Highly Efficient Low Noise Solutions in ECG Signals

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Abstract. This paper aims at helping researchers develop low-noise ECG monitors and analyze existing solutions for eliminating noise in ECG signals. A brief introduction of ECG signal, main kinds of noise in ECG signal and a summary of different kinds of low noise solutions is given. The components of the ECG signal and the origin of noise in the ECG signal are analyzed first. In order to find optimized solutions for eliminating the noise, highly effective solutions are listed and analyzed. Solutions are divided into three main directions, which are circuit design, signal processing and machine learning. Specific practical examples from former research and analyses for each direction help the reader understand and select different ways of eliminating noise in ECG signals. After introducing three directions, a summary and further improvement are given to help readers have a horizontal comparison between solutions.

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' 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]. Second, while the band range of the common ECG signal is 0.05~100 Hz and the energy of the ECG signal is measured in mV, the frequency and the energy of the noise can be rather high[2]. Besides, ECG signals' unique shapes are used by doctors to identify different symptoms. Since a slight noise interference will affect the final result, it is important to reduce noises in ECG signals. To extract ECG signals from different kinds of noise accurately, scientists worldwide gave their solutions with different techniques. Each of the solutions has its merit. However, with so many solutions, there is a lack of a systematic summary that can be used for readers to have a basic understanding of existing feasible solutions.

Aiming to solve the aforementioned questions, this article firstly introduced the basic concept of ECG monitoring and different kinds of noise problems in ECG monitoring. After that, this paper reviews three main directions for low ECG noise solutions: circuit design, signal processing and machine learning. In the circuit design part, amplifiers designing, various circuit topology and other modifications are discussed. Adaptive filtering and wavelet transform are typical solutions for signal...
processing. Binary selection and neural network are two key points for the listed machine learning approaches. Finally, a comparison for the three directions, their limitation and future improvement are given in this paper.

2. Classification of ECG signal
ECG signal is a coordinate graph of voltage versus time that records electrical activities caused by the heart contraction detected by the electrodes placed on the skin. 12-lead ECG, ten electrodes are placed on the patient's limbs, and the chest surface is usually used to measure the overall magnitude of the hearts' electrical potential.

ECG signal has three components: the P wave, which represents the depolarization of the atria; the QRS complex, which represents the depolarization of the ventricles; and the T wave, which represents the repolarization of the ventricles. The standard ECG signal is shown in Figure 1.

![Figure 1. A standard ECG waveform (Source: Google image).](image)

For experienced doctors, an ECG signal conveys a large amount of information about the structure of the heart and the function of its electrical conduction system. However, this information often interfered with noise generated during measurement, and the noise can be divided into continuous and transient noise.

2.1. Continuous noise
This noise is associated with signals from all the leads having a similar temporal distribution but with different intensity levels[3]. These noises dominate different frequency bands. The low-frequency range signifies baseline wander (BW), the medium frequency signifies the power line interference (PLI), and the high-frequency components signify the electromyography (EMG) noise.

2.1.1. Low-Pass: Baseline Wander (BW) noise
The variations in the impedance of electrodes and movements of patients can cause the baseline wander. This kind of disturbance especially exists in the exercise electrocardiograph and during ambulatory and Holter monitoring[3]. The frequency range of baseline wander is usually less than 1.0 Hz. Nevertheless, this range will be enlarged in the real situation. High-filtering is one of the approaches to remove the BW artifact from the ECG signal[4]. Another method based on empirical mode decomposition (EMD) and mathematical morphology (MM) is proposed[5].

2.1.2. Medium: Power-line interference (PLI) noise
The power-line interference represents a common noise source in the ECG and other physiologic signals recorded from the body surface. Cables transporting signals from the detective room to the signal processor are susceptible to electromagnetic interference. Reducing the PLI is challenging because such noise is characterized by a 50 or 60 Hz sinusoidal interference within the ECG signals' frequency range, sometimes accompanied by harmonics[3]. PLI noise is classified as a narrow band and can prevent the doctor from analyzing the ECG signal exactly, mainly due to the low-amplitude waveform making P-waves and T-waves unidentifiable boundary regions. Several techniques and approaches have been
developed and evaluated to remove such interference, such as band-stop finite impulse response (FIR), infinite impulse response (IIR) filtering, and adaptive filters. Studies also analyzed the performance of different filters for power line interference reduction in ECG signal and concluded that adaptive filters after tuning to some optimum values give the best result[6,7].

