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Two-stage Nonlocal Means Denoising of ECG Signals

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Abstract: Every type of biomedical signals is generated by physical activities in the body. In a present scenario some attention has been created by medical biometrics, including ECG (Electrocardiogram), DNA, blood pressure, EEG (Electroencephalogram) and heart rate [1]. An electrocardiogram (ECG) uses to trace and describes heart electrical activity and it recorded by electrodes placed on the body surface. In this paper, we study various filters which have been implemented for reduction of noise in ECG. Their performances are also compared based on the SNR values. But problem still same that noise can overlap the entire signal, so these cases the classical methods in signal denoising are not acceptable. So reduce that difficulty we propose a noval approach which based on the Non Local Mean (NLM) algorithm. The NLM was recently introduced in as a technique for processing nonlinear and non stationary signals.

Keywords: ECG signal, non-local means, wavelet and Denoising.

I. INTRODUCTION

ECG signal is a combination of PQRST waves. ECG used for detect heart related diseases where P wave , QRS wave and T wave are deferent function The electrocardiogram (ECG) is the recording of the cardiac activity and it is extensively used for diagnosis of heart diseases. It is also an essential tool to allow monitoring patients at home, thereby advancing telemedical applications. Recent contributions in this topic are reported in [2–4]. Inside the clinical environment under observation of ECG signals, the ECG signal having various types of noise or artifacts. The spread of ECG signal introduces noise or artifacts because of the poor channel conditions. In ECG enhancement, the goal is to separate the valid ECG from the undesired artifacts so as to present a signal that allows easy visual interpretation. Many approaches have been reported in the literature to address ECG enhancement. Some recent relevant contributions have proposed solutions using a wide range of different techniques.

In this letter, we briefly describe the NLM algorithm in second stage, and discuss its application in the context of ECG denoising. Here we present results for ECG denoising of signals with simulated additive noise. Positively, the NLM algorithm results are very best with compare to recently published wavelet denoising[5].

II. NOISES IN ECG SIGNAL

ECG measurements may be corrupted by many sorts of noise. The ones of primary interest are[3]:

a. Power line interference
b. Electrode contact noise
c. Motion artifacts
d. EMG noise
e. Instrumentation noise
f. AWGN

These artifacts strongly affects the ST segment, degrades the signal value, frequency resolution, produces great amplitude signals in ECG that can resemble PQRST waveforms show in fig.1, and masks tiny features that are important for clinical monitoring and diagnosis. Cancelation of these noises in ECG signals is an important task for better diagnosis. Many sources of signal contamination including additive high frequency noise (AWGN), motion or muscle artifacts, and baseline wander overlap signals of clinical interest in both time and frequency.

Figure.1. ECG signal

III. ECG DENOISING ALGORITHMS

Noise cancellation in ECG signal requires different-different strategies for different noise sources or types. However, in real situations ECG signals recordings are mainly highly corrupted by artifacts. Here basically two leading artifacts existing in ECG recordings which are: (1) high-frequency noise which produced by electromyogram induced noise, power line interferences, or mechanical forces acting on the electrodes; (2) baseline wander disturbances (BW). There are many useful methods for removing power line and baseline wander disturbances in our ECG signal by digital linear phase filtering [6]. This method can be used to reduce signal magnitude spectrum while preserving the signal time domain as much as possible. The disadvantage of this method is the computational requirements. This is mainly caused by a large number of multiplications involved in the time domain.

Random and stationary noise can be removed using a temporal averaging method. This method only offers effective performance if a large number of samples is used. Moreover, due to heart beats variability, it can cause considerable errors, producing distorted results, or extremely smooth waves.

There are many kinds of methods for denoising of ECG signals. In past few year various methods used for this purpose that is such as perfect reconstruction maximally decimated filter banks and nonlinear filter banks, advanced averaging, the wavelet transform[10], adaptive filtering[11], ICA(independent component analysis)[12], PCA(principal component analysis)[13], EMD (Empirical Mode Decomposition) based technique[14] and NLM(non-local mean algorithm).

