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# A review of ECG signal filtering approaches

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## Abstract

An electrocardiogram (ECG) quantifies the electrical activity of the heart to screen for different heart diseases, although it can be impacted by noise. ECG signal filtering is a crucial pre-processing step that reduces noise and emphasizes the characteristic waves in ECG data. In real-world applications, the ECG signal is contaminated by different types of noise. Separating the desired signal from noises produced by artifacts such as muscle noise, power line interference (PLI), baseline wandering (BW), and motion artifacts (MA) is a complicated task. In this paper, a quick review of various ECG signal denoising methods is introduced.

**Keywords:** Electrocardiogram; Power Line Interference; Filtering Techniques; Discrete Wavelet Transform; MSE

## 1. Introduction

Electrocardiogram (ECG) plays an important role in cardiac disease diagnosing. However, the design of an ECG monitor faces many challenges. A wearable ECG monitor is of great significance to users' been performed ECG real-time monitoring. With the wearable device, users can monitor their ECG without limitation of time, location or physical activity, which requires the ECG monitor to have great performance in noise elimination without distorting the original ECG signal [1-3]. As an electrical signal, ECG is susceptible to different kinds of noise. The main sources of this noise are electrical activities of other body muscles, baseline shift because of respiration, poor contact of electrodes, and equipment or electronic devices [4, 5]. Since the ECG is a non-stationary signal, normal filters cannot be effective to remove the noise; so, several techniques are used to do so for such types of signals. ECG signals have a wide variety of applications in the medical domain such as cardiorespiratory monitoring, seizure detection and monitoring, ECG-based biometrics authentication, real-time analysis of electrocardiographic rhythm, heart-rate variability analysis using smart electrocardiography patch, and study of cardiac ischemia [6–11]. These applications require a proper determination of the morphological and interval aspects of the recorded ECG signal, which are susceptible to various kinds of predominant noises such as base-line wander (BW), muscle artefacts (MA) or electromyogram (EMG) noise, channel noise (additive white Gaussian noise, AWGN), power-line interference (PLI), and miscellaneous noises such as composite noise (CN), random noise, electrode motion artefacts (EM), and instrumentation noise, making it challenging to determine disease-specific morphological anomalies in the ECG signals [5].

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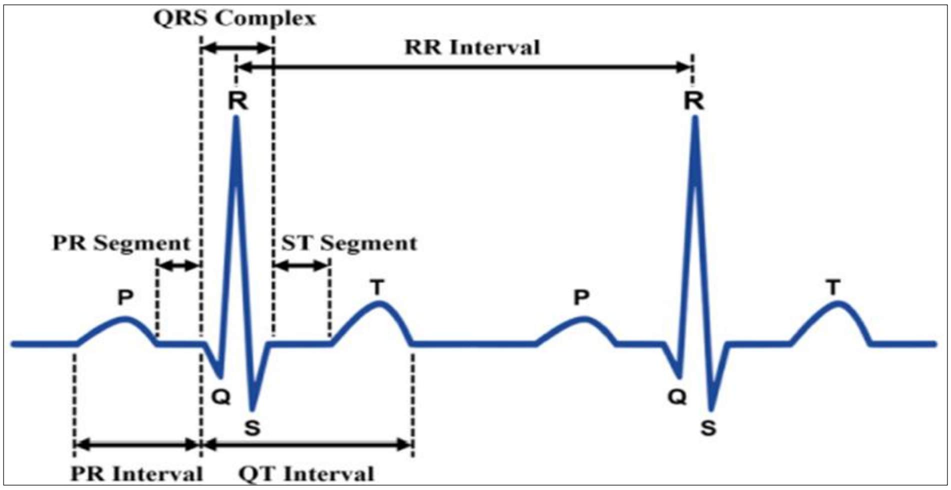


**Figure 1** Normal ECG signal [12]

## 2. Types of noises in ECG Signal

These noises and artefacts lie within the spectral range of interest and manifest themselves pre-dominantly as morphological features similar to the inherent aspects of the ECG or similar to any disease specific aspects a brief description of predominant noises in ECG is given below.

