ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 5, Issue 2, February 2016

Comparative Analysis of Non Local Means and Wavelet Transform

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***Abstract*— Digital filters are important part of digital signal processing. Due to their high accuracy and reliability we use these in our daily life, especially for biomedical signal processing. Digital filters have two basic functions: signal separation and signal restoration. Signal separation is necessary because signal corrupted with noises often leads to incorrect diagnosis. In this paper, two methods, that is, non local means (NLM) filtering technique and wavelet transform are explored for denoising the ECG signals, and results are developed using Matlab coding. The noisy ECG signals are synthesized by adding pulse signals and are then denoised at different levels by optimizing different parameters. The experimental results showed that the proposed techniques successfully denoised the noisy ECG signals by selecting appropriate input parameters. Finally, the peak signal to noise ratio (PSNR) and mean square error (MSE) were also evaluated to compare the performance of both methods.**

***Keywords*--- Denoising, ECG signals, mean square error, non local means filtering technique, peak signal to noise ratio, wavelet transform.**

I. INTRODUCTION

Electrocardiogram (ECG) signal is a graphical representation of cardiac activity and it is derived from electro (electrical activity), cardio (heart) and graph (write) [1]. It helps in identifying various heart diseases and heart abnormalities. An ECG is performed by placing electrodes on the skin over the heart. The electrical impulse is generated at SA node of heart known as pacemaker of heart and then moves to the atria, which are the top two chambers of heart, after that it passes through ventricles and reaches to purkinje fibers, during this process the voltage measurement between the electrodes varies, and this produces a graph of how heart is performing [2]. This electrical impulse is generated by depolarization and repolarization of heart muscle cells due to movement of Na+ and k+ ions in the blood. The ECG amplifying the tiny electrical changes on the skin that are caused when the heart muscle cells "depolarizes" during each heartbeat. At rest, each heart muscle cell has a charge across its outer wall i.e. on cell membrane. Reducing this charge towards zero is called de-polarization, which activates the mechanisms in

the cell that cause it to contract [3-5]. Potassium and sodium are minerals that work as electrolytes, and conduct electrical signals within fluid without the proper balance of electrolytes heart contractions become abnormal and the risk of heart attack increases [6-7]. In the standard 12-lead ECG the primary leads are connected to the limbs and that is why known as limb leads [8]. ECG signals have unique morphological characteristics (P-QRS-T complex). One normal P-QRS-T waveform is shown in figure1.

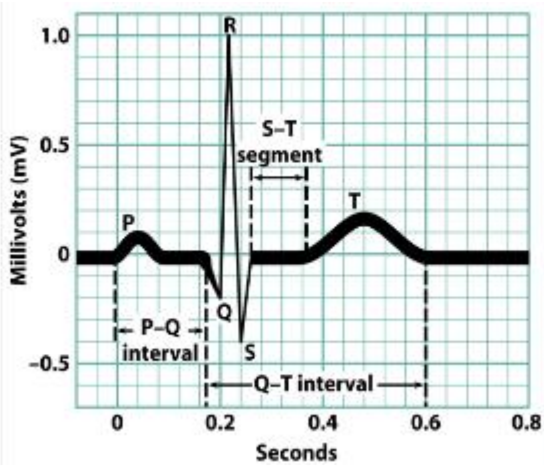

Fig. 1 Normal P-QRS-T Cycle

It is possible to diagnose many cardiac diseases by analyzing the variations of this morphology visually. The morphology and the heart rate reflect the cardiac health of human. Any disorder of heart beat or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia [9-11]. The ECG signal provides the information about heart position, chamber size, impulse origin and propagation, heart rhythm and conduction disturbances and changes in electrolyte concentrations [12]. Noises from various sources like muscular activities, 50/60Hz power line, skin stretching and electrode motion, movement of heart due to respiration, etc. can contaminate the ECG signal and affect the interpretation of ECG signal [13-15]. The motion artifact induced due to relative motion of electrodes is more prevalent during ambulatory conditions. It is still a challenging problem to remove the artifacts from ECG [16]. ECG is a periodic signal and it repeats according to heart rate. The components of cardiac cycles appear in a regular sequence P-QRS-T. The variations in the heart rate may affect the

Manuscript received Jan, 2016.
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durations of PQ and ST intervals, the durations of P wave, QRS complex and T wave [17].