A. Basic Nonlocal Means Algorithm:

In the paper [7] author have described the NLM algorithm, and briefly discuss its application in the context of ECG denoising. Nonlocal means denoising addresses the problem of recovering the true signal given a set of noisy observations, Non Local Means (NLM) is a signal de-noising process based on non-local averaging of all the pixels in a signal.

Nonlocal means denoising addresses the problem of recovering the true signal ugiven a set of noisy observations,

$$v = u + n \tag{1.1}$$

Where n is additive noise. For a given sample s, the estimate $\widehat{u}(s)$ is a weighted sum of values at other points t that are within some 'search neighbourhood' N(s)

$$\hat{u}(s) = \frac{1}{Z(s)} \sum_{t \in N(s)} w(s,t) v(t) \tag{1.2}$$

Where $Z(s) = \sum_t w(s,t)$ and the weights are;

$$w(s,t) = \exp\left(-\frac{\sum_{\delta \in \Delta}(v(s+\delta) - v(t+\delta))^2}{2L_\Delta \lambda^2}\right) \tag{1.3}$$

$$w(s,t) = \exp\left(-\frac{d^2(s,t)}{2L_\Delta \lambda^2}\right) \tag{1.4}$$

Where, λ is a bandwidth parameter, while Δ represents a local patch of samples surrounding s, containing L_Δ samples; a patch of the same shape also surrounds t. Here we have defined d^2 to denote the summed, squared point-by-point difference between samples in the patches cantered on s and t.

Here each patch is averaged with itself with weight w(s, s) = 1.To achieve a smoother result, a canter patch correction is often applied, i.e.

$$w(s,s) = \max_{t \in N(s), t \neq s} w(s,t) \tag{1.5}$$

B. Proposed Work:

The non-local means method will then be compared to other denoising methods using several measurements on the output signals. Instead it assumes the signal contains an extensive amount of self-similarity. In this paper, we briefly describe the NLM algorithm, and discuss its application in the context of ECG denoising. Basically, in the paper [7] author has described the NLM algorithm, and briefly discuss its application in the context of ECG denoising.

The novelty of NLM is that the weighting $w(s,t)$ depends on patch similarity, not on the physical distance between the point's s and t. Averaging similar patches helps to preserve edges, in contrast to more typical filtering

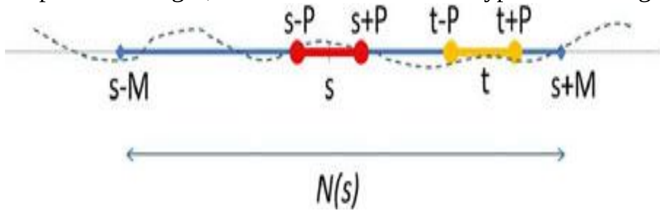

Figure 2 Design of NLM parameters.

In Figure 2, the small patch cantered on 's' is compared to patches cantered on other points 't' in N(s).Here we chose not to apply this correction, to avoid over smoothing the QRS complex.

In this method we add second stage non local mean filter (in fig. 3) at filtering section to finding almost same result. But here we take sharp edges of our ECG signals which are very important to evaluation of ECG signal.

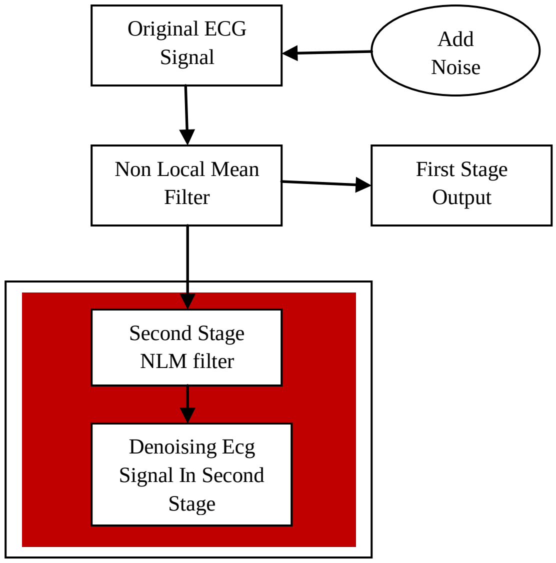

Figure 3 Block Diagram Proposed Method.

