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RESEARCH ARTICLE-ELECTRICAL ENGINEERING

Denoising of Electrocardiogram Signal Using S-Transform Based Time–Frequency Filtering Approach

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Abstract

Electrocardiogram (ECG) signals are damaged by various types of noise during acquisition and transmission which may mislead the analysis. In this paper, an automated denoising technique based on time–frequency filtering approach is proposed. The S-transform based time–frequency method with morphological processing is employed to visualize the spectrum of the ECG signal. The time–frequency plane is surface fitted to estimate the noise and then a threshold is used to eliminate it. The proposed method has been assessed with numerous abnormal and normal ECG signals selected from the MIT-BIH normal sinus rhythm database. Several noises with varying signal-to-noise ratio are considered for the simulation study. The results showed that the proposed technique is superior to the existing wavelet-based approach. It significantly reduces the mean square error, percentage root mean square difference and improves the signal-to-noise ratio (SNR). Moreover, at lower SNR condition, the proposed approach efficiently suppresses the noise. In the proposed approach, the requirement of the reference signal is eliminated; and at the same time, the structural information is preserved in the denoised signal.

Keywords ECG · S-transform · Denoising · Time–frequency filter · Wavelet transform · Surface fitting

1 Introduction

The electrocardiogram (ECG) is a physiological signal applied to sense different heart activities by means of an electrical signal. The state of the cardiovascular system can be determined by the ECG [1]. It is one of the prominent diagnostic tools applied for the investigation of different types of cardiac disorders. Many times, the ECG is corrupted from noises and artifacts and is therefore not suitable for further analysis. Moreover, the analysis becomes more challenging because of reduced signal energy. The noise distorts the ECG signal during acquisition as well as transmission. Various types of noises added in the ECG signal are electrode motion noise (EM), channel noise (Gaussian noise) [2], etc. The characteristic of the ECG signal changes drastically due to the presence of these unwanted spurious noises. Also, due to the presence of artifacts, such as muscle artifacts (MA) and baseline wander (BW), the signal quality degrades drastically [3]. A baseline drift mainly occurs due to coughing and breathing in the case of chest lead acquisition. It can also be because of arms or legs movements in the case of limb lead ECG acquisition. Another important reason for the distortion of the ECG signal is power line interference. It consists of 50/60 Hz pickup as well as distortion due to its harmonics. The electrode movements may change the electrode–skin impedance and generate electrode motion noise. The bioelectric activity resulting from the muscle contraction also affects the ECG signal. The poor channel conditioning may cause the introduction of Gaussian noise in the ECG signal during transmission [1, 2].

For the enhancement of the ECG signal, various techniques are used such as finite impulse response filter/ infinite impulse response (FIR/IIR) filtering, zero-phase filtering [4], nonparametric time–frequency analysis [5], independent component analysis (ICA) [6], Savitzky–Golay filtering [7], adaptive filtering [8], Empirical mode decomposition (EMD) [9], Bayesian filtering [10], Wavelet transform

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(WT) [6, 11, 12], singular value decomposition [13, 14] and S-transform [15]. Generally, during ECG signal acquisition, many types of noises are combined which severely distort the signal. Most of the denoising techniques have proposed toward reduction only of one type of noise [16, 17]. Uses of digital filters mainly focus on removing the baseline wander noise. The most challenging task for digital filters is the selection of the appropriate cut off frequency. Methods like ICA cannot be used for single-channel ECG signal because it needs availability of signals recorded from multiple channels [7]. EMD-based techniques have prerequisites such as prior information about the reference signal. EMD combined with the adaptive switching mean filter is employed in order to decrease the content of noise in the ECG signal with minimum distortion. The soft thresholding is used for preservation of the QRS complex but it harms the high-frequency content of ECG signal or ignores the noise in QRS region [18]. The wavelet is found to be a suitable tool in the analysis of fast transients present in the RR time series. The method developed using wavelet transform performs better than the existing methods which use windowing [19]. The ability of presenting the time–frequency related information of a signal makes the wavelet transform widely useful in signal analysis. The representation of ECG signal in the time–frequency domain helps in extracting the required information. This is the reason for the popularity of the wavelet transform for ECG signal enhancement [6–9, 20]. However, it has some limitations such as it exhibits poor frequency resolution and better time resolution for higher frequencies. Similarly, for low frequencies, it exhibits poor time resolution but good frequency resolution. The time–frequency information is represented on a time-scale plot instead of the time–frequency plot which makes it difficult to interpret information content of the signal. Ercelebi presented a technique in which an enhancement of ECG signal is performed using wavelet transform [20]. The wavelet decomposition is performed up to 4th level and soft thresholding is employed. This method was tested on several types of noises. In another reported technique, proposed by Poornachandra [11], the subband-dependent thresholding method is used where the decomposition level is fixed at the 3rd level. Li et al. [21] proposed a denoising algorithm by considering different combinations of the wavelet basis, input signal to noise ratio, shrinkage functions and threshold selection rules. This technique used stationary wavelet transform for the enhancement and found that Sym4, decomposed at level 5 with the Bayes threshold and hard shrinkage function gives the optimal result [21]. Kabir et al. used the Symlet 7 as the mother wavelet and the simulation result showed that the method reduced the noise from ECG signal [15]. Das and Ari [22] have proposed a denoising method based on the S-transform based masking of the ECG signal. Although it provided good results, it failed to remove the in-band noise and it is tested on Gaussian noise only. Vargas and Veiga [23] proposed a new ECG denoising method using the genetic algorithm minimization-based noise variation estimate (GAMNVE). All these methods removed the high-frequency noise and the inter segments of the QRS complexes. However, it unable to eliminate the noise present in the in-band of QRS complex and also distorts the low-frequency components.