II. NON LOCAL MEANS

Non local means (NLM) filtering technique also known as statistical neighborhood filter. This filtering technique can 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. Instead of closer one it consider the average of the time series values which have higher similarity and replace the value with weighed average of its neighborhood. On the other hand, however, due to the computational complexity, the similarity is calculated within a searching window instead of whole domain.

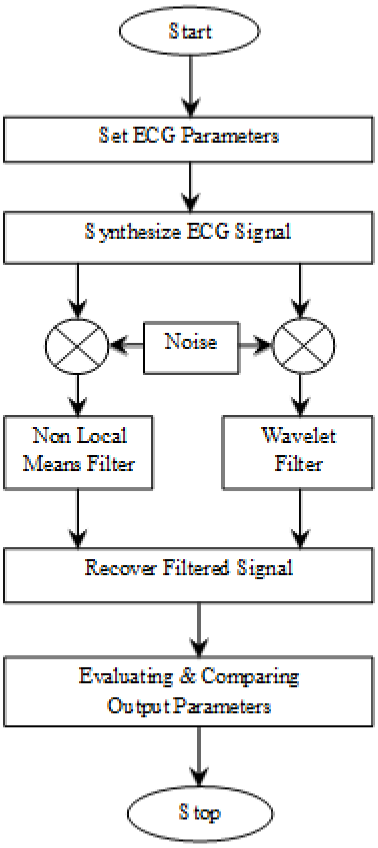


Fig. 2 Flow chart showing experimental steps followed in a sequential manner.

Non local means has primarily been used for image processing, but it has been reported in a 1D context in several papers. Due to the regularity assumptions on the original data of local methods, details and fine structures are smoothed out because they behave in all functional aspects as noise. The non-local means filter denoise the data up to a satisfactory level and also preserve the main geometrical configurations, the fine structure, and other important details.

III. WAVELET TRANSFORM

Wavelet transform is a pair of filters. Where one is a low pass filter (LPF) and the other is a high pass filter (HPF). If single stage wavelet filter is applied on a signal, then at the end we will get double data. If the original signal *x(t)* consists of N samples of data. The resulting approximation and detail coefficients are each of length N, for a total of 2N. There exists an alternative method to perform the decomposition using wavelets. By down sampling A and D to half of their lengths i.e. N/2, the total length of resulting signal can be maintained. The final output signals after down sampling are denoted as cA and cD. This process can be repeated several times, resulting in a tree structure called the decomposition tree. Wavelet transform can be used to analyze or decompose images or signals called decomposition.

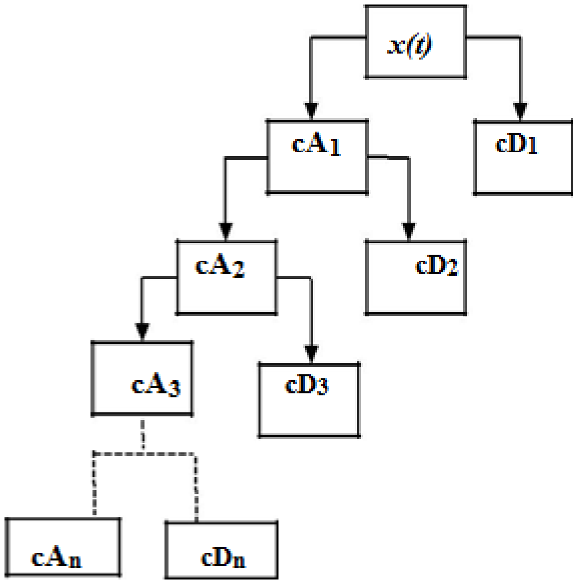


Fig. 3 Wavelet decomposition structure

The same components can be assembled back into the original signal without loss of information; this is called reconstruction or synthesis. Wavelet transform is an important tool for the de-noising of signals like ECG. There are number of wavelet families like haar, daubechies (Db), symlet, coiflet etc for analysis and synthesis of signal. In this paper, haar wavelet and coiflet wavelet are used. Haar wavelet is first and simplest wavelet. It represents the same wavelet as Daubechies db1. Coiflet wavelet was built by I. Daubechies at the request of R. Coif man.