C. Parameter Selection:

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.

Table: 1

Parameters	**Patch HW**	**P (Patch)**	**λ (bandwidth)**	**M (Samples)**
Values	10	1000	≈ 0.6	2000

IV. RESULTS

For simulations, we use data from the Physionet MIT-BIH arrythymia database (www.physionet.org). Here we take 3 signal as a input which is ecg100, old and young ages ECG. This all signal we take from Physionet site.

There is no universally accepted signal denoising quality measurement. Therefore, we compare our denoised signal both objectively and subjectively. For objective measurement or numerical measurement we present the widely used SNR and MSE for each observed signal, as there is no precise rule to select one measure over the other.

The comparative amount of signal and noise present in a waveform is generally classified by the SNR. In signal processing (both analog and digital communications) Signal-to-Noise Ratio which also knows S/N or SNR is measured signal strength relative to background noise. The retio is mainly measured in decibel (dB).

The mean squared error (MSE) is an estimation measurement the average of square of the errors. MSE is very highly risk function. The MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated.

$$\mathrm{SNRimp} = 10 \log_{10} \frac{\sum_{n=1}^{N}(v[n]-u[n])^2}{\sum_{n=1}^{N}(\hat{u}[n]-u[n])^2}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{n=1}^{N}(\hat{u}[n]-u[n])^2$$

Where N is the signal length in samples and “u and v” are as described earlier. Note that here we are assuming the Physionet signals are the true signals u; in reality these signals also contain noise, which the metrics above neglect, though at SNR the additive noise dominates.

We performed parameter tuning based on the first Physionet waveform ensemble and found good performance for P = 10samples, M ≥ 2000 samples, and λ = 0.6σ (in our simulated data the noise variance σ^2 is known; in practice it can be estimated from data or system characteristics).

Here we use MATLAB R2013a as a tool box to implement our method.

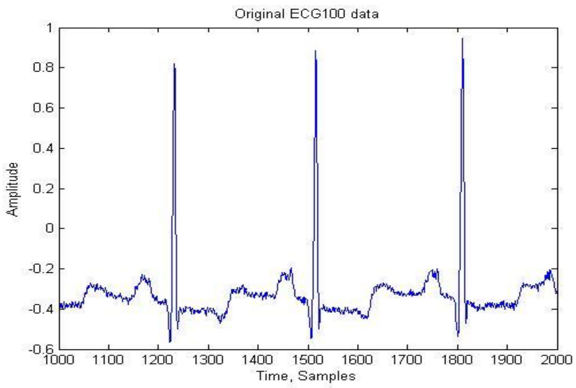

Figure 4 Input ECG signal (ecg100.txt)

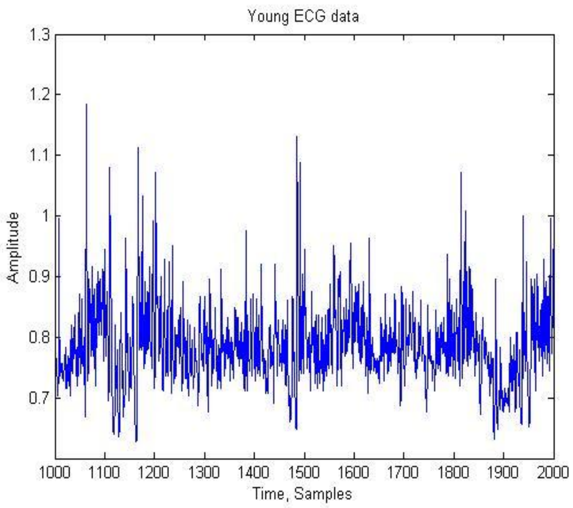

Figure 5 Input ECG signal (Young.txt)