These limitations of the above-mentioned methods are addressed in the proposed S-transform (ST)-based time–frequency filtering approach. The noisy ECG signal is visualized using the S-transform spectrum. Further, to estimate noise, the time–frequency plane is fitted with a surface fit, and then a threshold is used to eliminate the noise. The proposed algorithm is assessed in various noises such as channel noise, muscle noise, noise due to electrode motion, and baseline wander. The major contributions of the work are as follows:

- An S-transform based filtering method is proposed for the robust denoising of the ECG signal including the removal of in-band noise.
- It provides less mean square error, PRD and an improved SNR.
- The proposed method does not require the prior information about the signal or the reference signal for denoising and preserves the structural information.

2 Materials and Methods

2.1 S-Transform

The S-transform (ST) is a time–frequency analysis technique proposed by Stockwell et al. [24, 25]. It has close relation with the short-time Fourier transform (STFT) as well as with the wavelet transform (WT). In a way, it can be expressed as STFT with a frequency dependent parameter. In another way, it can be viewed as a phase-corrected WT. In contrast to the STFT, it uses a scalable and variable window length in analogy with wavelets. Also, the ST employs sinusoidal basis functions for analysis like Fourier transform (FT) and STFT. The basic functions are multiplied with Gaussian windows whose width varies with frequency. In this connection, ST results in true frequency as well as globally referenced phase of FT and STFT. Also, it results in a progressive resolution of WT. Besides, it provides a frequency invariant amplitude response unlike WT. Hence, ST provides frequency invariant amplitude response along with useful characteristics such as a progressive resolution and absolutely referenced phase information.

The S-transform finds applications in numerous areas such as biology and biomedical engineering [26], geophysics [27], electrical engineering [28], and mechanical engineering [29]. A Gauss window function located at $t = \tau$, when multiplied by signal $h(t)$ followed by the FT of the product, provides the local spectrum of a signal at time $t = \tau$. In ST, in order to obtain a local spectrum, a Gauss window function located at $t = \tau$, is multiplied by the signal $h(t)$. The product is then passed through a FT operation. The result obtained will be the S-transform of $h(t)$. The S-transform of a signal $h(t)$ is defined as follows:

$$S(t,f,\sigma) = \int_{-\infty}^{+\infty} h(\tau) g(t-\tau,\sigma)\, e^{-j2\pi f\tau}\, d\tau, \tag{1}$$

where t and τ indicate time variables, f denotes the frequency, $g(t-\tau,\sigma)$ represents Gaussian window whose midpoint is $\tau = t$ and defined as follows:

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

The width of the Gaussian window is inversely proportional to frequency as $\sigma = 1/f$. Hence, Eq. (2) becomes

$$g\left(t-\tau,\frac{1}{f}\right) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(t-\tau)^2 f^2}{2}} \tag{3}$$

and

$$S(t,f,\sigma) = \int_{-\infty}^{+\infty} h(\tau) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(t-\tau)^2 f^2}{2}} e^{-j2\pi f\tau} d\tau \tag{4}$$

The ST decomposes $h(t)$ into a function of time (t) and frequency (f). When the Gauss window is modified, the entire time axis is covered by collecting all possible values of τ. The parameter f controls the amplitude and width of the window function. Therefore, a multiple resolution at different frequencies is realized.

Since the ST represents the localized frequency spectrum, therefore, when we calculate the time average of local spectrum, we obtain the global spectrum, that is,

$$\int_{-\infty}^{+\infty} S(t,f) dt = H(f) \tag{5}$$

The signal $h(t)$ can be recovered by evaluating the inverse Fourier Transform as follows:

$$h(t) = \int_{-\infty}^{+\infty} \left\{ \int_{-\infty}^{+\infty} S(t,f) dt \right\} e^{j2\pi f\tau} df \tag{6}$$

The discrete version of ST for a signal $h[kT], k = 0, 1 \ldots N-1$ can be defined as (assuming $t \to jT$ and $f \to n/NT$ in (4))

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{N}}, \tag{7}$$

where function $H\left[\frac{n}{NT}\right]$ indicates the discrete Fourier transform of $h[kT]$

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=0}^{N-1} h[kT] e^{\frac{-j2\pi nk}{N}} \tag{8}$$

In a similar way, the discrete-time version of inverse ST can be defined as

$$h[kT] = \sum_{n=0}^{N-1} \left\{ \frac{1}{N} \sum_{j=0}^{N-1} S\left[jT, \frac{n}{NT}\right] \right\} e^{\frac{j2\pi nk}{N}}, \tag{9}$$

where $j, m, n = 0, 1 \ldots N-1$.

2.2 Wavelet Transform-Based ECG Signal Denoising Method

The wavelet transform has been widely used as a signal enhancement method. It is suitable for analyzing nonstationary signal. The noisy ECG signal is decomposed in different levels of resolution by applying WT. Further, thresholding is performed which considers limited WT coefficients. This process reduces the noise level in the signal. Then, inverse WT is applied on the obtained wavelet coefficients which result in an enhanced signal. The choice of the threshold value and the threshold function are critical in the denoising process. In literature, the performance of the Daubechies wavelet is found to be better compared to other wavelet functions [20, 30]. It may be due to its morphological similarity in structures with the ECG signal. Hence in this study, Daubechies-4 wavelet is used to decompose the ECG signal up to 4th level. For the purpose of thresholding, the soft thresholding method is employed.

