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A NOVEL APPROACH FOR DENOISING ELECTROCARDIOGRAM SIGNAL USING HYBRID TECHNIQUE

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Abstract

One of the core concerns in the area of Biomedical Signal Processing has been the extraction of pure cardiologic indices from noisy measurements. Frequently, it is found that treatment of the patient suffers due to improper information of Electrocardiogram (ECG) signal since it is highly prone to the disturbances such as noise contamination, artifacts and other signals interference. Therefore, an ECG signal must be denoised so that the misrepresentations can be eliminated from the original signal for the perfect diagnosing of the condition and performance of the heart. In this paper, hybrid techniques including combination of Median filter, Savitzky-Golay filter and Extended Kalman filter along with Discrete Wavelet Transform have been focussed for separation of noise from ECG signal. The hybrid methods for obtaining a clean ECG signal are designed and implemented in MATLAB environment by utilizing MIT-BIH Arrhythmia database. Performance of different algorithms is compared on the basis of signal to noise ratio (SNR) and mean square error (MSE) and it has been noticed that Extended Kalman filter followed by Discrete Wavelet Transform provides better results for both the parameters.

Keywords: Electrocardiogram, Denoising, Hybrid technique, SNR, MSE.

1. Introduction

Cardiac ailments are one of the leading bases of mortality over the entire world. Electrocardiogram (ECG) is convenient medical tool that detects, predicts and monitors rare cardiac events by measuring electrical activity versus time. The ECG signal comprises of three primary wave patterns: P wave, QRS complex, T wave and these waves correspond to far field induced by the phenomena of atrial depolarization, ventricular depolarization and ventricular repolarization [1].

Nomenclatures

A	Dilation parameter
B	Translation parameter
$f(.)$	Nonlinear process vector function
$g(.)$	Nonlinear observation vector function
K	k^{th} component or instant
K	Gain of Kalman filter
N	Number of samples
Q_k	State noise covariance matrix
R_k	Measurement noise covariance matrix
v_k	Measurement noise
w_k	State noise
x_k	State vector
$\hat{x}_{k/k-1}$	A priori estimate of x_k
$\hat{x}_{k/k}$	A posteriori estimate of x_k
$x(t)$	Original ECG signal
$\hat{x}(t)$	Smooth reconstructed version of ECG signal
y_k	Observation vector
$y(t)$	Signal used for defining wavelet transform

Greek Symbols

Ψ	Prototype Wavelet

Abbreviations

CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EKF	Extended Kalman Filter
EMG	Electromyography
MATLAB	Matrix Laboratory
MSE	Mean Square Error
SNR	Signal to Noise Ratio
WT	Wavelet Transform

The amplitudes of constituent wave peaks, duration and intervals of these waves impart clinically momentous information to cardiologists for diagnosis [2]. Proper characterization of waveform morphologies is entailed for the accurate extraction of information from ECG recordings, which further, necessitate the preservation of the amplitude and phase essential clinical characteristics and high noise attenuation [3]. Being an electrical signal, ECG is susceptible to noises generated by environmental and biological resources such as electromyography (EMG) interference, motion artifacts, electrode contact noise and instrumentation noise etc. While recording an ECG signal, major difficulty that comes into existence is baseline drift which mainly arises due to patient movement. An ECG wave with distinct characteristic feature points is shown in Fig. 1.

In literature, numerous attempts have been reported for the extraction of high-resolution ECG constituents from contaminated recordings and permit the measurement of subtle characteristics [4]. The adaptive filtering is one of the techniques that have been used for the noise reduction in ECG signals [5], but time consumption is significant. Wiener filter may not provide good results because of nonstationary characteristics of ECG signal as well as noise [6].

