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Optimization of PPG Signal Processing Based on Hybrid Filtering Technology

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Abstract: With the widespread adoption of wearable devices, pulse oximeters face challenges such as motion artifacts and environmental noise in dynamic scenarios, limiting their accuracy and reliability. This study focuses on optimizing a hybrid filtering framework combining low-pass filtering and LMS adaptive filtering to enhance the performance of photoplethysmography (PPG)-based oximetry. Utilizing a publicly available dataset from Biagetti et al., which includes PPG and triaxial accelerometer data from seven subjects under rest and exercise conditions, we implemented a dynamic low-pass filter with adjustable cutoff frequencies and an LMS algorithm with motion-dependent step size adaptation Comparative experiments with wavelet denoising demonstrated that the proposed framework achieved a signal-to-noise ratio (SNR) of 61.37 dB, a mean squared error (MSE) of 0.0029, and a correlation coefficient (R) of 0.9849, significantly outperforming conventional methods. Results validate the hybrid framework's effectiveness in suppressing noise while preserving physiological signal integrity, offering a robust solution for wearable health monitoring in dynamic environments.

Keywords: PPG signal, motion artifacts, LMS adaptive filtering, low-pass filter

1. Introduction

As the core medical sensor for monitoring heart rate and blood oxygen saturation, the pulse oximeter has expanded its application scope from traditional clinical medical scenarios to diversified fields like fitness and daily health management. The oximeter uses photoplethysmography (PPG) technology to non-invasively obtain human physiological signals. Its principle is to detect the absorption and reflection changes of specific wavelengths of light in human tissues, thereby inferring key physiological parameters such as heart rate and blood oxygen saturation. Despite being widely used for their convenience and non - invasiveness, pulse oximeters face challenges in enhancing their performance. Among them, motion artifacts and environmental noise are the main interference factors. This study aims to introduce hybrid filtering technology in oximeter signal processing by optimizing the signal processing algorithm to eliminate motion artifacts and environmental noise, and improve the accuracy, real-time and reliability of oximeter measurement. The main aim of this study is to compare traditional filtering technology with the new combined filtering method, specifically by integrating low - pass filtering and LMS adaptive filtering. We will conduct theoretical analysis, simulation experiments, and real - world trials to identify performance differences in noise suppression and signal quality improvement, clarify the advantages and limitations of different methods in various scenarios, verify the effectiveness of the optimized algorithm in reducing the

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impact of motion artifacts and environmental noise, and assess its practical application effect. The introduction explains the research background and objectives; the literature review analyzes the current status and challenges of signal filtering technology; the research method details the algorithm optimization and simulation experimental design; the results and discussion compare the performance differences of different methods; And the conclusion summarizes the research results and looks forward to future directions.

2. Literature review

2.1. Review of signal filtering technology

Photoplethysmography (PPG) technology has become a common method for wearable devices to monitor blood oxygen saturation (SpO_2) and heart rate due to its non-invasive, low-cost and high portability. However, during monitoring, motion artifacts (MA) seriously affect the quality of PPG signals. MA originates from human activities, and its spectrum (>0.1 Hz) highly overlaps with the main frequency range (0.5 - 5 Hz) of the effective PPG signal, resulting in signal distortion and measurement errors. In dynamic scenes, MA can cause the error of blood oxygen saturation measurement to exceed 5%. Traditional filtering technology is difficult to eliminate the frequency domain aliasing problem of MA and effective signals, and the development of low-power, high-robustness hybrid filters has become a research focus. Allen first quantitatively analyzed the interference mechanism of MA on PPG signals in 2007, but did not provide a specific suppression solution based on the technology level at that time [1]. In recent years, many researchers have continued to explore. In 2020, Jongshill Lee, Minseong Kim, and others used an independent component analysis (ICA) motion artifact elimination algorithm based on a PPG measurement system with a multi-channel multi-wavelength sensor to reduce the heart rate estimation error caused by motion artifacts in the PPG signal in intense exercise situations. However, this method still needs to strike a balance between hardware complexity and real-time performance [2]. Junyung Park et al. optimized the PPG signal processing process based on a new method of machine learning in 2022 [3]; Rabia Ahmed used deep learning and wavelet multi-resolution analysis capabilities to denoise the PPG signal in 2023, which can significantly reduce the MSE of the PPG signal under different types of noise [4]; Igendi et al. proposed the NSQI indicator in 2024, and specified NSQI < 0.293 as the high-quality discrimination threshold. This indicator better realizes remote heart rate monitoring and real-time analysis of mobile devices. Although this method has good real-time and low complexity characteristics, it still needs to further strike a balance between the power consumption and real-time performance of mobile devices [5]. In March 2025, Minerva guadalúpe vázquez domínguez et al. found that based on the spectral coherence criterion, the affine projection algorithm and the variable step-size affine projection algorithm were most effective in filtering out PPG signals contaminated by muscle noise, with the similarity scores between the filtered signals and the motion-free pulse signals being 94.25% and 94.67%, respectively [6].