### 2.1. Base-line wanders (BW)

Baseline wander (BW) is a low-frequency artefact in electrocardiogram (ECG) signal recordings of a subject [13]. BW removal is an important step in processing of ECG signals because BW makes interpretation of ECG recordings difficult. BLW are low frequency noise (0.05 - 3 Hz in stress tests). They are mainly due to movement during breathing, patient movements, poor contact between electrode cables and ECG recording equipment, inadequate skin preparation where the electrode is placed and dirty electrodes [13].

### 2.2. Power-line interference (PLI)

PLI is main contributor to ECG signal distortion. American Heart Association recommends that ECG recorders should have a 3dB frequency range extending from 0.67Hz to 150Hz [14]. PLI noise at 50Hz lies well within this frequency range. PLI noise is caused by the electromagnetic fields of 50Hz power line. PLI noise amplitude and frequency is not known in advance. Had that been the case it would be simple to remove it using any conventional filtering techniques [14].

### 2.3. Muscle Artefacts (MA)

MA or EMG noise is caused by electrical activities in muscles, which arise from eye and muscle movements and heartbeat. Typical sources of MA are muscle movements near the head region, like neck movements, swallowing, and so on. The electrical activities due to muscle contractions last for a duration of around 50 ms between DC and 10,000 Hz, the amplitude being around 10% FSD [5]. EMG leads to distortion of local waves of the ECG signals due to a frequency match in the range of 0.01–100 Hz.

### 2.4. Additive White Gaussian Noise (AWGN)

The AWGN or Channel noise introduces when ECG signal is transmitted through channels. This is due to the Poor channel conditions. It is mainly like white Gaussian noise which contains all frequency components [15]. Also, in case of wireless recording of the ECG signal it gets corrupted by the additive white Gaussian noise (AWGN). For the correct diagnosis, removal of AWGN from ECG signals becomes necessary as it affects the all the diagnostic features [16].

## 3. ECG Signal Denoising Methods

### 3.1. Empirical Mode Decomposition (EMD) based Method

EMD is an adaptive and efficient decomposition method capable of decomposing any complex signal into finite intrinsic mode functions (IMF). It is very suitable for processing nonlinear and non-stationary signals, such as ECG signals [17]. One of the key elements of EMD-based denoising is to determine the noise intrinsic mode functions (IMF). Traditional EMD denoising often directly discards the first IMF to achieve the removal of high-frequency noise; however, this method not only discards some important information but also does not completely denoise the signal. Therefore, the question of how to more accurately determine the order of IMF which needs to be denoised remains an active one [17].

### 3.2. Deep Learning (DL) based Method

In this category of ECG denoising, deep-learning-based models are constructed based on the functionality of a denoising autoencoder (DAE). It is an initial unsupervised learning step that maps inputs to intermediate representations [5]. An autoencoder is a machine learning model that has the function of regenerating an input signal with as much accuracy as possible. It works as a combination of two non-linear subparts, viz., encoder and decoder. The autoencoder-based denoising approach is discussed by Vincent et al. [5].

### 3.3. Discrete Wavelet Transform (DWT) based Method

The characterization of any signal is a tedious job and hence Fourier transforms play a major role in it. But, this transform is not suitable for analyzing ECG data as it ignores the present information and globalizes in different patterns. If a resolution of signal is too high, then the window size will be very wide. It gives a poor time resolution and vice versa. The window function width usually helps in presenting the signal. The contradiction between narrow band and wideband transforms refers to Gabor limit, which implies that one cannot simultaneously sharply localize a signal in both time and frequency domains. It is achieved only by localization of signal in both time and frequency using wavelet transform. It enlarges the signals in terms of wavelet function, and basically, it should only allow the variations in time extension instead of the shape. Furthermore, because of the Gabor limit of time − frequency analysis in the context of ECG analysis, usually, there is a trade-off between the time localization and frequency localization in wavelet transform: higher the required resolution in time localization, the lower the resolution in frequency localization has to be, and vice versa. Wavelet transforms are classified into continuous wavelet transform and discrete wavelet transform. DWT is a wavelet transform implementation with a distinct wavelet scales and interpretations in accordance with certain defined rules [18].

### 3.4. Sparsity-based Method

In this category of denoising, the ECG signal is denoised based on the sparse decomposition of the signal. The signal is fragmented into segments, and every segment is broken into sparse parts and residues. Then, these sparse parts are used to estimate clean signals, when the useful information in the signals is considered to be sparse [19]. The segments are decomposed using a non-linear optimisation method to find the sparsest representation [19].