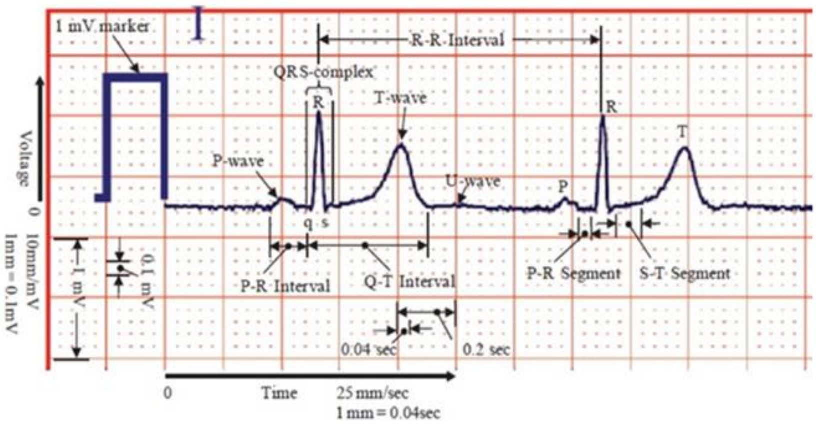

Fig. 1. ECG waveform [1].

An adaptive form of Kalman filter has been applied for enhancement of ECG signal in [7]. A great attention has been received by Wavelet Transform (WT) method for denoising of biomedical signals possessing multiresolution features such as ECG [8, 9]. Main significance of filtering based on WT is that the additive components of QRS complexes are kept even in the uppermost bands of decomposition [10].

In this paper, hybrid techniques are presented and applied on ECG signals for denoising purpose with a comparative approach. The hybrid algorithms include the implementation of Median; Savitzky-Golay and Extended Kalman filters followed by Discrete Wavelet Transform (DWT). The ECG recordings so utilized are available online as in [11]. In the presented work, these ECG signals additively contaminated by random noise are used and then for described methods, the original and denoised versions of the signals are compared for performance evaluation.

This paper is structured in four sections. Section 1 narrates the brief introduction and history of efforts made in the same field. Section 2 explores the materials, methods and current methodology. Section 3 presents the discussion of results. Section 4 concludes the paper.

2. Materials, Methods and Current Methodology

2.1. ECG database

In the proposed work, MIT-BIH arrhythmia database under Physionet site is exploited to acquire real ECG records for performance evaluation. The database comprises of 48 ECG records; each record is slightly over 30 minutes in duration and digitized at 360 Hz sampling frequency [12]. Data in header files includes the information about patient's age, medications, sex and leads utilized [13]. Randomly 10 ECG records are selected for reported work.

2.2. Median filter

The Median filter is frequently used to eradicate noise. The basic notion of median filtering is that the median of adjacent entry replaces each entry in the signal. The pattern of neighboring entries in the median filter is named as window which moves over the entire signal of interest [14]. After sorting all the entries in the window numerically, value in the middle is termed as median. It is manifested that this filter is not much effective as far as the major concern is RR interval preservation.

2.3. Savitzky-Golay filter

A technique based on Savitzky-Golay least-squares polynomial algorithm for smoothing of data is reported in [15]. Savitzky-Golay filter is essentially used to smooth out the noisy data by performing a local polynomial regression of degree k on a succession of values of at least k+1 points that are treated as being uniformly spaced in the succession. The order of a polynomial is specified by its degree indicating up to the fitting point of each frame of data. Frame size specifies the number of samples used to do the task of smoothing for every data point.

2.4. Extended Kalman filter (EKF)

The conventional Kalman filter is most widely used technique for linear dynamic models [16]. For nonlinear dynamic systems, the Extended Kalman filter (EKF) has been developed as a modified variant of conventional Kalman filter [17]. For a discrete nonlinear system $x_{k+1} = f(x_k, w_k)$ and its observation $y_k = g(x_k, v_k)$, linear approximation close to a reference point $(\hat{x}_k, \hat{w}_k, \hat{v}_k)$ can be formulated [18] as in Eq. (1).

