Efficient Filtering Framework for Electrocardiogram Denoising

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Abstract: *A simple and efficient method to remove white Gaussian noises and physiological noises from electrocardiogram (ECG) signals is presented. It is based on simple tools usually used in digital signal processing like moving average filter, median filter, baseline drift removal and peak detection. We show by several simulations that the proposed algorithm outperforms significantly conventional median filter and moving average filter and can be considered as a valid concurrent to the standard wavelet-based method.*

Keywords: *ECG denoising, Median filter, Moving average filter, Statistical estimation, Discrete Cosine Transform (DCT), Base wandering removal.*

Introduction

The electrocardiogram (ECG) which is the electric activity of the heart provides useful information for detection, diagnosis and treatment of cardiac diseases. An ECG signal can be corrupted by different types of noises. In our investigation both white Gaussian noises and real physiological noises are considered. Latest contributions in this subject are reported in [4–6, 9, 13, 16, 18, 19].

In the last few years, many researchers have proposed methods and approaches for electrocardiogram denoisings [1, 3, 11, 17]. Wavelet Transform is generally employed for ECG denoising due its ability to characterize time-frequency domain information of a time domain signal. Yadav et al. [19] has proposed a novel Non-local Wavelet Transform (NLWT) method for ECG signal denoising by exploiting the local and non-local redundancy present in the signal. Smital et al. [13] developed a method using dyadic Stationary Wavelet Transform (SWT) in the Wiener filter and also in the estimation of a noise-free signal. The number of decomposition levels and the impulse characteristics are the two most important factors considered in SWT.

A method based on Sparse Derivatives (SD) was presented in [9] where the artifacts are reduced by modeling the clean ECG signal as a sum of two signals whose second and third-order derivatives are sparse respectively. Tracey and Miller [16] suggested using a Nonlocal Means (NLM) approach to denoise ECG signals. This method can provide efficient denoising while minimizing signal distortion. Lahmiri [6] in his work presented a comparative study of ECG signal denoising by wavelet thresholding in Empirical Mode Decomposition - Discrete Wavelet Transform (EMD-DWT) and Variational Mode Decomposition - Discrete Wavelet Transform (VMD-DWT) domains. According to his work, the VMD can outperform the EMD in denoising the ECG signal. In addition, the NLM technique was adopted as a reference model, which was recently found to be effective in denoising ECG signals.

Adaptive filtering has been recently proposed for ECG signal denoising. The method presented in [4] is based on two algorithms. The first is a DWT for denoising, and the second is an Adaptive Dual Threshold Filter (ADTF). Wang et al. [18] presented a method based on the Adaptive Fourier Decomposition (AFD). This method is based on the assumption that the energy of the pure ECG signal is higher than that of the noise. Kumar et al. [5] proposed a method using EMD with non-local mean (NLM) for the cancelation of noise. In this method the edges of the ECG signal are successfully preserved.

I this paper, we propose a new framework for ECG enhancement based on some statistical tools and basic digital signal processing filters like Median Filter (MF) and Moving Average Filter (MAF).

Median filter and moving average filter are ones of the most popular methods extensively used in noise removal. Their window sizes play an important role in their performances. Larger or smaller windows lead to important distortions. For both filters we notice that if the window size is small, we get bad filtering performances for signals with slow variations and good performances for signals with extreme values and fast variations. Unlike with large windows, filtering is good for signals with slow variations and bad for signals with extreme values and fast variations (See Table 1).

Table 1. MF and MA window sizes influence on denoising ECG waves

	Moving average filter		***Median filter***	
Small window size	QRS waves	**Good**	QRS waves	Good
	P, T waves	**Bad**	P, T waves	Bad
Large window size	QRS waves	Bad	QRS waves	**Bad**
	P, T waves	Good	P, T waves	**Good**

Since ECG signals contain both types of variations, slow variations (P and T waves) and fast variations (QRS waves), so the simple use of MAF or MF cannot be efficient for the denoising of such signals (with large sliding windows, filtering is good for P and T waves but R-peaks are strongly attenuated, but with small sliding windows, filtering is bad for P and T waves but R-peaks are conserved (see Fig. 1).

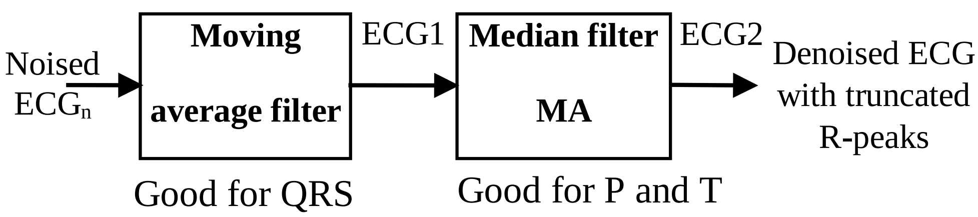


Fig. 1 MAF and MF influence on noised ECG

To address this problem, we propose in this investigation a framework in which we combine these two filters (MAF with small window size and MF with large window size) with a post-filter containing a thresholding operation having as a task the restoration of R-peaks attenuated by MF. To show the effectiveness of the introduced denoising method, several experimentations were performed over ECG records taken from MIT-arrhythmia database.

Method

The block diagram of the proposed ECG denoising method is shown in Fig. 2. This system is constituted of three stages: a moving average filter, median filter and a post-filter. In this work, three key ideas play a crucial role in the extraction of high-resolution cardiac signals from a noisy ECG: (1) Arrangement of MAF and MF; (2) Sizes of the sliding windows of MAF and MF and (3) R-peaks restoration.

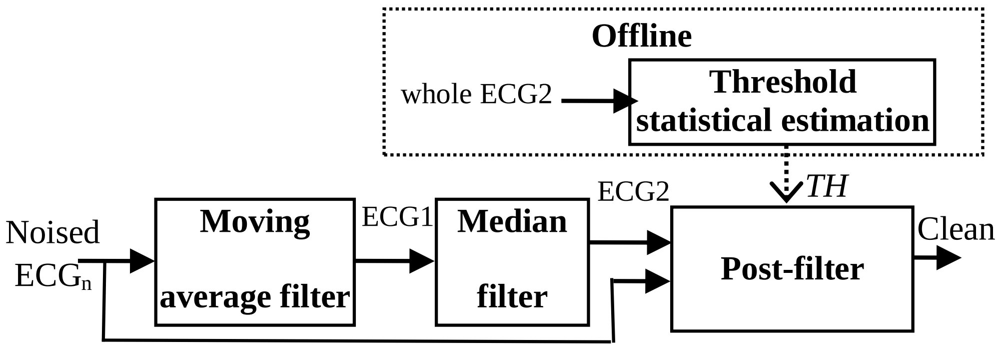


Fig. 2 Block diagram of the proposed method

Arrangement of the filters

In this work we have set the filters MAF and MF in series, by putting MA filter in the first position. There is no rule to do this choice, but according to extensive simulations and tests based on changing their positions (in some simulations, MA was set in the first position and in other simulations MA was set in the second position) it was found that when MAF occupy the first position the performances will be better.

Therefore, the arrangement of MF and MAF must be done as we show in Fig. 2, which means that the noised ECG must pass first by MAF and then pass through MF (we notice that with the opposite arrangement, performance degrades).

MAF design

A common technique for improving the signal-to-noise ratio of signal evolving with time is the MAF. In essence, the k^{th} value is replaced with the arithmetic mean of all the values in the range $(k-r)$ to $(k+r)$ of a moving window of rank r and width $(2r+1)$.

Our experimental results show that MAF has a good performance for QRS segments denoising when using low level of window sizes (see Table 1), which confirm the fact that MAF with small window size can be very benefit for the denoising of these segments. Therefore, this configuration is very efficient for denoising segments in ECG with high variations such as QRS segments.

In this first stage as shown in Fig. 2, moving average filtering is done with window size 3 $(r = 1)$, which is a low size in order to obtain good performances for denoising QRS segments. Mathematically, this filter is given by:

$$ECG_1(k) = \frac{1}{3}\sum_{i=-1}^{1} ECG_n(k+i), \tag{1}$$

where ECG_n is the input noised ECG signal, ECG_1 the output ECG signal obtained by passing ECG_n through MAF.