In summary, existing research has made significant progress in the MA suppression and quality assessment techniques of PPG and rPPG signals. However, for practical applications, especially the real-time monitoring needs of mobile and wearable devices, in the future, it is still necessary to continue to explore in-depth aspects such as algorithm complexity optimization, hardware power consumption reduction, and real-time performance improvement.

2.2. Problems with single filtering technology

Low - pass filters, while effective in removing high - frequency noise, struggle to distinguish target signals from noise during environmental noise interference, potentially filtering out useful high - frequency components crucial for blood oxygen saturation calculation. High - pass filters, on the other hand, can eliminate baseline interference but fail to handle low - frequency noise from daily exercise and may also remove low - frequency components of blood oxygen signals. Bandpass filters, which rely on precise frequency band division to enhance the signal - to - noise ratio, show poor adaptability in complex daily environments. Although adaptive filters can dynamically adjust parameters, they have high requirements for initial parameters and signal quality, are complex to calculate, consume high power, and affect the response speed of the device. Kalman filters perform well when processing linear signals and can quickly track physiological parameters, but they are highly dependent on the statistical values of noise signal characteristics, and the filtering effect is reduced in nonlinear environments.

2.3. Advantages of hybrid filtering technology

The low - pass filter effectively removes high - frequency noise and baseline drift, ensuring the stability of blood oxygen signals in static environments. Its cutoff frequency, adjusted dynamically (e.g., between 6Hz and 8Hz under different motion states) based on spectrum analysis and experimental data, enhances adaptability to environmental changes. Subsequently, the LMS algorithm, using the three - axis accelerometer signal, further filters the low - pass - filtered signal. It dynamically adjusts the step - size factor and filter coefficient, increasing the step size during rapid motion to quickly suppress artifacts and reducing it during static or low - intensity motion to maintain stability, thus adapting to various motion states and environmental conditions. The algorithm enhances the adaptability to different motion states, effectively reduces the interference of motion artifacts on the oximeter signal and ensures the extraction of high-precision signals of the oximeter in a dynamic environment. By combining low-pass filtering with LMS adaptive filtering, high-frequency noise and motion artifacts can be effectively removed, signal quality can be improved, and the accuracy and real-time performance of the oximeter signal can be improved. In actual scenarios, it demonstrates powerful real-time compensation capabilities to ensure high-precision measurement of the oximeter in complex environments. This overcomes the shortcomings of a single filtering technology and significantly enhances the performance of the oximeter in dynamic and complex environments.

3. Methodology

3.1. Single filter technology

3.1.1. Low pass filtering and butterworth low pass filter

The mathematical model of the low-pass filtering algorithm is as follows: Assume the input discrete signal is $x[n]$, the output of the low-pass filter is

$$y[n] = \alpha \cdot x[n] + (1 - \alpha) \cdot y[n - 1] \tag{1}$$

Among them, $y[n]$ is the output value of the n th sampling value after filtering; $x[n]$ is the n th sampling value; α is the smoothing factor of the filter (between 0 and 1), which determines the cutoff frequency of the filter. The low - pass filter permits low - frequency components to pass while suppressing high - frequency components through weighted averaging of the input signal. In other words, it eradicates rapidly varying noise or high - frequency interference by smoothing the signal, thus yielding a smoother signal output.

The practical application model designed according to the algorithm: Butterworth low-pass filter, has a flat passband response and smooth transition characteristics near the cutoff frequency. Its mathematical model is as follows:

Transfer Function:

$$H(s) = \frac{1}{1+\left(\frac{s}{\omega_c}\right)^{2n}} \tag{2}$$

$H(s)$ is the transfer function, s is a complex frequency domain variable, ω_c is the cutoff frequency, n is the filter order. Difference equation for discrete-time signal:

$$y[n] = \alpha_0 x[n] + \alpha_1 x[n-1] + \cdots + \alpha_M x[n-M] \tag{3}$$

$x[n]$ is the input signal, $y[n]$ is the output signal, $\alpha_0, \alpha_1, \cdots, \alpha_M$ is the filter coefficient determined by the cutoff frequency and the order [7].

