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Robust Approach of De-noising ECG Signal using Multi-Resolution Wavelet Transform

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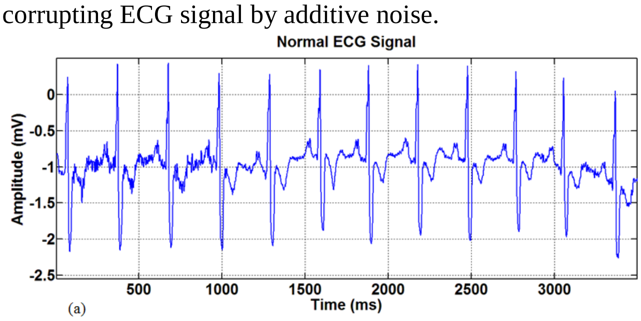
Abstract: ***The ECG signal expresses the behavior of human heart against time. The analysis of this signal performs great information for diagnosing different cardiac diseases. In other hand, the ECG signal used for analyzing must be clean from any type of noises that corrupted it by the external environment. In this paper, a new approach of ECG signal noise reduction is proposed to minimize noise from all parts of ECG signal and maintains main characteristics of ECG signal with lowest changes. The new approach applies simple scaling down operation on the detail resolution in the wavelet transform space of noisy signal. The proposed noise reduction approach is validated by some ECG records from MIT-BIH database. Also, the performance of the proposed approach is evaluated graphically using different SNR levels and some standard metrics. The results improve the ability of the proposed approach to reduce noise from the ECG signal with high accuracy in comparison to the existing methods of noise reduction.***

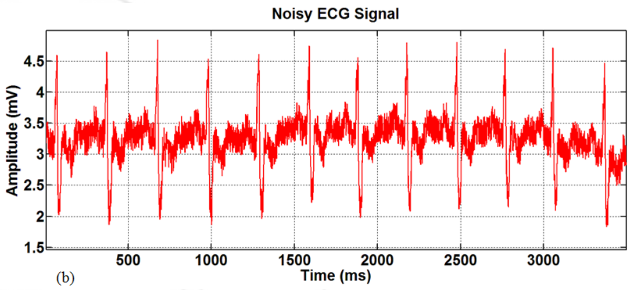
Keywords: ECG signal, Noise Reduction, Symlet Filter, Discrete Wavelet Transform, MIT-BIH

1. Introduction

The electrocardiogram (ECG) signal is a graphical registration of the electrical signal generated by the human heart against time [1, 2]. The ECG signal reflects the ionic current flow which causes the cardiac fibers to contract and subsequently relax [3]. The ECG signal is recorded due the potential difference between two electrodes attached directly to the surface of human body [4]. Reconstructing useful ECG information from the real noisy signal requires reliable signal de-noising techniques. The ECG signal contains important information that can be exploited in specific manner to recognize much variability's of the human heart activity. The clinical practices improve that many cardiac diseases can be diagnosed strictly based on ECG test [5]. On the other hand, the quality of ECG signal used for processing is most important to perform accurate outcomes. Like any electrical signal, the ECG signal is subjected to infection with various types of noises. Two types of noise are considered in ECG signal. The first type is cardiac noise which associated with atrial flutter, reduction of the isoelectric interval, or prolonged re-polarization. While the second type of noise is extra cardiac noise that can be caused by changes of electrode position, muscle contraction, or power line interference [6, 7]. In any cases, the noise inside ECG signal causes a big mistake with the analysis results of different ECG characteristics in amplitude and time interval. The two samples of ECG signals shown in Figure1 highlight clearly the effect of corrupting ECG signal by additive noise.



(a) Normal Signal



(b) Noisy Signal

Figure 1: The ECG Signal

In recent years, many approaches are proposed for ECG noise reduction. An adaptive filtering approach [8] based on artificial neural networks (ANN) and wavelet transform (WT) was proposed for ECG signal noise reduction. A new algorithm in empirical mode decomposition (EMD) and discrete wavelet transform (DWT) was investigated in [9]. This algorithm overcomes the limitation in conventional method of ECG noise reduction in preserving all characteristics of QRS complex in the presence of noise; also the finding results of signal to noise ratio (SNR) are perfect in comparison to some existing methods. In [10], another EMD based approach was proposed to eliminate the power line interference in ECG signals. An efficient and simple technique for cancellation of artifacts in ECG signals using normalized adaptive filters was presented in [11] as an application of wireless biotelemetry.

