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Extraction of Myopotentials in ECG Signal Using Median Filter via Adaptive Wavelet Weiner Filter

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Abstract: *One of the main problems in biomedical signal processing like electrocardiography is the parting of the wanted signal from dins caused by power line interference, body movements, inhalation and exhalation. Many types of digital filters are used to eradicate signal components from unwanted frequencies. It is difficult to apply for filters with fixed coefficients to reduce Biomedical Signal noises, because human behavior is not known depending on time. Adaptive filter technique is required to overcome this problem. In this paper type of adaptive and median filters are considered to decrease the ECG signal noises. Results of simulations in MATLAB are presented. Testing was performed on artificially noised signals. When creating an artificial interference, white Gaussian noise is used, whose power spectrum was modified according to a model of the power spectrum of an EMG signal.*

Keywords - *Broadband myopotentials (EMG) noise, ECG signal, Median Filter, Wavelet transform, Weiner filter.*

I. Introduction

Signal processing today is performed in the titanic majority of systems for ECG analysis and elucidation. The intention of ECG signal processing is manifold and comprises the improvement of measurement accuracy and reproducibility (when compared with manual measurements) and the extraction of information not readily available from the signal through pictorial assessment. In many situations, the ECG is recorded during ambulatory or energetic conditions such that the signal is corrupted by different types of noise, sometimes originating from another physiological. Hence, noise reduction represents another important objective of ECG signal processing; in fact, the waveforms is heavily screened by noise that their presence can only be revealed once appropriate signal processing has first been applied.

Electrocardiographic signals may be recorded on a long timescale (i.e., several days) for the purpose of identifying intermittently occurring disturbances in the heart beat. As a result, the produced ECG recording amounts to enormous data sizes that quickly fill up the available storage space. The Signals transmission across public telephone networks is another application in which large amounts of data are difficult. For all situations, data compression is an essential operation and consequently, represents another objective of ECG signal processing. Signal processing has subsidized expressively to a new understanding of the ECG and its dynamic properties as expressed by changes in rhythm and beat morphology. The biomedical signal processing field has advanced to the stage of practical application of signal processing and pattern analysis techniques for proficient and improved non-invasive diagnosis, online monitoring of critical patients, and rehabilitation, etc.

II. Signal Processing Of Ecg Signal

ECG signal is a graphical depiction of cardiac activity and it used to measure the various cardiac diseases and defects present in heart. ECG signals are poised of P wave, QRS complex, T wave and any deviance in these parameters indicate anomalies present in heart. The standard ECG signal is shown in Fig.1.

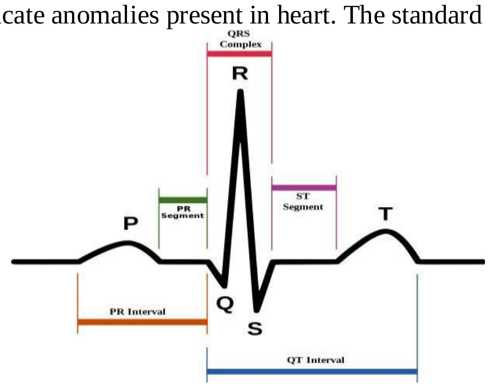

Fig-1: An standard ECG waveform

Electrocardiography (ECG) is the attainment of electrical activity of the heart captured over time by an external electrode attached to the skin. A typical plot of an ECG consist of the X-axis shows the time scale, each box (5mm) here corresponds to 20ms and the Y-axis shows the amplitude of the captured signal.
The first step in the design of an ECG system involves indulgent the nature of the signal that needs to be learned. The ECG signal be made up of of low amplitude voltages in the presence of high equipoises and noise. The large offsets are present in the system due to half-cell potential developed at the electrodes. Ag/AgCl (Silver-Silver chloride) is the common electrode used in ECG systems and has a maximum offset voltage of +/- 300Mv.