2.1.3. High-pass: Electromyography (EMG) noise
The EMG noise is caused by the contraction of muscles except for the heart. When people move their bodies, muscles around electrodes will contract, generating depolarization and repolarization waves. These waves will be detected by the electrodes and then appear in the ECG signals. The amplitude of EMG noise depends on the intensity and frequency of the muscles’ contraction. This noise is common in situations where patients are afraid of ECG examination, such as kids or people who cannot control themselves. EMG noise can be reduced by a thresholding operation that combines hard and soft thresholding features without showing the disadvantages of either of them[8].

2.2. Transient noise
Transient noise lasts for a short time and is typically categorized into white Gaussian noise (WGN). Since its instantaneous value indicates Gaussian distribution and power, its spectral density is distributed uniformly[3]. There are some examples of this noise: patient electrode motion artifact, instrumentation noise, etc. However, this noise cannot be defined in terms of frequency.

2.2.1. Patient electrode motion artifact
Motion artifacts from electrodes appear when the electrode/electrolyte equilibrium potential is disturbed. Artifacts from the skin are generated by the deformation of the skin under the electrode with the skin potential changed. Motion artifact is usually the most difficult type of noise to be detected because its spectrum completely overlaps that of the ECG, and its morphology often resembles that of P, QRS, and T waves[4]. Therefore, it is hardly detected when only using the ECG signal. There are several methods, including multi-resolution thresholding, wavelet-based methods, adaptive recurrent filter, high-pass filter (HPF), adaptive filter, and independent component analysis (ICA), to remove the motion artifact[9].

2.2.2. Instrumentation noise
The electrical device related to the ECG signal also contributes to noise. All the components in equipment like the electrodes, cables, amplifiers, converters are the major sources of instrumentation noise. This noise cannot be eliminated and can only be reduced by applying high-quality equipment and a well-designed circuit. The Johnson-Nyquist noise (also known as thermal noise) is a typical electrical noise resulting from the vibration of the electrons on conductors and is present in all electronic devices and media. The spectrum of this noise is given as

\[ V_n^2 = 4K_B TR \]  

Where \( K_B \) is the Boltzmann's constant, \( T \) is the temperature, and \( R \) is the resistance. This equation suggests that the resistor thermal noise is white for all frequencies; however, when the frequency gets higher than 100 Hz, the power spectrum becomes another type of noise called flicker noise. Flicker noise is a type of electronic noise with a 1/f power spectral density. Therefore, it is often referred to as 1/f noise or pink noise. One effective eliminating method is to move the target signal to a higher frequency and use a phase-sensitive detector to measure it. In this way, the flicker noise will be shifted to a higher frequency to be easily filtered out.

3. Methods to solve the noise in ECG signals
At present, three main ways for dealing with noise in ECG signals are circuit design, digital signal processing and machine learning.
3.1. Circuit designing

Circuit designing can effectively eliminate noise in ECG signals. In the following content, several popular solutions will be listed. Each of them involves the selection of electronic components or the design of circuit topology. The common goal is to eliminate undesirable signals without distorting the ECG signal by changing the circuit.

3.1.1. Amplifier optimizing

One important way to lower the noise level of the output is to optimize the amplifier's noise, which is one of the most important elements in the ECG detection device. The traditional amplifier is normally composed of transistors and resistors. Therefore, to optimize the noise of the amplifier, these two factors are taken into consideration firstly.

Resistors are usually responsible for the gain of the amplifier. However, they will cause unnecessary power consumption, noise and bad matching performance. Using transistors to replace resistors can eliminate noise to a certain degree[10]. Leon Fay used capacitors to replace the resistors, effectively reducing the power consumption and output noise[11]. Based on the previous two studies, Maryam Ghamati proposed using MOSCAP to replace the resistors, which solves the power and noise problem and minimizes the size of the amplifier compared to capacitors[12]. In general, the main idea of solving the noise problem caused by resistors is using other kinds of electronic components which can be used as a divider in the amplifying circuit and reduce the noise.