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 NLM filtering technique and Wavelet transform (coiflet and haar) to three original ECG100, ECG101, and ECG102 signals for denoising. After that, signals with 5dB, 10dB, 15dB, 20dB and 25dB noise were added into the original signals and then denoised. The original ECG102 and the denoised ECG102 signals with NLM, coif2 wavelet and haar wavelet are shown in fig. 4 and fig. 5(a), fig. (b), fig. (c) respectively. The original signal with 20 dB added noise is shown in figure 6.

After adding noise, the noisy signals were filtered out by selecting different NLM and wavelet transform parameters are shown in fig. 7(a), 7(b) and 7(c). Table 1, table 2, and table 3 shows the calculated MSE and PSNR for different input SNR levels for three different signals, Column diagrams for MSE and PSNR are shown in fig. 8(a), 8(b), 8(c) and fig. 9(a), 9(b), 9(c). From fig. 4 to fig. 7(c) we observe that NLM and Wavelet transform denoise the original and signal with 20dB added noise signal successfully and meet the target values. Both methods perform well but NLM preserve the edges very efficiently and remove the noise effectively. If we compare fig 4 & fig 5(a), 5(b), 5(c) 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 effect when we compare the fig 6 and fig 7(a), 7(b), & 7(c), where as coif2 wavelet does not remove the noise properly and haar wavelet over-smooth the signal and destroy the P and R waves amplitude. Tables and column diagrams show the variation in MSE and PSNR for three different signals with different input SNR levels.