2.1 Noises in ECG

The main sources of noise in ECG are

1. Baseline wander (low frequency noise)
2. Power line interference (50Hz or 60Hz noise from power lines).
3. Muscle noise or myopotentials (It is difficult to confiscate as it is in the same as the actual signal).

III. Adaptive Wavelet Wiener Filter And Median Filter

3.1 Stationary Wavelet Transform (SWT)

The WT is a widespread and effective method for signal processing, since it delivers evidence not only about the frequency characteristics of the signal, but also about the time characteristics of the signal. It is about signal examination in the time-scale domain. The wavelet decomposition can be described as iterative signal disintegration, using filter banks of low-pass and high pass filters (organized in a tree) with down sampling of their outputs.

3.2 Wavelet Filtering Method (WF)

The simple Wavelet Filter is based on an proper regulation of wavelet coefficients in the wavelet domain [2]. With regard to the character of ECG wavelet coefficients, it is effective to isolate the interference and the signal via thresholding. Effective thresholding requires (1) threshold value and (2) thresholding methods.

3.3 Wavelet Wiener Filtering Method (WWF)

From the factor $y_m(n)$, to guesstimate the noise-free coefficients $u_m(n)$, using the WWF method, which is based on the Wiener filtering theory applied in the wavelet domain[7],[8]. The procedure is illustrated in Fig.2.

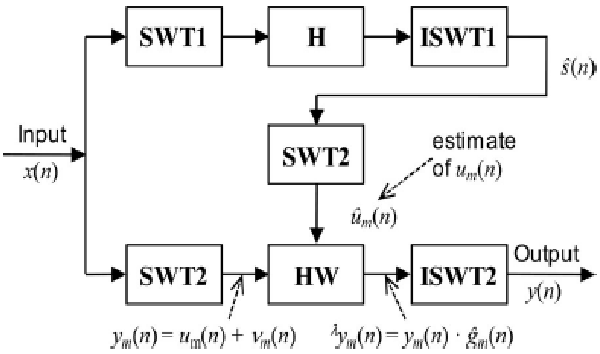

Fig-2: Block diagram of the WWF method.

The upper path is used to guesstimate the noise-free signal s(n); the lower path tools the Wiener filter in the wavelet domain. The upper path of the pattern consists of four blocks: the Wavelet Transform (SWT1), the alteration of the coefficients in block (H), the inverse wavelet transforms (ISWT1), and the wavelet transform (SWT2). The lower path of the scheme consists of three blocks: the wavelet transform (SWT2), the Wiener filter is used in the wavelet domain(HW), and the inverse wavelet transform (ISWT2).

3.4 Adaptive Wavelet Wiener Filtering Method (AWWF)

The most vital ones are the disintegration level of the WT, the thresholding method in the wavelet domain, and the wavelet filter banks used in the SWT1 and SWT2 transforms. The most important block is NE (Noise Estimate), where the SNR is estimated.

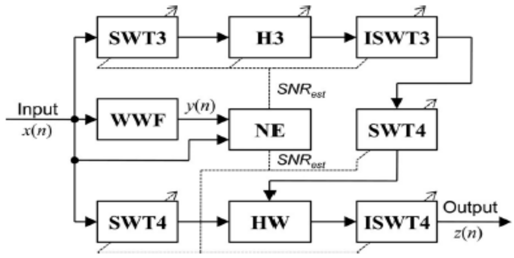

Fig-3: The AWWF method block diagram .

This block needs two inputs: the chief is the noisy signal x(n) and the jiffy is the estimate of the noise-free signal y(n) obtained by the WWF method with widespread parameters. The difference of these two signals gives an guesstimate of the input noise and the SNR can be calculated. The parameters in blocks SWT3, H3, ISWT3, SWT4 and IST4 are set up using the appraised SNR value.