Donoho [31] proposed a universal threshold for denoising purpose defined as:

$$\text{thr} = \sigma\sqrt{2\log_2(N)}, \tag{10}$$

where variable N indicates the length of the given data sample and σ is the standard deviation of the noise.

The soft thresholding method considers only coefficients (γ^j) above a certain threshold value. The remaining coefficients whose value is less than the threshold value are rejected. Hence, the wavelet coefficients can be represented as follows:

$$\gamma^j(k) = \begin{cases} \mathrm{sign}(\gamma^j(k)(|\gamma^j(k) - \mathrm{thr}|) & \text{if} \quad \gamma^j(k) > \mathrm{thr} \\ 0 & \text{if} \quad \gamma^j(k) < \mathrm{thr} \end{cases} \tag{11}$$

2.3 Proposed ECG Signal Denoising Method

The method proposed in this paper for enhancing the ECG signal using ST is described below. The corresponding flowchart is depicted in Fig. 1. The steps involved in the method are as follows:

Step1: Addition of noise is given to the ECG signal.

Step 2: The morphological filter corrects the presence of any basic variation when noisy signal is passed through it [32]. Morphological filtering extracts the information about the signal's shape using proper structuring elements. The morphological operation is a nonlinear operation. There are two basic morphological operators known as closing and opening operations in the filtering process.

The opening operation is employed to suppress the peaks present in the signal which uses mo as a linear structuring element. The closing operation is performed to suppress the pits of the signal which uses mc as a linear structuring element. Thus, a signal is obtained which is an estimate of the baseline wander (Sw). Next, a corrected reference signal R is extracted by subtracting the baseline wander signal from the ECG signal (h). Chu's method is used for this purpose [32].

$$Sw = h \circ mo \bullet mc \tag{12}$$

$$R = h - Sw, \tag{13}$$

where ($\circ$) and ($\bullet$) are the opening and closing operator, respectively.

Step 3: In this step, S-transform technique (ST) is applied to the baseline-corrected signal R which transforms it to the time–frequency domain [33].

Step 4: The high-frequency noise is removed using a mask in time–frequency domain. Generally, the ECG signal contains frequency information in a bandwidth of 20 Hz. Hence, the noise present above this range can be directly removed from the spectrum by applying a mask. In the time–frequency plane the mask has unity value where the signature of the ECG is present and zero elsewhere. Hence, it acts as a binary window. The signature of the ECG beats is retained by choosing an appropriate threshold (denoted by Th) in the spectrum. Thus, multiplication of the mask with the ST spectrum removes the high-frequency noise components.

$$\begin{aligned} S^1(t,f) &= S(t,f) \cdot m(t,f) \\ m(t,f) &= 0, \quad \text{for} \quad S(t,f) > \mathrm{Th}, \\ m(t,f) &= 1, \quad \text{for} \quad S(t,f) < \mathrm{Th} \end{aligned} \tag{14}$$

where $S(t,f)$ is the S-transform spectrum, $m(t,f)$ is the binary mask and Th is the threshold.

Step 5: Some extra background noises still exist in the lower frequency range which overlaps with the ECG beat spectrum and also the lower frequency components. This remains a challenge to remove these in-band noises. A two-stage surface adjustment is employed in the time–frequency plane (obtained using ST) which eliminates the in-band noise. First, in the time–frequency plane a better fit surface is employed by a least-squares adjustment which serves as a reference surface to estimate the noise [10]. Then, a difference surface is extracted from ST plane. In order to compute the difference surface, the reference surface is subtracted from the ST plane. On this difference surface, the data points below a threshold value are considered as a part of the background noise. Again, a second adjustment is performed in the same way as described above. The first adjustment is performed to extract the ECG signal components, whereas the second surface adjustment is performed to eliminate any residual in-band noise.

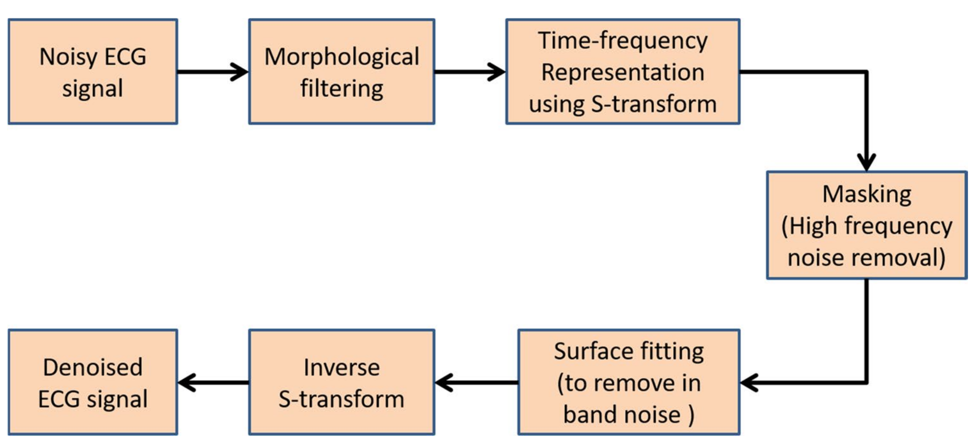

Fig. 1 Flowchart of the proposed denoising method

Step 6: After all these operations, the inverse ST is applied. This process results in denoised signal in the time domain.