The noise of transistors consists of two major types: flicker noise and thermal noise. The following methods are proposed to reduce the flicker noise: (1) using BJT and JFET instead of MOSFET (2) using a transistor with larger $W*L$. After these factors are settled, researchers are suggested to analyze the amplify circuit first to find out which transistor plays the major role in output noise to minimize the cost of optimization. After finding out the major transistors, researchers could draw flicker and thermal noise curves of major transistors versus $W*L$ to determine which kind of noise is the dominant noise source at a certain $W*L$ area like Figure 2[13].

![Figure 2. Noise curves versus W*L device area[13].](image)

In Figure 2, M4 and M5 are the transistors that need to be optimized. Different optimization strategies are used according to the different $W*L$ values (changing $W/L$, transconductance) for different dominant noise sources.

Except for changing the elements in the amplifier, another way to denoise the amplifier is changing its topology. For example, the capacitive feedback amplifier can efficiently solve the DC offset problem on the skin and gain a high CMRR. As shown in Figure 3 and Figure 4, Jie Zhang introduced an inverter-based amplifier with capacitive feedback, which can reduce thermal and flicker noise by a factor of $\sqrt{2}$[14].
3.1.2. Chopping circuit

Another popular topology for denoise the signal is Chopping by chopping(modulating) the signal with a square wave before sending it to OTA and then demodulating the output signal. After demodulation, the noise without being chopped before will be modulated to high frequency and can be easily separated from the signal by a low pass filter.
However, it is hard to minimize noise without increasing the power with this traditional structure shown in Figure 5. Therefore, Qi Zhang designed a new split current chopper modulation amplifier for further noise reduction, shown in Figure 6[15].

Figure 5. Traditional chopper amplifier[15].

Figure 6. Zhang's chopper amplifier[15].
This amplifier adds chopper modulation for the capacitor feedback to avoid inputting signals without being modulated. S1 modulates the input signal, S2 demodulates the signal to separate noise, and S3 ensures the circuit always has feedback. Compared to the traditional structure, Zhang's amplifier lowers the equivalent input noise from $3.15 \mu V/\sqrt{Hz}$ to $42 nV/\sqrt{Hz}$[15].

3.1.3. Notch filter
The measurement of ECG signal is infected by power-line interference and muscle contraction noise. Both noises always appear in a limited frequency range (38-45 Hz, 50/60 Hz)[16]. Therefore, researchers can use a notch filter to filter this noise with proper central frequency quickly. As shown in Figure 7, Weichao Dong provided a Double T-Notch filter which introduces positive feedback to narrow the resistance bandwidth[2]. By setting proper R and C, the power-line interference can be eliminated successfully.

3.1.4. Low-Pass filter
A low pass filter can separate the noise after chopping and unnecessary filter noise in high frequency since the ECG signal's information lies mainly in the low-frequency domain. However, the filter's cut-off frequency should be chosen carefully, which impacts the QRS complex wave and may lead to distortion[17].

3.1.5. Driven right-leg (DRL) circuit
To distinguish ECG signal from the common-mode voltage, the circuit should provide a rather high CMRR. However, most traditional amplifiers with high CMRR work with high power. A driven right-leg circuit can solve this problem, as shown in Figure 8. The buffer and OTA provide common mode feedback to reject the common-mode voltage[12]. Using DRL can reduce the electrode-skin impedance, which will also help reject the common-mode voltage[18].

By using a DRL circuit, the CMRR of the circuit can achieve a high value with an acceptable power cost.
3.2. Digital signal processing
There are many approaches proposed to reduce or remove the baseline wanders and power line interference. Digital signal processing is a conventional ECG denoising method. The most common method used is filtering using adaptive techniques, wavelet transform.

3.2.1. Adaptive filtering
The approach has a primary input containing the corrupted signal and a reference input containing noise correlated with the primary noise in some unknown way and can automatically adjust their parameters. Adaptive filtering has been proved to be effective in a variety of practical applications[19].

