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FPGA – Based Electrocardiography Signal Analysis System using (FIR) Filter

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ABSTRACT

The cardiovascular attack is a more dangerous than other diseases and it is measured by ECG (Electro cardiograph) signals which is like a noisy signal in real time, especially in the field of telemedicine environment. The noisy ECG signals have more motion artifacts, electrical interference, etc. An adaptive filtering approach based on Discrete Wavelet Transform and an artificial neural network is proposed to reduce the noise in ECG signal. The quality of de-noised signal is improved by SVM algorithm. This suggested approach can successfully take out a broad scope of noise and our method achieve up to almost 82% improvement on the SNR of de-noised signals. The MATLAB simulation results shown clearly about the improvement of ECG signal with SNR value.

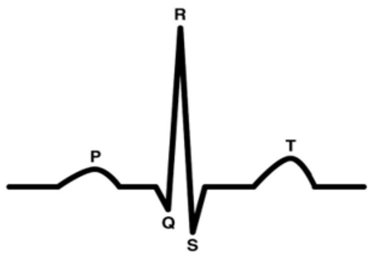
Keywords: *ECG; Signal to noise ratio; SVM algorithm; Discrete wavelet transforms.*

1.0 Introduction

Among the several health-threatening diseases, heart diseases have become a major public health issue with high mortality and distressful, which has placed a burden on the society. The ECG (ECG) signal is obtained from the human heart with rhythmic contractions. It presents the electrical action of heart muscles, and furnishes a really efficient means to detect heart diseases in clinical studies. With the assistance of today's technology, the telemedicine has gradually been given in hospitals, particularly in the application of remote ECG monitoring system [2] which allows to monitor patients' heart health in real time at home and to transfer sensor information to doctors at hospitals. The medical value refers to the characteristic information contained in the signal itself, which doctors can utilize to diagnose the health of the spirit. Thus, it is of great significance to de-noise the raw ECG signals.

ECG noise removal is very important for an accurate clinical diagnosis. At the present time, researchers are doing many researches in this ECG noise reduction part. The traditional approaches for ECG signal noise reduction include low-pass filters and filter banks [4] good enough for various noise.

Figure 1: Graphical Representation of ECG Signal



An adaptive filtering approach based on Discrete Wavelet Transform and an artificial neural network is proposed to reduce the noise in ECG signal. Presently, most of the neural network applications are centered along the ECG signal classification [4]. ECG signals are removed one by one, and the ''combined noise'' is considered and filtered. The final part closes the theme and discusses the management of future works.

The type of noise occurs in ECG signal is electrode motion, which is sensitive to current

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density and the waveform and frequency is dependent. The power line interference which has the diffraction and reflections. The white noise draws its name from white light, although light that appears white generally does not have a flat power spectral density over the visible band. The muscle contraction has the excitability, conductivity, contractility, extensibility, elasticity. The baseline, which has the approximate signals which satisfies segmentation properly.

2.0 Existing Methodologies

The noise reduction methods of ECG signals can be mainly divided into two categories: the traditional de-noising methods and the deep de-noising methods. The various filter method for ECG signal de-noising can be separated into as Kalman filter, FIR filter, IIR filter and filter banks. The methods of interference reduction is not fully considered to the local and global correlations of the ECG signals, and does not have good adaptability. The neural networks have been widely utilized in ECG de-noising. The proposed wavelet neural network (WNN) de-noising method, which combines the multi-resolution characteristic of the wavelet and the adaptive learning feature of the neural network [2].

Compared to this method the type of adaptive filtering technique based on wavelet transform is applied. During training, DWT is applied to break up the noisy ECG signal into wavelet coefficients. The Daubechies wavelet is one of the most commonly used orthogonal basis sets for discrete wavelet transform and has been successfully applied to the ECG signal feature extraction [4]. Once the wavelet transform coefficients are obtained, sub band thresholding is then executed on these coefficients. This thresholding step serves two purposes: it discards high frequency noise and also performs feature extraction of the ECG signal to provide the inputs to the neural net. As a consequence, there will be less unnecessary information from the neural network to process. During training, the neural network compares its output with a pre-recorded noise-free ECG signal and the error signal is used to update the weights of a neural network [4]. Comparatively the Fourier transform achieves the best SNR results. The Fourier transform can reveal the correlation of signals in the time and frequency domain, but the Fourier transform must analyze signals as a whole, therefore it cannot satisfy the requirements of real-time and local analysis of ECG signals. Though, the wavelet transform has good locality properties in both time and frequency domain, but it possesses no good adaptability. Later on the improvement adversarial method is more efficient [2].

