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ECG Signal Denoising With Non Local Means Filter

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Abstract: Electrocardiogram (ECG) is an important biomedical signal for analysing electrical activity of the heart during its contraction and expansion. Analysis of ECG becomes difficult if noise is augmented with the signal during acquisition. During recent years, several denoising techniques were analysed within the field of signal processing. In this paper, non-local means (NLM) filtering technique is explored for denoising the ECG signal and results are developed using Matlab coding. Non local means (NLM) uses concept of self-similarity. Due to the nature of the algorithm, the most favourable case for the NLM is the periodic case, like signals, a straight edge, curved edge, texture images and a complete line of pixels with a similar configuration. The noisy ECG signals are synthesized by adding pulse signals and are 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 power signal to noise ratio (PSNR) and mean square error (MSE) were also evaluated.

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

I. INTRODUCTION

Electrocardiogram (ECG) is a graphic recording of the flow of electrical current through the heart and it shows the medical state of heart. ECG contains important pointers to different types of diseases afflicting the heart. It is one of the important tools used by medical practitioner to examine the pathological and physiological condition of the heart. The electrocardiogram signals are irregular in nature and occur randomly at different time intervals during a day. This need for continuous monitoring 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 disease. Thus computer based automated analysis is recommended for early and accurate diagnosis (J. Moss et al, 1996). Fig. 1 shows the ECG with respect time obtained during one complete cardiac cycle.

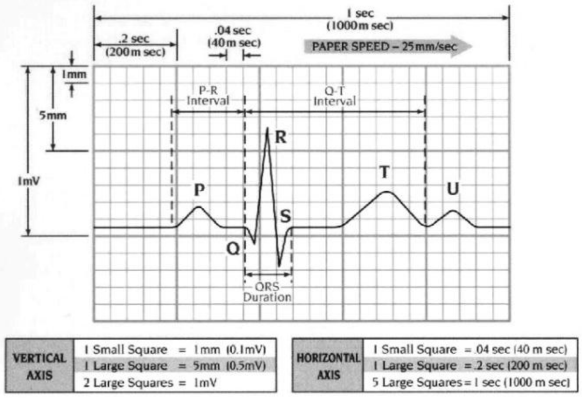

Fig.1 Complete cardiac cycle for one heart beat

This cycle is repeated with every heartbeat. The Heart is a very unique four-chambered pump and it has the ability to create electrical impulses on its own without any outside influences that provides the driving force for the circulation of blood in whole body. The electrical impulse begins at the pacemaker of heart, which we call the SA node. Then the impulse travels through the atria to the AV node, and then down through the ventricles, causing the heart to beat in a rhythmic and predictable way. With each heart beat the synchronized depolarization spreading through the heart and establish field potentials over the whole body. These potential differences can be detected by electrodes placed on the body's surface. The pattern of the ECG varies according to the electrodes position but certain features are always present. These features were labelled as PQRST by Einthoven. 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 Precordials lead (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 standardized locations (between intercostals rib spaces of sternum) on

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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 repolarisation and ventricles depolarization, and T wave represents repolarisation of ventricles (J. Moss et al 1996)

II. NON LOCAL MEANS (NLM)

Non local means (NLM) filtering also knows as statistical neighbourhood filter and was first introduced by (Buades et al, 2005). Their work has attracted over 1000 citations and many extensions of the original algorithm have been proposed Non local means (NLM), uses concept of Self-Similarity. Due to the nature of the algorithm, the most favourable case for the NLM is the periodic case, like signals, a straight edge, curved edge, texture images and a complete line of pixels with a similar configuration. 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 neighbourhoods around the time series value. NLM is an edge preserving denoising method. NLM filter consider the average of pixels which have higher similarity, instead of closer one. On the other hand, due to the computational complexity, the similarity is not calculated between any two pixels on the whole domain, but within a searching window, hence the term is "non local" and not "global".
In the non-local means algorithm, smoothed values are given by

$$S_i = \sum_{j \in N} w(i,j)\, y_j \qquad (1)$$

Where the weights are given by the function

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

Where vector Yi is an intensity value in the neighbourhood, around y_i, |Yi −Yj| 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's 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 neighbourhood 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 neighbourhoods that are too dissimilar to the neighbourhood, Yi under consideration. Duval et al. uses a pre-selection test based upon the norm of the difference between neighbourhoods. A more complex preselection method is described by (Buades et al, 2005). We use Duval et al.'s preselection test:

$$w(i,j) = \begin{cases} \frac{1}{z_i} e^{-\frac{|Y_i - Y_j|^2}{2\beta\sigma_n^2 |Y|}} & |Y_i - Y_j| < T \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

(Duval et al. 2011), suggests that values of T near 20 or 30 work well for 2D images. This threshold does make sense for denoising time series. We will consider thresholds of the type T = δ(maxYj−minYj)|Y|, where δ ∈ [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 5x5 or 7x7 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.