3 Results and Discussion

The proposed approach is assessed using the ECG signals taken from the benchmark Physionet bank repository and its performance is evaluated using various parameters. All the ECG recordings are collected from the MIT/BIH arrhythmia database [34]. All the recordings are of 10-second duration and sampled at 360 Hz sampling rate. We randomly selected the ECG signal from the database. From the database, three abnormal and two normal ECG records are selected. Several types of noises are added to the ECG signal, that is, additive white Gaussian noise, muscle noise, motion artifact noise and baseline wander. These noisy records are obtained from the MIT/BIH noise stress test database [35]. Efficiency of the method is evaluated against noises with three different SNR levels (0, 5 and 10 dB). The results obtained from the wavelet-based method and the proposed method are compared.

The performance parameters for finding the efficiency of the method are defined as follows.

1. Signal to noise ratio

$$\mathrm{SNR} = \frac{\sum_{t=0}^{t=L-1} h(t)^2}{\sum_{t=0}^{t=L-1} n(t)^2} \tag{15}$$

2. Mean square error (MSE)

$$\mathrm{MSE} = \sum_{t=0}^{t=L-1} \frac{(h(t) - \tilde{h}(t))^2}{L} \tag{16}$$

3. Percentage root mean square difference (PRD%)

$$\mathrm{PRD} = \sqrt{\frac{\sum_{t=0}^{t=L-1}\left(h(t) - \widetilde{h(t)}\right)^2}{\sum_{t=0}^{t=L-1} h(t)^2}} * 100 \tag{17}$$

In the above equations, original signal is $h(t)$, noise is $n(t)$, denoised signal is $\tilde{h}(t)$. The parameter L denotes the length of the ECG signal.

3.1 Experimental Results for Gaussian Noise

In the case of a wireless ambulatory ECG recording, the signals are sent through the channel to a remote location. These channels can be wireless channels, telephone lines, etc. During transmission, the channel noise corrupts the signal. The channel noise can be modeled as a Gaussian noise. Therefore, to simulate this condition,

Gaussian noise is added in the ECG signals. In Fig. 2, an original ECG signal is depicted (tape no. 230, MIT-BIH Arrhythmia Database). In Fig. 3, its time–frequency representation is shown. Figure 4 presents the spectrum of the ECG signal corrupted with 10 dB Gaussian noise and Fig. 5 depicts the time–frequency representation by ST of the denoised signal. For the purpose of comparison, the denoised output of the proposed method is presented in Fig. 6. Figure 6a shows the ECG signal of tape no. 230, MIT-BIH Arrhythmia Database and Fig. 6b depicts the same ECG signal corrupted with 10 dB Gaussian noise. Figure 6c represents the denoised ECG signal using the proposed method. The proposed method is compared with the wavelet-based denoising method. Both the methods remove the noises efficiently but the output of the WT method contains more distortion as the amplitude the signal changed. The lower amplitude of the R and S peak of the signal is distorted in the of WT method. In Table 1, a comparison is shown for SNR, MSE and PRD values of WT-based method and the proposed method. The results