$$\begin{cases} x_{k+1} \approx f(\hat{x}_k, \hat{w}_k) + A_k(x_k - \hat{x}_k) + F_k(w_k - \hat{w}_k) \\ y_k \approx g(\hat{x}_k, \hat{v}_k) + C_k(x_k - \hat{x}_k) + G_k(v_k - \hat{v}_k) \end{cases} \quad (1)$$

where, x_k defines the state vector and y_k is the observation vectors. A_k, C_k, F_k, and G_k are the Jacobian matrices as shown in Eq. (2).

$$\begin{cases} A_k = \left.\frac{\partial f(x, \hat{w}_k)}{\partial x}\right|_{x_k = \hat{x}_k} & F_k = \left.\frac{\partial f(\hat{x}_k, w_k)}{\partial w}\right|_{w = \hat{w}_k} \\ C_k = \left.\frac{\partial g(x, \hat{v}_k)}{\partial x}\right|_{x = \hat{x}_k} & G_k = \left.\frac{\partial g(\hat{x}_k, v)}{\partial v}\right|_{v = \hat{v}_k} \end{cases} \quad (2)$$

f (.) and g (.) are the nonlinear process and observation vector functions. The parameters v_k and w_k represent measurement noise and state noise with $R_k = E\{v_k v_k^T\}$ and $Q_k = E\{w_k w_k^T\}$ covariance matrices respectively. Hence, equations for EKF algorithm are expressed in Eqs. (3) and (4).

$$\begin{cases} \hat{x}_{k/k-1} = f(\hat{x}_{k-1/k-1}, 0) \\ P_{k/k-1} = A_k P_{k-1/k-1} A_k^T + F_k Q_k F_k^T \end{cases} \quad (3)$$

$$\begin{cases} \hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k[\, y_k - g(\hat{x}_{k/k-1}, 0)] \\ K_k = P_{k/k-1} C_k^T \left[C_k P_{k/k-1} C_k^T + G_K^T \right]^{-1} \\ P_{k/k} = P_{k/k-1} - K_k C_k P_{k/k-1} \end{cases} \tag{4}$$

where, $\hat{x}_{k/k-1} = E\{x_k |\, y_{k-1}, y_{k-2}, \ldots\ldots, y_1\}$ is state vector estimate at time instant, k given y_1 to y_{k-1} observations. $\hat{x}_{k/k} = E\{x_k |\, y_k, y_{k-1}, \ldots\ldots, y_1\}$ is state vector estimate at time instant k using y_1 to y_k observations. $P_{k/k-1}$ and $P_{k/k}$ are described in similar manner. The EKF facilitates linearization and denoising of ECG signals [19].

2.5. Wavelet transform (WT)

The wavelet transform due to its versatility becomes a convincing tool in biomedical signal processing. The ability to provide time-frequency analysis is fascinating element of WT [20]. WT works on multi-scale basis instead of single scale as in Fourier transform [21]. Denoising has been one of the several effectual applications of WT [22]. It is a suitable way of studying nonstationary indications such as ECG. Hence it becomes beneficial over other transforms since it has variable size window. Consequently it is appropriate for all frequencies. The wavelet transform of signal $y(t)$ is defined by Eq. (5) [23].

$$W_a\, y(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} y(t)\, \psi\left(\frac{t-b}{a}\right) dt$$
(5)

where, a=dilation parameter, b=translation parameter

WT is categorized as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transforms (DWT).

2.5.1. Discrete wavelet transform (DWT)

Recently in the field of signal processing, DWT is established as a well suitable tool since it provides good time resolution as well as frequency resolution at high and low frequencies respectively [24]. The two-level wavelet decomposition of a signal $y(n)$ is processed pictorially in Fig. 2.