The usual way to reduce a signal corrupted by noise is to pass it through a filter that suppresses the noise while leaving the desired signal unchanged. Filters could be divided into fixed filters and adaptive filters. The process to prove that building a fixed filter needs prior knowledge about both the desired signal and the additive noise while building an adaptive filter needs little is provided[19]. A basic model of adaptive filtering is proposed in Figure 9. It shows the theory about adaptive filtering.

![Figure 9. The adaptive noise canceling concept.](image)

The signal \( s \) refers to the desired signal, while the \( n_0 \) refers to the noise the sensor also receives. Signal \( n_1 \) is a signal uncorrelated with the desired signal but containing noise correlated with \( n_0 \) in some unknown way. For reference signal, whether the low-level signal contained will cause the noise-canceling useless is a problem. Bernard Widrow worked out the conclusion that adaptive canceling improves the signal-to-noise ratio by introducing only a little signal distortion. Therefore, it is possible to design a filter to change the \( n_1 \) to \( n_0 \) and the output \( z = s + n_0 - n_1 \) will equal to \( s \), the desired signal. Wiener proposed that the autocorrelation function of a wide-sense-stationary random process can be converted to the spectral density function by Fourier integral. Given the concept of the autocorrelation function, when a signal containing noise passes through the calculation of the autocorrelation function, the desired signal can remain relatively unchanged while the noise will get close to zero because of its uncertainty. The filtered signal can be transformed to the power spectrum, which is easier to be analyzed.
Thakor et al. proposed a least mean square (LMS) algorithm based on an adaptive recurrent filter[20]. The impulse response of QRS complexes could be collected by the LMS and used to detect the arrhythmia in ambulatory ECG because the reference inputs to the LMS algorithm were deterministic functions. It was defined by a periodically extended, truncated set of orthonormal basis functions[21]. As a result, the LMS algorithm operated on an instantaneous basis. Meanwhile, the weight vector would be updated every time the new sample got based on an instantaneous gradient estimate. However, Muhammad Zia Ur Rahman simulated the MIT-BIH database with various noises and showed that sign-based algorithms have a better performance than the LMS[21].

3.2.2. Wavelet transform

Wavelet transform is a relatively new method to simultaneously get spectrum, temporal information and characteristics from a goal signal. It is more flexible than the short-time Fourier transform (STFT)[22]. It is now applied in many biomedical signals, including ECG signals. Wavelet transform can be divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

Cuiwei Li discussed how to detect the characteristic of ECG signals using wavelet transforms[23]. She proposed an algorithm based on wavelet transform using a quadratic spline wavelet to detect the QRS complex, the T wave and the P wave. ECG signals can be easily characterized with multiscale information. Besides, it could be concluded that the QRS complex could be effectively distinguished from various noise and interference, given that the QRS complex appears at a different position from the artifact. Although she also proposed higher-order spline wavelets to do the same job, the results' onsets and offsets of P and T waves could not be easily identified, not satisfying the requirement of morphological diagnosis.

Agante and Marques analyzed algorithms that filter white Gaussian noise and 50 Hz PLI noise from ECG signals[24]. They applied two soft-thresholding techniques: Donoho's statistical threshold estimator and a method proposed by themselves. In the research, they tested the performances of different types of wavelets. The results showed that the estimator performed better in filtering the white Gaussian noise with little influence on the ECG signal. The algorithm they developed had a better performance in terms of PLI noise, but it was only effective when the signal-noise ratio (SNR) was high. Besides, the data obtained proved that wavelets that corresponded to ECG shape the most could reach the best result that the filtered signal had the highest correlation coefficient with the original signal.

In conclusion, wavelet processing is an effective alternative to classical filtering because of its ability to consider the frequency content and contain the time content. Therefore, the interference caused by filtering operation can be minimized in the signal morphology.

3.3. Machine learning

Recently, machine learning has been widely used in various fields with great performance. Thus, it becomes an innovative approach to solve noise problem in the ECG signals. Machine learning is defined as a study that can allow computers to study even if they are not coded completely. The basic working principle for machine learning is that use an existed database. Data features are extracted, remembered, and then used to identify new sets of data. Using certain formulated patterns, with data fed in, can solve almost all kinds of problems related to detection and recognition, which are virtues of machine learning[25]. Of note, machine learning was used in filter selection and noise detection to achieve low-noise ECG signals[17, 25].