III. METHODOLOGY

In this work, three ECG signals are synthesized by setting and optimizing different parameters. For creating ECG signals, time series elements are 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 synthesized as s(t)= x(t)+n(t) where x(t) is the original ECG and n(t) is the noise signal. The added noise signals are pulse signals with 5 dB, 10dB, 15dB, 20dB and 25dB signal power.

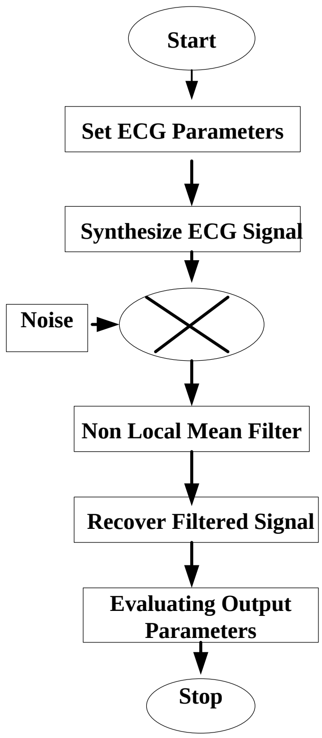

Fig. 2 Flow chart showing experimental steps followed in a sequential manner

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Here, we examine parameter selection for ECG denoising. The key NLM parameters are the patch size, specified as a half-width P (so $L\Delta = 2P + 1$), the size of N(s), specified as a half-width M, and the bandwidth λ. The bandwidth λ is a key parameter that controls the amount of smoothing applied. An overly small λ will cause noise fluctuations to have too much influence in the weighting different patches and resulting in insufficient averaging; an overly large λ will cause dissimilar patches to appear similar, resulting in blur. (Ville et al, 2011) used the sure criterion for parameter selection and noted that for their test set, a good overall choice of lambda is 0.5 σ, where σ is the noise standard deviation. The patch half-width P selects the scale on which patches are compared, and should generally be similar to the size of features of interest. For ECG signals, a reasonable choice for P is the half-width of the high-amplitude "R" ECG complex. (Brian Tracey et al, 2012) say that increasing the neighbourhood half-width M (resulting in a "less local" search) should lead to better performance. However, a larger search window maps directly to increased computation, even in the case of the fast algorithms. For ECG denoising of the QRS complex, setting M large enough to include multiple heartbeats allows multiple QRS regions with potentially similar morphology to be compared. Note that the shape of high-amplitude QRS regions is naturally protected, as differences between even visually similar peaks are typically large, resulting in low weights and thus little smoothing of these regions.

IV. RESULT AND DISCUSSION

For simulations, ECG signals were 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 pulse signals with different SNR levels were added to achieve target mean square error (MSE) and Power signal-to-noise ratio (PSNR) levels. The testing was initiated by applying the proposed algorithm to three original ECG100, ECG101, and ECG102 signals. After that, signals with 5dB, 10dB, 15dB, 20dB and 25dB noise were introduced into the original signals. The original ECG102 and the denoised ECG102 signals are shown in figure 3 and figure 4 respectively.

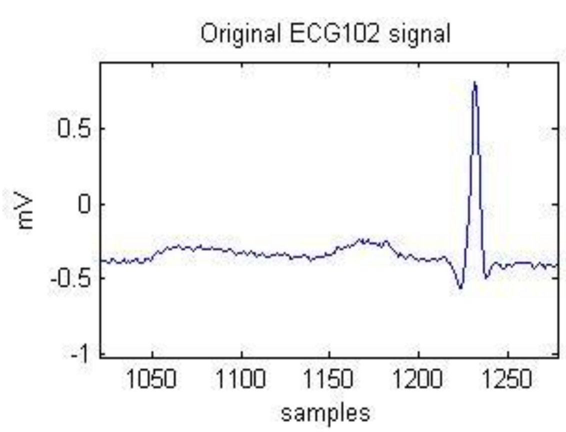

Fig. 3 Original synthesized ECG signal

The original signal with 20 dB added noise is shown in figure 5. After adding noise, the noisy signal was filtered out by selecting different NLM parameters and is shown in figure 6. Table.1 shows the calculated MSE and PSNR for different input SNR levels, with $\lambda = 0.7\sigma$, patch half-width P=10 and the neighbourhood search width M=5000. Column diagrams for MSE and PSNR are shown in figure 7 and figure 8.

