ECG Signal Analysis Using S-Domain

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Abstract

Electrocardiogram (ECG), which is a noninvasive technique, is used generally as a primary diagnostic tool for cardiovascular diseases. In real-time scenario, noises like channel noise, muscle artifacts, electrode motion and baseline wander are often embedded with ECG signals during acquisition and transmission. In this paper, an automatic ECG signal enhancement technique is proposed to remove noise components from time–frequency domain represented noisy ECG signal. Stockwell transform (S-Transform) is used in this work to represent the noisy ECG signal in time–frequency domain. Next, masking and filtering technique is applied to remove unwanted noise components from time– frequency domain. The proposed technique does not require any prior information like R-peak position or reference signal as auxiliary signal. This method is evaluated on ECG signals which are available in MIT-BIH Arrhythmia database. The experimental results demonstrate that the proposed method shows better signal to noise ratio (SNR) and lower root means square error (RMSE) compared to earlier reported wavelet transform with soft thresholding (WT-Soft) and wavelet transform with sub band dependent threshold (WT-Sub band) based technique. To quantify the significant difference among all methods, the performances of different ECG enhancement techniques at 1.25 dB input SNR level are compared using analysis of variance (ANOVA) based statistical evaluation technique and it is seen that the proposed method yields superior performance compared to other methods. R-peak detection test is also conducted on enhanced ECG signal in addition to SNR and RMSE to evaluate the quality of biology-related information preserved in the enhanced ECG signal. The performance of R-peak detection for denoised ECG signals, in terms of sensitivity and positive predictivity using proposed enhancement method, is also better than WT-Soft, WT-Sub band methods, and validates the superiority of the proposed method

Keywords

Baseline wander, Denoising, Electrocardiogram (ECG), Electrode motion, Gaussian noise, Muscle Artifacts, Signal Enhancement, S-Transform

I. Introduction

Electrocardiogram (ECG) is a non-invasive technique that is used as a diagnostic tool for cardiovascular diseases. ECG signal is widely used as a fundamental tool for detection and diagnosis of heart disorders. Since, ECG is the most commonly recorded signal for the patient monitoring and examination process, it is important to be able reliably and quickly detect the cardiac disorders. ECG would be much more useful as a diagnostic tool if unwanted noise embedded in the signal is removed. For wireless and tele cardiology application, the efficient transmission of ECG signals over telephone lines, mobile communication, and satellite communication is becoming more and more important. During acquisition and transmission, ECG signals are generally affected by different noises like channel noise, muscle artifacts, electrode motion and baseline wander.

Muscle artifacts are introduced due to muscle activity and electrode motion is caused by the shift in electrode location. Baseline wander is the variation in isoelectric line of ECG which can occur during respiration. Poor channel conditions can also introduce noise in the ECG signal during its transmission. All these noises can corrupt the signal thereby making its analysis difficult and error prone. Hence noisy ECG signals should be enhanced by removing the noise components for further processing.

Various techniques have been reported in the literature for enhancement of ECG signal including techniques like fuzzy multi wavelet denoising, independent component analysis, wavelet denoising and least mean square (LMS) algorithm based adaptive filter. However, most of these reported techniques generally concentrated only on one kind of noise type. Few reported techniques show significant per-formance for enhancement of ECG signals embedded with differ-ent types of noises. However, these techniques require prior information of the signal to work efficiently such as the position of the R-peak for empirical mode decomposition (EMD) based technique and a reference signal for the least mean square (LMS) algorithm based method. This kind of information is difficult to obtain when the noise level is very high. The wavelet transform (WT) based techniques are more popular and widely used because of its ability to characterize time–frequency domain information of a time domain signal. Ercelebi reported an ECG signal enhancement technique based on 4th level decom-posed coefficients of Daubechies wavelet with soft thresholding when the ECG signal is corrupted with base line wander, muscle artifact, electrode motion noises. In another reported literature Poornachandra proposed an ECG signal enhancement techni-que using 3rd level decomposed coefficients of Daubechies wavelet with subband dependent thresholding. This reported work applied on baseline wander, muscle artifact, electrode motion and Gaussian noises. However, the amplitude of the wavelet transform is dependent on the frequency. Wavelet trans-form also has other limitations such as having better frequency resolution and poor time resolution for low frequencies and vice versa for high frequencies. It also has locally referenced phase.