3.5 Median Filter

The median filter is ordinarily used to ease noise in an image. The median filter cogitates apiece pixel in the image in turn and looks at its proximate neighbors to decide whether or not it is symbolic of its surroundings. Instead of simply supplanting the pixel value with the mean of neighboring pixel values, it supplants it with the median of those values. The median is designed by first sorting all the pixel values from the contiguous neighborhood into numerical order and then replacing the pixel being deliberated with the middle pixel value.

3.6 Algorithm for Proposed Technology

The Proposed Algorithm is précised as follows:
Step 1: Create a noise-free ECG signal.
Step 2: Add the white gaussian noise as artificial interference. The goal of the algorithm is to confiscate the EMG (muscle) noise.
Step 3: Engendering the artificial noise must have similar power range as the muscle noise.
Step 4: Customary the input signal to noise ratio (SNR) from -5 to 55 db.
Step 5: Change the decomposition level of the WT, the thresholding technique in wavelet domain, the threshold multiplier and wavelet filter bank used in SWT1 and SWT2.
Step 6: Reckon the noise estimate (ne).
Step 7: The threshold multiplier varies the standard deviation.
Step 8: Finally, estimate the signal to noise ratio for the output.

IV. Results

4.1 Input Signal:

The ECG records the electrical commotion of the heart, where each heart beat is revealed as a series of electrical waves characterized by peaks and valleys. Any ECG gives two kinds of information. The duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or slow or irregular and the amount of electrical activity passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked. ECG signal is created with length of 640. It is shown in fig.4.

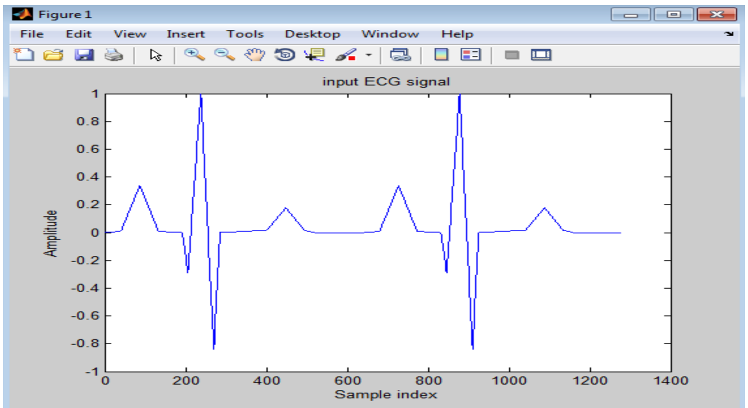

Fig-4: Input ECG Signal

4.2 Noise Added ECG Signal:

Add a known noise to ECG signal, then badge it through your algorithm to get a denoised signal, then associate between original signal and denoised signal and look at performance parameter (SNR). White Gaussian Noise is added as the interference signal. It is displayed in fig.5.

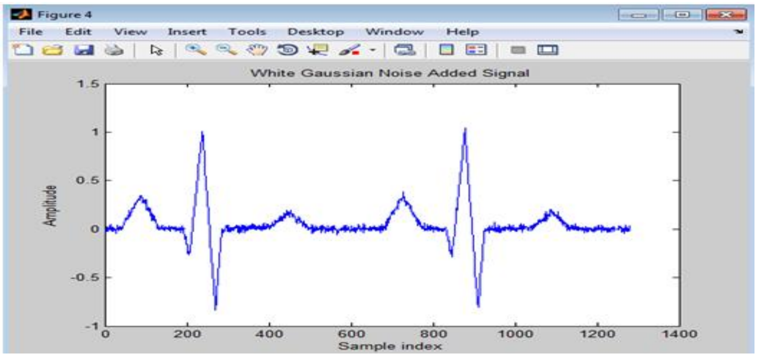

Fig-5: Noise added ECG Signal

4.3 WF Filtered ECG Signal:

Wiener filter use the arithmetic individualities for noise removing process like reference signal or secondary recorded ECG signal. It can change its factor to get the optimal results, so then it is also called as optimal filter, Wiener filter theory provides for finest filtering by taking into account the statistical characteristics of the signal and noise processes. The filter parameters are heightened with reference to a performance condition, the output is guaranteed to be the best achievable result under the circumstances imposed and the information provided. The Noise signal is removed using the WF method is shown in fig.6.