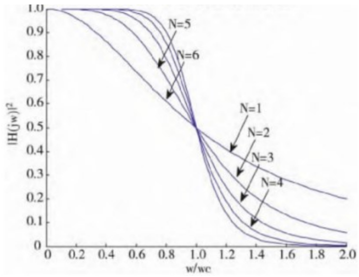

Figure 1: Butterworth filter frequency characteristics

The outstanding feature of the Butterworth low-pass filter is that its frequency response has maximum flatness within the passband. It can filter out high-frequency noise in a smooth manner. According to Figure 1, the amplitude response of the filter drops rapidly at the cutoff frequency, with an attenuation rate of 20n dB/dec (n is the filter order), As the order n increases, the attenuation effect becomes more significant, and the ability to suppress high-frequency signals increases [7]. The Butterworth low-pass filter has a flat passband response and a smooth frequency response transition band, which is conducive to stable signal processing and has no ripples, making it suitable for high-precision signal scenarios. However, it decreases slowly near the cutoff frequency, especially at low orders, and has poor noise reduction effects for strong high-frequency noise signals. Therefore, in scenarios with extremely high precision requirements and complex noise environments, due to the transition characteristics near the cutoff frequency and the limited attenuation rate, the performance is difficult to meet the requirements.

3.1.2. LMS adaptive filtering

The LMS adaptive filtering algorithm aims to minimize the mean square error by adjusting the filter weights according to the error signal, which is defined as the difference between the expected output and the actual output. This algorithm employs the gradient - descent method to iteratively update the filter weights in the direction opposite to the gradient of the error function, ensuring that the output approximates the expected signal as closely as possible. The principle block diagram of the adaptive filter is shown in Figure 2.

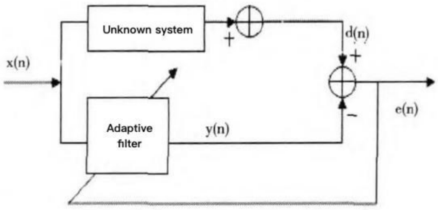

Figure 2: Adaptive filter principle block diagram

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The mathematical model of the LMS adaptive filtering algorithm is as follows:
1. Initialize filter coefficients $w_i(0)$
2. For each time step n , there is the following iteration formula:
Calculate the filter output:

$$y(n) = w(n)^T x = \sum_{k=0}^{M-1} w_i(n)x(n-i) \tag{4}$$

Calculate the error function:

$$e(n) = d(n) - y(n) \tag{5}$$

Update filter coefficients:

$$w_i(n+1) = w_i(n) + 2\mu e(n)x(n) \tag{6}$$

Among them, $x(n)$ is the input signal, $d(n)$is the expected output value, $e(n)$is the error signal, $w(n)$is the filter weight vector, $w_n = [w_0(n), w_1(n), w_2(n), \ldots, w_{M-1}(n)]^T$; M is the filter order; μ is the step size factor [8].

3.2. Design framework of hybrid filtering technology

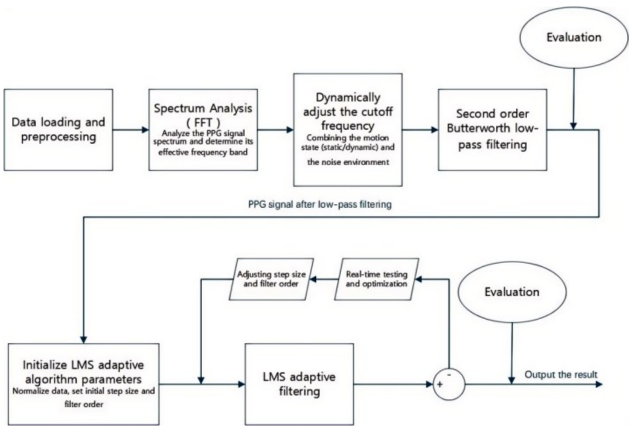

Figure 3: Design framework of hybrid filtering technology

As depicted in Figure 3, the process commences with data loading and preprocessing. Subsequently, the effective frequency band is ascertained through FFT spectrum analysis. Based on the motion state and environmental factors, a dynamic cutoff frequency is assigned to the processed signal, and a second - order Butterworth low - pass filter is utilized to eliminate certain high - frequency noise. The second step is to perform LMS adaptive filtering. First, the algorithm parameters are initialized, including data normalization, setting the step size and filter order, and then the step size is dynamically adjusted during the test to suppress motion artifacts. In this step, the effect is continuously evaluated using indicators such as the signal quality index, the process is optimized, and a closed-loop feedback is formed. Finally, a PPG signal with both robustness and adaptability is output.