Note that this stage does not denoise effectively the P and T segments, and this is the reason to consider the second stage (see Fig. 2) which will be discussed in the following subsection.

MF design

The median filter is a nonlinear digital filtering technique, often used to remove noise from signals. It's a nonlinear local filter whose output value is the middle element of a sorted array of amplitude values from the filter window (it replaces the signal value with the median of those values).

This filter is set to be a second stage in the proposed framework in order to overcome the drawback of the first stage which is the low denoising quality for segments P and T. Note that based on our simulated experimentations on real ECG signals, it is found that for choosing large window size for this filter, the denoising performances are very satisfactory for the denoising of segments P and T. This fact confirms that this construction is very efficient for denoising segments in ECG with low variations.

In this second stage, ECG1 is passed through a median filter with large window size 11. This operation is implemented by sliding the window of size 11 over signal ECG_1 one sample at time. MF procedure is given by:

$$\begin{aligned} ECG_2(k) = median[&ECG_1(k-5),\ ECG_1(k-4),\ \ldots,\\ &ECG_1(k),\ \ldots,\ ECG_1(k+4),\ ECG_1(k+5)], \end{aligned} \tag{2}$$

where ECG_2 is the output ECG signal obtained by passing ECG_1 through the MF.

It is known in the literature that the MF truncate the high peaks of any signal (see Fig. 3) [14], therefore, it will destroy the R-peaks due their fast variations, as a consequence, R-peaks are severally attenuated (the reason is they are considered as outliers by MF), which will cause the loose of some signal details. To address this problem, a post filtering processing is needed which is the purpose of the next subsection.

Stages MAF and MA are summarized in Table 1 in which we show their advantages and drawbacks.

Post-filter design and R-peaks restoration

Note that the signal ECG_2 is well denoised except it has R waves truncated, which gives a distorted ECG signal (See Fig. 4). So, the main goal of the third stage is to allow the restoration of loosed R-peaks caused by the median filter. The third stage is constituted of two blocks, a post filter block (Fig. 5) and a threshold statistical estimation block (Fig. 6).

Post-filter. Post-filter block is composed of a thresholding processing and another MF with small window size. Thresholding sub block has three inputs: the clean but distorted ECG_2

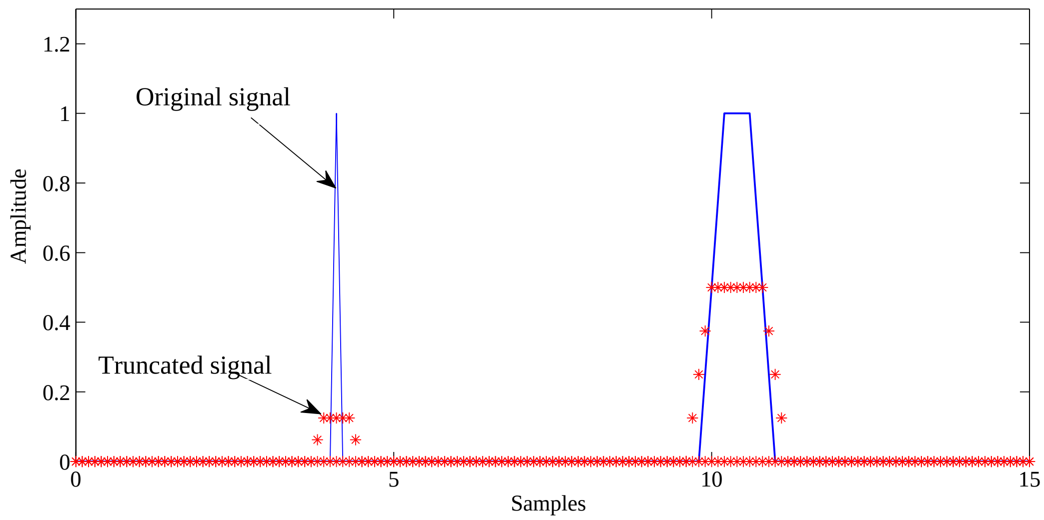


Fig. 3 Truncation effect of MF

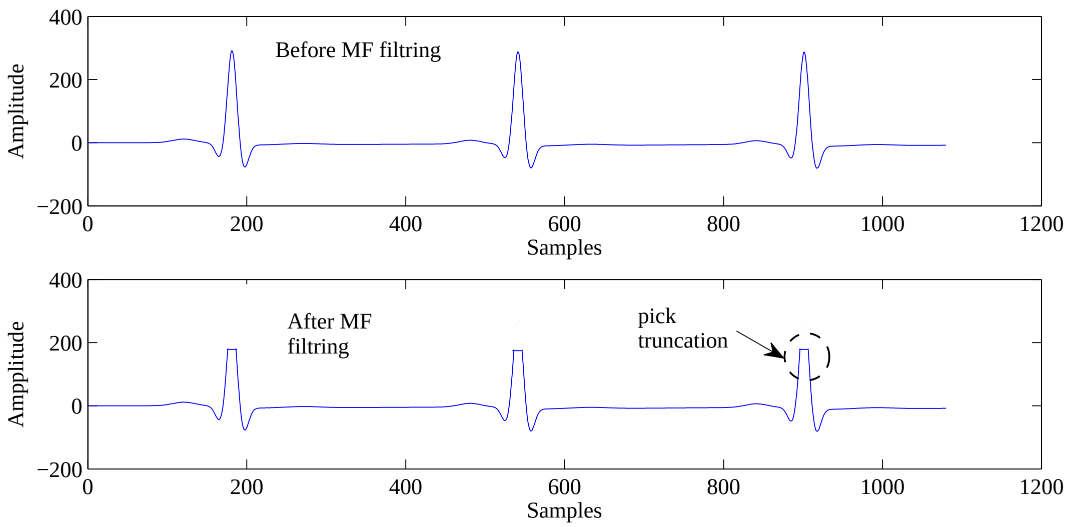


Fig. 4 MF effect on R-peaks

signal, the noised ECG_n signal and a threshold value TH (delivred from the threshold statistical estimation block) and one output denoted by ECG_3 (Fig. 5). During thresholding process, loosed R-peaks are restored via a thresholding module using a threshold value TH which physically represents an ECG amplitude measured in [mV] or in binary level.

Restoration is achieved by the following thresholding process on both ECG_2 and ECG_n as follows:

$$ECG_3(k) = \begin{cases} ECG_2(k) & \text{if } ECG_2(k) < TH \\ ECG_n(k) & \text{if } ECG_2(k) > TH \end{cases} \tag{3}$$

Eq. 3 works as follows: since R-peaks are strongly attenuated in ECG_2, we can fix some threshold TH located on R-wave amplitude of the denoised ECG_2 with which we can do the following correction:

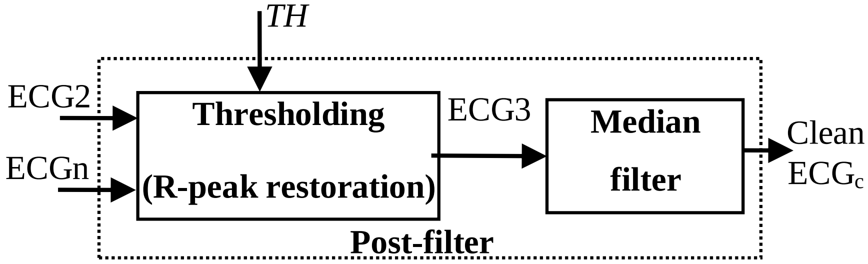


Fig. 5 Internal framework of the post-filter

- $ECG_2(k)$ smaller than TH means that we can conserve $ECG_2(k)$ amplitudes for all ECG's waves ($ECG_3(k) = ECG_2(k)$).
- $ECG_2(k)$ greater than TH means that R-peaks of $ECG_2(k)$ are attenuated, consequently, we must restore them by replacing $ECG_2(k)$ R-peaks by those of measurements $ECG_n(k)$ ($ECG_3(k) = ECG_n(k)$).

Eq. (3) can introduce discontinuities or spikes during R-peaks restoration. To overcome this problem, another MF with small window size is added after the thresholding processing block in order to smoothing such discontinuities.

Threshold estimation

The threshold TH is used to restore the loosed R-peaks as given in Eq. (3). It is determined automatically in an off line manner by the threshold statistical estimation block shown in Fig. 6 using the whole noised signal ECG_n as an input.