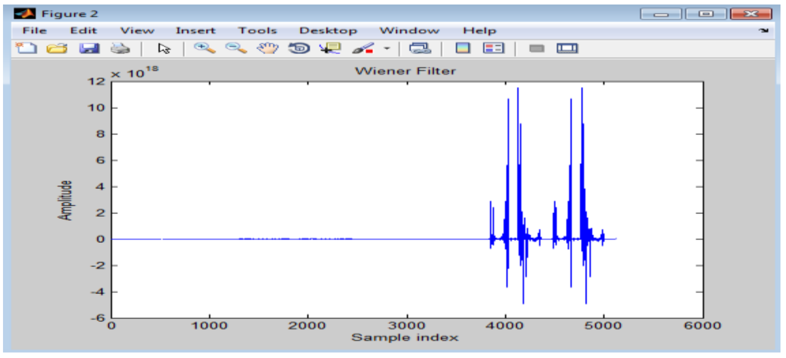

Fig-6: WF Filtered ECG Signal

4.4 WWF Filtered ECG Signal:

The technique of WWF method for de-noising contains two steps and can be described as follows: Stage 1: The signal-noise mixture is putrefied in wavelet domain; the wavelet coefficients are shrinked using wavelet domain filter; the "pilot estimate" of the signal is calculated by inverse wavelet transform of the shrinked wavelet coefficients and finally the coefficients estimate in wavelet domain is obtained. Stage 2: The wavelet coefficients of the signal-noise concoction in domain and their estimate obtained in Stage 1 are used to design an optimal in MSE sense Wiener Filter. The Noise signal is removed using the WWF method is shown in fig.7.

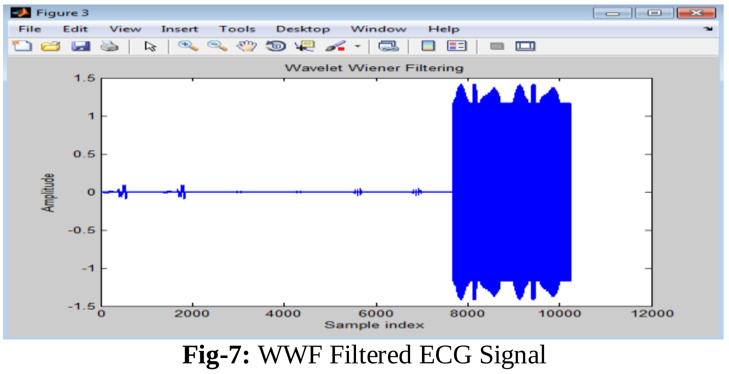

Fig-7: WWF Filtered ECG Signal

4.5 AWWF Filtered ECG Signal:

Adaptive Wavelet Weiner filters are self-designing filters founded on an algorithm which allows the filter to “learn” the initial input information and to trajectory them, if they are time varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal, it considers adaptive impulse correlated filter which requires the signal and a reference input. The least mean square algorithm is used to change the weights of this filter in order to minimize the error and evaluate the deterministic component through filter output. The white Gaussian noise signal is removed using the Adaptive Wavelet Weiner Filtering (AWWF). The final output is shown in fig.8.