3.3. Experimental data

The data used in this study comes from the paper "Dataset from PPG wireless sensor for activity monitoring" (Data in brief 29 (2020) 105044) [9] published by Biagetti et al. in Data in Brief. The dataset contains photoplethysmography (PPG) signals collected by the Maxim Integrated MAXREFDES100 wireless sensor worn on the wrist, as well as triaxial accelerometer signals collected synchronously with it. Biagetti et al. collected PPG and accelerometer data from seven

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subjects in different activity states such as resting, squatting, and stepping. The dataset provides 15 PPG signal samples and corresponding 15 triaxial accelerometer signal samples for each subject, with a sampling frequency of 400 Hz. In the dataset, the PPG signal value corresponds to the ADC output of the photodetector, with a pulse width of 118μs, a resolution of 16 bits, a full-scale range of 8192nA, and is lit by a green LED; the triaxial accelerometer signal value corresponds to the MEMS output, with a resolution of 10 bits and a left-aligned ±2g scale. In order to facilitate subsequent analysis and evaluate the performance of the algorithm, this study used the PPG signal data and triaxial acceleration data of the second stepping movement (step2) of subject 1 (S1) in the dataset as experimental data. The data visualization results are as Figure 4 and Figure 5.

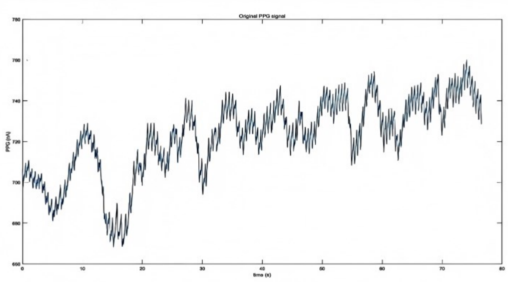

Figure 4: Original PPG signal

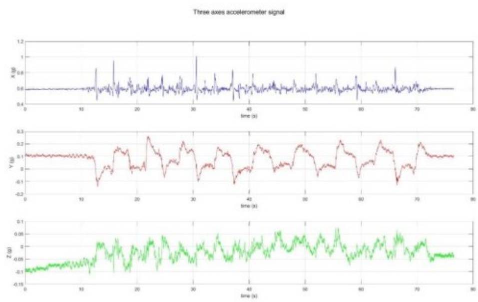

Figure 5: Three axis accelerometer signal

3.4. Parameter settings

In the signal processing process, in order to optimize the PPG signal filtering effect and minimize motion artifacts and noise interference, key parameters need to be pre-set.

3.4.1. ADC full-scale range and ADC resolution

The ADC full-scale range defines the maximum current value that the analog-to-digital converter can measure. This study uses the MAXREFDES100 wireless sensor and sets the full-scale range to 8192 nA based on the original data set. This parameter is directly related to the conversion accuracy between the ADC output digital value and the actual current intensity and is the basis for PPG signal strength calibration. The ADC resolution determines the discrete level of the analog signal. According to the original data set, this study uses 16-bit resolution. Higher resolution can more accurately capture subtle changes in the PPG signal. Its quantization accuracy is calculated as: the current value represented by each ADC unit = ADC full-scale range / (2^ADC resolution) [10].

3.4.2. Dynamic cutoff frequency

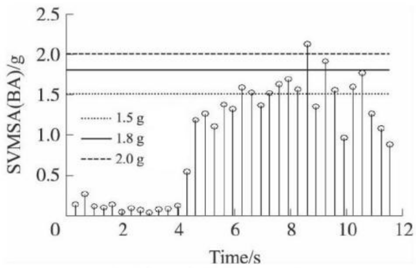

Figure 6: Acceleration signal amplitude vector when strenuous movement state (after smoothing)

As the key parameter of the low-pass filter, this study adopts a dynamic adjustment strategy based on the triaxial accelerometer data. According to Figure 6, when the average acceleration is less than 0.5g, it is defined as a static state, and its dynamic cutoff frequency is set to 4Hz; when the average acceleration is between 0.5g and 1.8g, it is defined as a slight movement state, and its dynamic cutoff frequency is set to 6Hz; when the average acceleration is higher than 1.8g, it is defined as a strenuous movement state, and its dynamic cutoff frequency is set to 8Hz [11-12]. This parameter setting can completely filter out high-frequency noise when static and retain signal details when moving, which directly affects the signal-to-noise ratio of the PPG signal and the accuracy of subsequent heart rate and blood oxygen saturation calculations.