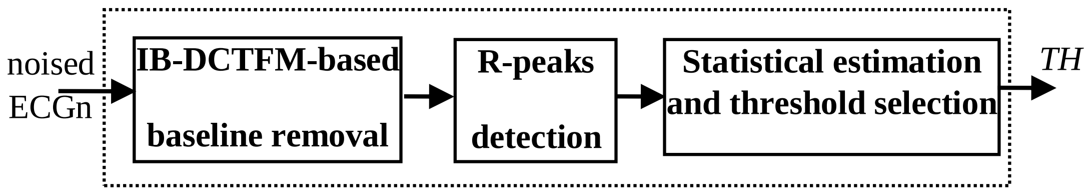


Fig. 6 Threshold statistical estimation (offline operation)

Let's define the threshold TH as a function of amplitudes of R-peaks in ECG_n, so an R-peak detection is needed and will be performed by the second sub block in Fig. 6.

There is an unavoidable difficulty that one can encounter in R-peaks detection which is the presence of low-frequency component in ECG (from 0.05 Hz to 0.5 Hz), causing the wandering of the isoelectric line called baseline. This base line wandering is caused by patient breathing or movement, cable moving during the recording, etc. This phenomenon will also cause the wandering of the R-peaks as shown in Fig. 7. which will make the task of R-peaks detection more difficult.

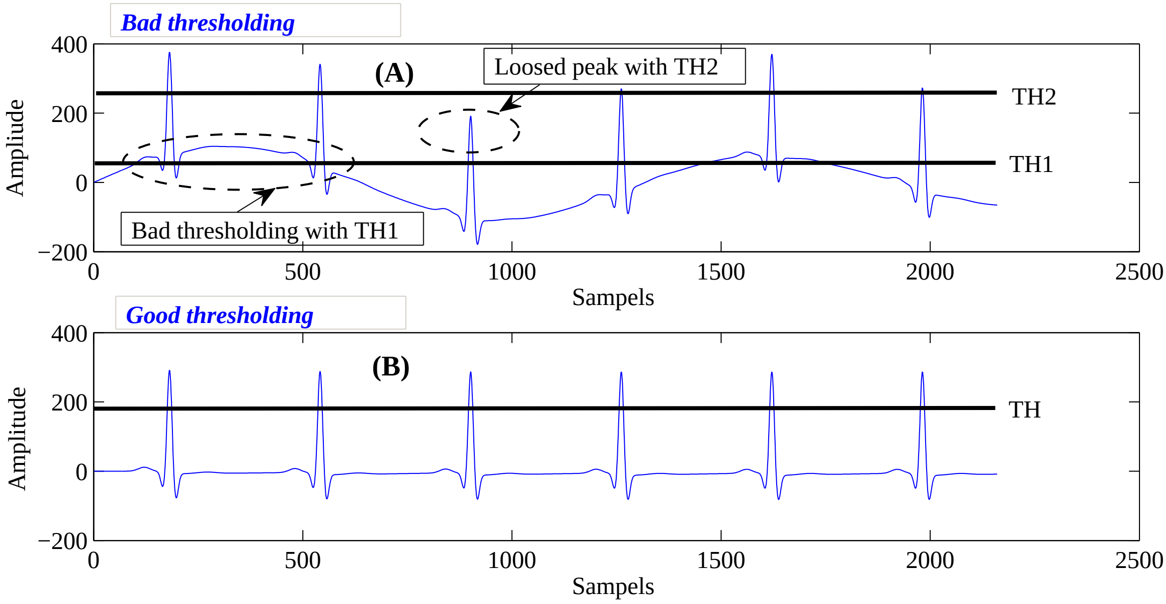


Fig. 7 R-peaks wandering and its influence on TH selection

Baseline wandering removal

Baseline wander (BW) is a common low frequency artifact in electrocardiogram signals. To facilitate R-peaks detection, BW needs to be reduced or removed. This removing action will be assured by sub block 1 in Fig. 6. Generally, methods used to reduce this kind of disturbance can be divided into two groups: methods based on BW estimation and methods based on high-pass filtering. The second approach will be adopted in this paper where we consider the index blocked DCT filtering method (IB-DCTFM) [12] in which the frequency index K is chosen as:

$$K = 2 \times N \times f_0 / F_s, \tag{4}$$

where N is time domain data length, f_0 frequency of index K and F_s the sampling frequency. By choosing $f_0 = 0.5$ Hz which is the max of low-frequency components in ECG, we can eliminate the frequency range of the ECG in which the baseline wandering lie just by changing all DCT indexes bellow K with zero. By using inverse DCT transformation, an ECG signal ECG_2 without baseline wandering is obtained (DCT filtered).

R-peaks detection

Noised ECG_n DCT-filtered will be passed to R-peaks detection sub block (second sub block in Fig. 6) which will give us a vector R_p of ECG_n R-peaks with length N. For more details about the used R-peaks detection method, see our recently published method in [10].

Threshold estimation

Assuming that components of R_p are normally distributed (which is checked by plotting histograms of R_p for most considered ECG signals in MIT-BIH arrhythmia database), then expectation value and variance of R_p will be $\mu = E(R_p)$ and $\sigma^2 = E[(R_p - \mu)^2]$, respectively.

Expectation value is estimated by using the following mean formula:

$$\mu = \frac{\sum_{i=1}^{N} R_p^i}{N}. \tag{5}$$

It is known in statistics that 99.74% of R_p components fall within $\mu \pm 3\sigma$, therefore the following threshold TH is proposed:

$$TH = \mu - 3\sigma. \tag{6}$$

Intuition behind choosing this threshold is shown in Fig. 8. This choice will assure that TH will be below 99.74% of peaks.

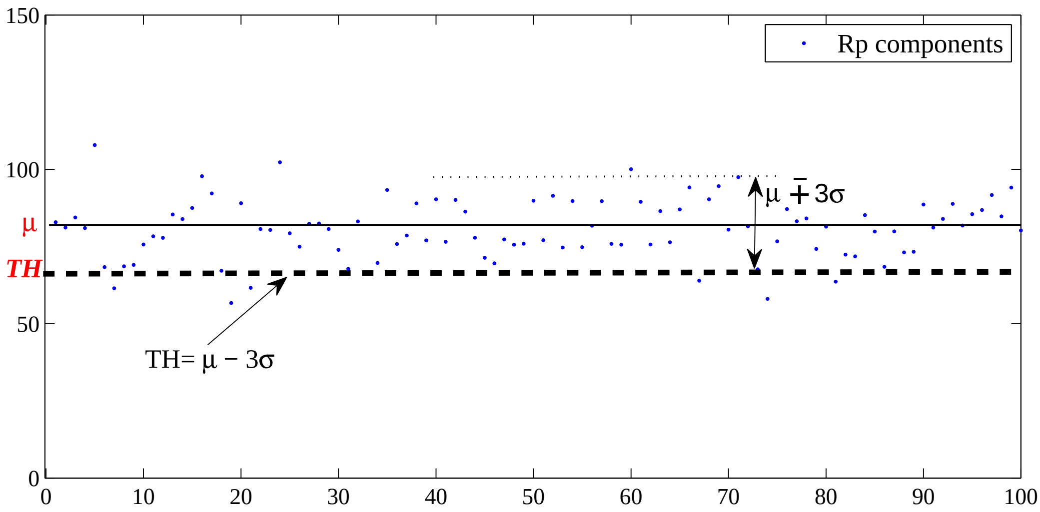


Fig. 8 R-peaks wandering and its influence on TH selection

Mean value estimation and threshold selection are done in the third sub block of threshold statistical estimation (Fig. 6). Equation. 6 will guarantee that 99.87% of attenuated R-peaks will be restored.

Simulation results

ECG signals used in this experiment are taken from MIT-BIH arrhythmia database which is recorded at a sampling rate of 360 Hz and resolution of 11 bits/sample [7].

In order to check denoising performances, we compare our results with those obtained with MAF, MF and wavelet-based method.

First we use record 103.dat as a clean ECG signal, and then we add to it a white noise and two real noise records taken from MIT-BIH noise stress test database [8] to generate a noisy ECG with various input SNRs (signal to noise ratio). The used noise stresses are the muscle artifact "ma" record and the electrode motion "em" record.