2.1 Proposing method

In the proposed method we used the arrangement design for analyzing electrocardiography (ECG) signals. This methodology employs high pass least-square linear phase Adaptive Finite Impulse Response (FIR) filtering technique to filter out the baseline wander noise embedded in the input ECG signal to the system. The baseline wander is a low frequency signal and its configuration is more near to the line segment. The particular noise can be murdered in my future deeds. Feature extracted from DWT is applied to stand for the ripples. They are implemented in the Xilinx system generator (XSG) and it is coded in Verilog and simulated in Xilinx 14.5 tools.

3.0 Simulations

Using the MIT-BIH Arrhythmia Database as well as the MIT-BIH Noise Stress Test Database in Physio Bank as experimental datasets. We have chosen these three noises namely Electrode Motion Artifact (EM), Baseline Wander (BW) and Muscle Artifact (MA) noises are recorded from the MIT-BIH as noise data, presenting the three main characters of the ECG noise [2]. These discs are gathered up from volunteers by the professional ECG acquisition devices. The length of each record is 30 minutes and the sampling frequency is 360 Hz. As the ECG signal has a certain periodicity, it is appropriate to divide the signal record and use the signal in a heartbeat period as a training sample. Looking at the learning characteristics of the neural networks, the ECG signal samples are normalized by Min-Max normalization as follows:

$$\text{Normailsed } (x_k) = \frac{x_k - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where, it represents the maximum and the minimum values of *x* respectively [2]. In this paper [4] the five different types of noise are described and they are Baseline Wander (BW), Electrode Motion Artifact (EM), Muscle Contraction (MC), White Noise (WN), and 60 Hz Power-line Interference (PI).

The first three types of noise (i.e., baseline wander, electrode motion artifact, and muscle contraction) is obtained using a Holter recorder and standard electrodes for ambulatory ECG monitoring on a human subject. The remaining two noise data (i.e., white noise and power-line interference) are generated using MATLAB. After training, the next few samples (also with noise) can be used for testing.

3.1 Quality of signals and its outputs

Figure 2: Characteristics of ECG Signals

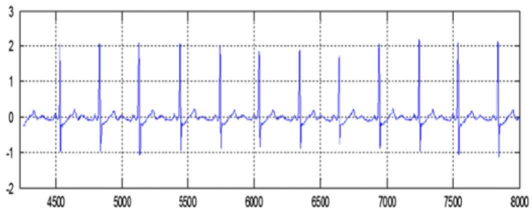


Figure 3: Denoising Results of PI in ECG Signals (a) Before Filtering (b) After Filtering

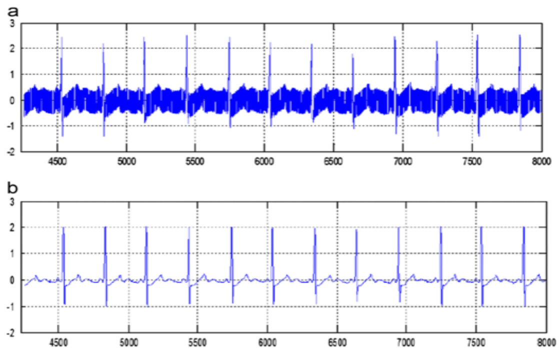


Figure 4: Denoising Results in ECG Signals for White Noise (a) Before Filtering (b) After Filtering

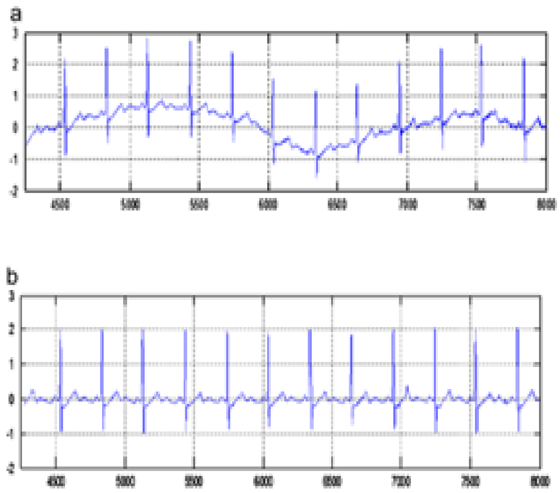


Figure 5: Denoising Results in ECG Signals in EM Noise (a) Before Filtering. (b) After Filtering

