A HYBRID ALGORITHM FOR ECG SIGNAL ARTIFACTS REMOVAL

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ABSTRACT

A clean signal is an ultimate prerequisite to obtain good results and correct understanding of a physiological process. Noisy signals can lead to false diagnosis or misinterpretations. ECG signal is sensitive in nature and gets affected by different noise types during acquisition. This paper presents a hybrid denoising algorithm based on Empirical Mode Decomposition (EMD) and Wavelet Transform (WT) for denoising electrocardiogram (ECG) signals. The algorithm performs Empirical mode decomposition and decomposes the signal into intrinsic mode functions (IMFs). Selected noisy IMF is decomposed by wavelet transform and IMF coefficients are thresholded to remove the noisy components. Denoised IMF is reconstructed by taking inverse wavelet transform and added back to the signal. The algorithm is tested over stress ECG dataset corrupted with baseline wandering and electrode movement artifacts. The algorithm is further tested by adding synthetic white Gaussian noise to the signal in the range 5-20 dB. Signal-to-noise ratio (SNR) and Covariance parameters are used to evaluate the performance of the proposed algorithm with the existing standard methods. The subjective and objective comparison suggests a better performance by the proposed algorithm in comparison to its standard counterparts.

KEYWORDS

Denoising, Empirical Mode Decomposition, Wavelet transform, Electrocardiogram.

1. INTRODUCTION

Signal represents a set of information that describes the state of the system using variables generally varying with respect to the time. There is a very high probability of information corruption in process of acquisition or transmission due to acquisition system error, communication loss, and the addition of other environmental noises. Corrupted signal can mislead the analysis and causes false interpretation. In every other study involving a signal, it is essential to keep the signal clear from noise.

An Electrocardiogram (ECG) represents the electrical activity of the heart. It can be used to monitor heart activities and to diagnose underlying ailments. The frequency band for ECG signals varies from 0.5-150 Hz and is very sensitive to noise interference[1]. This interference could be from internal sources such as EMG signals; or external sources such as power line interference and recording electrode movement. It is essential to filter the signal before further processing, but filtering becomes challenging due to the diverse nature of artifacts and interferences [2].

Literature states various artifact removal methods, using wavelet transform, wavelet packet transform, independent component analysis(ICA), principal component analysis (PCA), adaptive linear neural networks,[3][4][5][6][7], and spatiotemporal filters, etc. [8][9]. Sometimes these methods are fused together to improve the performance of the individual method. For example; combining PCA with other nonlinear methods like ICA and wavelets can make a faster algorithm[5]. Principal component analysis is a fast algorithm and uses the first two statistical moments of the data, assuming noise sources are uncorrelated. ICA is another good approach that works on the blind source separation principle and demands an equal number of signal observations to the independent source.

Wavelet-based denoising is famous in the time-scale domain. It decomposes the signal and then allows to apply different thresholding [10]. It is used to de-noise various physiological signals like electrooculogram (EOG), electromyogram (EMG), continuous electroencephalogram (EEG), and also the epileptic EEG signal [11]. It is also used in its other forms like wavelet packet transform and a combination of other methods like ICA, PCA [12] [13].wavelet transform and ICA have been used for EKG and ocular artifact removal [14] [15]. The combination of wavelet and PCA have also been used in applications like industrial fluidized catalytic unit, monitoring the auto-correlated measurements, and biological electron tomography [16] [17]. Some comparative studies have been done that suggest mayer wavelet as a good function to be used in de-noising epileptic while db8 for healthy subjects[11].

Empirical mode decomposition is another tool that can be used to denoise signals. Conventional Empirical Mode Decomposition (EMD) based methods remove the noisy intrinsic mode functions (IMFs) from the signal. This will result in the loss of a lot of information. Different algorithms are suggested to improve the performance of EMD- based algorithms and to avoid information loss. Zhang et al. suggested an adaptive thresholding approach for the removal of IMFs. Some of the parameters considered include eigen period and energy of IMFs [18]. In another approach proposed by Bouny et.al, higher-order statistics like kurtosis is used to select noisy IMFs. This selection is followed by thresholding and denoised ECG signal reconstruction [19]. Kumar et.al. proposed a technique in which the output of EMD is given to another framework that is based on the non-local mean technique. This technique helps to preserve the details of the ECG signal-like edges [20]. In another approach proposed by Zhnag et.al., the sample entropy is used to select the noisy IMFs. As per the algorithm, noisy IMFs can be arranged in the order of entropy value, and then thresholding can be applied [21]. A lot of focus is given to design algorithms for the selection of noisy IMFs.