For evaluation purposes, Signal to Error Ratio (SNR) and Mean Squared Error (MSE) criterions will be used. These evaluators are defined as follows:

$$SNR_{in} = 10 \times \log\left(\frac{\sum_i |x_c(i)|^2}{\sum_{i=1} |n(i)|^2}\right), \tag{7}$$

$$SNR_{out} = 10 \times \log\left(\frac{\sum_i |x_c(i)|^2}{\sum_{i=1} |x_c(i) - \hat{x}(i)|^2}\right), \tag{8}$$

$$MSE = \sum_{i=1} \frac{(x_c(i) - \hat{x}(i))^2}{N}, \tag{9}$$

where, x_c is the clean ECG signal, $\hat{x}$ is the denoised ECG signal, and n is the noise and N the number of samples.

Experiment results for record 103.dat are shown in Fig. 9, where for each input SNR, 100 monte Carlo runs are performed to obtain an average output SNR value for each filter.

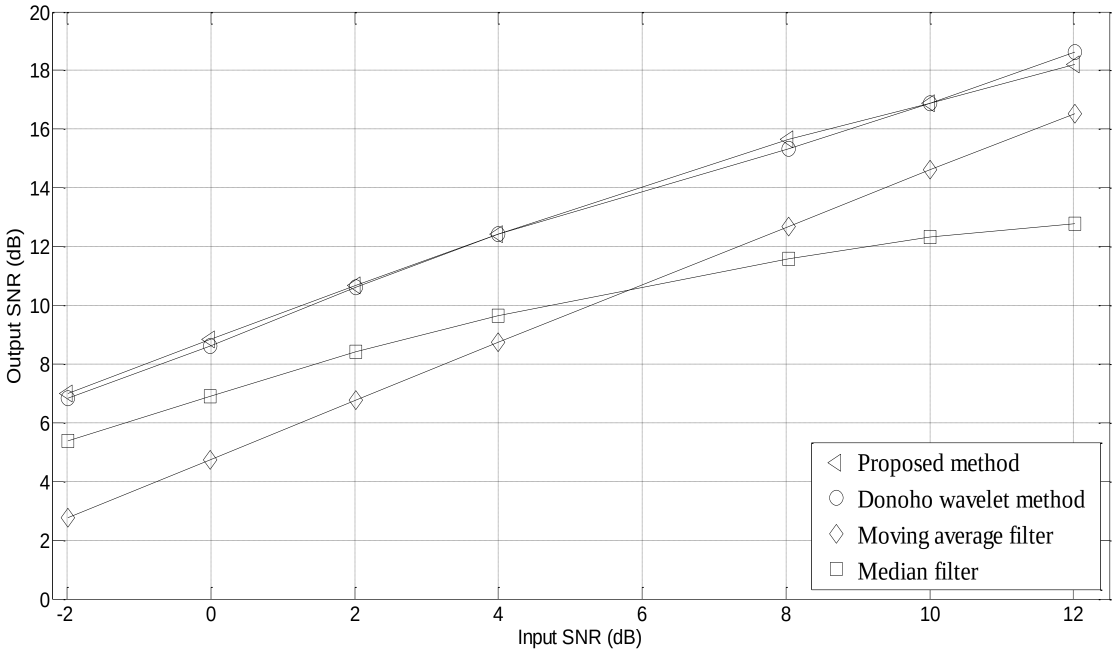


Fig. 9 Average output SNR (dB) versus different input SNRs (dB) of ECG record 103.dat for discussed filtering methods

Fig. 9 shows clearly the superiority of the proposed method compared to MAF and MF, and how can be very close to wavelet-based method implemented here as proposed in [**?**, 15] with 4-level discrete wavelet transform (DWT) decomposition, using bior4.4 wavelet (CDF 9/7) and hard universal thresholding.

Table 2 lists the SNRs of the proposed algorithm and wavelet-based method where for the real ECG signals 103.dat, 113.dat, 122.dat and 221.dat. We can see that the proposed method achieves performance better (or similar) than wavelet-based method.

The same ascertainment is also confirmed from Table 3 where we use another type of performance measure which is the MSE.

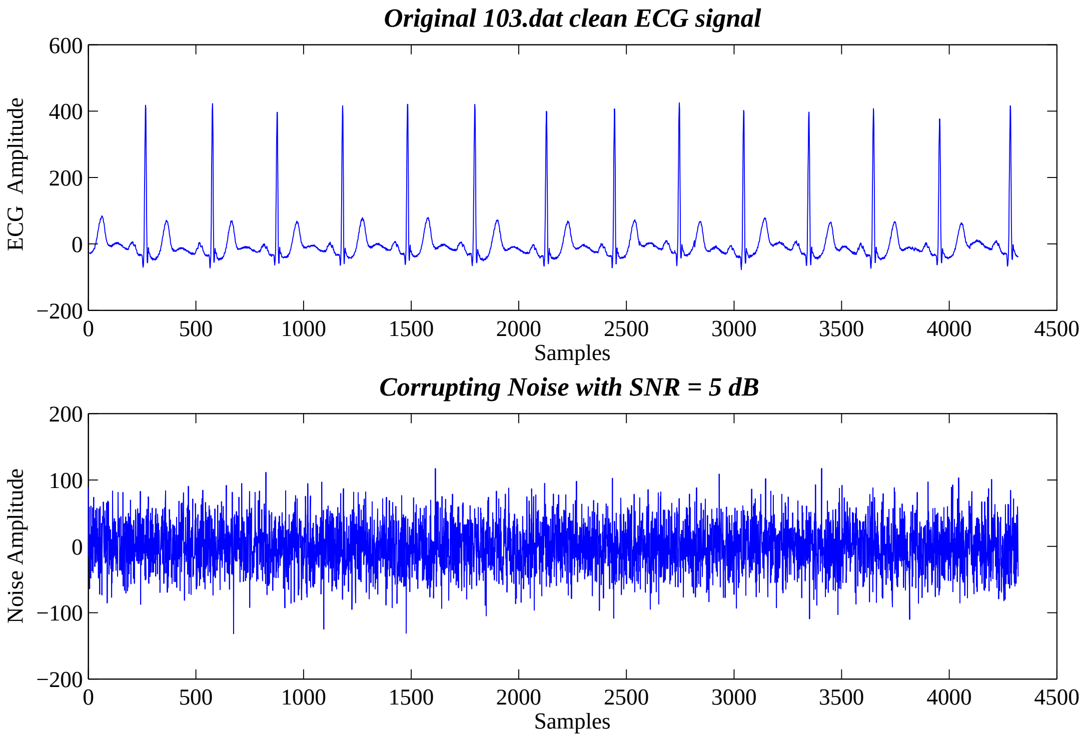
For a visual inspection, we show in Figs. 10-13 the denoising efficiency of the proposed method on records 103.dat, 113.dat, 122.dat and 221.dat, respectively.

Table 2. Denoising performance (SNR) of the proposed method and wavelet-based method for several records taken from MIT-BIH database

ECG file	Input SNR -2dB		Input SNR 5dB		Input SNR 10dB	
	Proposed	*DWT*	*Proposed*	*DWT*	*Proposed*	*DWT*
103.dat	7.0461	5.3553	13.2733	12.1109	16.8924	16.1826
113.dat	5.1634	5.8560	12.1568	12.5063	16.6713	16.4477
122.dat	7.0983	5.9144	13.3726	12.2962	17.3730	15.7040
221.dat	7.0713	6.3926	13.5739	11.8226	17.8490	16.6016

Table 3. Denoising performance (MSE) of the proposed method and wavelet-based method for several records taken from MIT-BIH database.