In this paper, a novel method for ECG signal enhancement is proposed using Stockwell transform (S-Transform) to overcome the afore-mentioned limitations. This method can be applied to enhance the ECG signal from different noises which often get embedded with ECG signal during its acquisition and transmission. During acquisition of ECG signal in real time environment, the different types of noises such as channel noise, muscle artifacts, electrode motion, and base line wander are often embedded with ECG signal. Muscle artifacts are due to movement of muscle between skin and electrode. Motion artifacts are transient baseline change due to electrode skin impedance with electrode motion. Base line drift may be caused in chest-lead ECG signals by coughing and breathing with large movement of the chest, or when an arm or leg is moved in the case of limb-lead ECG acquisition. This work proposes an automatic and generalized approach for ECG signal enhancement technique. Beside this, the proposed method does not require any prior information like R-peak position or reference signal as auxiliary signal. The S-Transform, derived by Stockwell et al, is closely related to the Wavelet transform (WT) and short time Fourier transform (STFT). The S-Transform (ST) has a similar form to the STFT except that the width of window varies with frequency. The S-Transform has three characteristics that distinguish it from wavelet transform: (i) frequency invariant amplitude response, (ii) progressive resolution and (iii) absolutely referenced phase information. Besides, the ST uses time–frequency axis rather than the time-scale axis used in the WT]. Therefore, the interpretation on the frequency information in the ST is straighter forward than in the WT, which will be beneficial to remove noise components. ST is used to represent the noisy ECG in time– frequency domain. An automatic mask window and morphologi-cal filtering technique is applied to this time–frequency domain represented noisy signal for removing the noises. The proposed algorithm is evaluated for noises such as white Gaussian noise, muscle artifact, electrode motion, and baseline wander. Performance of the proposed algorithm is evaluated by means of signal to noise ratio (SNR) and root mean square error (RMSE). Experimental results show that the proposed method yields superior performance compared to commonly used wavelet transform with soft thresholding (WT-Soft) and wavelet transform with subband threshold (WT-Subband) based techniques. The performance of different ECG enhancement techniques at 1.25 dB input SNR level is also compared using analysis of variance (ANOVA) based statistical evaluation method to quantify the significant difference among all methods, and the proposed method yields superior performance compared to other methods. The performance of R-peak detection for denoised ECG signals in terms of sensitivity and positive predictivity using proposed enhancement method is also better than WT-Soft, WT-Subband methods and it validates the superior performance of the pro-posed method.

II. Proposed Methodology

The objective of the proposed algorithm is to achieve enhanced signal by selecting the required frequencies and removing the noise components. The block diagram of proposed S-Transform based ECG enhancement is shown in Fig. 1 and the different steps are explained below

*Step*1: *Time–frequency domain representation*: The S-Transform [14] is used to obtain the time–frequency representation of a time domain noisy ECG signal. The continuous S-Transform $S(\tau,f)$ of a noisy ECG signal $h(t)$ at time $t=\tau$ and frequency f is defined as

$$S(\tau,f)=\int_{-\infty}^{\infty}h(t)\frac{|f|}{\sqrt{2\pi}}e^{-((\tau-t)^2f^2)/2}e^{-i2\pi ft}\,dt \tag{1}$$

A voice $S(\tau,f_o)$ is defined as a one dimensional function of time for a constant frequency f_o, which shows how the amplitude and phase for this exact frequency changes over time. If the time series $h(t)$ is windowed (or multiplied point by point) with a window function (Gaussian function) $g(t)$ then the resulting spectrum is

$$H(f)=\int_{-\infty}^{\infty}h(t)g(t)e^{-i2\pi ft}\,dt \tag{2}$$

where generalized Gaussian function is

$$g(t)=\frac{1}{\sigma\sqrt{2\pi}}e^{-t^2/2\sigma^2} \tag{3}$$

and then allowing the Gaussian to be a function of translation τ and dilation (or window width) σ

$$S(\tau,f,\sigma)=\int_{-\infty}^{\infty}h(t)\frac{1}{\sigma\sqrt{2\pi}}e^{-(t-\tau)^2/2\sigma^2}e^{-i2\pi ft}\,dt \tag{4}$$