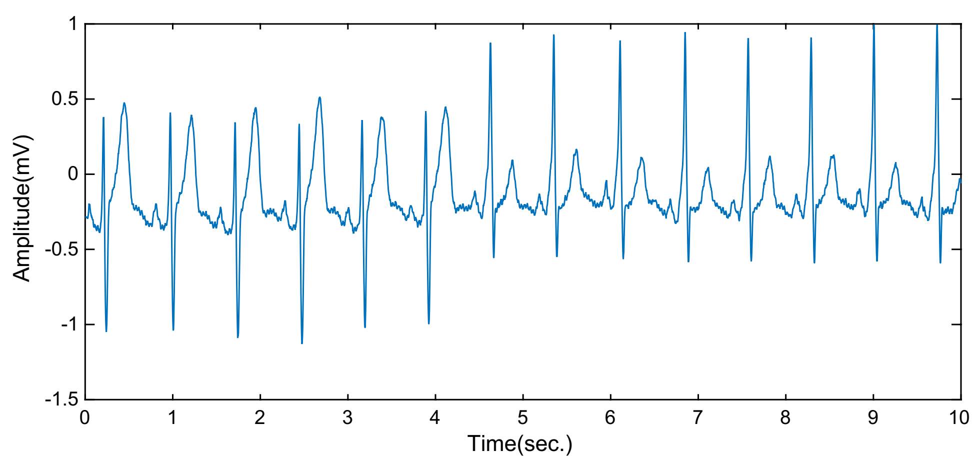

Fig. 2 ECG signal from tape no. 230 of MIT-BIH Arrhythmia Database

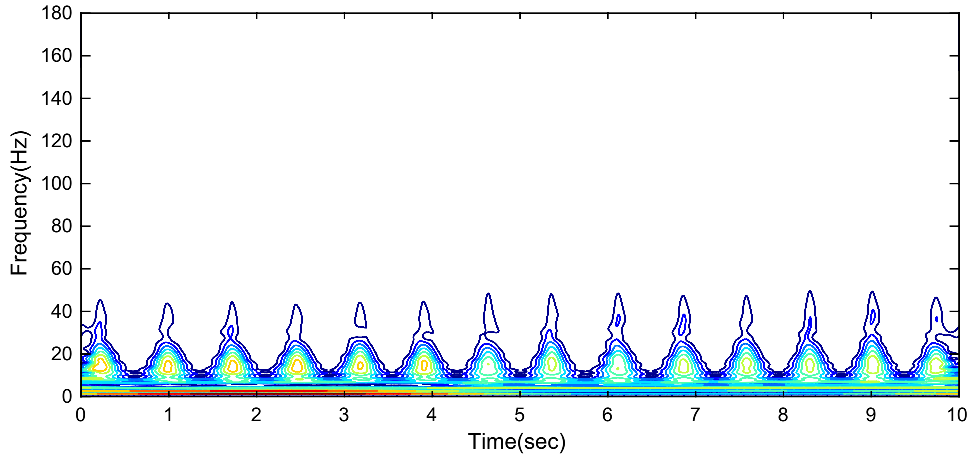

Fig. 3 Time–frequency spectrum of the ECG signal obtained from tape no. 230

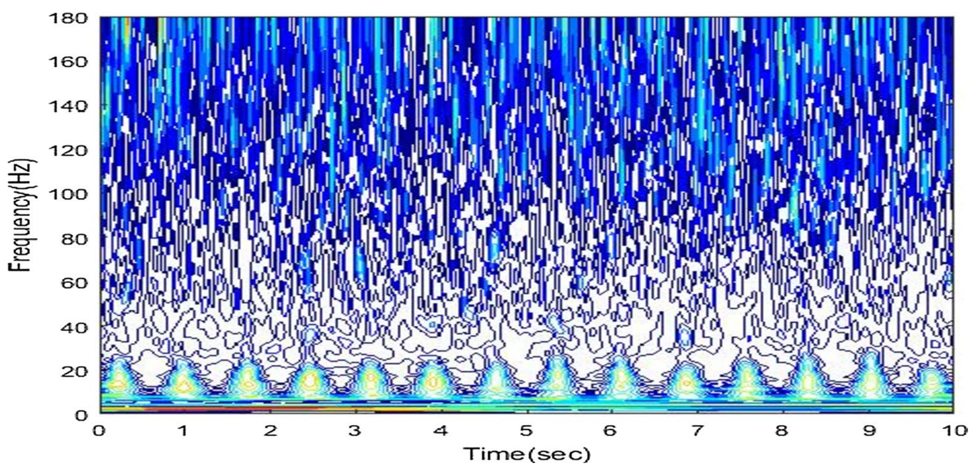

Fig. 4 Time–frequency spectrum of the corrupted ECG signal with 10 dB Gaussian noise

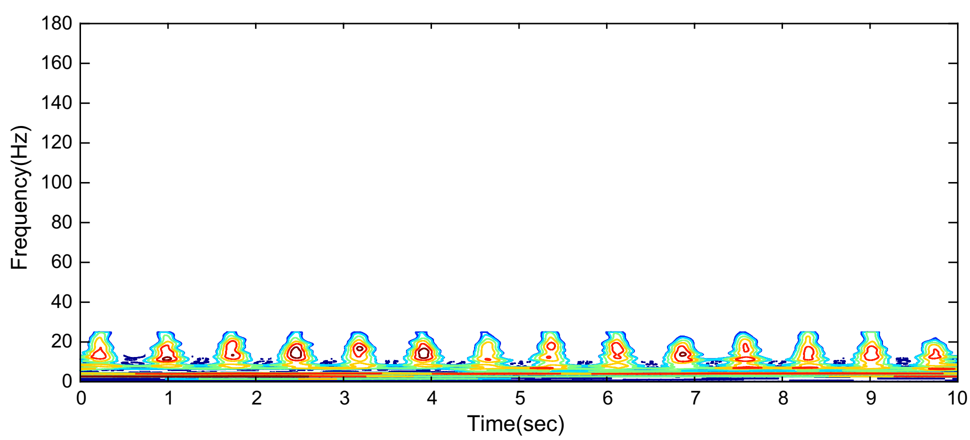

Fig. 5 Time–frequency spectrum obtained by S-transform of the denoised signal

of five different records from MIT-BIH Arrhythmia database are presented. These results show that the proposed method gives better providing higher values of SNR and lower values of MSE. For example, for tape no. 213 with input SNR 0 dB and 10 dB, the proposed method shows an output SNR of 10.1757 and 16.5775 dB but for the same record the WT method shows an output SNR of 6.5962 and 10.2993 dB, respectively. Similarly, the MSE comparison shows better performance of the proposed method providing an MSE of 0.0737 and 0.0132 for input SNR 0and 5 dB, respectively, which are lower than the results of the WT method, that is, 0.1160 and 0.0494, respectively. The

