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Research Article

Denoising of ECG signals using Non Local Means Filtering Technique

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Abstract

Electrocardiogram (ECG) is an important biomedical signal for analyzing heart activity. Analysis of ECG becomes difficult if noise is augmented with the signal during acquisition. During recent years, several denoising techniques were analyzed within the field of signal processing. In this paper, non local means (NLM) filtering technique is explored for denoising the ECG signal. The noisy ECG signal is synthesized by adding pulse signals and is then denoised at different levels by optimizing various NLM parameters. The experimental results showed that the proposed technique successfully denoised the noisy ECG signals by selecting appropriate input NLM parameters. Finally, the signal to noise ratio (SNR) and mean square error (MSE) were also evaluated.

Keywords: *Non local means, ECG, denoising, filter, biomedical signals, peak signal to noise ratio, mean square error.*

1. Introduction

The medical state of the heart is determined by the shape of the Electrocardiogram, which contains important pointers to different types of diseases afflicting the heart (J.T.Catalano, 2002). However, the electrocardiogram signals are irregular in nature and occur randomly at different time intervals during a day. This arises the need for continuous monitoring of the ECG signals, which by nature are complex to comprehend and hence there is a possibility of the analyst missing vital information which can be crucial in determining the nature of the disease. Thus computer based automated analysis is recommended for early and accurate diagnosis (J. Moss *et al*, 1996) The ECG waveform is shown in the Fig. 1.

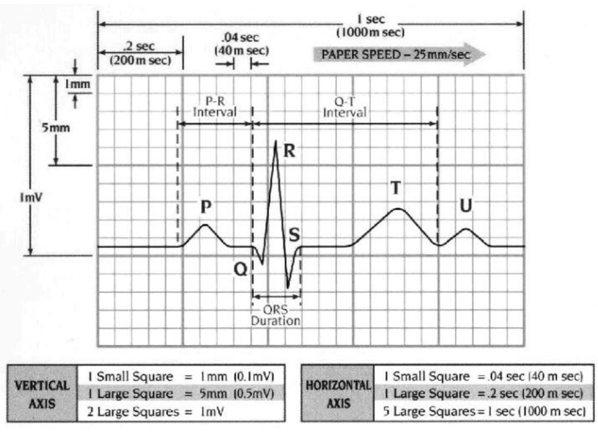

Fig. 1 Basic ECG signal and their parameters

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The ECG waveform can be broken down into three important parts each denoting a peak on the either side represented by P, QRS, T, each of them represent a vital processes in the heart. The ECG signal is typically in the range of 2 mV and requires a recording bandwidth of 0.1 to 120 Hz. ECG system contains 12 leads. Six limb leads (Lead I, Lead II, Lead III, aVr, aVL and aVf) and six Precordial leads (V1, V2, V3, V4, V5 and V6). Each limb lead shows information about different areas of the left ventricle. Lead I, Lead II, and Lead III are bipolar leads and aVr, aVL, aVf are unipolar leads. Precordial leads also called chest leads and they are unipolar leads. Unipolar leads use the heart's centre as negative pole. The ECG is acquired by a non-invasive technique, i.e. placing electrodes at standardised locations (between intercostal rib space of sternum) on the skin of the patient (P. E. McSharry *et al*, 2003). In case of a disease afflicting the heart, the waves get distorted according to the area which is not functioning normally. The amplitude and duration of the P-QRS-T-U wave contains useful information about the nature of disease related to heart. In bradycardia less P-QRS-T-U waves occur in one minute recording than normal and in tachycardia more P-QRS-T-U waves occur. U wave occur in rare case, normally P-QRS-T waves occur. P wave represent Atrial depolarization, QRS represent both atrial repolarization and ventricles depolarization, and T wave represents repolarization of ventricles. Waveform produced by the heart's electrical current are recorder on graph paper by the heated stylus. ECG paper consists of vertical and horizontal lines that form a grid. Grid allows measurement of the size and frequency of wave complexes for comparison to normal ranges. The horizontal axis of the ECG represents time (Acharya *et al*,2002). The amplitude of the wave is determined by counting the number of small blocks from the baseline.

