The commonly used methods for ECG Power-line interference removal

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Abstract. The amplitude of electrocardiogram (ECG) signals is on the millivolt level, and is susceptible to interference from human respiration, muscle tremors, and device circuits during the acquisition process, resulting in baseline drift, electromyographic (EMG) interference, and power line interference. Power line interference is a significant noise source in physiological signal acquisition among these. This article explores several methods to reduce the impact of power frequency interference. By analyzing wavelet transforms, adaptive filtering, and smoothing filters, commonly used methods are evaluated to determine their advantages and limitations. Experimental results show that the smoothed filtering method produces the highest SNR and lowest MSE of the electrocardiogram signal after denoising, resulting in the best denoising effect and thorough filtering. The denoising effect of wavelet transform and adaptive filter is poor. But the different methods for power line interference elimination should be applied according to the data acquisition requirements and equipment performance in response to different situations.

Keywords: ECG, power-line Interference, wavelet threshold, adaptive notch filter, smoothing filtering.

1. Introduction

With the continuous development of modern society, medical technology has made great progress and the treatment system has increasingly perfected. However, at the same time, social progress has led to a faster pace of life and increased stress on individuals, which has resulted in a rising incidence and mortality rate of cardiovascular disease [1]. According to relevant statistics, there are up to tens of millions of deaths each year worldwide due to cardiovascular disease.

Human research on ECG has developed a relatively mature system, and it has been applied to medical research and clinical treatment. The ECG signal reflects the physiological activity of myocardial cells on the body surface. It can convey information about the human body's physiological and pathological conditions, intuitively reflecting the heart's activity and representing the health status of the body. ECG shows the heart's condition and is an important clinical diagnostic tool for cardiovascular diseases [2].

Therefore, the ECG signal plays an obvious role in providing early warning of human safety. However, during the acquisition of ECG signals, a large amount of interference information is introduced by the daily activities of the human body, among which power line interference is a significant noise source in physiological signal acquisition. Power line interference is mainly caused by the unstable alternating current in the acquisition equipment, which causes electromagnetic reactions in the circuit during the ECG signal acquisition process, resulting in power line interference with a fixed frequency of 50 Hz or 60 Hz. The noise component is mainly a sine wave, appearing as a high amplitude peak at 50 Hz or 60 Hz in the frequency spectrum, and the amplitude can reach up to 50% of the amplitude of the ECG signal [3].

Familiar methods for eliminating power line interference, including wavelet thresholding, adaptive notch filtering, and smoothing filtering, are compared and analyzed in terms of minimizing the mean square error (MSE) and signal-to-noise ratio (SNR), as well as algorithm structure. The most suitable interference elimination method is chosen according to different scenarios and equipment conditions.

2. Effectiveness evaluation method and source

In this paper, signal-to-noise ratio (SNR) and mean square error (MSE) are selected as objective evaluation criteria for comparing the effectiveness of denoising methods on electrocardiogram signals. They are defined as shown in equations (1) and (2):

$$SNR = 10\lg\left(\sum_{n=1}^{N}\frac{y(n)^2}{[x(n)-y(n)]^2}\right) \tag{1}$$

$$MSE = \frac{\sum_{n=1}^{N}[x(n)-y(n)]^2}{N} \tag{2}$$

Here, y(n) represents the clean electrocardiogram signal, x(n) represents the denoised electrocardiogram signal, and N denotes the number of samples in the electrocardiogram signal. As indicated by the above equations, a higher SNR and a lower MSE indicate better denoising performance, while the opposite suggests poorer denoising performance.

In addition to calculating the SNR and MSE, this paper also chooses six ECG features, namely, P wave, QRS complex, T wave, ST segment, R-R interval, and P-R interval, as well as the amplitude changes in noise frequency, as intuitive evaluation criteria for denoising performance when comparing the effectiveness of smoothing filters and adaptive filters.