ECG file	Input SNR -2dB		Input SNR 5dB		Input SNR 10dB	
	Proposed	*DWT*	*Proposed*	*DWT*	*Proposed*	*DWT*
103.dat	1870.5	2086.8	260.2584	382.0813	120.6819	162.1919
113.dat	3827.2	3504.8	589.2843	639.3415	142.3947	197.1289
122.dat	2209.3	2398.5	480.9522	550.4340	98.2579	192.1519
221.dat	1395.4	1461.1	195.0584	302.1061	86.5746	114.9457



a)

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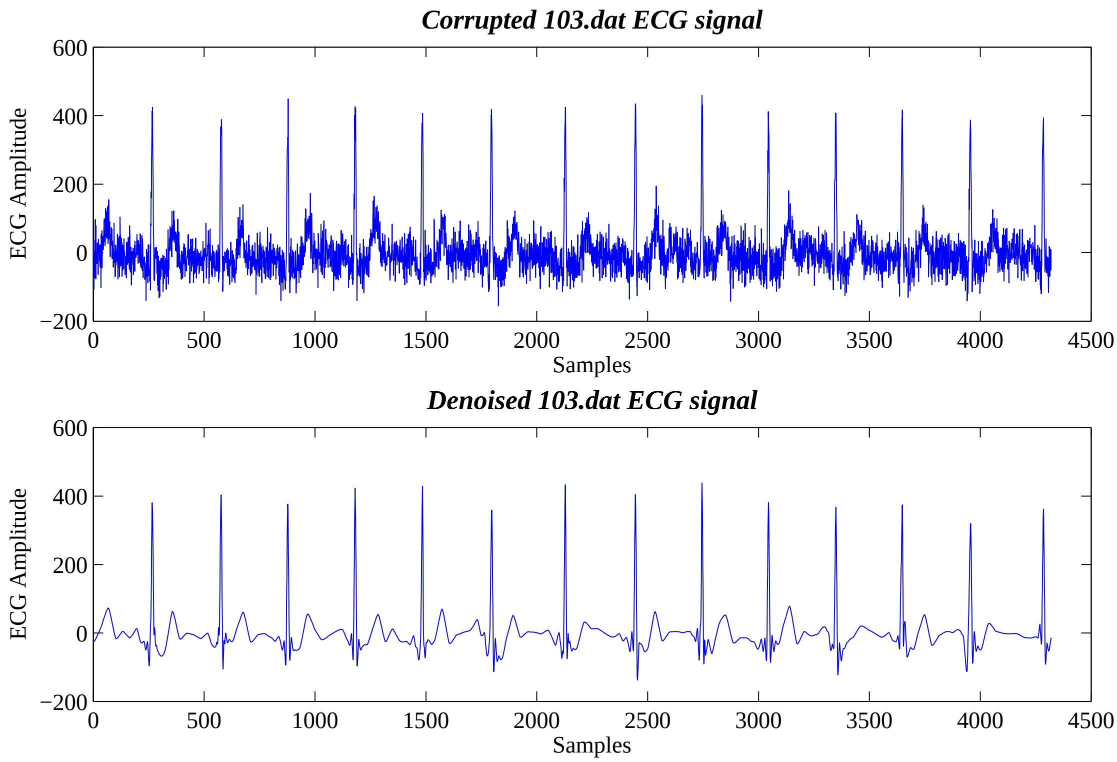
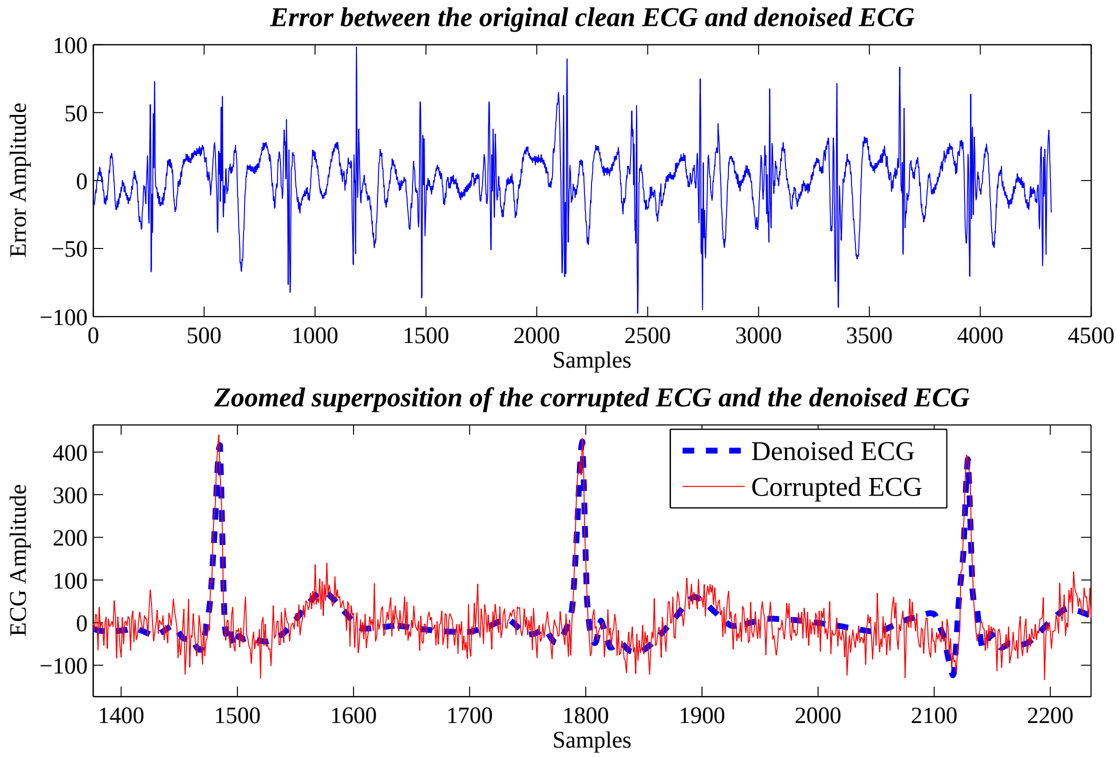
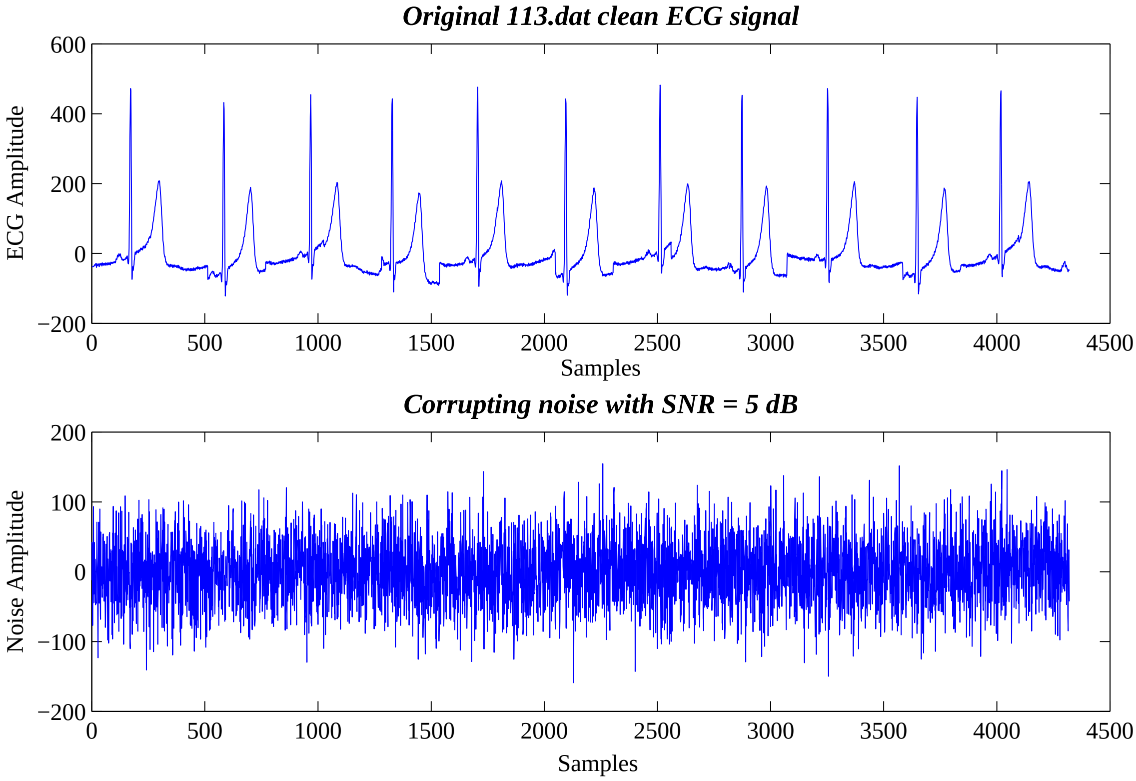


b)