In that direction, we are proposing a hybrid algorithm based on EMD and Wavelet that is used to remove baseline wandering and electrode movement artifacts. The paper follows the methodology shown in figure 1. Section 2 gives the details of the methodology followed. Section 3 gives the result analysis done to obtain the best parameters and a comparative analysis with the standard methods.

2. MATERIALS AND METHODS

2.1. Methodology

This section gives the complete methodology followed for de-noising the ECG signal as shown in figure 1. Baseline wandering and electrode movement artifacts are added to the clean ECG signal. The signal is preprocessed and empirical mode decomposition is performed. First IMF(IMF1) is selected and further decomposed using wavelet transform. At the different decomposition levels, the coefficients are modified and IMF1 is reconstructed after applying the inverse wavelet transform. Modified IMF1 is then added back to the signal to give the clean signal as output.

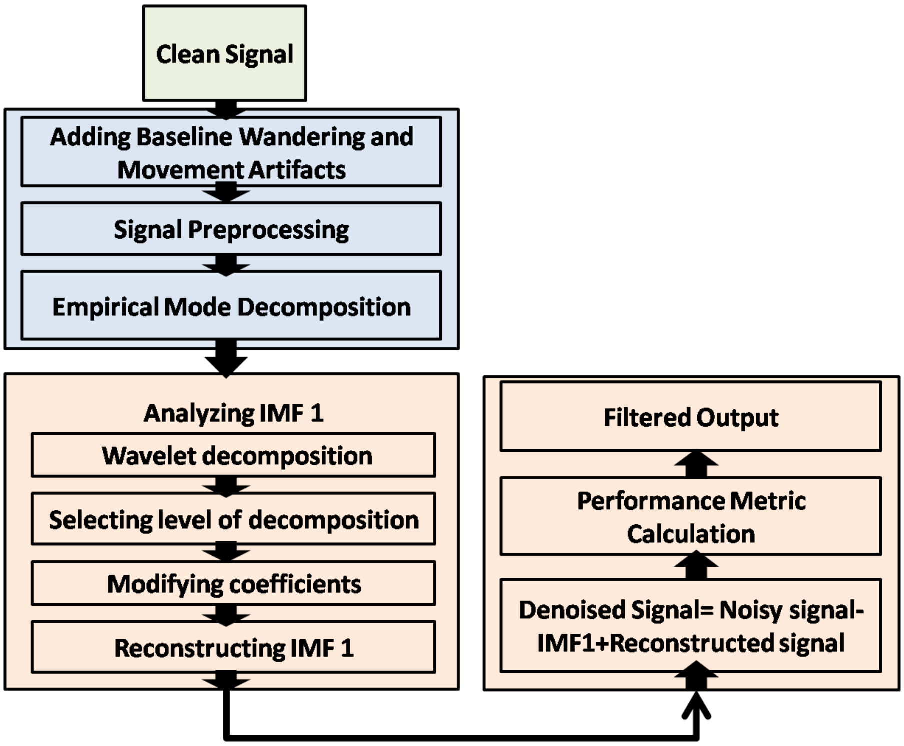

Figure. 1. Proposed Methodology

2.2. Dataset and signal pre-processing

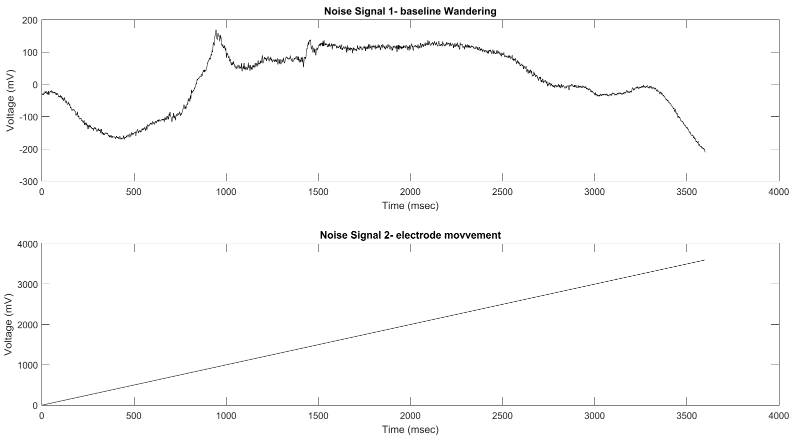

Figure. 2. Noise artifacts (a) Baseline wandering (b) Electrode Movement

The dataset is taken from MIT-BIH Noise Stress Test Database [22]. Two noise artifacts named baseline wandering and electrode movement are also downloaded from the same source. Figure 2(a) & (b) shows the baseline wandering and electrode movement artifacts used in the current analysis. ECG signals from this database are selected for a better reliability in practical application. A noisy signal is prepared by adding these two artifacts to clean ECG signal as shown in figure 3.

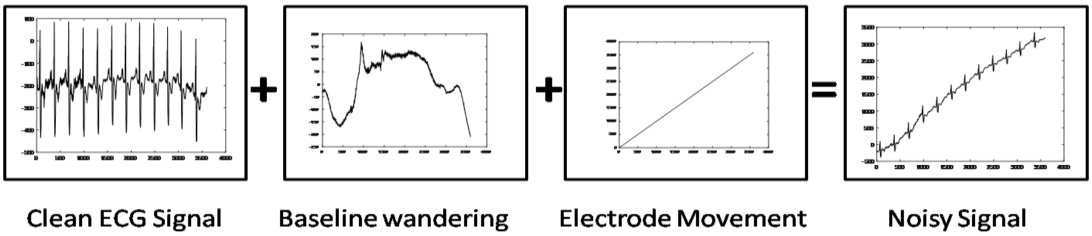

Figure. 3. Signal preparation