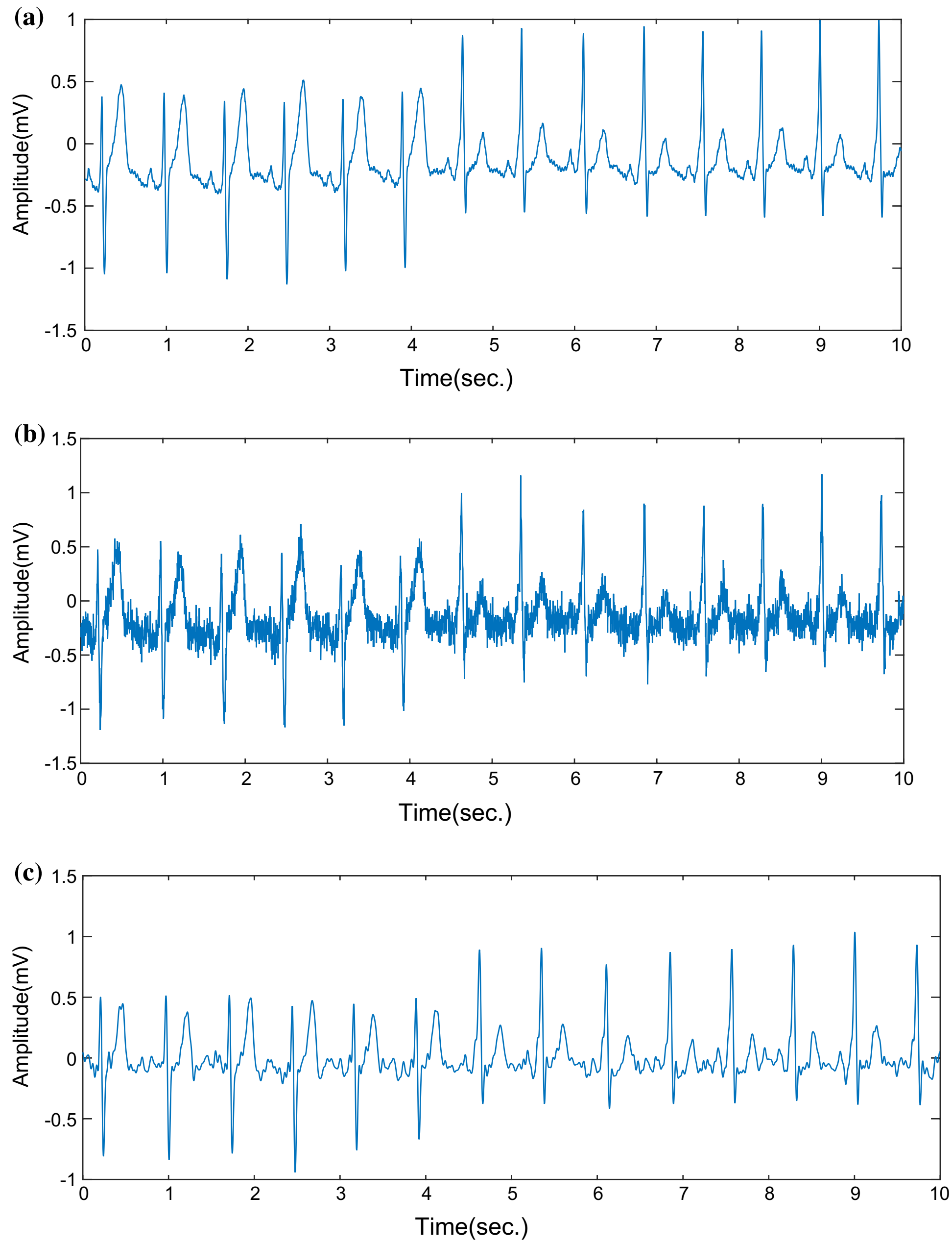

Fig. 6 **a** ECG signal (tape no. 230 of MIT-BIH arrhythmia database), **b** the ECG signal corrupted with 10 dB Gaussian noise. **c** Denoised signal using the proposed method

PRD values are also less in the proposed method as compared to the WT method.

The noise due to artifacts such as muscle artifacts (MA), baseline wander (BW) and electrode motion artifacts (EM) become probable during ECG signal acquisition. The noises used in this work are available in the Noise stress test database. These extracted noises are added to the test signals taken from MIT/BIH Arrhythmia database.

3.2 Muscle Artifact Noise

Various strengths of the muscle artifact are added to the ECG signals. The comparison of performance evaluation parameters such as SNR and MSE are presented in Table 1. The comparison of the values of the SNR and MSE is performed for the signal enhanced using the WT method and the proposed method. Consequently, it can be noticed that the WT method provides only a minor improvement in the SNR and MSE values whereas the proposed method provides better results than wavelet transform. For example, the record no 231 with an input SNR of 0 dB, 5 dB and 10 dB, the proposed method resulted in an output SNR of 8.4938, 10.3402 and 11.6975 dB, respectively. On the other hand, for the same record, the WT method provides the output SNR of only 0.0762, 4.6648 and 9.0371 dB, respectively. Hence, it can be clearly seen that for 5 dB

Table 1 Performance comparison of the proposed method and wavelet transform method for Gaussian noise and muscle artifact noise

MIT/BIH tape No	Input SNR	Gaussian Noise						Muscle Artifact Noise					
		Proposed ST-based Method			WT Method			Proposed ST-based Method			WT Method		
		SNR	MSE	PRD	SNR	MSE	PRD	SNR	MSE	PRD	SNR	MSE	PRD
103	0	7.378	0.0287	43.49	6.765	0.032	45.89	7.624	0.0262	41.56	0.057	0.149	99.34
	5	10.26	0.0145	30.91	9.628	0.0165	33.00	10.61	0.013	29.46	4.715	0.051	58.10
	10	12.33	0.0107	24.15	12.26	0.007	21.41	11.93	0.010	26.50	9.285	0.0179	34.33
118	0	9.453	0.0523	32.78	10.505	0.100	29.83	7.939	0.0737	40.08	0.5965	0.988	93.36
	5	13.17	0.0221	21.95	13.04	0.051	21.27	11.86	0.030	26.19	5.357	0.330	53.96
	10	15.85	0.010	16.120	15.70	0.030	16.39	12.95	0.023	22.50	9.942	0.1149	31.83
213	0	10.17	0.073	30.98	6.596	0.116	46.79	9.133	0.064	36.27	0.0456	0.524	99.47
	5	13.89	0.0313	20.18	8.310	0.0782	38.41	14.62	0.026	19.43	4.315	0.196	60.84
	10	16.57	0.0172	14.97	10.29	0.0494	30.55	16.62	0.018	15.78	8.424	0.196	60.844
230	0	7.964	0.014	41.60	6.276	0.050	48.54	7.8563	0.0166	45.41	0.049	0.2126	99.42
	5	12.64	0.004	23.78	8.954	0.0274	38.66	9.335	0.009	34.13	4.523	0.007	59.40
	10	14.91	0.002	18.19	11.91	0.013	25.36	11.25	0.006	27.35	8.785	0.028	36.36
231	0	8.259	0.006	38.64	5.7986	0.0244	51.29	8.493	0.006	37.26	0.076	0.091	99.12
	5	12.81	0.002	23.23	9.264	0.011	34.41	10.34	0.004	30.40	4.664	0.031	58.44
	10	13.82	0.001	20.35	11.85	0.006	25.52	11.69	0.0032	27.18	9.037	0.0116	35.33