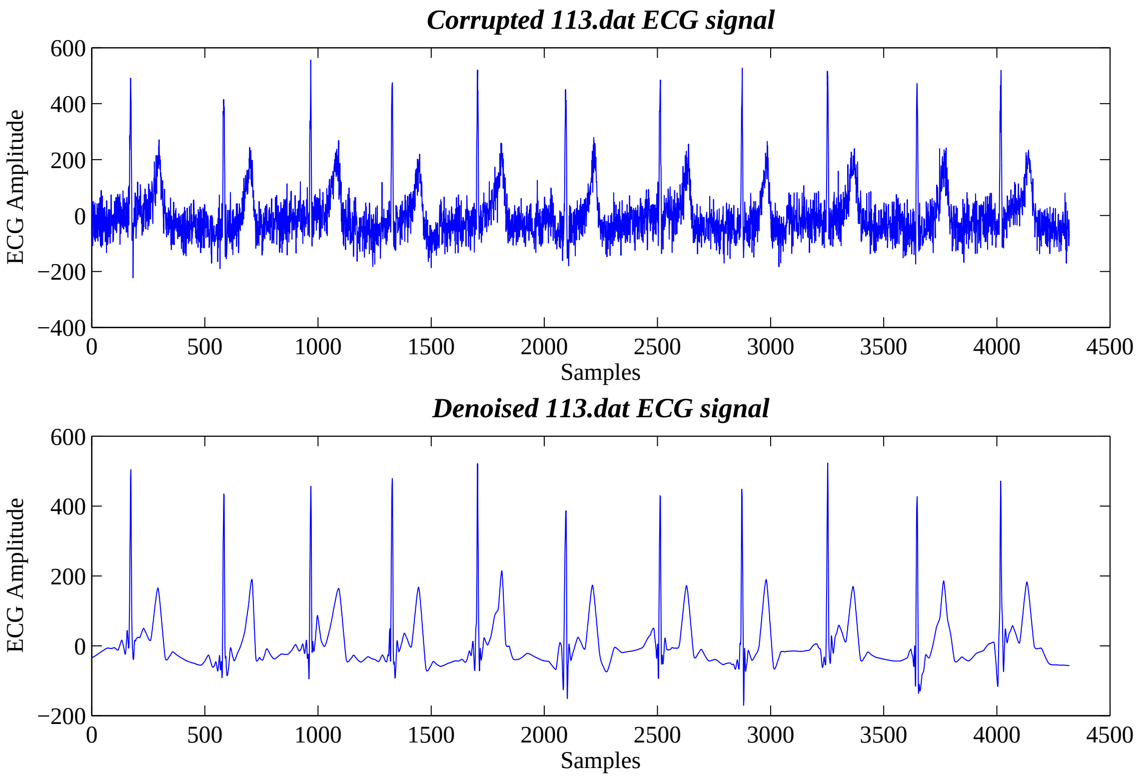


c)

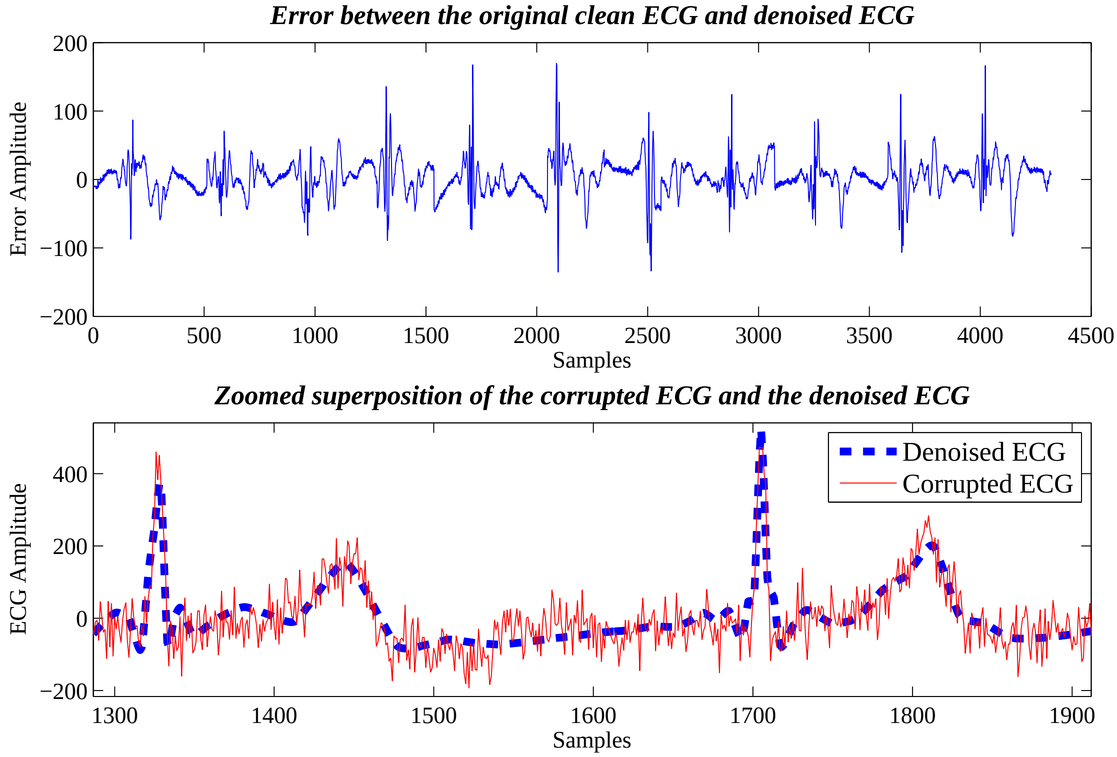
Fig. 10 ECG denoising using the proposed method with input SNR=5 dB for ECG 103.dat


Original 113.dat clean ECG signal
ECG Amplitude
Samples
Corrupting noise with SNR = 5 dB
Noise Amplitude
Samples

a)

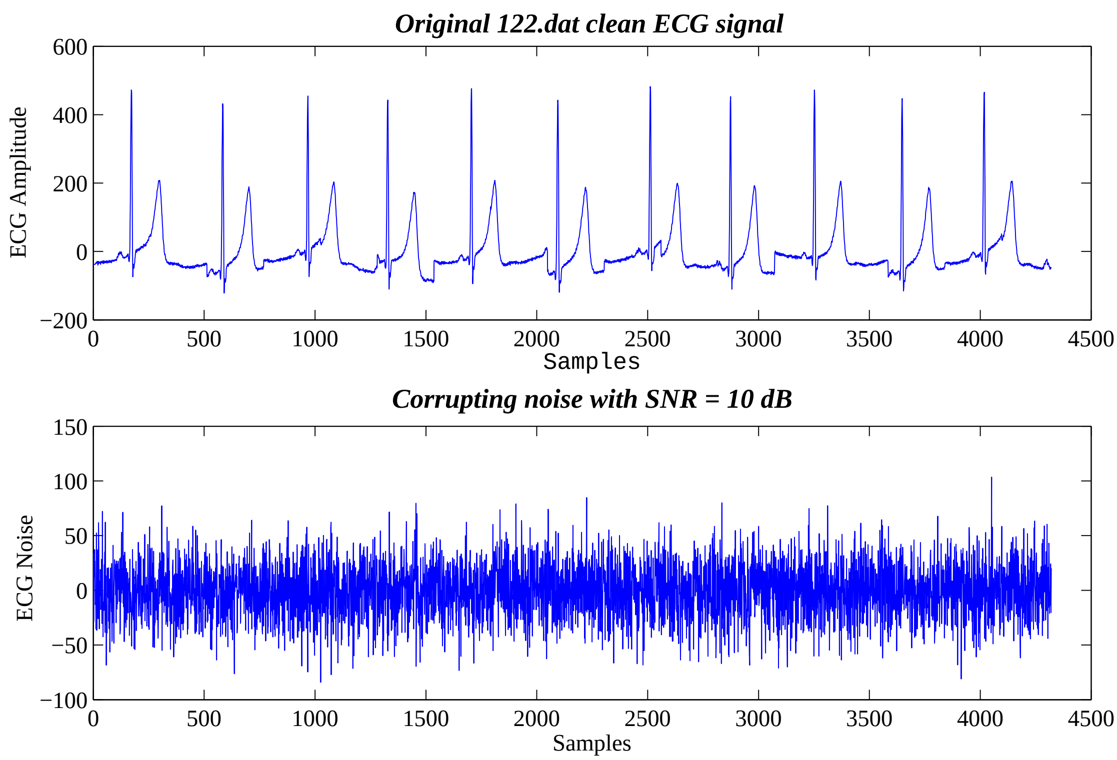

Corrupted 113.dat ECG signal
ECG Amplitude
Samples
Denoised 113.dat ECG signal
ECG Amplitude
Samples

b)