2.3 Empirical mode decomposition

Empirical mode decomposition (EMD) is a technique to decompose the signal into intrinsic mode functions (IMFs). EMD performs the decompositions at different resolutions and separates the signal into different components based on given criteria over several iterations. These components are the physically meaningful components that can be analyzed and some physical interpretation can be made. EMD can be used to decompose the noisy signal and remove the noisy component from the signal.
EMD process for any signal x(t) can be defined as:

$$x(t) = \sum_{n=1}^{L-1} In(t) + RL(t) \tag{1}$$

Where L =decomposition level, In(t) represent IMFs, RL(t) = residal signal.

2.4 Wavelet Decomposition

Wavelet transform is a time-frequency domain transformation that transforms the signal without affecting its shape using suitable mother wavelet. It decomposes the data into details and coefficients as in equation 1.

$$X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \overline{\psi\left(\frac{t-b}{a}\right)} X(t)dt \tag{2}$$

Where a= scaling function, b= translating function, ψ=wavelet function or mother wavelet
Wavelet transform allows the signal processing at different decomposition levels by providing data in the form of details and coefficients. It offers a number of basis functions like haar, Daubechies, Meyer, biorthogonal etc. Selected IMF is decomposed and analyzed using wavelet transform.
Proposed algorithm follows following steps:
1. Let a clean signal x(t).
2. Artifacts are added to signal

$$x1(t)=b(t)+e(t) \quad . \tag{3}$$

where b(t)- Baseline wandering artifact, e(t)- Electrode movement artifact
3. Band pass filtering is applied to give x2(t) as output.
4. Filtered signal is decomposed by EMD to give 5 IMFs.