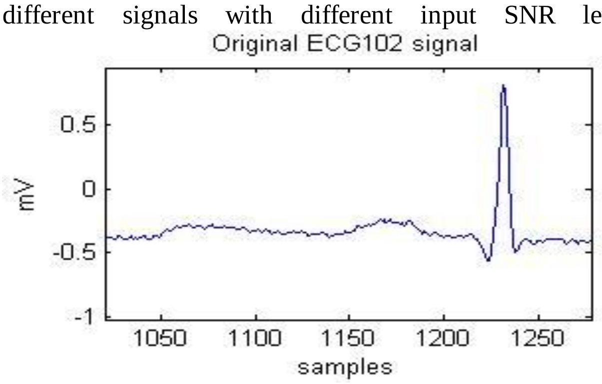


Fig. 4 Original ECG102 signal

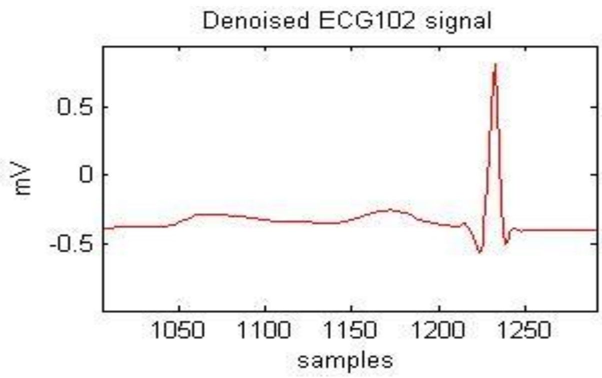


Fig. 5(a) Denoised ECG102 signal with NLM

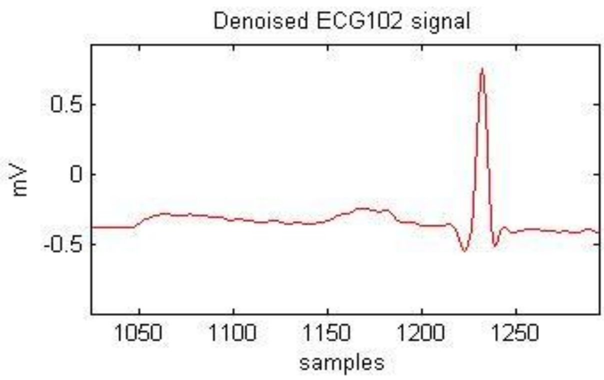


Fig. 5(b) Denoised ECG102 signal with Coif2 wavelet

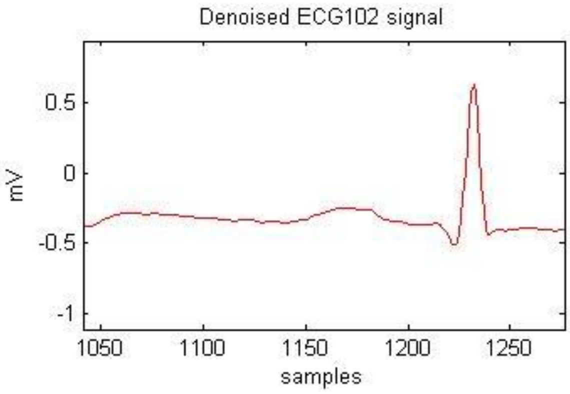


Fig. 5(c) Denoised ECG102 signal with Haar wavelet

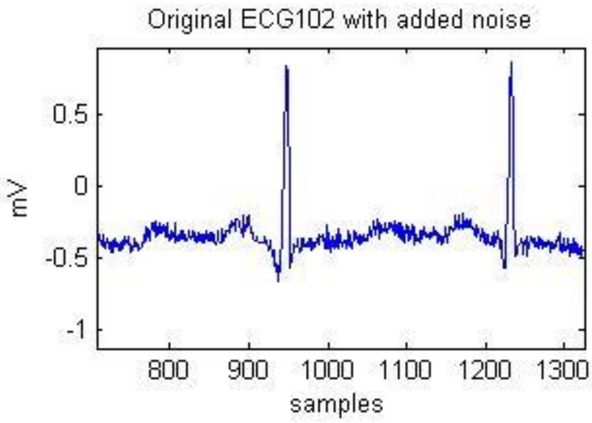


Fig.6 Original ECG102 signal with added 20dB SNR

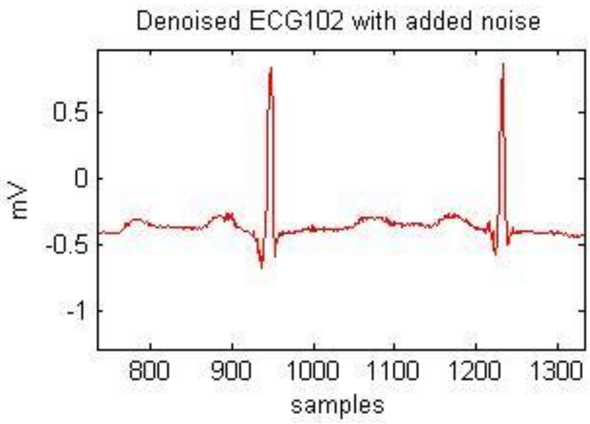
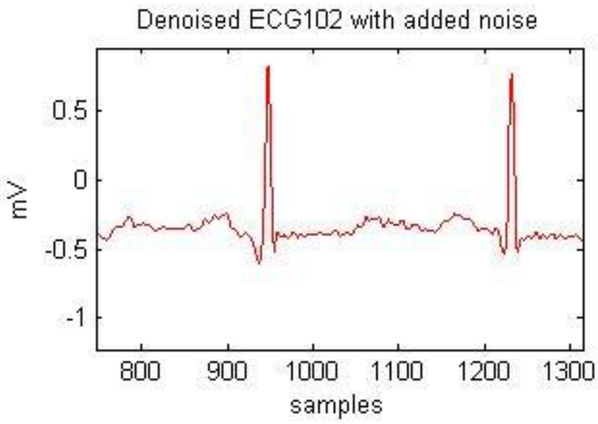


Fig. 7(a) Denoised ECG102 signal with NLM after added 20dB SNR



ISSN: 2278 – 909X
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Fig. 7(b) Denoised ECG102 signal with Coif2 wavelet after added 20dB SNR