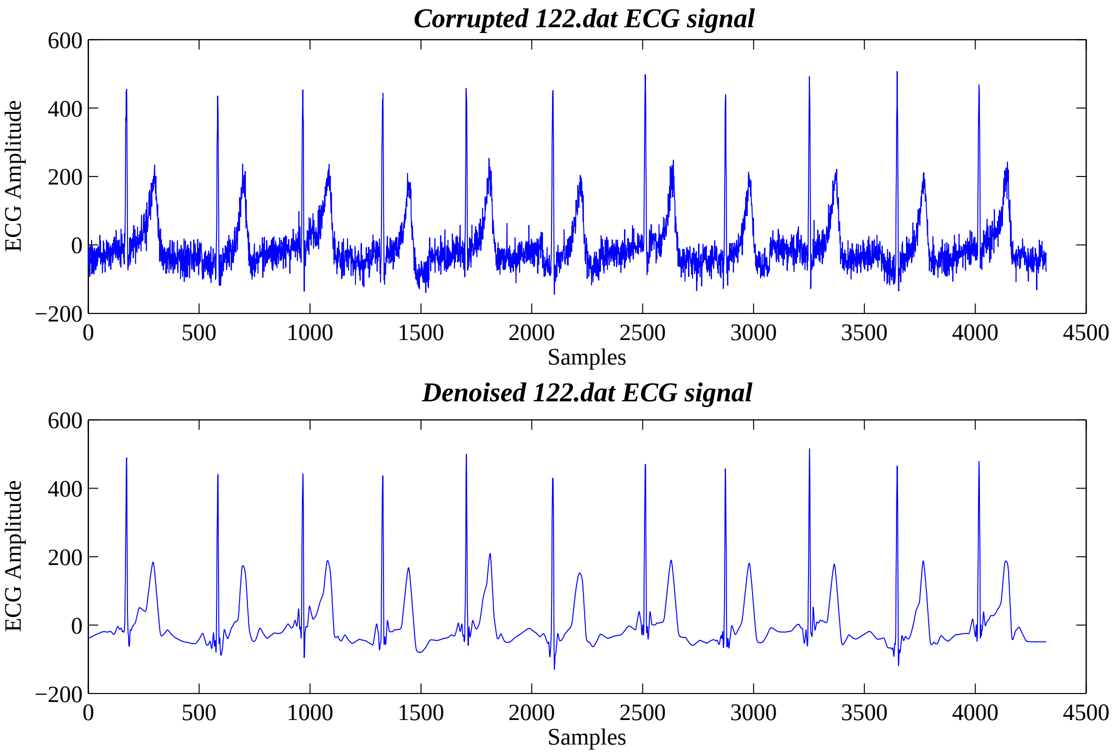


c)

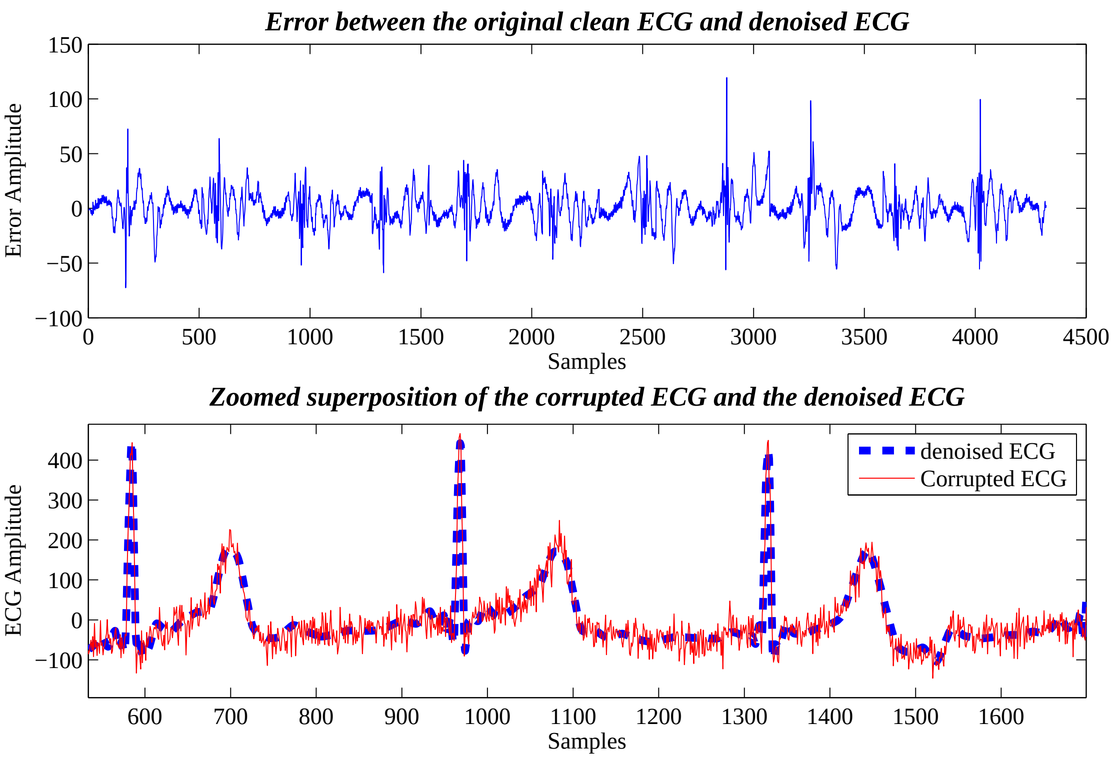
Fig. 11 ECG denoising using the proposed method with input SNR=5 dB for ECG 113.dat



a)

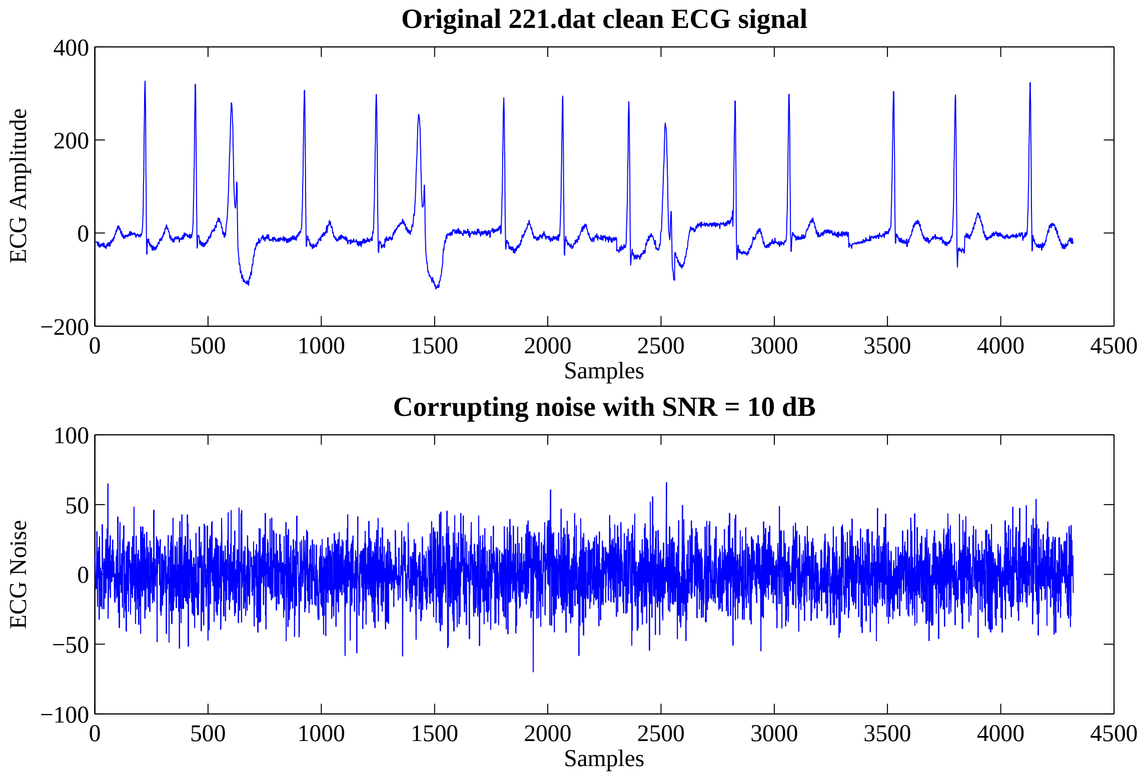


b)