This is a special case of the multi-resolution Fourier transform because there are three independent variables in it, it is also impractical as a tool for analysis. Simplification can be achieved by adding the constraint restricting the width of the window to σ to be proportional to the period (or inverse of the frequency)

$$\sigma(f)=\frac{1}{|f|}$$

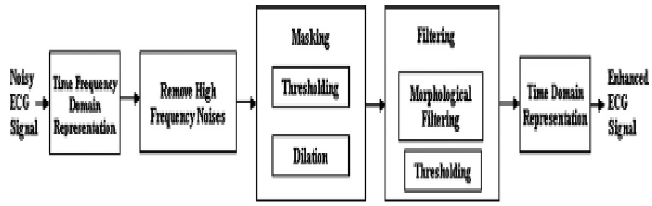

Fig. 1. Block diagram of proposed ECG enhancement technique.

The discrete S-Transform of the noisy ECG signal h[k,T] is given

$$S\left[jT,\frac{n}{NT}\right]=\sum_{m=0}^{N-1}H\left[\frac{m+n}{NT}\right]e^{-2\pi^2m^2/n^2}e^{i2\pi mj/N} \tag{5}$$

where $H[n/NT]$ is the Fourier transform of $h[kT]$ and j, m, $n=0,1,\ldots,(N-1)$. Algorithm 1 shows the computing procedure of discrete S-Transform [12].

Algorithm 1. Discrete S-Transform.

1. Calculate the FFT of the N-point time series.
2. Shift the spectrum such that the voice frequency becomes zero frequency. A ‘‘voice’’ is a one dimensional function of time for a constant frequency.
3. Multiply this shifted spectrum to an N-point Gaussian window function.
4. N point IFFT is done to obtain the corresponding voice frequency.
5. These steps are iterated for all the voice frequencies.

The time–frequency domain representation of a noisy ECG signal at 5 dB SNR level is shown in Fig. 2(a).

Step2: Remove high frequency noises: The objective of this step is to remove high frequency noise components by applying frequency domain thresholding. A clean ECG signal generally has a bandwidth of 0.05–100 Hz. However, ECG signals of different beat types available in MIT-BIH Arrhythmia database has shown that it contain important information within 200 Hz. Hence a frequency domain threshold has been defined at 200 Hz such that the frequency components below 200 Hz are retained and frequency components above 200 Hz are removed.
Fig. 2(b) shows the time–frequency domain representation S_1 after removing high frequency noises.
Step3: Masking: The objective of masking is to remove noise components whose frequencies are between the QRS complexes of time–frequency domain represented S_1. Firstly, the output of the previous step, S_1 is thresholded by selecting an appropriate

threshold as T_m. The binary matrix B is obtained as follows:

$$B[m,n] = \begin{cases} 1 & \text{if } S_1[m,n] > T_m \\ 0 & \text{if } S_1[m,n] \le T_m \end{cases} \tag{6}$$

where m represents row and n refers to column of S_1 and B. T_m is the selected optimum threshold value. This threshold value T_m is selected such that the ratio of between-class variance σ_B^2 to the total-class variance σ_T^2 [17] is maximized. These two variables can be computed as follows [18]:

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \tag{7}$$

$$\sigma_T^2 = \sum_{i=1}^{L} (i - \mu_T)^2 P_i \tag{8}$$

where

$$\omega_0 = \sum_{i=1}^{T_m} P_i \quad \text{and} \quad \omega_1 = \sum_{i=T_m+1}^{L} P_i$$

$$\mu_0 = \sum_{i=1}^{T_m} (iP_i)/\omega_0 \quad \text{and} \quad \mu_1 = \sum_{i=T_m+1}^{L} (iP_i)/\omega_1$$

$$P_i = n_i/N\left(P_i \ge 0, \sum_{i=1}^{L} P_i = 1\right)$$

N is the total numbers of elements of S_1 matrix, n_i is the number of elements at i-th intensity level, P_i is estimated Probability at i-th intensity level, ω_0 and ω_1 are total estimated probability of all intensity level for binary '0' and '1' class respectively, μ_0 and μ_1 are estimated mean of intensity level for binary '0' and '1' class respectively and μ_T is estimated total mean of intensity level of S_1 matrix.