and 10 dB input SNR value the output SNR given by WT method is less than the input value. Similarly, the MSE value comparison indicates that the MSE values obtained using the proposed method are 0.0062, 0.0042, 0.0038, respectively. These MSE values are lesser than the output MSE provided by the WT method, that is, 0.0910, 0.0316 and 0.0116 for 0, 5, 10 dB input SNR, respectively.

3.3 Electrode Motion Noise

A similar analysis is performed by adding various strengths of electrode motion noise to the ECG recordings. Table 2 presents the values of parameters SNR, MSE and PRD of the denoised signal obtained using the WT method and the proposed signal enhancement method. The comparison of

Table 2 Performance comparison of the proposed method and wavelet transform method for Electrode Motion and Baseline

MIT/BIH tape no	Input SNR	Electrode motion noise						Baseline wander noise					
		Proposed ST-based Method			WT method			Proposed ST-based method			WT method		
		SNR	MSE	PRD	SNR	MSE	PRD	SNR	MSE	PRD	SNR	MSE	PRD
103	0	8.368	0.022	38.15	0.024	0.1526	100.24	11.11	0.011	27.81	0.027	0.152	100.3
	5	10.33	0.014	30.41	4.900	0.0491	56.88	11.86	0.009	25.50	4.935	0.0487	56.65
	10	10.43	0.010	26.79	9.746	0.0161	32.56	12.6466	0.008	23.31	9.824	0.015	32.26
118	0	7.568	0.198	41.83	0.010	1.136	100.1	13.78	0.047	20.46	0.020	1.139	100.2
	5	11.59	0.078	26.32	4.910	0.366	56.81	15.32	0.033	17.12	4.940	0.363	56.62
	10	14.95	0.036	17.89	9.745	0.120	32.56	15.32	0.033	17.12	4.940	0.363	56.62
213	0	6.417	0.175	47.76	0.215	0.556	102.5	14.30	0.028	19..27	0.114	0.543	101.3
	5	11.08	0.069	27.91	4.471	0.189	59.75	16.52	0.017	14.92	4.649	0.180	58.34
	10	14.40	0.027	19.04	8.879	0.068	35.97	17.72	0.012	12.99	9.086	0.0654	35.13
230	0	6.118	0.0197	49.44	0.084	0.219	100.9	11.34	0.0059	27.08	0.044	0.217	100.5
	5	8.245	0.0121	38.70	4.816	0.070	57.43	11.58	0.005	26.34	4.881	0.0699	57.00
	10	10.06	0.008	31.40	9.543	0.023	33.33	11.79	0.005	25.73	9.643	0.0233	32.94
231	0	7.138	0.008	43.96	0.092	0.0946	101.07	10.95	0.003	28.33	0.051	0.093	100.5
	5	9.758	0.004	32.51	4.800	0.003	57.53	11.38	0.003	26.94	4.858	0.030	57.15
	10	11.01	0.003	31.40	9.539	0.010	33.34	11.61	0.003	26.25	9.609	0.010	33.07

results shows that the WT method provides improvement in the quality of the signal; however, the proposed method provides significantly better performance. It can be observed that the record no. 118 with an input SNR of 0 dB, 5 dB and 10 dB provides an output SNR of 7.5684, 11.5916 and 14.9454, respectively, whereas for the same record the WT is able to provide the output SNR of only 0.0108, 4.9109 and 9.7459, respectively. The values of these parameters clearly indicate that for all the given input SNR values the output SNR shown by the WT method is less than the input value. Similarly, the MSE values shown by the proposed method are 0.1985, 0.0786 and 0.0363 which are much lower than those of the WT method, which gives MSE values of 0.5438, 0.1803 and 0.0654 for 0, 5, 10 dB input SNR, respectively.

3.4 Baseline Wander Noise

In this study, the baseline wander noise of various strengths is added to the ECG signals. Table 2 presents the values of parameters SNR, MSE and PRD of the denoised signal obtained using the WT method and the proposed enhancement method. The comparison shows that the WT method provides inferior signal quality as compared to the proposed method. For example, the record no. 213 with an input SNR of 0 dB, 5 dB and 10 dB provides an output SNR of 14.3004, 16.5241 and 17.7277 for 0, 5 and 10 dB input SNR, respectively whereas for the same record the WT is able to provide the output SNR of only 0.1147, 4.6498 and 9.0861. It is clearly seen that for all the input SNR values the output SNR shown by the WT method is less than the input value. Similarly, the MSE comparison shows that the MSE values of the proposed method are 0.0285, 0.0171, 0.0129 which are much lower than those of the WT method which gives MSE values of 0.5438, 0.1803, 0.0654 for 0, 5, 10 dB input SNR, respectively.