$$y'(t) = \sum_{n=1}^{5} In(t) + RL(t) \tag{4}$$

5. I1(t), First IMF carries most of the noise. So it is removed from the signal.

$$x3(t)=x2(t)-I1(t) \tag{5}$$

This step will lead to loss in information from signal.
6. I1(t) is processed separately using wavelet transform. The noisy frequency coefficients of this IMF are thresholded and removed.
7. IMF1 is reconstructed as IMF1' and added back to x3 from step 5 to give x4 as output.

$$x4(t)=x3+I1(t)' \tag{6}$$

8. Signal is reconstructed back to give an artifact free ECG signal y(t) .

2.5 Performance measures

These measures provide quantitative analysis of the results obtained in the form of some value or quantity, unlike the qualitative measures that are subjective and depend on human observation. Signal to-noise ratio (SNR) and mean square error (MSE) and covariance are such measures.

1. Signal to Noise Ratio

This ratio represents the signals to noise power [13]. Higher the value of SNR, lesser will be the noise in the reconstructed signal. The basic expression of SNR is:

$$\mathrm{SNR} = \frac{\mathrm{Power}_{\mathrm{signal}}}{\mathrm{Power}_{\mathrm{noise}}} \tag{7}$$

Equation (7) modifies according to the signal parameters available. Expressions below show the SNR with the assumption mentioned.

$\mathrm{SNR} = \frac{\sigma^2_{\mathrm{signal}}}{\sigma^2_{\mathrm{noise}}}$; For a signal with zero mean and known variance.

$\mathrm{SNR} = \frac{\mu}{\sigma}$; For nonnegative variables

In our case, the expression used is given in eq. (8) and (9) [23]:

$$\mathrm{SNR}_{\mathrm{before\ denoising}} = 20\log_{10}\left(\max\left|\mathrm{X}_{\mathrm{noisy\ signal}}/\mathrm{std}(\mathrm{X}_{\mathrm{noisy\ signal}})\right|\right) \tag{8}$$

$$\mathrm{SNR}_{\mathrm{after\ denoising}} = 20\log_{10}\left(\max\left|\mathrm{X}_{\mathrm{denoised\ signal}}/\mathrm{std}(\mathrm{X}_{\mathrm{denoised\ signal}})\right|\right) \tag{9}$$

2. Mean Square Error

This parameter shows the error difference between the original signal and the reconstructed de-noised signal [24]. The lesser the value of measure better will be the quality of the reconstructed signal.

$$\text{Mean Square Error (Original, noisy)} = \frac{\sum_{t=1}^{n}(\mathrm{Xoriginal} - \mathrm{Xnoisy})^2}{n} \tag{10}$$

$$\text{Mean Square Error(Original, denoised)} = \frac{\sum_{t=1}^{n}(\mathrm{Xoriginal} - \mathrm{Xdenoised})^2}{n} \tag{11}$$

3. Covariance metric

It is a measure of the variance of the variables; and is used here to evaluate the performance of the algorithm when applied to input ECG signals [25]. Equation (12) & (13) gives the metric for the noisy and the de-noised signals.

$$\text{Covariance (Original, noisy)} = \frac{\sum((\mathrm{Xoriginal} - \overline{\mathrm{Xoriginal}}) - (\mathrm{Xnoisy} - \overline{\mathrm{Xnoisy}}))}{n-1} \tag{12}$$

$$\text{Covariance (Original, denoised)} = \frac{\sum((\mathrm{Xoriginal} - \overline{\mathrm{Xoriginal}}) - (\mathrm{Xdenoised} - \overline{\mathrm{Xdenoised}}))}{n-1} \tag{13}$$

3. RESULTS

This section tests the performance of algorithm on noisy signal prepared by corrupting clean ECG signal with baseline wondering and electrode movement artifacts. The algorithm is further tested by clean ECG signal with synthetic white Gaussian noise of 5dB, 10dB, 15dB, and 20 dB.

3.1. Removing Baseline wandering and movement artifact

Noisy ECG signal is band pass filtered and decomposed to 05 intrinsic mode functions by empirical mode decomposition as shown in figure 4.