The output binary matrix B is dilated using a structuring element A_1 [19] as follows:

$$B \oplus A_1 = \{x \mid (\hat{A}_1)_x \cap B \ne \emptyset\} \tag{9}$$

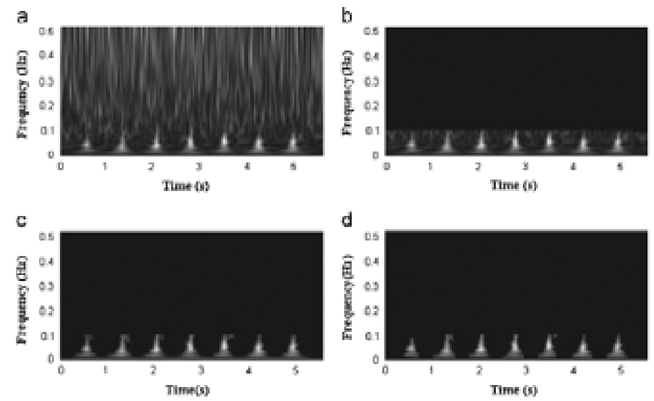

Fig. 2. Different stages of proposed method: (a) Time–frequency domain representation of noisy ECG signal at 5 dB SNR. (b) Time–frequency domain representation of ECG signal after removing high frequency noise. (c) Time–frequency domain representation of ECG signal after masking. (d) Time–frequency domain representation of ECG signal after filtering.

III. Experimental Results

The proposed algorithm is also tested on the ECG data available from online MIT-BIH Arrhythmia database. This data-base contains 48 different ECG signals with 30 min duration which are sampled at 360 Hz. Noise is added to these signals that result 0 dB, 1.25 dB and 5 dB SNR. These noisy ECG signals are denoised using proposed method. The performance of the proposed method is compared with WT-Soft and WT-Subband methods that are commonly used for ECG enhancement. The performance of this method is evaluated based on the SNR and RMSE. The SNR can be represented as follows:

$$SNR = \frac{\sum_{t=0}^{L-1} h(t)^2}{\sum_{t=0}^{L-1} n(t)^2}$$

where h(t) is the ECG signal and n(t) is the noise signal. In this paper, RMSE is used to evaluate the quality of the information which is preserved in the denoised ECG signal. RMSE is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=0}^{L-1}(h(t) - \hat{h}(t))^2}{L}}$$

where the numerator part is the square error, hðt Þ is the reconstructed ECG signal and L is the length of the ECG signal.

The proposed method is tested on different noises that are generally embedded with ECG signal during its transmission and acquisition, i.e., channel noise, muscle artifacts, electrode motion and baseline wander. A multi-point low pass filter is used in this paper for enhancement of the noisy signal and the results are compared with performance of the proposed method. In this filter, to obtain the lower amplitude detail, the number of points and spacing are chosen empirically for best filter as 61 and 20 respectively. A threshold value as 2.5 mV is selected empirically and the amplitude above the threshold level are added to lower amplitude detail for obtaining the filtered signal. The experimen-tal result shows that the performance of the proposed method is better than this multi-point low pass filter for each ECG signal of MIT-BIH database. Both, multi-point low pass filter and proposed methods are tested on noisy ECG signal at 1.25 dB SNR. The average values of the SNR and MSE are seen using multi-point low pass filter 6.06 dB and 0.511 for Gaussian noise, 1.54 dB and 0.841 for muscle artifact noise, 0.982 dB and 0.895 for electrode motion and 0.676 dB and 0.928 for baseline wander noise respectively. The SNR and MSE performance of the proposed method are 9.77 dB and 0.33 for Gaussian noise, 9.66 dB and 0.329 for muscle artifact, 7.01 dB and 0.45 for electrode noise motion and 11.38 dB and 0.27 for baseline wander noise respectively.

