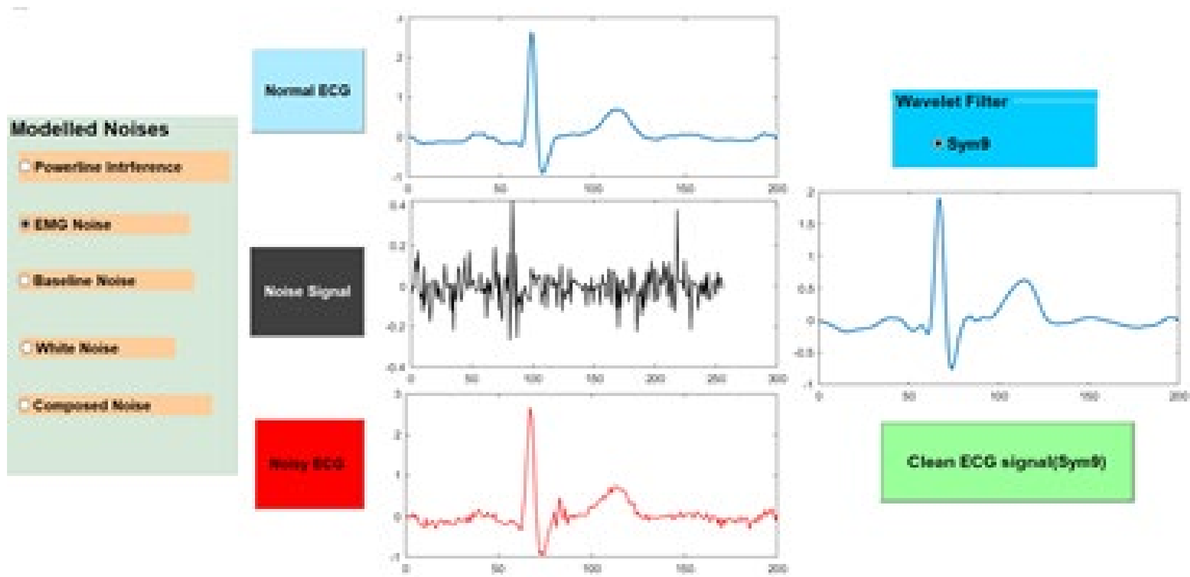

Fig. 6 *GUI systems for the visual implementation of normal ECG, EMG noise and clean ECG signal using WT denoising method*

3.1.4 White Gaussian Noise (WGN)

WGN noise was modeled with a sampling frequency of 200 Hz (the black signal) then added in time domain into the original normal ECG signal to represent noisy ECG with WGN noise (the red signal). Then, the ECG signal was denoised by the WT denoising method using sym9 mother WT as shown in the Figure 7. It can watch the suspension of the WGN noise when contrasted with the raw noisy ECG signal (the blue signal).