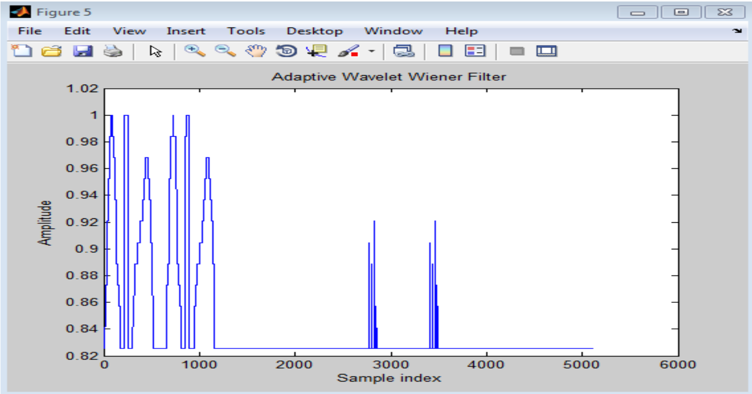

Fig-8: AWWF Filtered ECG Signal

4.6.1 Median Filtered ECG Signal

The foremost idea of the median filter is to track through the signal entry by entry, switching each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most apparent window is just the first few foregoing and following entries, whereas for 2D (or higher-dimensional) signals. Purpose of digital median filter is smoothing signals by taking the median of odd number of uninterrupted sampling points. The median filter thus uses both previous and forthcoming values for predicting the current point. The filtered ECG signal using Median Filter is shown in fig.9.

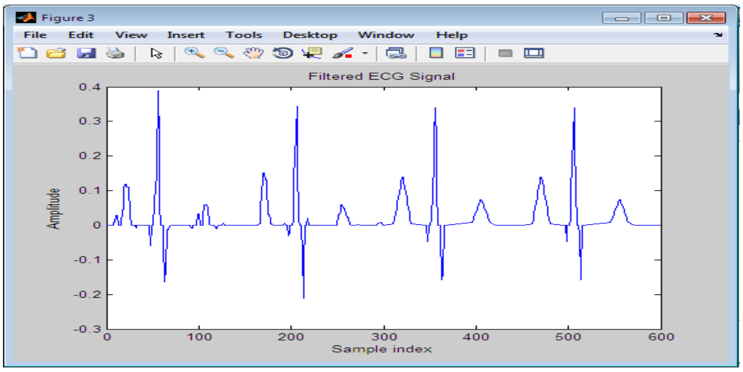

Fig-9: Median Filtered ECG Signal

4.7 Filter Performance

Filter performance is clarified using the Signal to Noise Ratio (SNR). SNR is defined as the proportion of signal power to the noise power, often expressed in decibels. Low SNR causes slow connection or dropped connection due to interference or weak signal power. The various filter performance with respect to SNR is shown in fig.10.

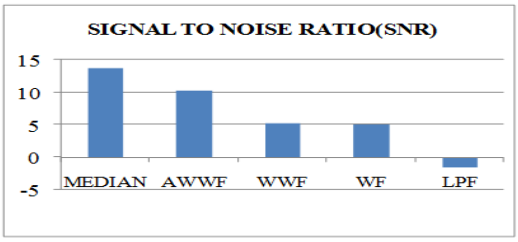

Fig-10: Filter Performance in terms of SNR

4.8 Myopotential Reduction Indices

Myopotential inhibition during permanent pacing with unipolar leads is a well-recognized medical problem. The reduction of myopotentials by Median Filter method is better when compared to the other methods. The Myopotential reduction indices are shown in the table I.

Table-1: Performance Metrics of Different Method

S.NO	PARAMETER USED	SNR(dB)
1	MF Method	13.7
2	AWWF Method	10.3
3	WWF Method	5.2
4	WF Method	5.1
5	LPF Method	-1.6

V. Conclusion

The proposed Median and AWWF algorithm affords better filtering results than another tested algorithm. The Proposed algorithm is adaptive in two ways. The first alteration lies in the division of the signal into individual fragments, each with about constant level of noise. The second alteration is within individual fragments. The proposed method runs signal to noise ratio of 13.7 dB. The future augmentation is to design filter which provide high signal to noise ratio (SNR) compared to others Method.

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