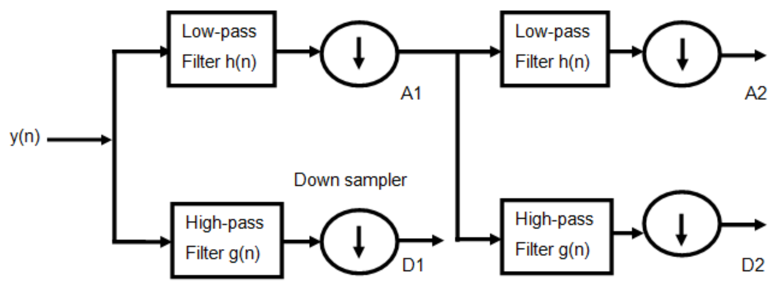

Fig. 2. Two level decomposition with DWT.

The input signal is convoluted with designed filters to produce a decomposed version of signal. The filtered signal is then down sampled. The signal decomposition results in detail and approximation coefficients [25].

2.6. Current methodology

For enhancement of results in further processing, denoising is the pre-processing stage. ECG signals are utilized after being contaminated with random noise. These noisy signals are then applied to the inputs of the three hybrid methods. For evaluating performance of hybrid techniques, signal to noise ratio (SNR) and mean square error (MSE) parameters are used. The Eqs. (6) and (7) define the expression for SNR and MSE respectively [14].

$$SNR(in\ dB) = \left(\frac{\Sigma_i |x(i)|^2}{\Sigma_i |x(i) - \hat{x}(i)|^2}\right) \tag{6}$$

$$MSE = \frac{\Sigma_i (x(i) - \hat{x}(i))^2}{N} \tag{7}$$

where $x(t)$ is original ECG signal and $\hat{x}(t)$ is smooth reconstructed version of signal. The detailed procedure for current approach is as follows:

1. Loading ECG signal from Physionet.org to MATLAB environment.
2. Generation and addition of noise to ECG signal.
3. Employing Smooth filter for removing baseline drift.
4. Apply Median (order-12), Savitzky-Golay (order-19) and EKF filters on ECG signal.
5. Compute SNR and MSE for filtered ECG signal.
6. Then signal is decomposed by using DWT with 8 levels of decomposition and thresholding is applied.
7. Compute SNR and MSE for hybrid techniques.

Figure 3 depicts the flow of stages in denoising process.

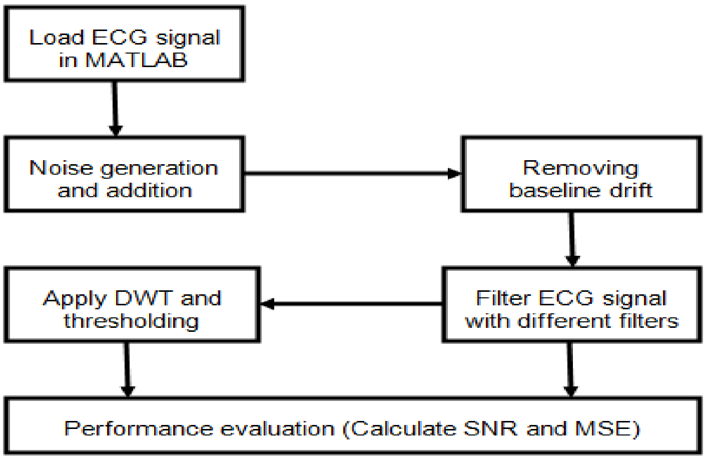

Fig. 3. Flow diagram showing stages of denoising.

3. Results and Discussion

The ECG signal analysis essentially begins with pre-processing stage which involves separation of noise present in the signal. While recording ECG, the signal gets degraded due to various forms of noise including baseline wander, power line interference and muscle artifacts which makes it difficult to extract precise and clinically useful information from the signal for diagnosis of cardiac diseases. In order to facilitate a clean ECG signal, hybrid techniques are presented in this work and a comparison is made between focussed techniques. Hybrid methods involve implementation of Median filter; Savitzky-Golay filter and EKF in combination with DWT. The filters offer denoising of ECG signal to some extent. The DWT allows successful denoising of the nonstationary ECG signals. The Bior3.1 wavelet is utilized for signal decomposition since it has been proved that it gives better results in terms of SNR and MSE than other wavelet families [26]. Hence, for obtaining clean ECG signal with morphological characteristics, filters and DWT are used together forming hybrid configurations.