In recent years, the development of simulated electrocardiogram (ECG) signal technology has become more mature and played a significant role in the field of clinical medicine. Simulated ECG signals have the advantages of simple acquisition methods, low noise interference, and a wide variety of simulated ECG types compared to actual ECG signals. Currently, simulated ECG signals are mainly used for calibration and evaluation of ECG equipment, research on various pathological ECG signals, the establishment of standard databases, and ECG knowledge teaching. Studies have shown that ECG signals themselves satisfy periodicity and Dirichlet conditions, and thus can be simulated using the Fourier series. The QRS complex can be represented by a triangular wave, and the P and T waves can be represented by sine waves. Actual collected ECG signals are difficult to guarantee cleanliness and are often affected by noise, making it challenging to satisfy conditions for calculating signal-to-noise ratio and mean square deviation. To obtain pure ECG signals, ideal simulated ECG signals were used as experimental data in this study [4].

3. Method analysis and results

3.1. Wavelet threshold

Wavelet threshold is a method that uses appropriate threshold functions to modify the wavelet coefficients obtained after wavelet transformation, to make noise reduction. Donoho's wavelet threshold method is implemented through the following three basic steps [5,6].

(1) Perform wavelet decomposition on the noisy signal s(t): choose appropriate wavelet basis and decomposition level j and apply wavelet threshold to the signal to get wavelet coefficients $\omega_{j,k}$ on each level.

(2) Apply threshold processing to the coefficients obtained from wavelet decomposition: choose the appropriate threshold function and threshold value, and perform threshold processing on the

DOI: 10.54254/2755-2721/11/20230270

wavelet coefficients$\omega_{j,k}$on each level obtained after wavelet decomposition, to get the wavelet estimate coefficients.

(3) Perform wavelet inverse transform: reconstruct the threshold-processed wavelet coefficients to obtain the denoised signal ŝ(t).

Traditional threshold functions include hard threshold and soft threshold, and the threshold functions are shown as follows:

Hard thresholding function:

$$\hat{\omega}_{j,k} = \begin{cases} \omega_{j,k} & |\omega_{j,k}| \geqslant \lambda \\ 0 & |\omega_{j,k}| < \lambda \end{cases} \tag{3}$$

Soft thresholding function:

$$\hat{\omega}_{j,k} = \begin{cases} \text{sign}\left(| \ \omega_{j,k}\right)\left(|\omega_{j,k}| - \lambda\right) & |\omega_{j,k}| \geqslant \lambda \\ 0 & |\omega_{j,k}| < \lambda \end{cases} \tag{4}$$

To evaluate the denoising performance of three different wavelet algorithms and various wavelet basis functions on ECG signals, simulation experiments were conducted in the Matlab 2012 environment. The ECG signal data for the simulation experiment were obtained from the MIT-BIH database, with the signal number 117. Gaussian white noise was randomly added to the signal to simulate the composite characteristics of noise such as myoelectric interference and motion artifacts. The ECG signal was decomposed into three levels using wavelet decomposition, and the wavelet basis functions used were bior6.8, coif5, and sym8, which are the highest version wavelet basis functions available in Matlab 2012 [5]. The SNR and MSE of hard thresholding function are shown in Table 1. The SNR and MSE of soft thresholding function are shown in Table 2.

Table 1. Hard thresholding function [5].

Wavelet function Result	SNR	MSE
BIothogonal (bio6.8)	16.5790	0.0017
Coiflet (coif5)	11.9678	0.0051
Symlet (sym8)	16.3566	0.0018

Table 2. Soft thresholding function [5].

Wavelet function Result	SNR	MSE
BIothogonal (bio6.8)	14.9352	0.0025
Coiflet (coif5)	10.8626	0.0066
Symlet (sym8)	14.0690	0.0031

3.2. Smooth filtering

The smoothing filter is a filtering method that enhances low frequencies and suppresses high frequencies. As the main frequency distribution of electrocardiogram (ECG) signals lies between 0.05 Hz and 45 Hz, the 50 Hz power interference belongs to high-frequency interference relative to ECG signals and can therefore be eliminated by using the smoothing filter. In this study, the five-point, third-order smoothing filter in the smoothing filter method was used for denoising. The denoising principle is to take the five data points adjacent to each data point in the ECG signal, including the point itself, and fit a third-order curve using the least squares method. The data value at the corresponding position on the third-order curve is then selected as the filtered result. The advantage of this method is that it can preserve peak values, and the denoising effect on the edge data of ECG signals is better [4]. The denoising process is shown in the formula [4,7].