3.4.3. Step size factor μ

The step size factor μ is a key parameter of the LMS adaptive filtering algorithm. The step size factor μ is a key parameter of the LMS adaptive filtering algorithm. It directly affects the convergence speed and steady-state offset of the adaptive filter. The larger the μ, the faster the algorithm converges, but the larger the steady-state offset. On the contrary, the smaller the μ, the slower the algorithm converges and the smaller the steady-state offset. Therefore, it is necessary to select a suitable step size factor according to the needs of the actual application so that the convergence speed and steady-state offset can achieve a good compromise and meet the requirements of the system. In this study, the initial setting was $\mu = 0.01$. After a large number of simulation convergence tests, it was finally adjusted to 0.0005 to avoid iterative oscillation and ensure the stable mean square convergence of the algorithm [13].

3.4.4. Filter order L

The filter order L determines the length of the past input signal used by the LMS adaptive filter, which affects its ability to adapt to dynamic changes in the signal. For the same input $x(n)$, the smaller L is, the lower the computational complexity is, the larger the range of the step size factor μ is, the faster the filter converges, the corresponding steady-state offset is reduced, and the system is more stable. However, for FIR filters, the smaller the filter order L is, the less it can approximate the ideal pulse and frequency response characteristics. In addition, the unknown system to be estimated is generally regarded as an infinite impulse response (IIR), so selecting an FIR filter structure with too low an order will not be able to approximate the expected response well. Therefore, for a system with a known or unknown structure, in order to obtain a better filtering effect, we will try to increase L as much as possible. At the same time, a higher order can more accurately model complex motion artifacts in the PPG signal, but it will increase the computational complexity and convergence time. Its selection refers to the duration of motion artifacts in the PPG signal and the real-time requirements of the system. In this study, $L = 900$ [13].

3.4.5. Adaptive step function

To further optimize the performance of the LMS adaptive filtering algorithm, this study adopts an adaptive step size adjustment strategy to dynamically adjust the step size according to the amplitude of the triaxial accelerometer. The function is defined as follows:

$$\mu(n) = \frac{1}{1+|a_x(n)|+|a_y(n)|+|a_z(n)|} \tag{7}$$

$a_x(n), a_y(n)$ and $a_z(n)$ are the three-axis acceleration values of the nth sampling point. This function can ensure that the algorithm increases the step size to accelerate convergence when the

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motion intensity is high, and reduces the step size to improve stability and reduce steady-state errors when the motion intensity is low.

3.5. Evaluation indicators

3.5.1. Signal-to-noise ratio (SNR)

An indicator that measures the ratio of signal strength to noise strength, usually expressed in decibels (dB). It is used to quantify the ratio of useful information to noise in a signal. In this study, SNR is used to evaluate the effects of low-pass filtering and LMS adaptive filtering. The higher the SNR, the smaller the noise component in the filtered signal and the higher the signal quality. The calculation formula is as follows:

$$\mathrm{SNR} = 10 \times \log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) \tag{8}$$

Among them, P_{signal} is the average power of the signal, P_{noise} is the average power of the noise.

3.5.2. Mean square error (MSE)

The average of the squares of the differences between the predicted value and the true value is a common indicator for measuring signal or data errors. In this study, MSE is used to measure the error between the filtered signal and the true or expected signal. The smaller the MSE, the better the performance of the filter, the smaller the error, and the more accurate the processing effect. The calculation formula is as follows:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{9}$$

Among them, y_i is the true value, $\hat{y}_i$ is the predicted value, N is the number of data points [14].

3.5.3. Correlation coefficient (R)

An indicator that measures the strength of the linear relationship between two signals, and its value range is (-1, 1). A correlation coefficient of 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no linear correlation. The calculation formula is as follows:

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{10}$$

Among them, x_i and y_i are the values of the two signals, $\bar{x}$ and $\bar{y}$ are their means.

3.6. Signal processing flow

3.6.1. Data preprocessing

The original PPG signal is represented by the ADC value and needs to be converted to the actual current value. The conversion formula is:

$$\text{PPG Current} = \frac{\text{ADC value}}{65535} \times 8192 \tag{11}$$

This maps the digital signal to the actual current value to ensure that the signal unit is consistent. The accelerometer raw data is the output value of the MEMS sensor with a 10-bit resolution. The conversion formula is:

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$$\text{Scale Factor} = \frac{4}{102400} \tag{12}$$

Then use this scale factor to multiply \`X\`, \`Y\`, and \`Z\` respectively to obtain the acceleration values \`X_g\`, \`Y_g\`, and \`Z_g\`, and convert the original digital signal to the actual acceleration value.