The hybrid methods are applied on ECG signals of Physionet.org site under the MIT-BIH arrhythmia database. The Electrocardiogram records are chosen randomly and utilized records are 100, 103, 105, 117, 118, 119, 121, 123, 203 and 231. The projected work includes the removal of baseline drift and other noises. The random noise is then added to ECG signals. The baseline drift is removed by smoothing the data using a smooth filter with an odd span. Figure 4 shows (a) original ECG signal and (b) ECG signal with baseline drift removed. Although the ECG sample is for 30 minutes duration but for simplification, in reported work it is shown for 10 seconds.

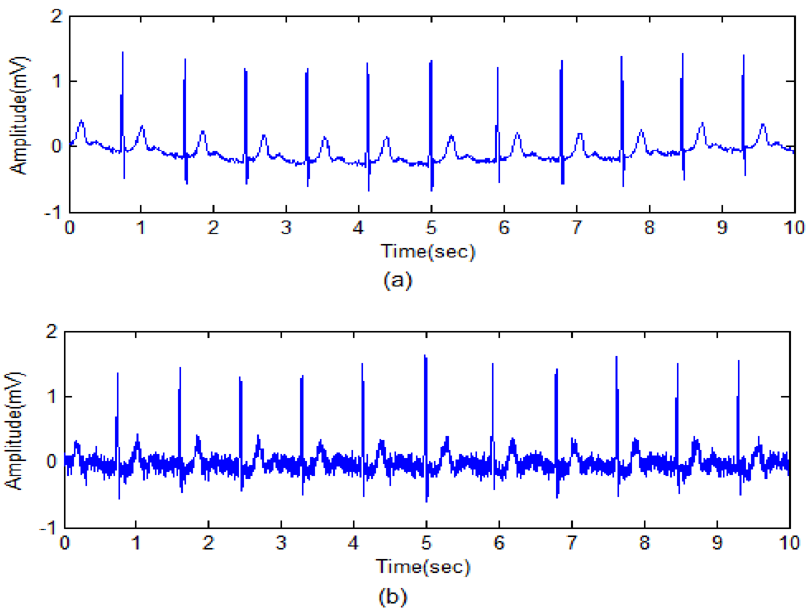

Fig. 4. (a) Original ECG signal record no. 103 and (b) Noisy ECG signal record no. 103 with removed baseline drift.

The performance parameters i.e. SNR and MSE for different filters are shown in Table 1 and the denoised version of ECG signal for filters is shown in Fig. 5.