$$\overline{Y_{-2}} = \frac{1}{70}(69Y_{-2} + 4Y_{-1} - 6Y_0 + 4Y_1 - Y_2) \tag{5}$$

$$\overline{Y_{-1}} = \frac{1}{35}(2Y_{-2} + 27Y_{-1} + 12Y_0 - 8Y_1 + 2Y_2) \tag{6}$$

$$\overline{Y_0} = \frac{1}{35}(-3Y_{-2} + 12Y_{-1} + 17Y_0 + 12Y_1 - 3Y_2) \tag{7}$$

$$\overline{Y_1} = \frac{1}{35}(2Y_{-2} - 8Y_{-1} + 12Y_0 + 27Y_1 + 2Y_2) \tag{8}$$

$$\overline{Y_2} = \frac{1}{35}(-Y_{-2} + 4Y_{-1} - 6Y_0 + 4Y_1 + 69Y_2) \tag{9}$$

In this equation, Y_0 represents the original electrocardiogram (ECG) data point, and Y_{-1}, Y_{-2}, Y_1, and Y_2 represent the adjacent four data points within the left and right neighborhoods of Y_0. Y^- represents the denoised data point, and formulas (5) and (6) are used to process the leftmost data point, while formulas (8) and (9) are used to process the rightmost data point. All other data points are processed using formula (7) [4].

Evaluation parameters of the experimentally simulated denoising of the electrocardiogram (ECG) signal are shown in the Table 3.

Table 3. Smooth filtering denosing [4].

Characteristic value	Weak power frequency interference	Severe power frequency interference	Ideal electrocardiogram signal
P wave	0.23	0.23	0.23
T wave	0.35	0.35	0.35
QRS complex	1.49	1.47	1.57
S-T	horizontal	horizontal	horizontal
R-R interval	0.827	0.827	0.827
P-R interval	0.041	0.041	0.041
SNR	38.7948	32.8623	——
MSE	0.0003	0.0006	——

The spectrum diagram is shown in the Figure1 and Figure 2.

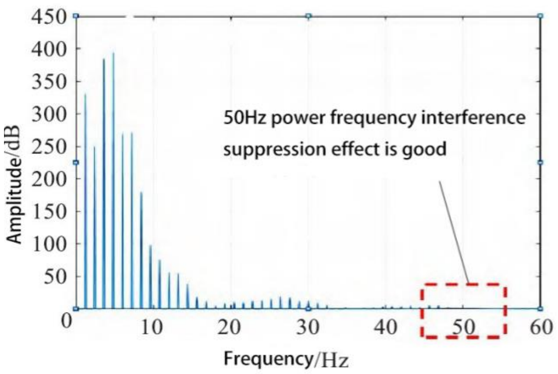

Figure 1. Weak frequency after denoising [4].

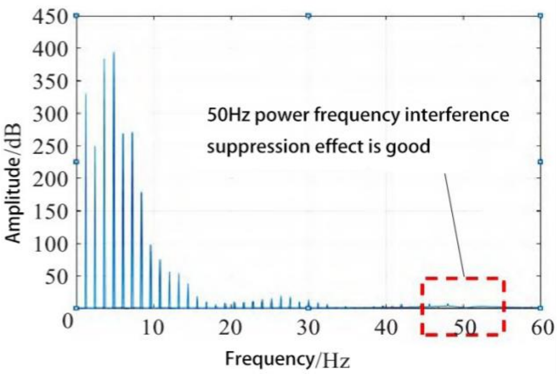

Figure 2. Severe frequency after denoising [4].

By observing Figures 1 and 2, it can be observed that the smoothing filter has a good effect on removing 50 Hz power-line interference, and the filtering effect is quite thorough. However, it also removes useful electrocardiogram (ECG) signals within the frequency range of 40-50 Hz, which is the frequency distribution range of the R-wave. Therefore, it may have a slight impact on the R-wave. As the power-line interference increases, the impact of the smoothing filter will gradually spread to lower frequency components, thereby swallowing useful ECG signals [4].