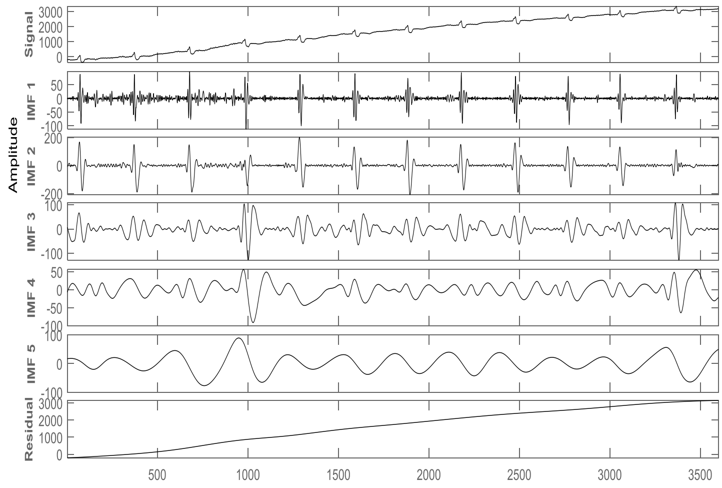

Figure 4. Empirical Mode Decompositions (05 IMFs) of noisy ECG Signal

The first IMF is then extracted and subtracted from the noisy signal. The subtracted IMF is further processed using the wavelet transform. This IMF is decomposed using wavelet transform and noisy details are removed from it. The processed IMF is then added back to the signal and signal is reconstructed. Denoised signal quality is further checked via both subjective and objective analysis.

Subjective analysis: Figure 5 shows the output of the proposed algorithm that is subjectively compared with the other standard algorithms including EMD based and Wavelet-PCA based. Subjective analysis suggests that out of three methods wavelet-PCA based method and proposed method performs better. These two methods can be further compared quantitatively.

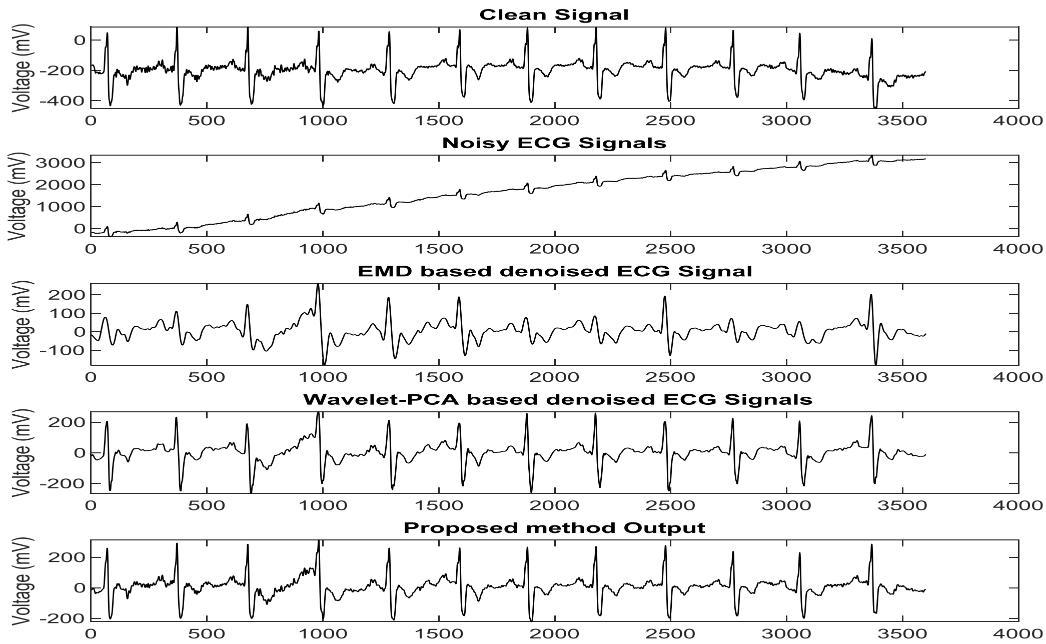

Figure 5. Qualitative analysis (top to bottom) (a) Clean ECG signal (b) Noisy ECG signal (c) EMD based denoised signal (d) Wavelet-PCA based denoised signal (e) Proposed method output

Quantitative analysis: Literature suggest SNR limit of 18dB for a robust ECG waveform analysis[26]. Considering this observation, the output of the two selected methods is compared using SNR, and Covariance. A higher SNR is obtained using the proposed algorithm. A comparison of the covariance parameter suggests that the value obtained by the proposed algorithm is closer to the value of the clean signal. A value closer to the original value suggests the similarity of a filtered signal to that of a clean signal. Table 1 gives the summary of quantitative parameters.