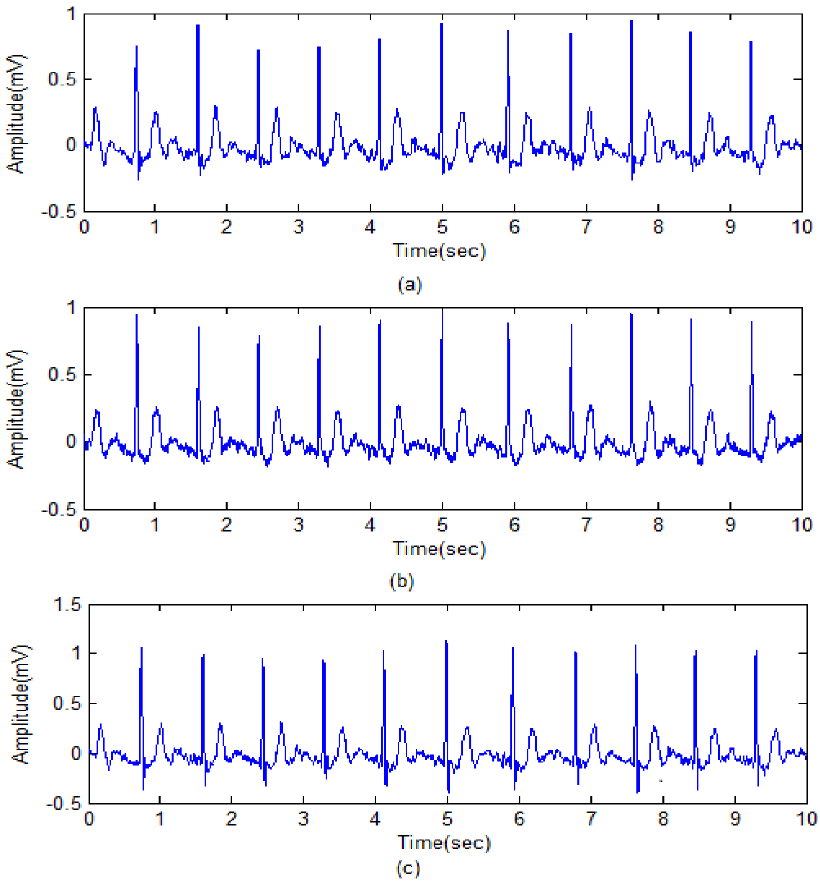

Fig. 5. ECG signal denoised with (a) Median filter, (b) Savitzky- Golay filter and (c) Extended Kalman filter.

Table 1. Values of SNR (in dB) and MSE of different filters.

ECG	Median Filter		Savitzky-Golay Filter		EKF	
Signal No.	SNR	MSE	SNR	MSE	SNR	MSE
100	1.794	4.49e-02	3.300	4.55e-02	4.002	5.2e-03
103	2.512	1.80e-02	3.735	1.78e-02	4.184	1.62e-02
105	4.518	1.65e-02	5.353	1.63e-02	7.197	1.8e-03
117	2.966	27.96e-02	3.922	27.83e-02	5.198	1.82e-02
118	3.610	41.75e-02	4.459	41.35e-02	5.238	1.97e-02
119	5.615	24.49e-02	6.021	24.46e-02	7.925	1.01e-02
121	3.083	41.30e-02	4.225	40.44e-02	5.413	7.4e-03
123	2.527	19.61e-02	3.929	19.14e-02	4.369	9.9e-03
203	2.797	1.19e-02	3.676	1.10e-02	5.7202	7.6e-03
231	4.590	2.38e-02	5.001	2.36e-02	6.302	7.9e-03

In Table 1, a comparison is shown between performance of different filters on the basis of computed SNR and MSE. It is observed that EKF filter provides fine results among all three filters. For improving the results of denoising, the filtered signal is decomposed with DWT and further thresholding is performed to separate the noise content. Resulting denoised ECG waveforms after employing hybrid techniques are illustrated in Fig. 6.