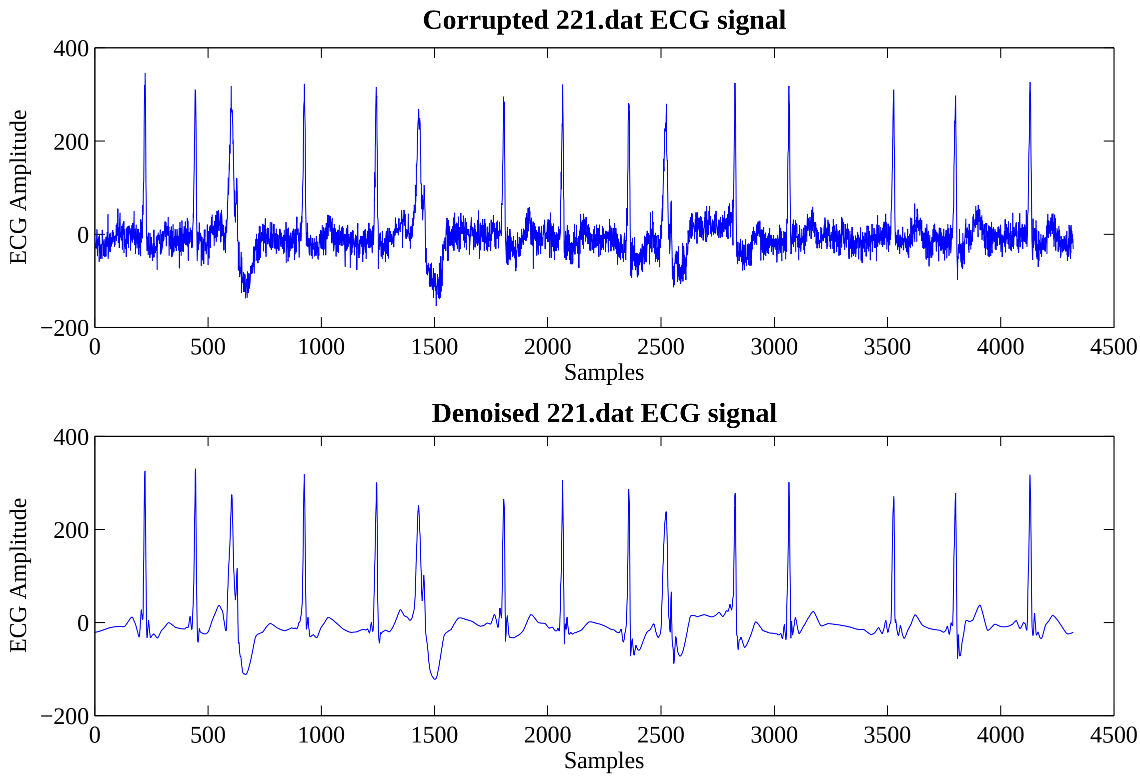


c)

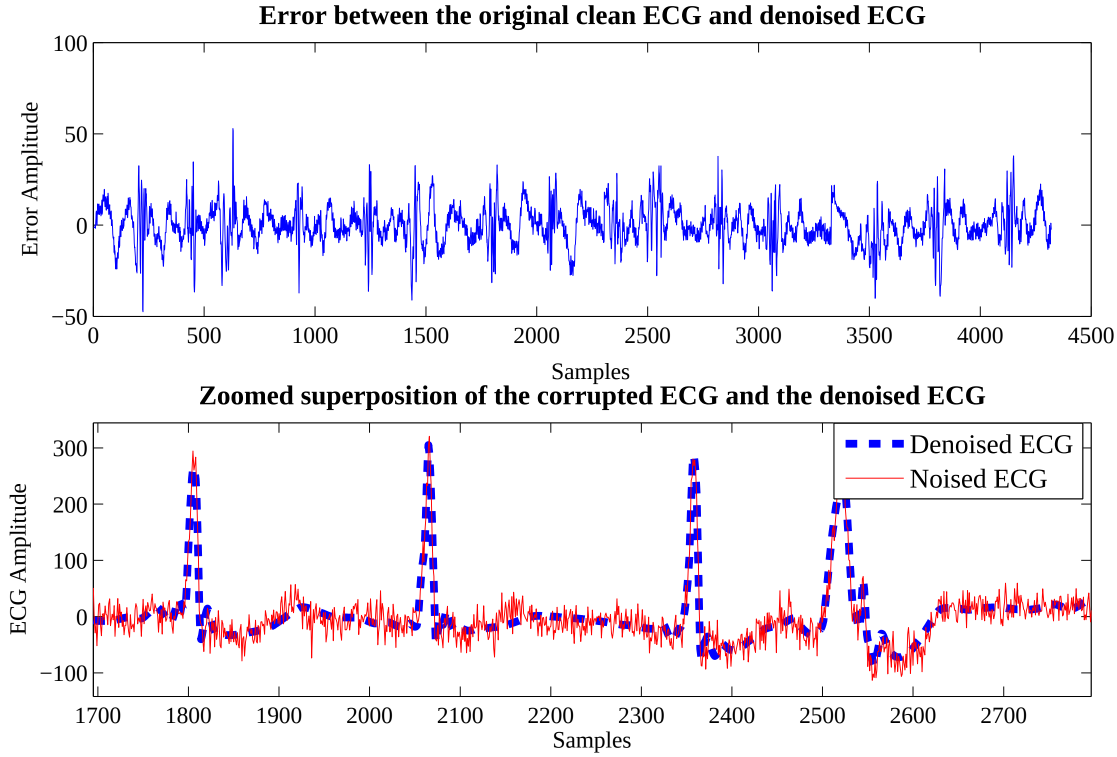
Fig. 12 ECG denoising using the proposed method with input SNR = 10 dB for ECG 122.dat


Original 221.dat clean ECG signal
ECG Amplitude
Samples
Corrupting noise with SNR = 10 dB
ECG Noise
Samples

a)


Corrupted 221.dat ECG signal
ECG Amplitude
Samples
Denoised 221.dat ECG signal
ECG Amplitude
Samples

b)



c)

Fig. 13 ECG denoising using the proposed method with input SNR = 10 dB for ECG 221.dat

Conclusion

In this paper we have shown that with judicious combination of conventional digital signal processing tools like median filter, moving average filter, R-peaks detection, and statistical estimation, satisfactory ECG denoising results have been obtained.

The results obtained with this structure outperforms the results obtained with moving average or median filter taken alone and can be an important concurrent to the state of the art standard wavelet-based method implemented in Matlab.

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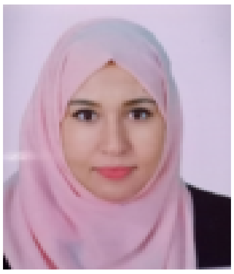

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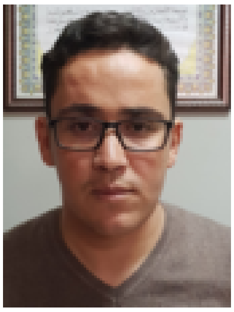

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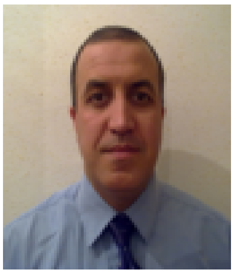

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