A. Experimental Results with Gaussian Noise

Noise due to poor channel conditions can be modelled using white Gaussian noise. Hence, Gaussian noise is artificially added to ECG data that are available in MIT-BIH database. Fig. 4 represents the time–frequency representation of enhanced ECG signal using short time Fourier transform (STFT) and Wigner–Ville transform (WVT) based method from noisy ECG signal. It is clearly seen from the figures, the methods reported in, is unable to enhance the ECG signal. The Wigner–Ville transform provides very high time and frequency resolution but the presence of cross terms due to bilinear structure makes difficult the interpretation of the time–frequency representation]. Therefore, at low SNR level this method could not able to denoise the signal. On the other hand, for STFT, the resolution depends on the selection of fixed window length used. Thus, WVT and STFT based technique are not able to provide significant performance for ECG signal enhancement.

Fig. 5(a) shows the original ECG (MIT-BIH tape no. 230) and Fig. 5(b) shows the ECG to which white Gaussian noise is added resulting in an SNR of 1.25 dB. Fig. 5(c)–(e) depicts the denoised ECG signal using WT with soft threshold (WT-Soft), WT with subband dependent threshold (WT-Subband) based techni-ques and proposed method respectively. Though both methods remove majority of the noise, it can be clearly seen from Fig. 5(c) and (d) that WT-Soft and WT-Subband methods output have more distortions. The amplitude of the wavelet transform is dependent on the frequency whereas S-Transform provides uni-form amplitude response for all frequencies. This effect is observed in the WT-Soft and WT-Subband methods output which have lower R-peak and S-peak amplitudes.

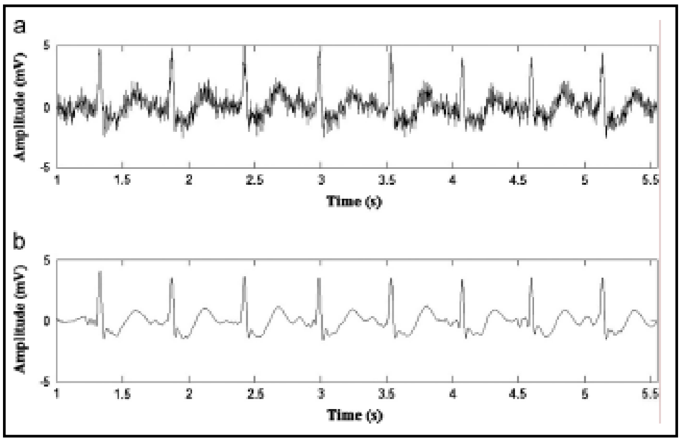

Fig. 3 . ECG signals: (a) Noisy ECG signal with Gaussian noise at 5 dB SNR. (b) Enhanced ECG signal.

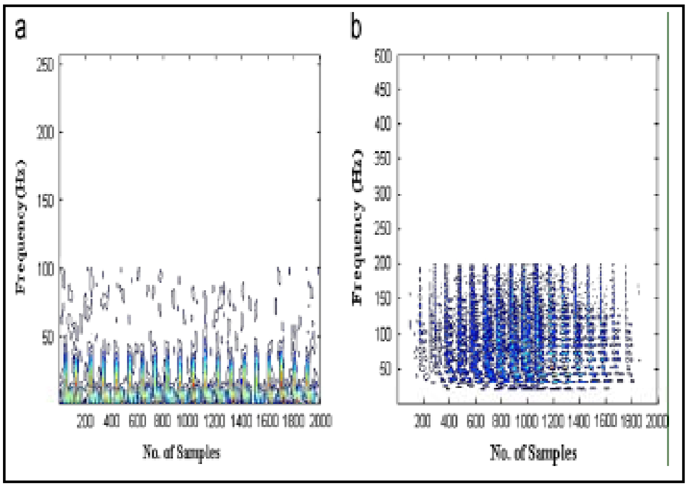

Fig. 4. Time–frequency domain representation of enhanced ECG signal from 5 dB SNR level noisy signal using (a) Short time Fourier transform (STFT). (b) Wigner–Ville transform.

B. Experimental Results with Real Case Noise

Real case noises such as muscle artifacts (MA), electrode motion (EM), and baseline wander (BW) are more probable during ECG acquisition. These types of noises are more significant during stress test. For evaluating the proposed methodology, these noises are taken from the noise stress database and added to ECG data from MIT-BIH database.