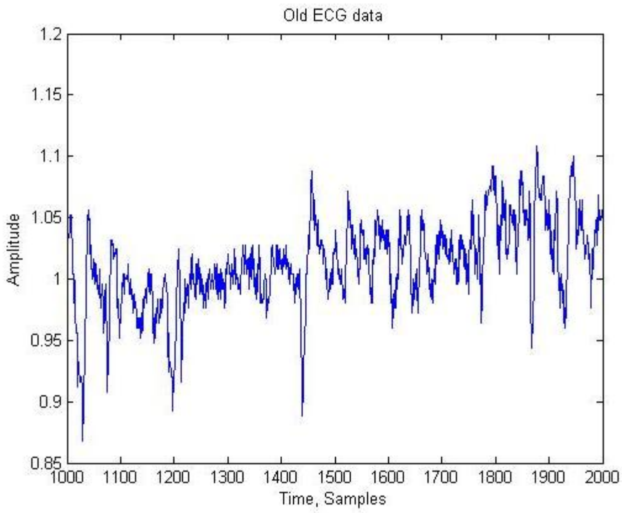

Figure 6 Input ECG signal (Old.txt)

Here we take three different ECG signals as a input which show in figure 4, 5and 6 that’s all signal we taking from PhysioNet site.

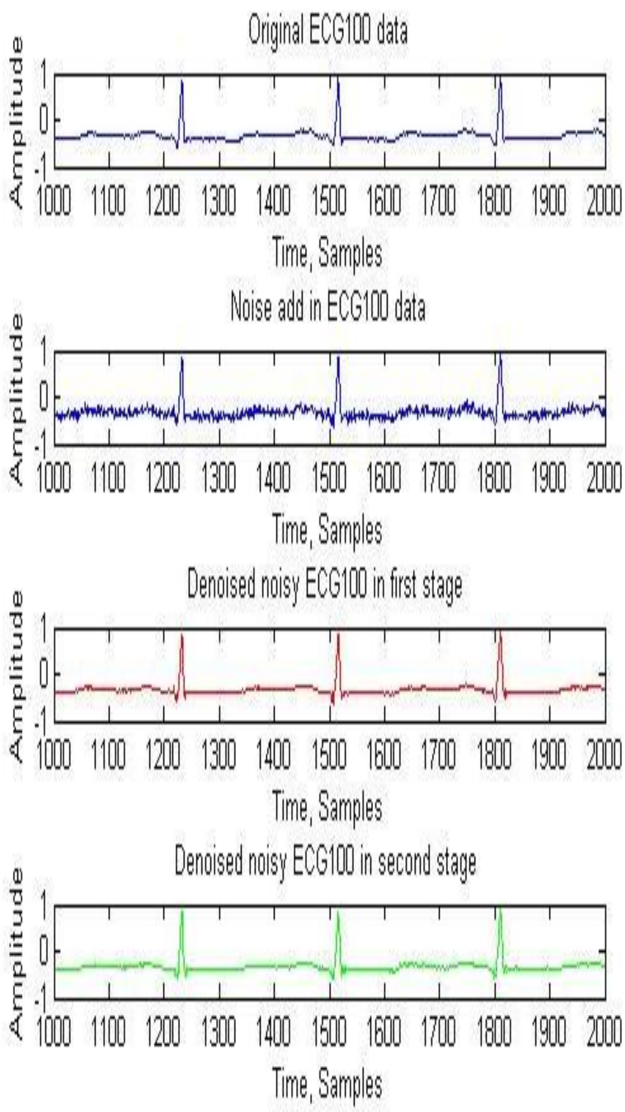

Figure 7 Denoising ECG Signal by proposed method (ecg100.txt)