Table I. Performance Metric

	Signal to Noise Ratio (SNR)	Covariance*
Noisy Signal	23.0064	2.6143e+03
WT-PCA Method	26.7260	4.6027e+03
Proposed Method	**29.8460**	**4.7123e+03**

*Covariance value of clean signal is 5.1210e+03.

3.2. Removing white Gaussian noise

The algorithm is further tested by adding white Gaussian noise of 5-20 dB to clean ECG signal. The performance is compared using statistical parameters.
Subjective analysis: Figure 6 shows the output of the proposed algorithm that is subjectively compared with the other standard algorithms including EMD-based and Wavelet-PCA based. Subjective results suggest good performance by the proposed method. There is some event issue at sample point 2000 corresponding to noise levels 5dB and10dB as shown in figures 6(a) & (b). This point can be further investigated. Figures 6 (c) & (d) display a very good output ECG signal for noise levels 15dB and 20dB.

Quantitative analysis: The output of the two selected methods is compared using SNR and Covariance. A higher SNR is obtained using the proposed algorithm. A comparison of covariance parameter suggests that the value obtained by the proposed algorithm is closer to the value of the clean signal. Table2 gives the summary of quantitative parameters.

Table 2. Performance metric for Signal to Noise Ratio (SNR) and Covariance

	Signal to Noise Ratio (SNR)				Covariance			
	5dB	**10dB**	**15dB**	**20dB**	**5dB**	**10dB**	**15dB**	**20dB**
Noisy Signal	4.6494	4.0310	4.4036	6.5318	5.1204e+03	5.1171e+03	5.1149e+03	5.1157e+03
WT-PCA Method	26.8022	26.8294	27.0367	26.7917	4.4857e+03	4.4821e+03	4.4785e+03	4.4721e+03
Proposed Method	**29.3806**	**29.4316**	**30.0990**	**30.2552**	**4.6920e+03**	**4.6787e+03**	**4.5661e+03**	**4.5763e+03**

*Covariance value of clean signal is 5.1210e+03.