In this paper, a new approach of ECG signal noise reduction using wavelet transform has been proposed. The new approach applies evaluated scaling operations on detail part of wavelet space along 2 levels. The new approach minimizing noise from all ECG waves (P-QRS-T). Also, the reconstructed ECG signal takes smooth shape with less noise. The new approach is validated with some ECG signals collected from MIT-BIH [12] arrhythmia database with different amount of noise.

2. Proposed Noise Reduction Approach

The details of each signal corrupted by external noise are updated, because the noise events are added to the original signal and become a part of this signal. This scenario is considered for all types of noise with different levels. The noisy signals can be found in different application, but when noisy signal uses by certain system, the first step of this system must be filtered it to overcome any disturbance in system behavior. Selection of suitable filter for each noise type is most important in all scientific fields, because some types of noises take special texture which make traditional or standard filters fail to remove or minimize it.

In the field of biomedical signal, each signal handles important medical information. One of these signals is the ECG signal which expressed the human heart behavior against time as a graphical diagram. The ECG signal is recorded using a special machine through some electrodes attached directly to human body. As mentioned previously, specific types of noise are added to the recorded ECG signal which causes some variation in output signal. This variation leads to unreal behavior for all ECG waves, which means all decisions build on analyzing this signal are not accurately. Of course, this problem can be solved by applying special filter to remove added noise, but in other hand the main characteristics may not changed hardly to safe medical information inside as much as possible.

This study addresses this problem by a new approach of noise reduction. The new approach applies simple scaling method on wavelet space of noisy signal. The wavelet transform (WT) analysis entire signal by expressing it as the combination of the sum of the product of the wavelet coefficients and mother wavelet. The wavelet coefficients are different for various wavelet filters used in transformation. When DWT is used for analyzing, both high and low frequency components are passed through a series of high and low pass filters, respectively with different cut-off frequency. Thus, DWT splits the signal into two main parts in each scale: approximate and detail resolution. The process of decomposition entire signal into different frequency bands with different resolutions band facilitates signal analysis in easy manner. In general, the approximate resolution of DWT contains low frequencies of the signal that handles effective information while detail resolution contains high frequencies of the signal that contains in most cases high percent of noise added.

In general, signal denosing using DWT must be passes through three steps: signal decomposition, thresholding of wavelet coefficients, and signal reconstruction [13]. With respect to the first step, the proposed approach applies noise reduction on detail resolution of wavelet level one and two using symlet wavelet filters with 8 coefficients (sym8). In first level, the detail part is scaled with a certain value Tr1. The scaled value is obtained by analyzing many ECG records before and after corrupting by noise and then fix the suitable scale needed to minimize the data in detail space to match clean one. The evaluated scaling factor is (0.07). The same strategy is followed in second level but with different scaling factor, also the data below a fixed threshold is minimized in order to keep useful information for reconstruction. The evaluated scaling factor is (0.005). The general block diagram of the proposed approach of ECG signal noise reduction is shown in Figure 2 with wavelet hierarchy for 2 levels.

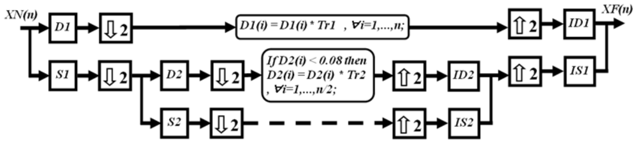


Figure 2: General block diagram for the proposed approach of ECG signal with wavelet hierarchy for 2 levels

3. Evaluation Metrics

There are three quantitative metrics (SNR, mean square error (MSE), percent root mean square difference (PRD)) which are mostly used to evaluate the performance of de-noising approaches [3, 9, 14, 15]. The first metric SNR defined in Eq.1 determines the amount of noise in reconstructed signal X_F due to original clean signal X_O and noisy signal X_N. The second and third metrics (MSE, PRD) defined in Eq.2 and Eq.3, respectively determines the percent of similarity between original and reconstructed signal.