3.3. Adaptive filter

The traditional design method of band-stop filters has the drawback of only being able to filter fixed frequencies [8]. When the filtered frequency deviates, the filtering effect will significantly decrease. Filters designed using adaptive methods can overcome these drawbacks. They can automatically adapt to changing environments and system requirements and can extrapolate from a limited number of training signals or patterns to adapt to new environments. The weight adjustment algorithms of adaptive filtering can be divided into two categories: the least mean square (LMS) method and the recursive least square (RLS) method. Although the RLS algorithm converges faster, it requires more computations. The LMS algorithm is simple and easy to implement [8]. In this paper, all adaptive filters are implemented using the LMS algorithm [9].

A typical LMS adaptive filter as shown in Figure 3 includes a digital filter H(z) and an adaptive algorithm. H(z) performs the required signal processing to obtain y(n). Simultaneously, the desired signal d(n) is added and subtracted from y(n) to obtain e(n), which is input to the adaptive algorithm. The coefficients of the system H(z) are continually improved through the adaptive algorithm. If the desired signal d(n) contains both useful signals and noise, then the system is continually improved, and the output y(n) approximates the estimated noise [10].

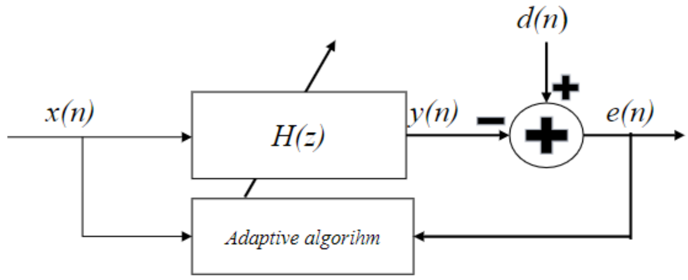

Figure 3. LMS adaptive filter [10].

This article adopts the commonly used LMS algorithm as the adaptive filtering algorithm in this experiment, and its filtering process is shown in the Figure 4.

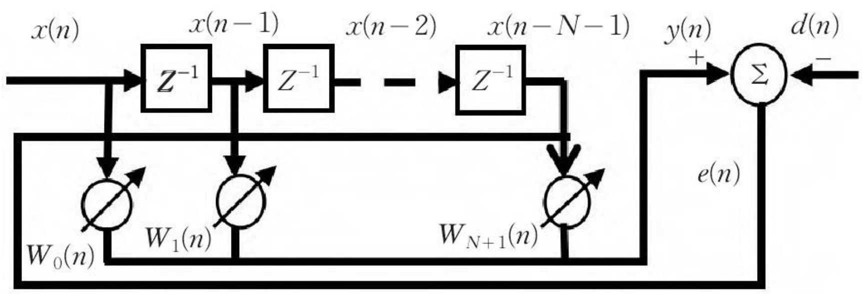

Figure 4. LMS algorithm [4].

In the figure, x(n) represents the noisy ECG signal, which is filtered by a filter with an adjustable coefficient W(n) to output the denoised signal y(n). The error signal e(n) is obtained by comparing the output signal y(n) with the ideal ECG signal d(n). If e(n) does not meet the expected requirements, it is fed back to the filter, and the filter automatically adjusts the coefficient W(n) for the next filtering, thereby achieving the purpose of automatic filtering [6]. The filtering algorithm is shown as follows.

$$y(n) = \sum_{i=1}^{M} W_i x(n-i) \tag{10}$$

$$W(n+1) = W(n) + 2\mu e(n) x(n) \tag{11}$$

The symbol M represents the number of sampling points in the electrocardiogram (ECG) signal, and μ denotes the step size, which is the time interval between the filtering before and after. The evaluation parameters for denoising the ECG signal after experimental simulation are shown in Table 4. The summary of results are shown in Table 5.

Table 4. Adaptive filter [4].

Characteristic value	Weak power frequency interference	Severe power frequency interference	Ideal electrocardiogram signal
P wave	0.22	0.20±0.10	0.23
T wave	0.35	0.34±0.10	0.35
QRS complex	1.57	1.56±0.10	1.57
S-T	horizontal	translation±0.1mV	horizontal
R-R interval	0.827	0.827	0.827
P-R interval	0.041	0.041	0.041
SNR	31.8544	22.5168	——
MSE	0.0006	0.0015	——

Table 5. Results summary.