Fig. 6 shows the experiment results for MA noise. Fig. 6(a) shows the original ECG (MIT-BIH tape no. 230) and Fig. 6(b) shows the ECG to which MA noise is added resulting in an SNR of 1.25 dB. Fig. 6(c)–(e) shown the output of WT-Soft, WT-Subband and proposed techniques. Similarly Fig. 7(a)–(e) shows the experiment results for EM noise and Fig. 8(a)–(e) shows the experiment results for BW. The real case noises have frequency components in the same range as that of the original ECG signal. Output signals shown in Figs. 6– 8 prove that WT-Soft and WT-Subband fail to remove these noise components and hence does not improve the signal quality. Meanwhile, the proposed method performs time–frequency domain filtering by using an appropriate mask and hence exhibits better enhancement of signal quality.

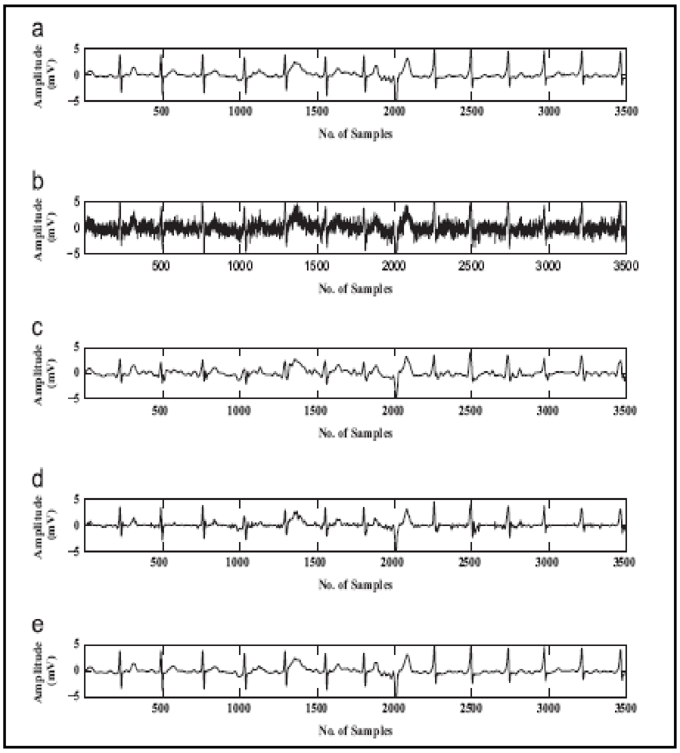

Fig. 5. (a) Original ECG signal (MIT-BIH tape no. 230). (b) Noisy ECG signal with Gaussian noise at 1.25 dB SNR level. Enhancement of noisy ECG signal using (c) WT-Soft method. (d) WT-Subband method. (e) Proposed method.

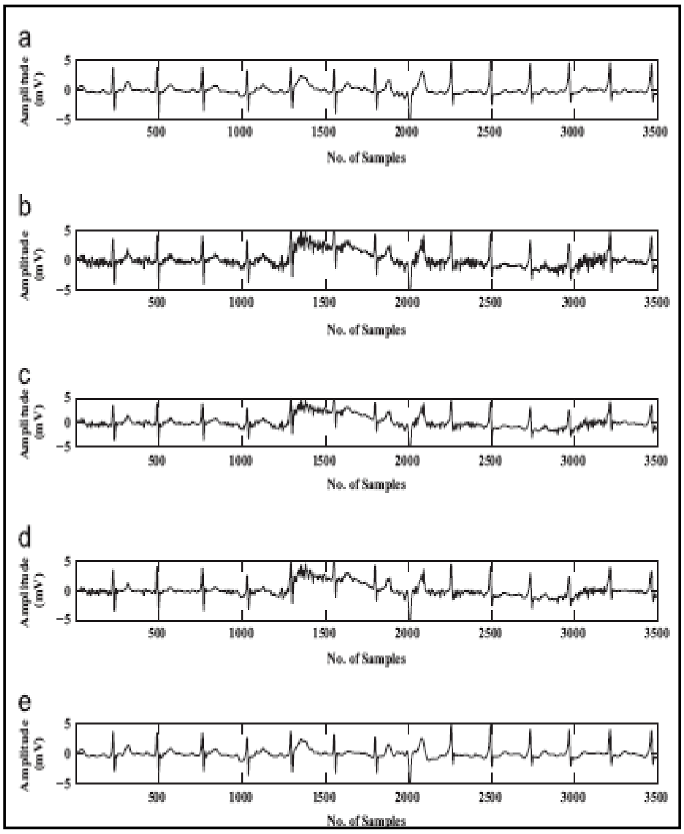

Fig. 6. (a) Original ECG signal (MIT-BIH tape no. 230). (b) Noisy ECG signal with muscle artifacts (MA) noise at 1.25 dB SNR level. Enhancement of noisy ECG signal using (c) WT-Soft method. (d)

WT-Subband method. (e) Proposed method.