3.5 R-Peak Detection

In the present work, the R-peak detection test is employed to validate the performance. The R-peak test also evaluates the quality of information preserved in the enhanced signal. The R-peak detection algorithm is applied to the denoised signals obtained by the proposed method. In this study, we have used the Shannon energy envelope (SEE) method. A first-order differentiation of the denoised ECG signal is employed for getting the slope information and then it is normalized. The bipolar output of differentiation is converted to unipolar using the Shannon energy function. The output of the Shannon energy is filtered using a moving average filter which in turn provides a smooth envelope. Finally, the R-peaks are detected from the envelope by applying a threshold. The result obtained is compared with the database annotated values. Tables 3 and 4 show the comparative result of records 118 and 230.

Table 3 R-peak detection of MIT/BIH record no. 118

No. of beats	Position of R-peaks from the database	Position of R-peak after denoising
R1	0.189	0.197
R2	1.025	1.030
R3	1.872	1.880
R4	2.722	2.730
R5	3.567	3.575
R6	4.408	4.416
R7	5.219	5.227
R8	6.042	6.050
R9	6.875	6.883
R10	7.683	7.691
R11	8.483	8.488
R12	9.344	9.352
Total no. of beats detected	12 Beats	12 Beats

Table 4 R-peak detection of MIT/BIH record no. 230

No. of beats	Position of R-peaks from the database	Position of R-peak after denoising
R1	0.208	0.213
R2	0.969	0.977
R3	1.711	1.716
R4	2.444	2.450
R5	3.161	3.169
R6	3.889	3.897
R7	4.292	4.297
R8	4.628	4.633
R9	5.350	5.358
R10	6.108	6.116
R11	6.853	6.858
R12	7.572	7.577
R13	8.292	8.297
R14	9.0.8	9.013
R15	9.728	9.736
Total no. of beats detected	15 Beats	15 Beats

For records 118 and 230, there are a total of 12 and 15 beats present in the database. It can be inferred from Tables 3 and 4 that the proposed enhancement method results in100% accuracy because it detects all the peaks available in the selected signals. The positions of such R-peaks also match exactly with the peak positions available in the database. It shows that the proposed ECG signal enhancement method is efficient in denoising the signal without affecting the R-peaks

Table 5 Performance comparison between the proposed method with existing denoising methods on AWGN noise

Evaluation parameters	MIT/BIH tape no	Input SNR	Methods			
			Proposed method	S-transform based masking [22]	Genetic algorithm-based noise estimate (GAMNVE) [23]	EMDASMF [18]
Output SNR	103	5	10.26	9.82	10.71	9.24
MSE			0.0145	0.0704	–	–
PRD			30.91	–	29.24	34.55
Output SNR	103	10	12.33	14.57	–	–
MSE			0.0107	0.0407	–	–
PRD			24.15	–	–	–
Output SNR	231	5	12.81	11.67	–	–
MSE			0.002	0.0349	–	–
PRD			32.51	–	–	–
Output SNR	231	10	13.82	14.85	–	–
MSE			0.001	0.0242	–	–
PRD			31.40	–	–	–

and their positions. The proposed denoising method performed well under all noise environments, without affecting the quality of the signal significantly. The proposed method is reliably able to reduce the noise, even at low values of the input SNR level. Moreover, the proposed method does not depend on availability of any reference signal. Furthermore, the proposed method does not depend on any prior information for signal enhancement. For example, no information of the R-peak position is needed for signal enhancement. Also, it is able to preserve the quality of the structural information in the enhanced signal.

3.6 Performance Comparison with Exiting Methods

The proposed method is compared with the existing methods for denoising the ECG signal. To have a proper evaluation, the methods that use the same recording of the MIT/BIH dataset with same noise level is used. Further, the AWGN is used as baseline for better comparison. The performance comparison of all the methods is shown in Table 5. The performance of the proposed method is compared for tape number 103 and 231and for input SNR 5 dB and 10 dB cases. On comparing the output SNR values, it is observed that the proposed method outperformed the S-transform based masking method as well as EMDASMF-based method. However, output SNR values for Genetic algorithm-based method are relatively better than the proposed method. Similar pattern can be observed for the parameter PRD. It should be noted that in GAMNVE, several threshold values and best function (η_1, η_2 or, η_3) need to be estimated optimally using Genetic algorithm. On the other hand, in the proposed method, only threshold value for surface fitting is chosen. Furthermore, the proposed method outperformed the S-transform masking method for all the tapes used and input SNR values as indicated in Table 5. Therefore, the results show that the proposed method outperforms the EMDASMF and S-transform masking and comparable to the GAMNVE method.

4 Conclusion

In this paper, a robust approach is proposed based on the S-transform for denoising the ECG signal. Its performance is investigated by comparing it with the existing methods. The result obtained from various simulation experiments on a wide variety of ECG signals reveals the improved performance of the proposed approach over the wavelet-based techniques. It significantly eliminates the noise present in the in-band of the QRS complex and preserves the low-frequency components of the ECG signal. The proposed method uses a masking technique that significantly reduces the high-frequency noises. The background noises present in the in-band and very low frequency signatures of the ECG signal are handled by the surface fitting and thresholding method. The experimental results show that the proposed method provides improved SNR, MSE and PRD values.

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