Result	SNR	MSE
BIothogonal(bio6.8)	16.5790	0.0017
Coiflet(coif5)	11.9678	0.0051
Symlet(sym8)	16.3566	0.0018
Smooth filtering(weak)	38.7948	0.0003
Smooth filtering(serve)	32.8623	0.0006
Adaptive filtering(weak)	31.8544	0.0006
Adaptive filtering(serve)	22.5168	0.0015

4. Conclusion

This article compares experimental data of ideal electrocardiogram (ECG) signals with those contaminated by power frequency interference (PFI) and evaluates the performance of three denoising algorithms through measures such as signal-to-noise ratio and frequency domain characteristics. According to Table 5, the research findings show that:

Wavelet thresholding, either hard or soft, is subject to factors that inevitably affect denoising performance. Given the non-stationary nature of ECG signals, the large discrepancies among different wavelet coefficients and the significant differences in signal-to-noise ratio present challenges to the use of wavelet transforms. Moreover, the Biorthogonal wavelet function is more suitable than Coiflet and Symlet wavelet functions for denoising ECG signals. Therefore, the use of wavelet coefficient-related denoising and Biorthogonal wavelet functions achieves the best denoising performance and is suitable for practical application in ECG signal denoising.

DOI: 10.54254/2755-2721/11/20230270

The ECG signal denoised by the smoothing filter has the highest SNR, the lowest MSE, and the most thorough removal of noise, but it can also have a certain impact on the ECG signal as the level of PFI interference increases.

The adaptive filtering method removes weak PFI interference more thoroughly but is less effective for severe PFI interference and can cause distortion of the P wave to some extent. Compared with the above two methods, the SNR of the adaptive filtering method is intermediate.

This article focuses on eliminating PFI interference through digital filtering and discusses three common methods. However, it does not cover hardware aspects or actual situations. Further research is needed to address real-world conditions. As the denoising of ECG signals continues to improve, it will further enhance their practicality in clinical applications, and have significant practical implications for improving ECG clinical diagnosis methods and even realizing automated ECG medical diagnosis.

References

[1] Wong M H, Louie J and Chun Y 2021 A priori dietary patterns and cardiovascular dise ase incidence in adult population-based studies: a review of recent evidence *Crit. Rev. Food Sci. Nutr.* 62(22) p 11-16 doi: 10.1080/10408398.2021.1897517.

[2] Veer K, Mathur P and Sharma T 2022 ECG for Cardiovascular Diseases Using Soft Co mputing Algorithms *Current Signal Transduction Therapy* 17(3)

[3] Kair M A and Shahnaz C 2012 Denoising of ECG signals based on noise reduction alg orithms in EMD and wavelet domains *Biomed. Sig. Process. Control* 7(5) p 481-489 doi: 10.1016/j.bspc.2011.11.003.

[4] Yang C, Nie C, Che M, Ruan X and Fan R 2020 Evaluation and Analysis of Ecg Den oising Effect *Comp. Eng. Appl.* 58(01) p 300-312

[5] Zhang J 2017 Research on Denoising of ECG Signals Based on Wavelet Transform *Co mp. Knowl. Tech.* 13(31) p 227-229

[6] Singh O and Sunkaria R K 2017 ECG signal denoising via empirical wavelet transform *Australas Phys. Eng. Sci. Med.* 40 p 219–229 doi: 10.1007/s13246-016-0510-6.

[7] Sameni R 2017 Online filtering using piecewise smoothness priors: Application to norma l and abnormal electrocardiogram denoising *Signal Process.* 133 p 52-63 doi: 10.10 16/j.sigpro.2016.10.019.

[8] Jenitta J and Rajeswari A 2013 Denoising of ECG signal based on improved adaptive fi lter with EMD and EEMD *IEEE Conf. Inf. Commun. Tech.* p 957-962 doi: 10.1109/ CICT.2013.6558234.

[9] Jenkal W, Latif R, Toumanari A, Dliou A, B'Charri O and Maoulainine F M R 2016 An efficient algorithm of ECG signal denoising using the adaptive dual threshold filt er and the discrete wavelet transform *Biocybern. Biomed. Eng.* 36(3) p 499-508 doi: 10.1016/j.bbe.2016.04.001.

[10] Li Y and Guo F 2023 Estimation and Elimination of ECG Dual Frequency Interferenc e by LMS Adaptive Filter *Safety & EMC* 01 p 66-71