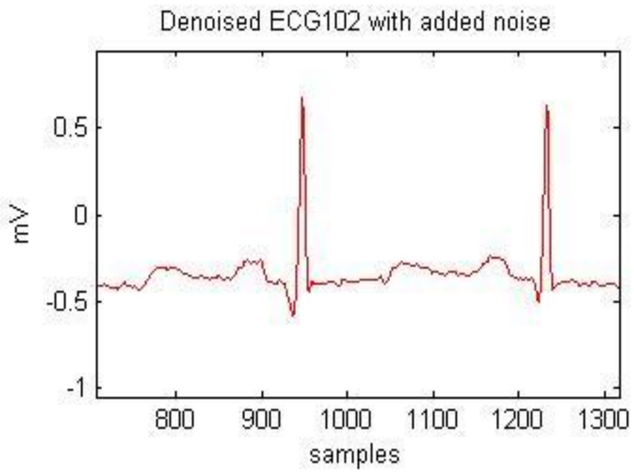

Fig. 7(c) Denoised ECG102 signal with Haar wavelet after added 20dB SNR

Table 1 MSE and PSNR for NLM

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

Table 2 MSE and PSNR for Coif2 wavelet

Mean Square Error & Power Signal to Noise Ratio for Coiflet2 Wavelet						
SNR	MSE			PSNR		
LEVEL	ECG100	ECG101	ECG102	ECG100	ECG101	ECG102
5dB	0.02556	0.02579	0.02495	64.0895	64.051	64.1936
10dB	0.01682	0.01652	0.01693	65.9053	65.9856	65.8794
15dB	0.01914	0.01885	0.01897	65.3464	65.412	65.3851
20dB	0.02045	0.0203	0.02067	65.0576	65.0901	65.0113
25dB	0.0221	0.02165	0.02189	64.7213	64.8111	64.7616

Table 3 MSE and PSNR for Haar wavelet

Mean Square Error & Power Signal to Noise Ratio for Haar Wavelet						
SNR	MSE			PSNR		
LEVEL	ECG100	ECG101	ECG102	ECG100	ECG101	ECG102
5dB	0.04309	0.04279	0.04374	61.8215	61.8511	61.7559
10dB	0.05186	0.05156	0.05176	61.0168	61.0413	61.0249
15dB	0.0555	0.05521	0.05489	60.7217	60.7447	60.7702
20dB	0.05346	0.05317	0.05341	60.8843	60.9081	60.8883
25dB	0.05229	0.05199	0.05216	60.9809	61.0052	60.9915

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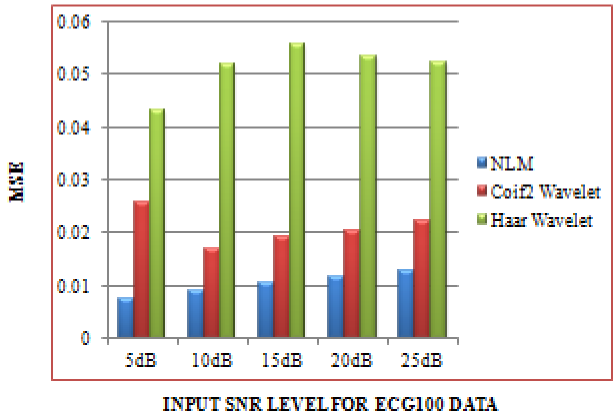