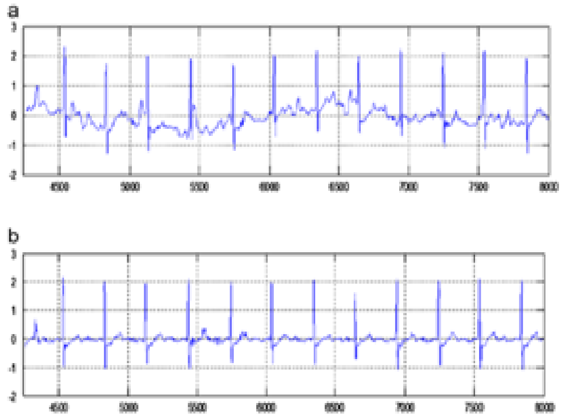


Figure 6: Denoising Results in Removing the EM&BW Noise. a) Noisy Signal b) Denoised Signal

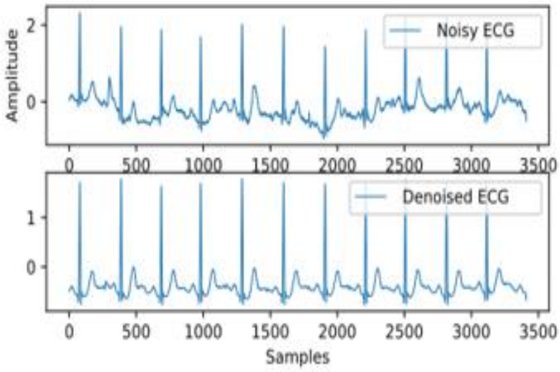
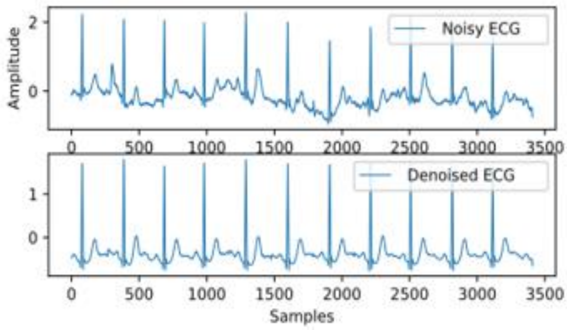


Figure 7: Denoising Results in Removing the EM&MA Noise. a) Noisy Signal b) Denoised Signal



4.0 Results and Discussions

In this survey, we found a fresh perspective on the adversarial method, i.e., the adversarial method has the ability to determine the remainder between the input and the yield. This causes the de-noising ECG signals with the adversarial method. An adversarial de-noising method of ECG signals is performed by our method which reduces the various cases of effective noise in ECG signals by a single adversarial model. This result verifies that the adversarial method has more power on generalization capability than other deep learning method [2] which gives an effective output of 82.12%. The other method which employs the pattern of a traditional filter group to get rid of noise from ECG signal. The four traditional filters employed in this report include a low-pass filter (with a cutoff frequency of 90 Hz), a high-pass filter (with a cutoff frequency of 0.5 Hz), a notch filter at 60 Hz (to remove power-line interference), and a fifth-order averaging filter to polish the overall sign. All four filters are connected in cascaded form. A SNR improvement of **6.52 dB** is obtained [4].

Table 1: SNR Values at Individual Stage

Noise	SNR (dB) post filter	SNR (dB) improvement
Traditional filter groups	16.24	6.52
DWT filtering	10.22	0.5
Proposed approach	25.43	15.72
Total	Pre filter = 9.72dB	Post filter = 6.52dB

Table 2: Denoising of BW Noise for Different SNR Levels [2]

SNR	Noise type	Original ECG	Noisy ECG	Denoised ECG	Improvement
0dB	BW	87.67%	85.96%	88.02%	**82.06%**
1.25dB	BW	84.56%	84.59%	87.86%	**83.27%**
5 DB	BW	84.96%	87.57%	88.61%	**81.04%**
Avg	**-**	**85.73%**	**86.04%**	**88.16%**	**82.12%**

5.0 Conclusions

Adversarial method has efficient output with respect to the appropriate time and frequency. Because we analyzed the results mentioned in the table and the consequences faced by the use of other techniques. The systematic examination of adversarial de-noising method of ECG signals, i.e., getting a high-quality of useful signals from the noisy ECG signals using the adversarial method. Consideration is based on the adversarial method, which accumulates knowledge on the data continuously and plays in between the generator and the discriminator. First, we have established a new view on the adversarial method to explain why it can be used for noise reduction. Secondly, a new loss function that acts as a more effective alternative for getting high quality signals. Thirdly, an adversarial de-noising method of ECG signals, which make total utilization of the generalization capability of the adversarial method and their simulations. Thus, the quality of signals assessed by the SVM algorithm.

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