Abnormal waveforms could indicate problems with the monitor. Artifacts may result from excessive movement such as patient is experiences chill, anxiety or seizures. Other cause of abnormal waveform may be improper application of electrodes, short circuit in the cable, electrical interference from other equipment in the room, static electricity from inadequate room humidity. Weak signal may result from improper electrode application (E. N. Bruce, 2001). It occur if the QRS complex too small to register or cable failure. Wandering baseline problem occur if electrodes are positioned over bone or if patient is restless. It may reflect chest wall movement during respiration. Fuzzy baseline problem occur due to electrical interference from other equipment and if the patient bed is improperly grounded. No waveform can result from disconnected electrode, dry electrode gel, cable failure and improper electrode placement. Accurate analysis of ECG signals becomes difficult if it is corrupted by noise during acquisition. Thus, noise removal becomes an essential part in ECG preprocessing for better performance in ECG analysis and characterization. Many denoising techniques have been reported in the literature for ECG denoising such as adaptive filtering (C. H. Chang *et al*, 2010). statistical techniques like independent component analysis (D. L. Donoho, 1995). fuzzy multiwavelet denoising (S. Arya *et al*, 2012). and wavelet denoising. The wavelet based technique is more popular and shows better performance than the earlier methods (B.N. Singh *et al*, 2006). Daubechies-4 (dB4) wavelet with soft thresholding shows the best performance among all wavelet families. Wavelet transform have been widely used for denoising of ECG signal because of its ability to characterize time frequency information where two types of thresholding are used to enhance the ECG signal.

In this paper, a method for ECG denoising based on non local means filtering is proposed, where noisy signal are automatically determined based on selected parameters. The idea is to clean up the signal, and then set some dynamic threshold, so that any signal crossing the threshold is considered a peak. The results are evaluated and analysed. This paper is organized as follows. Section II gives the theoretical background on non-local means filtering. Section III explains the proposed method and Section IV shows the results and discussions. Finally the conclusion is given in section V.

2. Non local means filtering

Non local means (NLM) filtering also knows as statistical neighborhood filter and was first introduced by (Buades *et al*, 2005). The objective of this filtering technique is to fix the problems associated with local smoothing filters by calculating the smoothed value as a weighted average of other values in the time series based upon the similarity between the neighborhoods around the time series values (G. G. Casas *et al*, 2013) (P. Couple *et al*, 2007)(V. Duval *et al*, 2011). Non-local means has primarily been used for image processing, but it has been mentioned in a 1D context in several papers (G. G. Casas *et al*, 2013)(B. Tracey *et al*, 2012)(S. Zoican, 2010). We use a modification of this algorithm for efficient 3D medical image processing by (Coup´e *et al*,2007). In the non-local means algorithm, smoothed values are given by

$$S_i = \sum_{j \in N} w(i,j) y_j$$

where the weights are given by the function

$$w(i,j) = \frac{1}{z_i} e^{-\frac{|Y_i - Y_j|^2}{2\beta\sigma_n^2|Y|}}$$

where vector Y_i is an intensity value in the neighborhood, around y_i, $|Y_i - Y_j|$ is the difference in intensity values during the proposed interval, $|Y|$ is the sample size, and β is a parameter chosen by the analyst to control the amount of smoothing. According to (Coup´e *et al*. 2007), β varies between 0.0 and 1.0, with values of β closer to 1.0 better for high levels of noise and values of β closer to 0.5 better for lower levels of noise.

(Duval *et al*.2011) notes that neighborhood pre-selection can improve the results of the non-local means algorithm by assigning a weight of 0 to the y_j values that have neighborhoods that are too dissimilar to the neighborhood, Y_i, under consideration. Duval *et al*. uses a pre-selection test based upon the norm of the difference between neighborhoods. A more complex preselection method is described by (Buades *et al*, 2005). We use Duval *et al*.'s preselection test:

$$w(i,j) = \begin{cases} \frac{1}{z_i} e^{-\frac{|Y_i - Y_j|^2}{2\beta\sigma_n^2|Y|}} & |Y_i - Y_j| < T \\ 0 & \text{otherwise} \end{cases}$$

(Duval *et al*. 2011), suggests that values of T near 20 or 30 work well for 2D images. This threshold does make sense for denosing time series. We will consider thresholds of the type $T = \delta(\max Y_j - \min Y_j)|Y|$, where $\delta \in [0.0,1.0]$. This threshold is a percentage of an approximation of the maximum intensity interval distance. Duval *et al*. recommends window sizes of 5 or 7 for 2D image processing. As before, it is uncertain if these results translate to 1D time series denoising. In this algorithm, the analyst can control the amount of smoothing via *β*, the preselection parameter δ, the window size, and the portion of the time series that is compared.