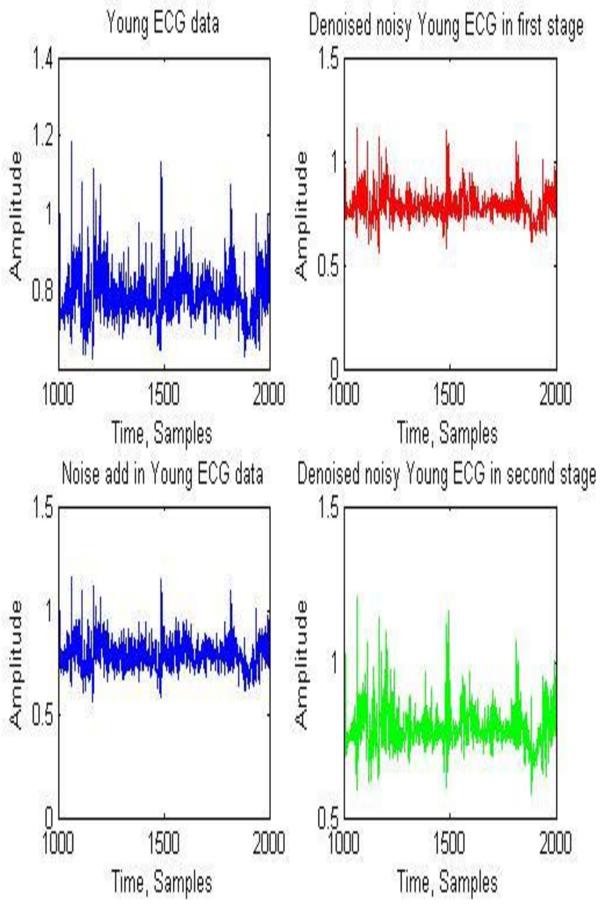

Figure 8 Denoising ECG Signal by proposed method (Young.txt)

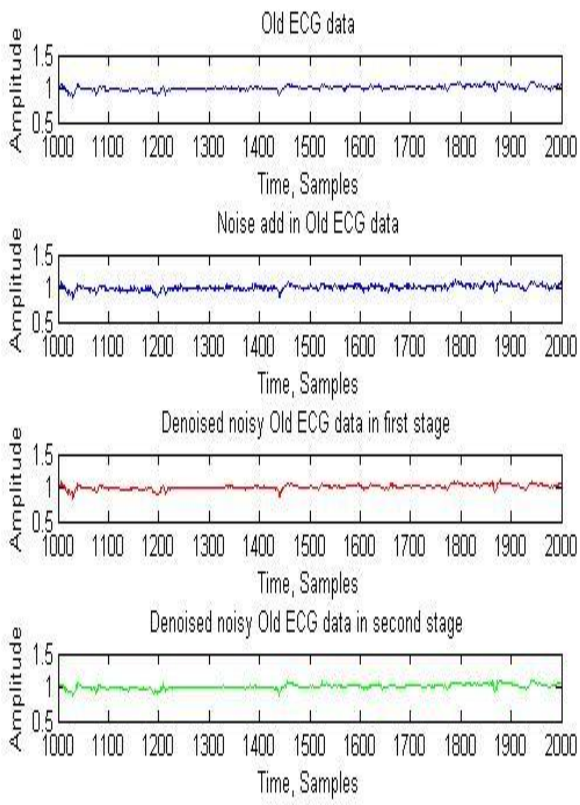

Figure 9 Denoising ECG Signal by proposed method (Old.txt)

Table 2 SNR and MSE Calculations in Proposed Method.

S.N	Algorithm	Parameters	
		SNR	MSE
1	Haar	10.2594	33.7614
2	Daubechies	10.2664	33.7343
3	Symlets	10.2766	33.6947
4	Coiflets	10.2722	33.7120
5	Proposed method	10.2798	33.6823