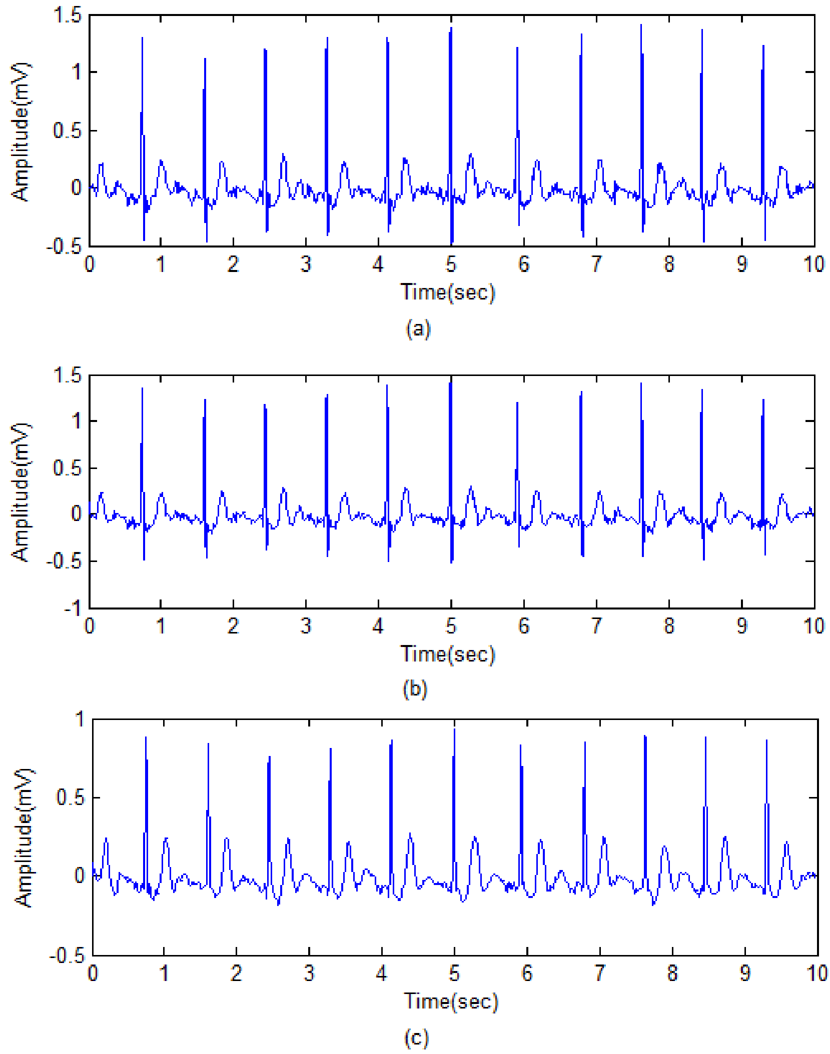

Fig. 6. Waveforms showing denoising of ECG signal with (a) Median filter followed by DWT, (b) Savitzky-Golay filter followed by DWT and (c) EKF followed by DWT.

The performance parameters for focussed hybrid techniques are evaluated in Table 2.

Table 2. Values of SNR (in dB) and MSE for hybrid techniques.

ECG Signal No.	Median Filter followed by DWT		Savitzky-Golay Filter followed by DWT		EKF followed by DWT	
	SNR	MSE	SNR	MSE	SNR	MSE
100	14.577	7.1698e-04	16.880	2.4593e-04	17.318	1.1527e-04
103	15.260	0.18e-02	17.545	7.5487e-04	18.254	3.5523e-04
105	15.937	2.7826e-04	17.538	1.6242e-04	19.166	8.8037e-05
117	15.595	0.21e-02	17.623	0.11e-02	18.936	4.9632e-04
118	14.362	0.24e-02	15.917	0.14e-02	16.809	6.7589e-04
119	16.340	0.17e-02	18.339	9.3615e-04	19.418	4.6363e-04
121	15.273	8.9354e-04	17.605	4.5024e-04	19.056	2.1597e-04
123	15.141	0.12e-02	17.195	5.2543e-04	18.191	2.3639e-04
203	11.829	0.19e-02	12.569	0.16e-02	15.168	6.0348e-04
231	15.962	9.8828e-04	17.537	5.9988e-04	18.435	3.5045e-04

4. Conclusions

This paper explores three hybrid techniques for denoising of ECG signal. Ten electrocardiogram signals have been used to validate the described algorithm. Difficulties emerge mainly from the huge diversity of the waveforms, the noise and the artifacts going with the ECG signals. The strength of reported work is the approach of using the different filters and an influential tool i.e. wavelet transform together to denoise the ECG signals. Simulated results for projected methods shown in Table 2 reveal higher SNR and lower MSE values, which are always required, for EKF followed by DWT. The results in Table 2 clearly depict the superiority of proposed technique over the other techniques.

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