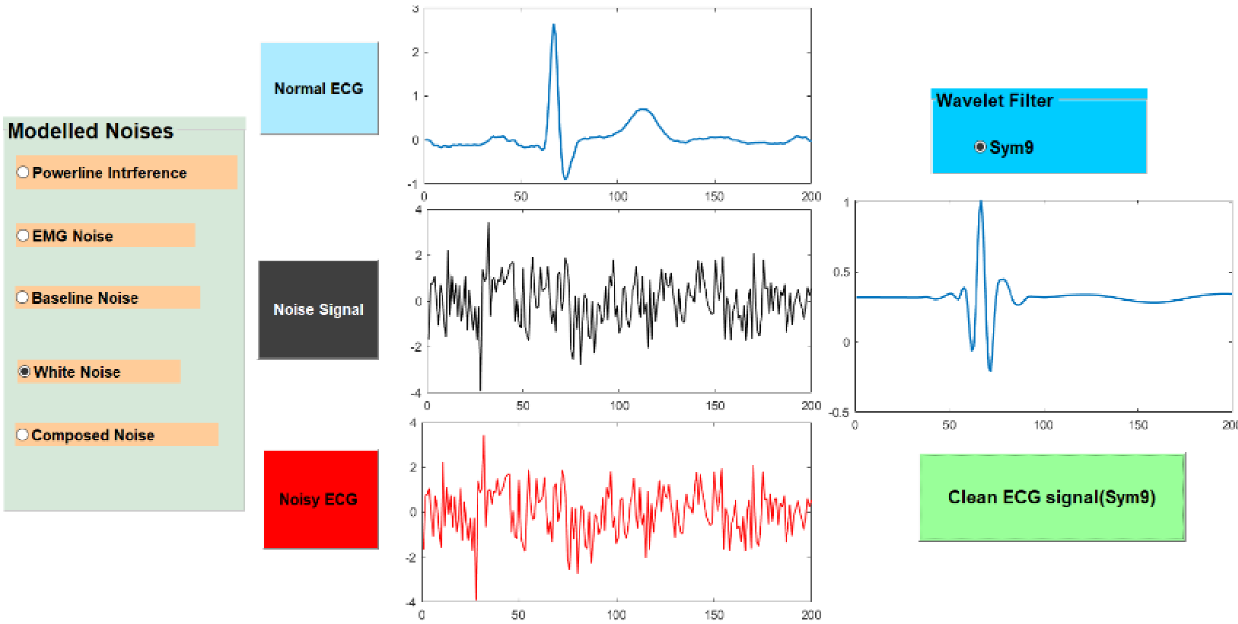

Fig. 7 *GUI systems for the visual implementation of normal ECG, WGN noise and clean ECG signal using WT denoising method*

Moreover, the ECG contaminated by composite noises like $PLI + BW$ and / or $EMG + BW$. The composite noise (the black signal) then added in time domain into the original normal ECG signal to represent ECG_Cn (the red signal). Then, the ECG signal was denoised by the WT denoising method using sym9 mother WT as shown in the Figure 8. It can watch the suspension of the composite noise when contrasted with the raw noisy ECG signal (the blue signal).

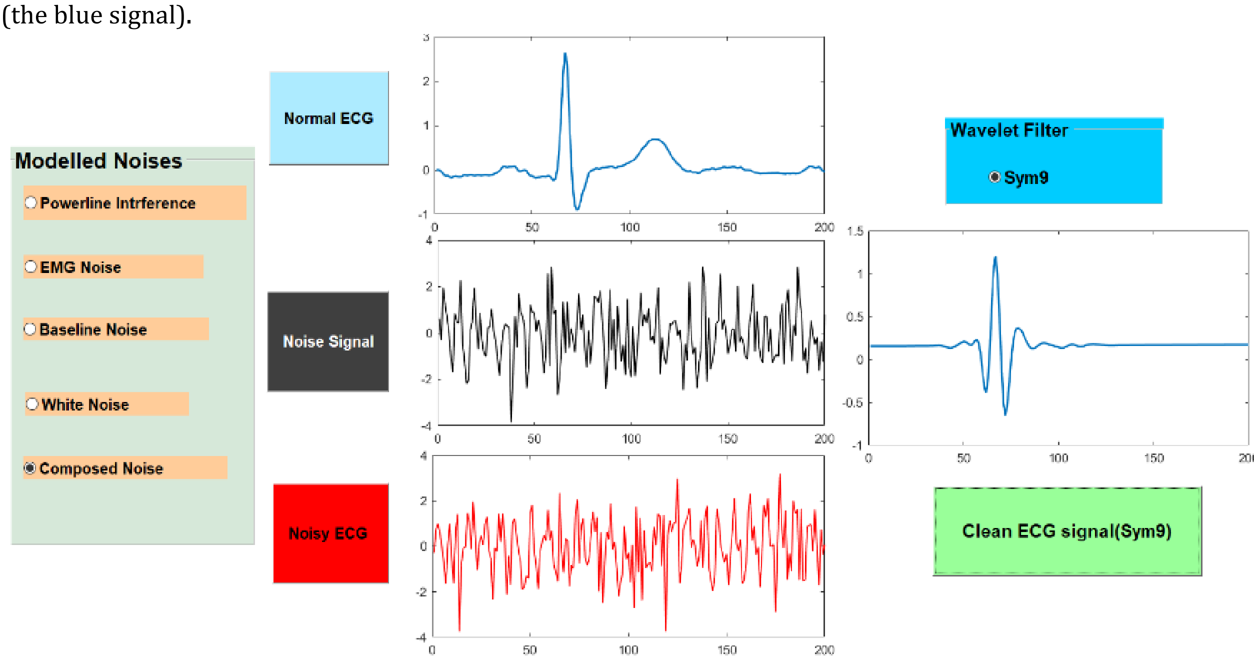

Fig. 8 *GUI systems for the visual implementation of normal ECG, composite noise and clean ECG signal using WT denoising method*

3.2 Denoising Technique Performance Evaluation

The WT denoising technique results were summarized by conducting the $XCorr$ and the other for MSE, respectively. Figure 9 presents the XCorr comparative plot between the noisy ECG signals and the ECG signals after denoising using WT technique. PLI, EMG and BW had higher correlation values compare to Gaussian and

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CompN ($PLI > EMG > BW > CompN > Gaussian$). Moreover, Figure 10 illustrates the MSE comparative plot between the noisy ECG signals and the ECG signals after denoising using WT technique. EMG, PLI and BW had lower MSE values compare to Gaussian and CompN ($EMG > PLI > BW > CompN > Gaussian$)These results suggest that the proposed models of noise to the ECG signal were significantly effect on the normal ECG.