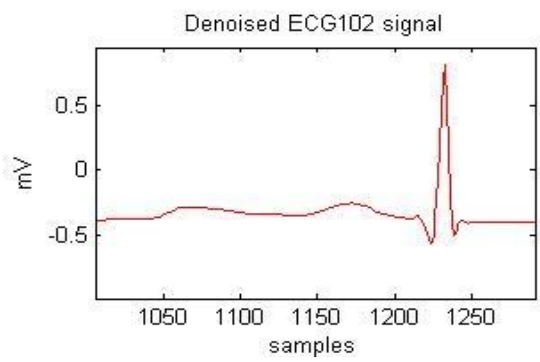

Fig. 4 Original ECG signal after denoising

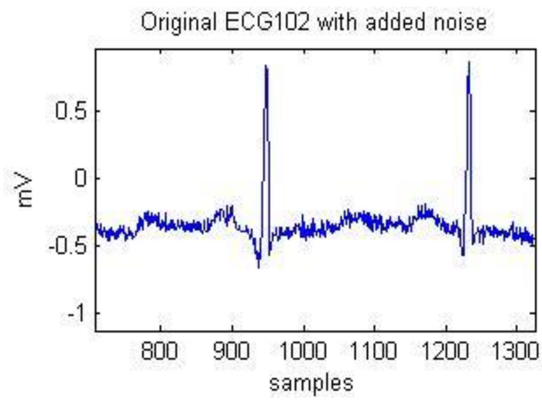

Fig. 5 Original signal with 20dB added SNR

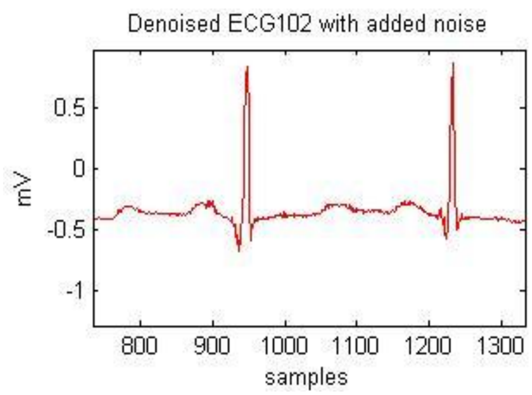

Fig. 6 Denoised signal after 20dB added SNR

From figure 3 to figure 6 we observe that NLM denoise the original and signal with 20dB added noise signal successfully and meet the target values. NLM preserve the edges very efficiently and remove the noise effectively. If we compare figure 3 & figure 4, we see that NLM does not affect the P, Q, R, S and T waves amplitude and shape but it remove the noise properly, similarly we can see this when we compare the figure 5 and figure 6.

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TABLE 1 MSE AND PSNR FOR DIFFERENT NOISE LEVELS

Mean Square Error & Power Signal to Noise Ratio for NLM						
SNR	MSE			PSNR		
LEVEL	ECG100	ECG101	ECG102	ECG100	ECG101	ECG102
5dB	0.00744	0.00761	0.00746	69.4507	69.3607	69.4376
10dB	0.00914	0.00907	0.00905	68.4917	68.5899	68.5991
15dB	0.01059	0.0103	0.01048	67.9171	68.0351	67.9619
20dB	0.01162	0.01141	0.01157	67.5142	67.5906	67.5316
25dB	0.01287	0.01274	0.01276	67.0688	67.1133	67.1076

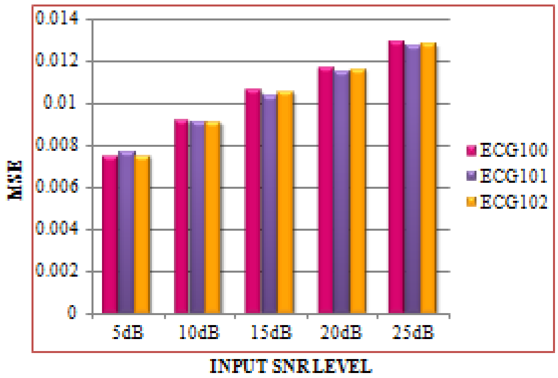

Fig. 7 MSE for different signals for different noise levels

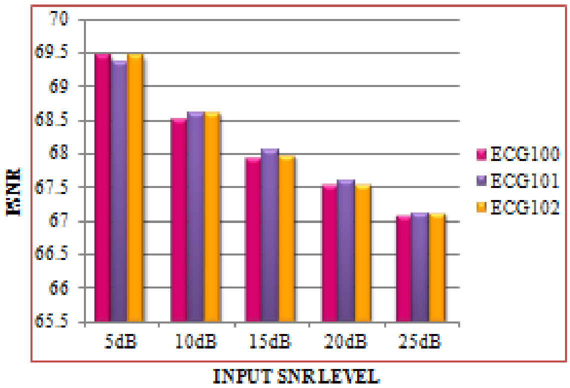

Fig. 8 PSNR for different signals for different noise levels

Figure 7 and figure 8 shows the variation in PSNR and MSE for three different signals with different input SNR levels. Figure 7 and figure 8 shows that MSE increases and PSNR decreases when we move from 5 dB level to 25 dB noise level for all test signals.

V. CONCLUSION

In this paper we have demonstrated non local means based filtering algorithm to denoise the ECG signals, this technique is effective but little time consuming. It is possible to remove noise up to the satisfactory level without reducing the actual signal strength by optimizing NLM parameters. Our present work shows the effect of MSE and PSNR with respect to the different noise levels that is the MSE increases and PSNR decreases when we move from 5 dB level to 25 dB noise levels for all test signals.

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