### 3.5. Bayesian-Filter-based Method

A classical problem in estimation theory is the estimation of the hidden states that are observable through a set of measurements, of a system with an underlying dynamic model. The well-known Kalman filter (KF) is one such method and under certain general constraints, it can be proved to be the optimal filter in the MMSE sense. The conventional KF assumes a linear model for the system dynamics and observation equations. In practice however, most systems are nonlinear in nature and in order to extend the idea of conventional KF to such systems, several variants of the original KF have been developed [20].

### 3.6. Adaptive Filtering based Method

An adaptive filter uses iterative computations to minimize the error "in modelling the relationship between two signals in real time". Fig. 2 shows a basic diagram of an adaptive filter. Here, the input $s_1$ represents the ECG which is observed with the additive noise n. The reference signal s is either a pure noise generator or a signal related to n. Since the n and $s_1$ are uncorrelated, then $E[e^2] = E[(n - y)^2] + E[s_1^2]$ [4]

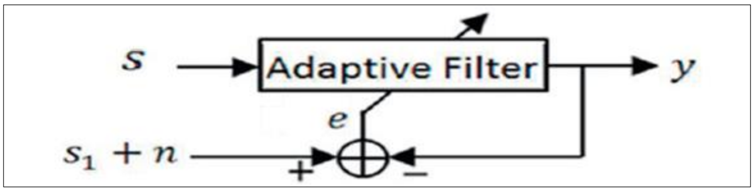


**Figure 2** A general diagram of an adaptive filter [4]

### 3.7. Savitzky-Golay Filtering Method

Savitzky-Golay (S-G) is one of the filters which can smoothen out the signal without much destroying its original properties. Polynomial degree and frame size are the two parameters of S-G filter and the performance of S-G filter mostly depends on them. A Savitzky-Golay (SG) filter, widely used in signal processing applications, is a finite-impulse-response low-pass filter obtained by a local polynomial regression on noisy observations in the least-squares sense [21].

## 4. Performance Metrics of ECG Signal Filtering Approaches

There are three benchmark metrics for the analysis of different denoising methods. These are root-mean-square error (RMSE), percentage-root-mean-square difference (PRD), and improvement in signal-to-noise ratio (SNRimp). RMSE is the root of the squared error difference between the denoised and original ECG signals. It is used for determining the variance between the output predicted by the denoising model and the actual signal. A smaller value of RMSE implies the better performance of the model. PRD computes the total distortion present in the denoised signal. A lower PRD represents a better quality of the denoised signal. SNRimp is the improvement in the SNR levels between the input and the output. The performance evaluation criteria can be defined as follows [5, 22]:

$$\begin{aligned} \mathrm{RMSE} &= \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\left[x(n)-\hat{x}(n)\right]^2} \\ \mathrm{SNR_{imp}} &= \mathrm{SNR_{out}} - \mathrm{SNR_{in}} \end{aligned} \quad (1)$$

where $\mathrm{SNR_{in}}$ and $\mathrm{SNR_{out}}$ are as follows:

$$\mathrm{SNR_{out}} = 10 \times \log_{10}\left(\frac{\sum_{n=0}^{N-1}\left[x(n)\right]^2}{\sum_{n=0}^{N-1}\left[\hat{x}(n)-x(n)\right]^2}\right) \quad (2)$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=0}^{N-1}\left[x(n)-\hat{x}(n)\right]^2}{\sum_{n=0}^{N-1}\left[x(n)\right]^2}} \times 100 \quad (3)$$

Where N is the number of data points.

## 5. Conclusion

Different noises are included in ECG signals, and methods for reducing them are introduced in this paper. ECG signals represent electrical heart voltage and are usually used to classify cardiac disease, so it is crucial to reduce noise in the signal. ECG filtering is a pre-processing step in many research papers. It finds several applications in the field of medical signal and image processing. Also, this paper presents ECG signal filtering techniques for various types of noise such as power line interference, baseline wander, electrode contact noise, Electromyogram (EMG) noise, and motion artifacts.

## Compliance with ethical standards

*Disclosure of conflict of interest*

All authors declare that they have no conflicts of interest.

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