3.3.1. Filter selection

Parvin states that during the traditional digital signal processing approach using filtering, output signals that come from various filters may have different SNR, and different filters optimize the result for different signals[26]. In order to provide a method to automatically select one superior filter from two, the wavelet and elliptical filtering methods specified in this study, a machine learning method was applied using a neural network[26].
First, since selecting the better filter between two could be treated as a binary selection problem, the typical convolution neural network (CNN) method was chosen for its ability to deal with unknown variation in the input data with optimizing function and parameters settled. After basic data from MIT-BIH normal sinus rhythm database was obtained, it was modified to contain more noise. Then, for the modified signals, principal components analysis (PCA) and independent analysis (ICA) were applied to extract the main features and improve the efficiency of data storing, and two filterings were used for every signal with performance assigned. Finally, under the security of a window signal which eliminates corrupted signals, the system is trained, tested and applied to new data[26]. Its performance reached 92.80% accuracy, and a demonstration is shown in Figure 10.

![Figure 10](image)

Figure 10. Graphs showing: (a) the clean signal \( x_a \), (b) showing noisy signal \( z_a \), (c) filtered signal using an optimum elliptical filter, (d) filtered signal using a wavelet filter, (e) clean signal \( x_b \), (f) showing noisy signal \( z_b \), (g) filtered signal using an elliptical filter, and (h) being the filtered signal using an optimum wavelet filter. The target waveforms and the green dotted lines that represent each signal's RMS values[26].

3.3.2. Noise detection

Unlike Parvin, Ansari derived a method that distinguishes usable and unusable ECG signals directly without being filtered first, so the unusable signals were abandoned, and usable signals were directly put into diagnosing. With a graph showing the distribution of signals with different SNR and the edge between usable signals and unusable signals in Figure 11, a machine learning solution was built up also using a neural network[27].

![Figure 11](image)

Figure 11. Distributions of SNR−1 for usable and unusable ECG signals (two distinct distributions on the two sides of the dashed line). The uniform distribution on the left side of the CNT line generates usable representations, while the one on the right generates unusable representations[27].
Similarly, Ansari used data obtained from MIT-BIH normal sinus rhythm database to make noisy signals with different SNR. With these signals, the critical noise threshold (CNT) was determined to classify the signals into usable and unusable parts, which transferred the problem to a binary selection problem. Then, the whole system using CNN was put into learning, testing and examining. This system reached an accuracy of 95% finally[27].

There are only limited approaches that apply machine learning methods directly to ECG low noise solutions. The more appealing choice is implementing machine learning for feature-extracting, classifying, and symptom-diagnosing, using pure, low-noise signals as input[28, 29]. Thus, it is suggested that if an efficient solution for ECG low noise using machine learning is provided, a complete system that takes the raw ECG signals as input and outputs low-noise signals with diagnosing results could be constructed and will become a considerable improvement.

4. Conclusions

ECG signals, various noises involved in ECG signals and solutions for eliminating them are reviewed in this article. ECG signals measure electrical heart potential and are mainly used to diagnose cardiac disease, so it is important to reduce contamination in the signal. ECG noises have various sources like the patient body, external interference and flaws of electrodes and circuits. For circuit design approaches, improvements are made on sizing transistors, using equivalent components to replace resistances, and applying various circuit topologies such as chopping circuits, filtering circuits, and DRL circuits. These modifications need to consider all kinds of circuit features and unavoidably change real components, which is usually uneconomical compared with other methods. Digital signal processing approaches are mainly based on adaptive filtering and wavelet transform. Having great performance without modifying the real circuit, these ways are widely used and considered capable for ECG denoising. The finally introduced method is machine learning. The two innovative ideas have a feature in common: they both use a neural network to achieve a binary selection task, with one separating usable signal from unusable signals while the other identifies the better filter between two for different pieces of signals. However, there are many other situations where a binary selection model will not apply, so more advanced methods need to be established.

Lowering noises of ECG signals has been developing significantly in recent years. However, there are still directions that could be worked on. Since there are 12 leads in total, using signals from different leads could be considered an efficient way to cancel the inner noise. In addition, since the previous study usually only focuses on one aspect among the three, it is suggested to develop an approach integrating all these methods to achieve better overall performance.

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