$$SNR[db] = 10\log_{10}\frac{\sum_{i=1}^{N} X_o^2\,(i)}{\sum_{i=1}^{N}(X_o(i)-X_F(i))^2} \qquad (1)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_o(i)-X_F(i))^2 \qquad (2)$$

$$SNR[db] = \sqrt{\frac{\sum_{i=1}^{N}(X_o(i)-X_F(i))^2}{\sum_{i=1}^{N} X_o^2\,(i)}} \times 100 \qquad (3)$$

4. Simulation Results

Two simulations were conducted to validate performance of the proposed approach. The ECG records used for validation are collected from MIT-BIH arrhythmia database [12]. This database contains 48 ECG records of (30 min long). Only seven records (100, 103, 104, 105, 106, 115, and 215) are selected for validation which already selected by some existing methods to facilitate the comparison of findings results.

Graphical Evaluation: The first simulation was conducted by applying the proposed noise reduction approach on the single record with different levels of random noise (5, 10, 15, 20, and 25 dB). The original and noisy signals for each input SNR level are shown in Figure 3 as well as the clean signal obtained the proposed approach of noise reduction. Also, the SNR value of reconstructing signal due to different input SNR levels are shown in Figure 4.

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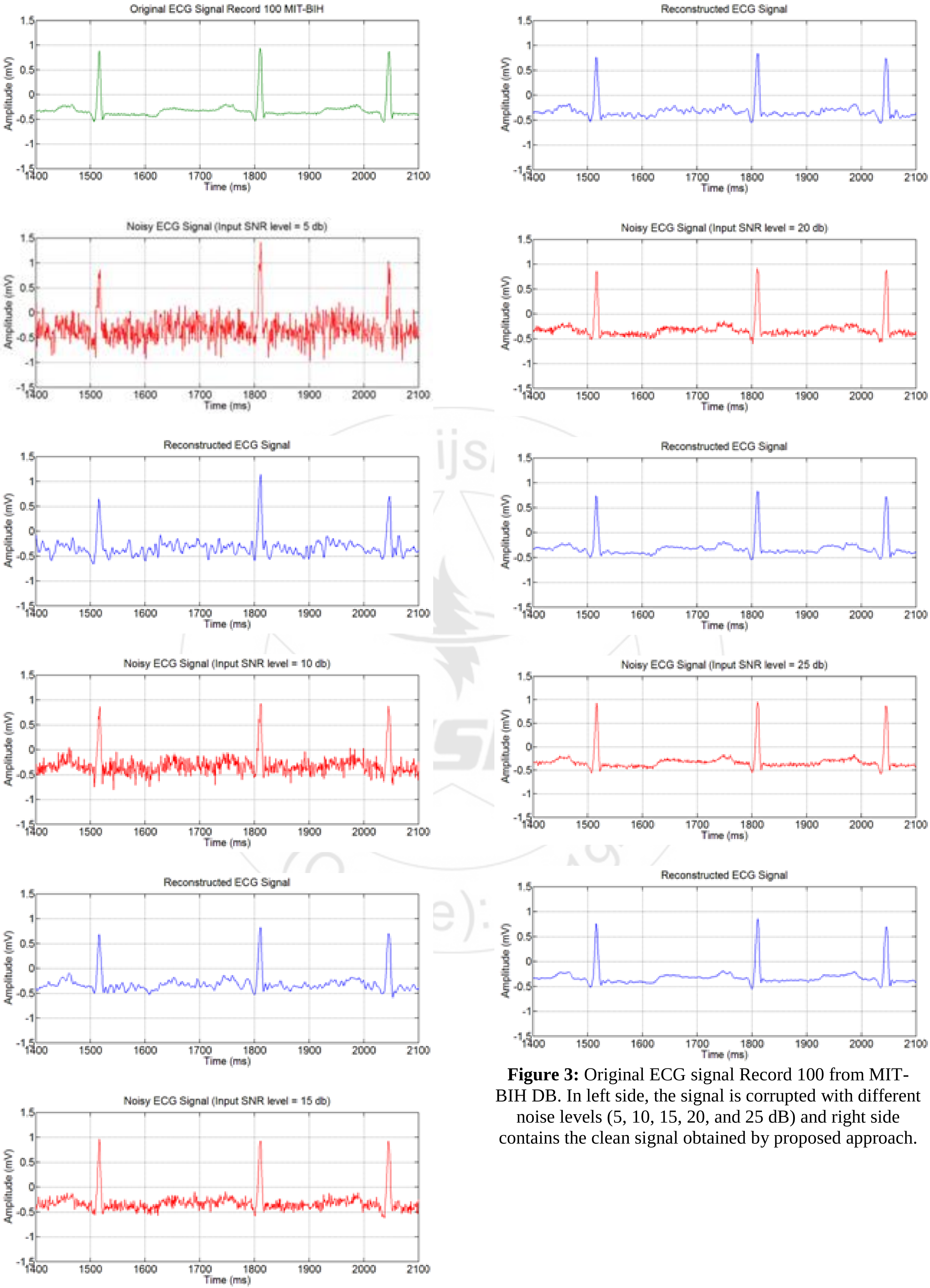