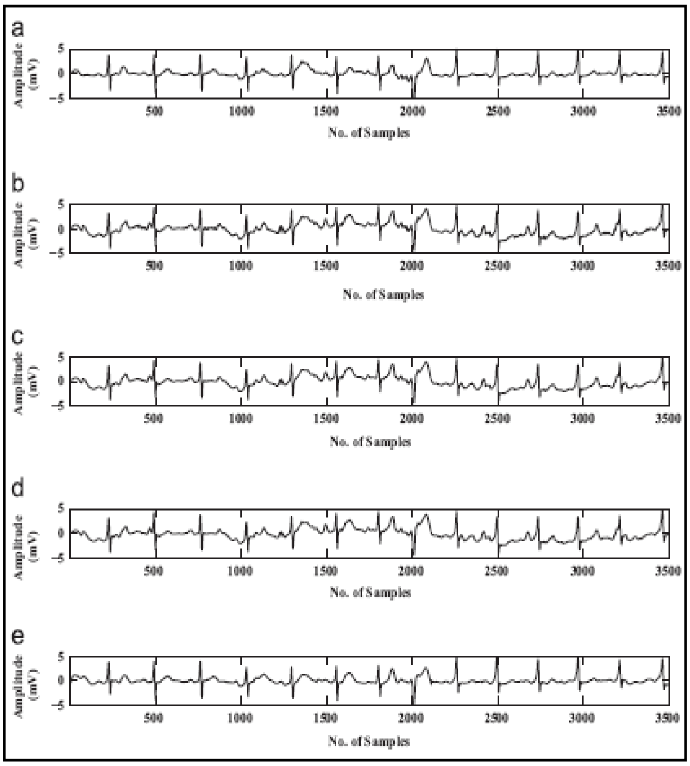

Fig. 7. (a) Original ECG signal (MIT-BIH tape no. 230). (b) Noisy ECG signal with electrode motion (EM) noise at 1.25 dB SNR level. Enhancement of noisy ECG signal using (c) WT-Soft method. (d) WT-Subband method. (e) Proposed method.

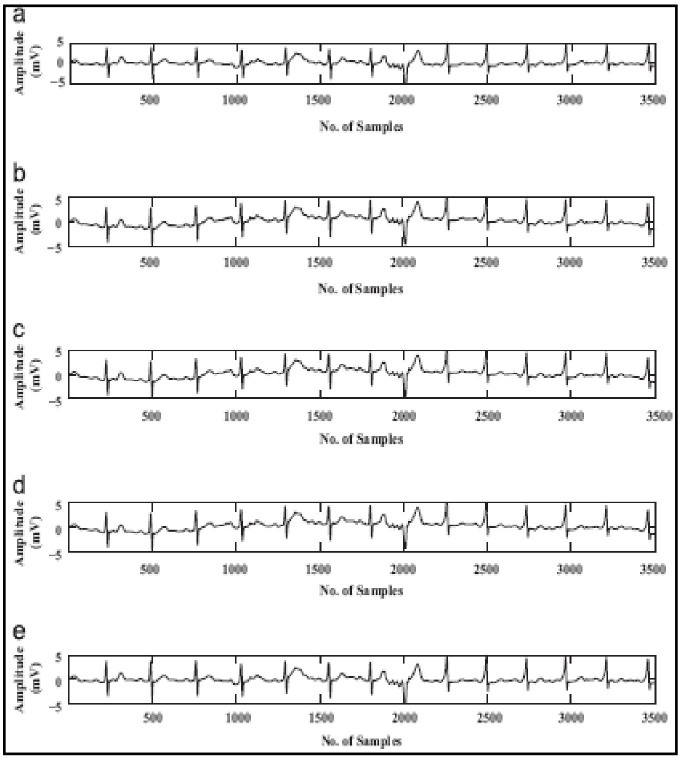

Fig. 8. (a) Original ECG signal (MIT-BIH tape no. 230). (b) Noisy ECG signal with baseline wander (BW) at 1.25 dB SNR level. Enhancement of noisy ECG signal using (c) WT-Soft method. (d) WT-Subband method. (e) Proposed method.