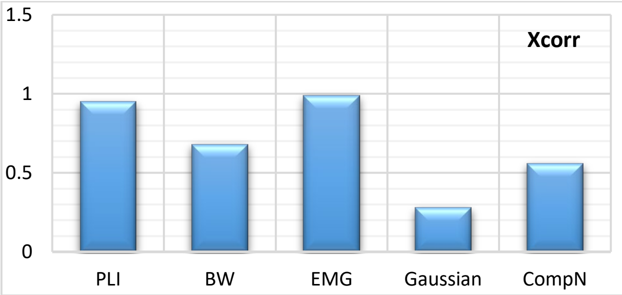

Fig. 9 *Comparative plot of correlation coefficients between the noisy ECG signals and the ECG signals after denoising using WT technique*

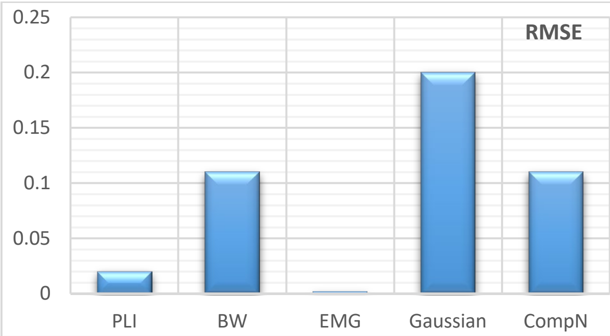

Fig. 10 *Comparative plot of mean square error between the noisy ECG signals and the ECG signals after denoising using WT technique*

Further inspection of the results from Figure 11 showed that PRD around 17% for BW, 20% for EMG, 30% for Gaussian and 47% for PLI which reflects acceptable errors. Considering the fact that noise modelling for each type of noise was computed based on specific discrete transformations of the signal which results less signal distortion, therefore, the proposed noise models could be used in applications that require a high precision signal.

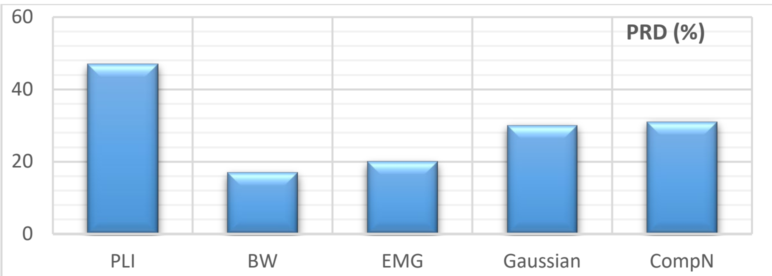

Fig. 11 *Comparative plot of percentage root mean square difference between the modeled noisy signals and the samples of the original ECG*

4. Conclusion

The examination of human activity relies heavily on ECG, thus in this study, ECG signal subjected to four different noise sources. PLI, EMG, BW, WGN and composite noise have been artificially modelled and the synthesized noisy ECG signals were obtained by adding the noises models to the normal ECG signal. Moreover, the clean ECG signals from the generated noisy ECG signals using WT de-noising method have been reconstructed. Furthermore, the GUI system for visual representation and adaptive enhancement on noise modeling in ECG-based signal processing has been developed. PRD have been measured between the modeled noisy signals and the samples of the original ECG. $XCorr$ and $RMSE$ have been performed between the noisy ECG signals and the denoised ones which resulted from WT denoising techniques initially to evaluate the effectiveness of the WT denoising technique. As a future work, we consider extracting features from ECG signals and optimize them for different kinds of heart diseases. Applying wavelet neural network (WNN) for ECG signal modeling and noise reduction. Using Particle Swarm Optimization (PSO) algorithm to remove high-frequency noise. ECG could be as a valuable marker for inspecting the background activity in the identification of patients with VaD and stroke-related MCI.

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Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

*NKQ: **Analysis, and interpretation** of the ECG data for the work; drafting the manuscript. AB: **drafting the manuscript**. AAA: **drafting the manuscript**. SHMA: **Support the article by fund**. SAA: **revising the work** critically for important intellectual content and final approval of the version to be published. All authors read and approved the final manuscript.*

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