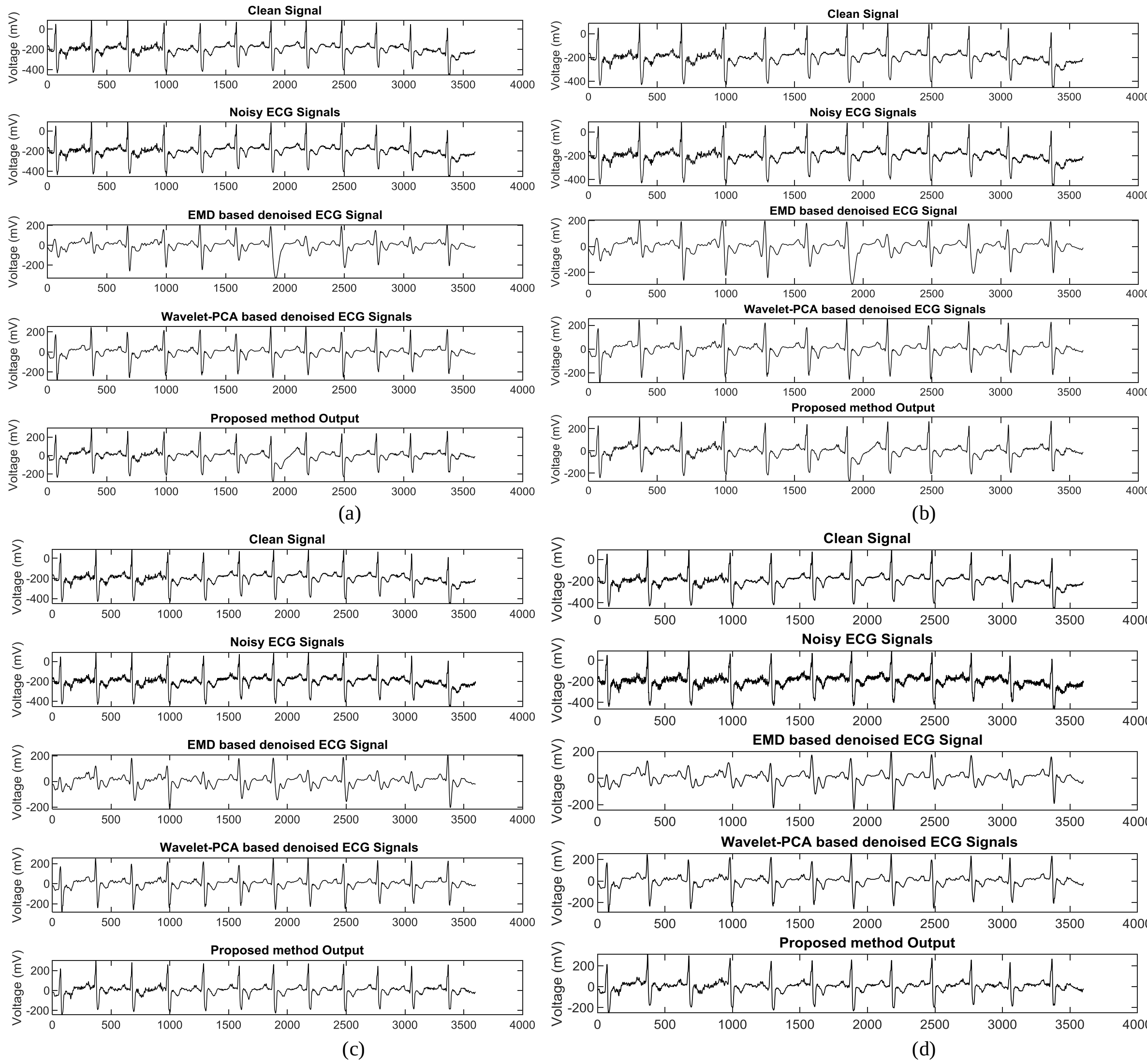

Figure 6. Denoising results with; (a) 5dB (b) 10dB (c) 15dB (d) 20dB of white Gaussian noise

4. DISCUSSION AND CONCLUSION

This paper proposed a hybrid algorithm based on EMD and WT. The proposed approach aims to combine these two methods to remove the artifacts while preserving the signal content. Figure 5 and Table 1 give the result of filtering ECG signal corrupted with baseline wandering and electrode movement artifacts as obtained from the MIT-BIH database. A higher SNR and similar covariance values are observed for the filtered signal. The algorithm is also tested for synthetic interference with white Gaussian noise (WGN) of 5dB, 10dB, 15dB, and 20dB. Figures 6 gives the filtering results for ECG signal corrupted with WGN of 5dB, 10dB, 15dB, and 20dB respectively. Figures 6(c) & 6 (d) display better performance by the proposed method. Table 2 & 3 gives the statistical feature to compare the performance of methods that suggest higher SNR and covariance value close to the original signal for the proposed method.

The proposed hybrid algorithm is fast and has lower computational demand as it is based on EMD and wavelets. The algorithm tries to preserve the shape and other physical characteristics like the amplitude of the ECG signal. Generally, the signal losses its amplitude after going through the denoising. In this algorithm, the amplitude is preserved as the noisy IMF is processed and added back to the signal. Comparative analysis suggests a higher signal-to-noise ratio. The covariance value of the output signal by the proposed method is closer to the covariance value of the clean ECG signal in comparison to the other method. Overall, the proposed method shows better performance than its existing counterparts. Studying the process of denoising, improvements are suggested to make the process more reliable. The algorithm can be further improved and an adaptive approach can be developed to select the decomposition level of noisy IMFs. This will make the denoising process more robust.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

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