Figure 3: Original ECG signal Record 100 from MIT-BIH DB. In left side, the signal is corrupted with different noise levels (5, 10, 15, 20, and 25 dB) and right side contains the clean signal obtained by proposed approach.

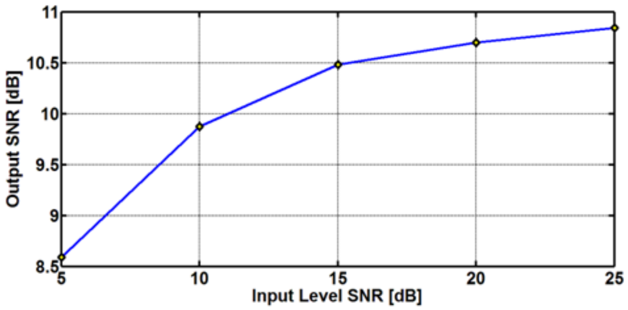

Figure 4: Relation between Input Level SNR[dB] and output SNR [dB]

Analytic Evaluation: The analytic evaluation of the proposed approach was performed by calculating MSE and PRD metric for all dataset which selected for validation. The validation results obtained with the proposed noise reduction approach and other five existing method that processed same datasets are given in table 1. The simulation results show that the proposed approach successes to reduce noise from the noisy ECG signals in high precision in comparison to the results of existing methods.

Table 1: Performance Comparison of standard noise reduction metrics (MSE, PRD) in seven ECG records from MIT-BIH DB

Method	Metric	ECG records of MIT-BIH DB						
		100	103	104	105	106	115	215
Proposed work	MSE PRD (%)	0.00087 37.56	0.0011 31.40	0.0018 35.06	0.00045 30.70	0.0019 27.55	0.0018 22.35	0.00062 43.36
EMD and WT [9]	MSE PRD (%)	0.0019 11.8	0.0024 12.5	0.0029 15.0	0.0032 13.8	0.00093 14.0	0.0024 8.0	0.0028 20.5
ICA test [16]	MSE PRD (%)	0.0026 13.5	0.0029 13.5	0.0036 17.2	0.0031 13.5	0.0012 12.3	0.003 9.5	0.0029 21.0
WT soft Th. [14]	MSE PRD (%)	0.026 13.9	0.003 14.0	0.0042 18.0	0.003 13.4	0.0013 14.0	0.0035 15.5	0.0029 21.0
EMD soft [17]	MSE PRD (%)	0.009 25.5	0.01 25.5	0.0141 32.75	0.0228 37.8	0.0356 25.5	0.0094 16.5	0.0105 39.85

5. Conclusion

In this study, a new approach of ECG signal noise reduction has been proposed. The new approach follows simple scaling operation that applied on the WT detail resolution of noisy signal along two levels using symlet wavelet filter with eight coefficients. The proposed approach successes to reduce largest percent of noise from all parts of ECG signal. Also, the new noise reduction approach is characterized by simple implementation, reliability for different SNR levels, and reconstructed signal with high accuracy. Simulation results of the standard metrics related to noise reduction show that the new approach performs more accurate outcomes in comparison with the existing methods of ECG signal noise reduction.

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