Fig. 8(a) Column diagram for MSE for ECG100

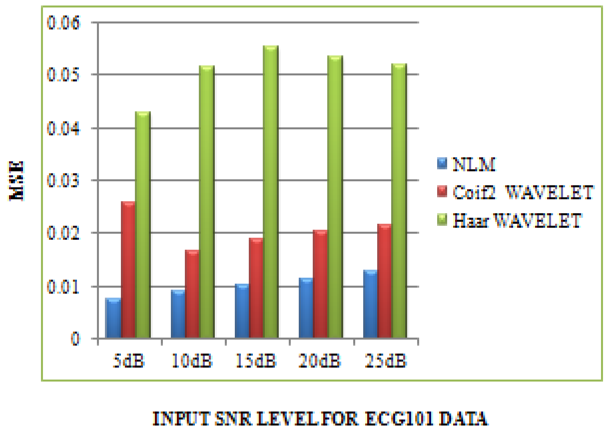

Fig. 8(b) Column diagram for MSE for ECG101

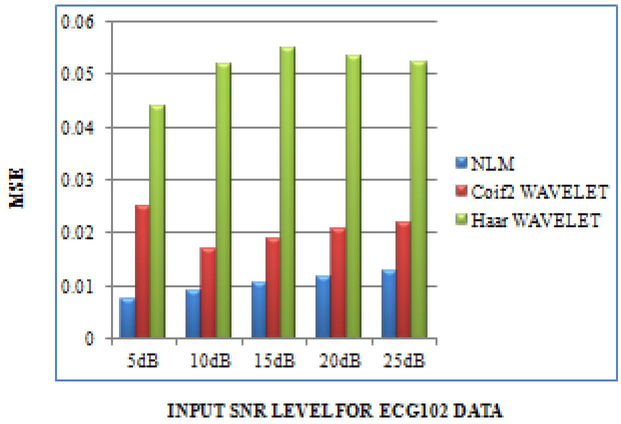

Fig. 8(c) Column diagram for MSE for ECG102

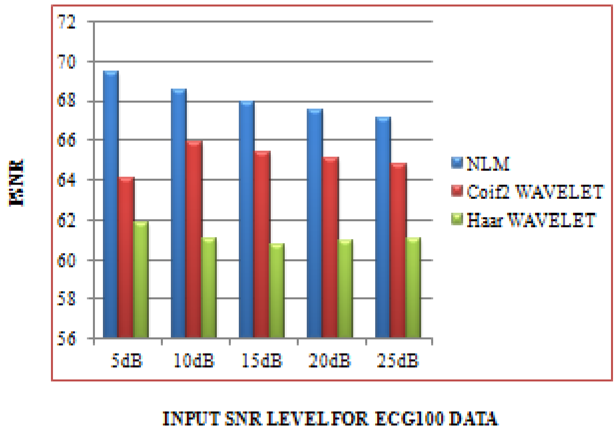

Fig. 9(a) Column diagram for PSNR for ECG100

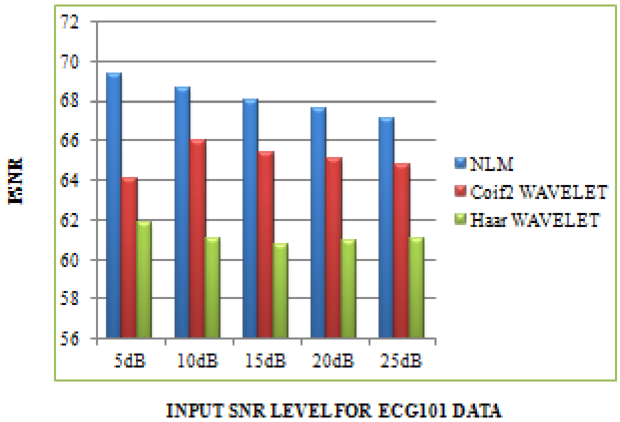

Fig. 9(b) Column diagram for PSNR for ECG101

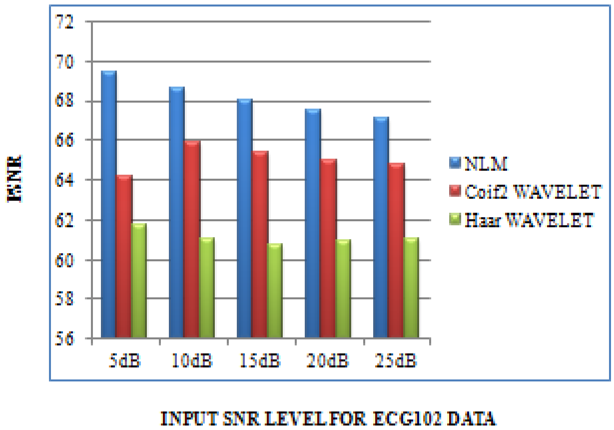

Fig. 9(c) Column diagram for PSNR for ECG102

V. CONCLUSION

In this paper we have demonstrated non local means based filtering technique and wavelet transform to denoise the ECG signals. In this we observe that NLM technique is very effective but little time consuming as compare to wavelet transform. NLM preserve the amplitude and original shape of signal after denoising. Both the method remove noise up to the satisfactory level without reducing the actual signal strength but NLM gives better result.

For different comparative analysis coif2 and haar wavelets are displayed from wavelet family. Our results show that NLM gives better result than wavelet when we compare MSE and PSNR values for synthesized ECG signals.

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