IV. Discussion

The experimental results show that the performance of the proposed method always better compared to WT-Soft and WT-Subband methods for a broad range of ECG signals. WT-Soft and WT-Subband based approach uses wavelet based technique whereas the proposed method employs S-Transform based technique. S-Transform enjoys several advantages com-pared to wavelets like progressive resolution, frequency invariant amplitude response and absolutely reference phase information as mentioned in Section 1. Beside this, the proposed method contains masking and filtering technique which strongly reduce background noise. This process may
also contribute to attain a good SNR and RMSE in addition to the performance of the S-Transform. The masking and filtering techniques are used here to remove noise components whose frequencies lie between the frequency range of the QRS complexes. Out of four different noise cases, it is seen that the performance of the proposed method for few beats of noisy ECG signal with motion artifact shows an attenuation of T waveforms and the smaller peak amplitude of QRS wave but it is better than any of WT based technique. This is because the morphology of the motion artifact often resembles that of P, QRS and T waves and in more specific, the frequency spectrum of this noise completely overlaps than that of ECG signal.
The proposed automatic ECG enhancement technique can be implemented in real-time for denoising of ECG signal. This method does not require any reference signal as auxiliary signal or prior information like R-peak position. A frequency domain fixed thresholding removes the high frequency noises from noisy ECG signal. The algorithm automatically adjusts the thresholds and parameters periodically to adapt the changes of noise condi-tion. This adaptive approach provides the accurate use of ECG signals in real-time like, QRS morphologies detection, and diag-nosis of heart diseases. Without affecting much signal quality even at low input SNR level, the proposed technique is able to reduce the noise efficiently and reliably. The proposed algorithm also preserves the quality of the structural information in the enhanced ECG signal. During acquisition and transmission of ECG signal in real time environment, the different types of noises such as channel noise, muscle artifacts, electrode motion, and baseline wander are often embedded with ECG signal. For all noise cases the proposed algorithm performs better compared to other established WT-Soft and WT-Subband methods.

V. Conclusions

Enhancement of ECG signals is required for accurate analysis of heart's condition. This paper proposes a S-Transform based ECG signal enhancement technique which does not require any reference signal as auxiliary signal or prior information like R-peak position. The noise components are removed from the time–frequency domain represented noisy ECG signal by automatic binary masking and filtering. S-Transform is used in this work to represent the noisy ECG signal in time–frequency domain. The proposed method is evaluated for different noises like white Gaussian noise, muscle artifacts, electrode motion and baseline wander at three different SNR levels, i.e., 0 dB, 1.25 dB and 5 dB. The ECG signals which are available in MIT-BIH Arrhythmia database are used to conduct the experiments. The results show that the proposed method performs better with higher SNR and lower RMSE compared to WT with soft threshold and WT with sub band dependent threshold based techniques which are usually used as an ECG signal enhancement technique.

Table 1 : R-peak detection performance of enhanced ECG signal using WT-Soft, WT-Subband and proposed method.

Noise type	MIT-BIH tape no.	Enhanced ECG signal using					
		WT-Soft method		WT-Subband method		Proposed method	
		Se (%)	+P (%)	Se (%)	+P (%)	Se (%)	+P (%)
Gaussian	103	99.47	99.00	99.62	99.62	99.66	99.62
	230	98.89	98.37	99.56	99.34	99.78	99.82
Muscle artifacts	103	99.52	96.11	99.76	96.29	99.86	98.95
	230	99.73	96.44	99.87	96.20	99.91	97.24
EM noise	103	99.76	99.76	99.86	99.76	99.95	99.95
	230	99.73	99.47	99.82	99.47	99.87	99.73
Baseline wander	103	99.66	99.86	99.81	99.86	99.86	99.90
	230	99.73	99.73	99.82	99.78	99.87	99.82
Average		99.56	98.59	99.76	98.79	99.84	99.38

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