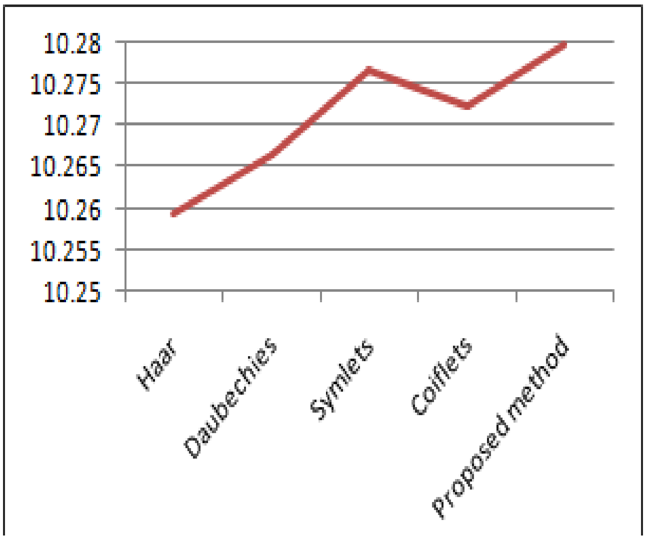

Figure 10 SNR Improvement Graph

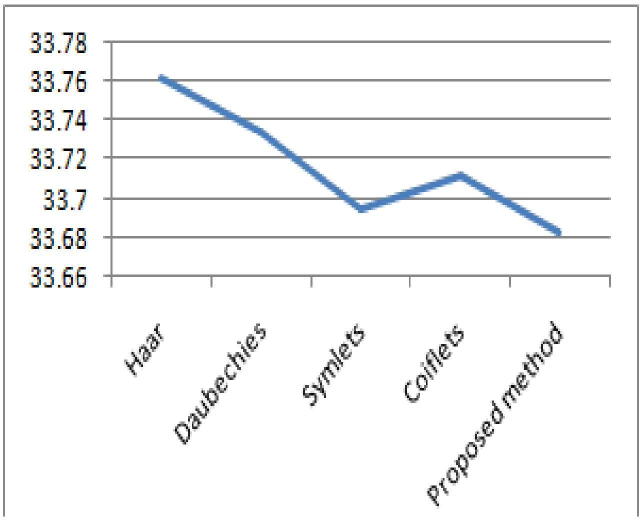

Figure 11 MSE Decline Graph

In the above table we easily saw that proposed method results figure 7 are batter when we compare it to deferent kind of wavelet filters. Here we calculate SNR and MSE value at different filters like haar, daubechies, symlets, coiflets and proposed method, where we take second stage of NLM we find sharp edges which is very useful for cardiologist and that's why we prefer proposed method for ECG signal denoising.

V. CONCLUSIONS

In this dissertation, we have firstly applied a 1-D implementation of the non local means denoising algorithm, which has received significant attention in signal processing, to denoising of ECG signals. The results are promising;

suggesting the method can provided denoising while minimizing signal distortion. We have noted some limitations of the method and suggest possible avenues for the application and improvement of the technique. Given the success of patch-based methods in signal processing, we are optimistic that NLM and related methods may be useful in denoising biomedical signals.

Finally we applied two levels NLM based method for denoising of ECG signal is proposed. The proposed technique is evaluated on SNR where white gaussian noise is artificially added with original signal. Performance of the proposed method shows almost same results as compare to SNR and MSE performances for gaussian noise compared to existing technique which is used as an ECG signal denoising technique.

Finally, in [7] shows all three metrics calculated across the full dataset as a function of SNR. They also shows results for two algorithms presented in [5]; a wavelet soft thresholding algorithm (with threshold learned from a training set), and a hybrid empirical mode decomposition/wavelet denoising method. NLM achieves lower signal distortion than the other methods, reducing MSE. NLM gives better SNR to the other methods.

VI. FUTURE WORK

We have shown that a straightforward application of NLM to ECG denoising gives SNR improvements competitive with state-of-the-art wavelet denoising while causing noticeably less signal distortion We next discuss some limitations and possible extensions of the method.

Here we have applied NLM to denoising of ECGs with additive white Gaussian noise. While this denoising problem is of interest [5], other ECG denoising schemes have focused on more structured artifacts such as those caused by motion or muscle activity [8,9].

As noted earlier, it will be also important to develop an algorithm to adjust the step-size dynamically, which could be useful to adapt the algorithm to different noise sources.

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