3. Methodology

In this work, ECG signal is synthesized by setting and optimizing different parameters. For creating ECG signal, time series elements were synthesized that contain features similar to those in real world data. The proposed noise removal method using non local means technique is illustrated by a flow chart as in Fig. 2. The noisy signal s(t) is introduced in the synthesized ECG signal as *s(t)= x(t)+n(t)* where *x(t)* is the original ECG and *n(t)* is the noise signal. The added noise signal is a pulse signal with 10 dB signal power.

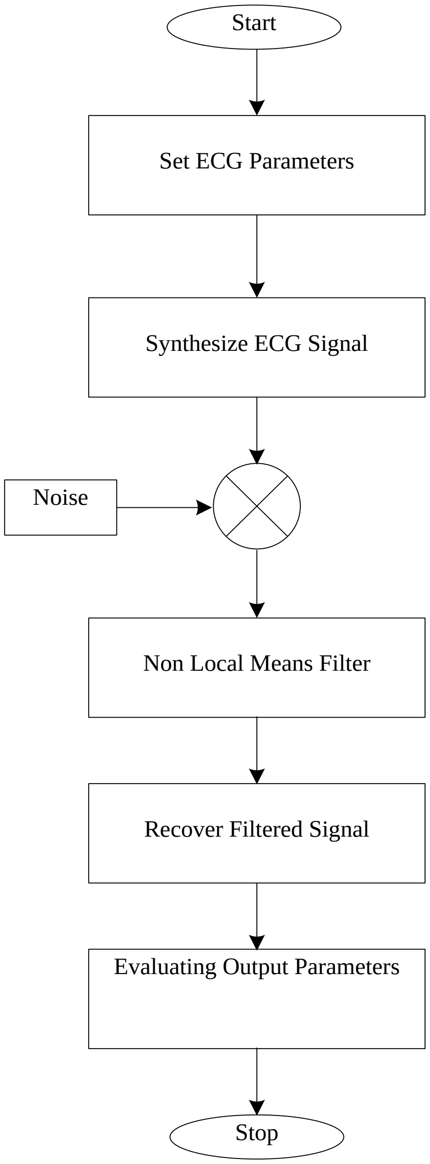

Fig. 2 Flow chart sowing experimental steps followed in a sequential manner

The noisy input signal is then processed by a non local means filter that automatically adjusts its own impulse response through a least-squares algorithm. In this experiment the size of the small features in samples were varied in between 1 to 20. Also, the neighborhood search width was set in-between 700 and 1000. The bandwidth was adjusted at 60%. The objective is to produce an output signal that is a best fit in the required domain to smooth the signal. This is accomplished by optimizing the maximum search distance and adjusting the filter through the proposed algorithm to minimize the total signal power. Theoretically, non-local means should work better on longer time series. An area of future research would be to consider this stability analysis on significantly longer time series. It is known that the computation time is much longer and the pre-selection is much more significant for non-local means on large time series.

4. Results and Discussions

In our simulation, we employ non-local means filtering technique for analyzing and denoising ECG signals. In this, a single ECG signal is synthesized by selecting and optimizing different parameters as shown in Fig 3.

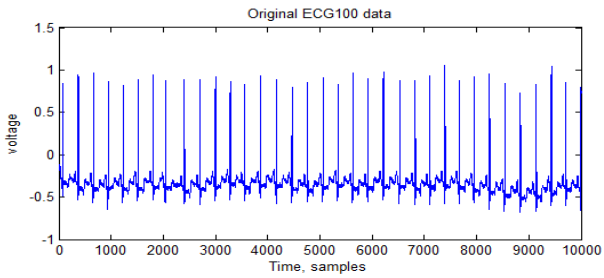

Fig. 3 Original synthesized ECG signal.

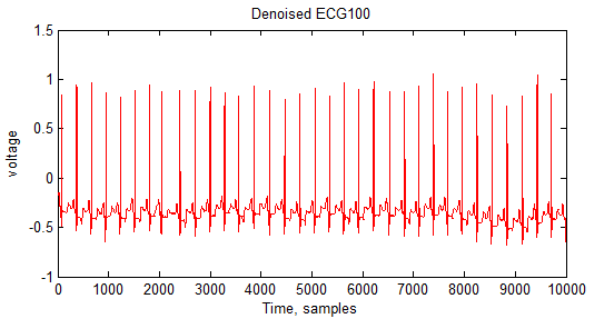

Fig. 4 Original ECG signal after denoising

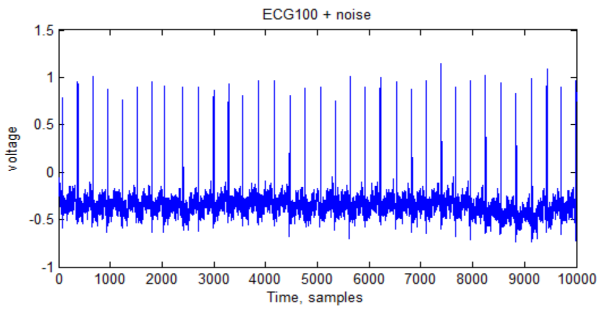

Fig. 5 Original ECG signal added with noise

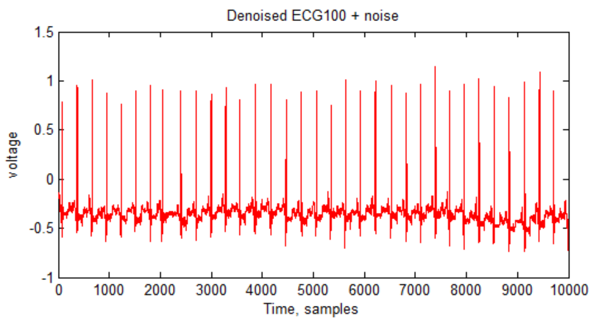

Fig. 6 Denoised ECG signal with P=100.

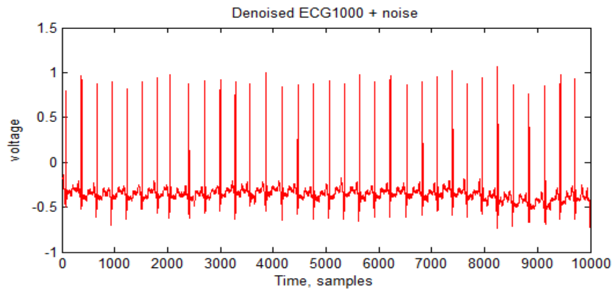

Fig. 7 Denoised ECG signal with P=1000.

Table 1 Comparison of PSNR and MSE

Comparison between signals	Peak Signal to Noise Ratio (PSNR) dB			Mean Square Error (MSE) %		
	R	G	B	R	G	B
Original and denoised ECG signal with P=100	44.73	39.34	34.99	2.20	7.63	20.76
Original and denoised ECG signal with P=1000	44.73	39.34	34.99	2.20	7.63	20.76
Noisy and denoised ECG signal with P=100	45.77	40.02	34.42	1.73	6.52	23.64
Noisy and denoised ECG signal with P=1000	45.94	40.31	34.83	1.67	6.09	21.52

The testing was initiated by applying the proposed algorithm to an original signal. The results showed that the original signal and the denoised signal as shown in Fig. 4 are more or less same. After that, noise was introduced into the original signal as show in Fig. 5. After adding noise, the signal is to be filtered. The noisy signal was then filtered out by selecting different NLM parameters. In first case, the neighborhood search width, P was selected to be at 100 while size of smallest feature in a sample was selected to be 5. The resultant filtered signal obtained is shown in Fig 6. Similarly, the same noisy signal is then again filtered out by selecting the neighborhood search width, P = 1000 while size of smallest feature in a sample was selected to be 10. In this case, filtered signal obtained is shown in Fig. 7. The obtained results were then compared by evaluating their peak signal to noise ratio (PSNR) and mean square error (MSE) as shown in table 1.

Conclusions

A non local means based filtering method is proposed in this work. The results show that the NLM based filtering technique is effective but little time consuming. It is possible to remove noise upto the satisfactory level by optimizing NLM parameters. However if we keep on increasing the bandwidth, the resultant denoised signals will gets saturated. Non-local means offers a consistent improvement in SNR, and the parameter β has an important impact on the performance of non-local means. In our future work, different types of noises will be considered in the experiments for parameter settings. Non-local means should theoretically perform better with longer time series, where more matching neighbourhoods are possible. This possibility will also remain under investigation in future.

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