3.6.2. Low-pass filtering

First, the PPG signal is subjected to Fourier transform (FFT) spectrum analysis to determine the effective frequency band. The low-pass filter cutoff frequency range can be initially set to 6 Hz to 8 Hz, and then the cutoff frequency of the low-pass filter can be dynamically adjusted according to the motion state and noise environment changes in the experimental data [11].

In the low-pass filtering stage, a second-order Butterworth low-pass filter is used to filter the PPG signal. The second-order Butterworth filter has a flat passband response and good frequency characteristics, which can effectively remove high-frequency noise and retain low-frequency signals. The filtfilt function is then used for zero-phase filtering to avoid introducing phase delay in the filtering process and ensure the accuracy of the filtering effect.

3.6.3. LMS adaptive filtering

During the initialization of the LMS adaptive filtering algorithm, following numerous data experiments, the filter order is configured to 900, and the initial step size is set to 0.0005 to preclude algorithm oscillation. The reference signal is composed of a historical window of three-axis accelerometer data, which is used to predict PPG signal motion artifacts. Enter the LMS adaptive filter main loop and minimize the signal error by gradually adjusting the filter weights. Construct a reference signal vector using the past filter_order acceleration values (X, Y, Z axis); the filter output is the weighted sum of the accelerometer signals. The error $e(n)$ is the difference between the expected output (normalized PPG signal) and the filter output $y(n)$; the formula is updated by the LMS algorithm:

$$w_i(n+1) = w_i(n) + 2\mu e(n)x(n) \tag{6}$$

Among them, $w_i(n)$ is the filter weight vector, $w_n = [w_0(n), w_1(n), w_2(n), \ldots, w_{M-1}(n)]^T$; M is the filter order; μ is the step size factor, $x(n)$ is the current reference signal. The step size $\mu(n)$ affects the convergence speed and stability of the LMS algorithm. During high-intensity exercise (stepping, waving), the step size should be increased to accelerate convergence. The step size adjustment formula is:

$$\mu(n) = \frac{1}{1+|a_x(n)|+|a_y(n)|+|a_z(n)|} \tag{7}$$

The effectiveness of the LMS algorithm in dealing with fast motion artifacts is tested in real time under motion, and the system is ensured to operate stably by minimizing errors. When fast motion is detected, the LMS algorithm automatically increases the step size to quickly adjust the filter coefficients to suppress signal fluctuations; when stationary or in low-intensity motion, the step size is reduced to keep the filter coefficients stable and avoid over-adjustment. Finally, a convergence verification is performed to ensure the rationality of the parameters.

4. Results

The PPG signal after low-pass filtering is shown in Figure 7. PPG signal result after LMS adaptive filtering is shown in Figure 8.

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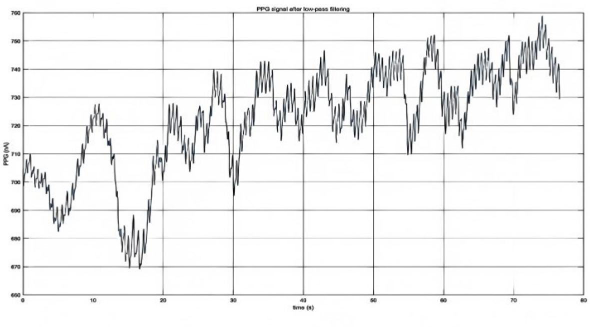

Figure 7: PPG signal after low-pass filtering

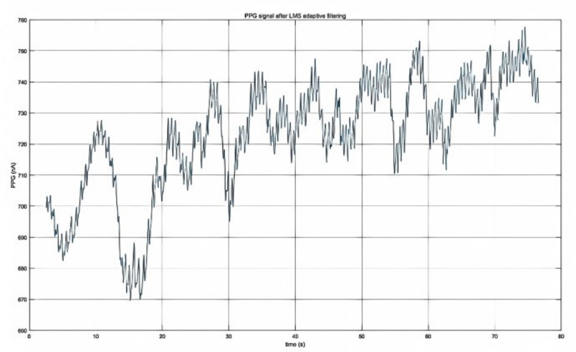

Figure 8: PPG signal after LMS adaptive filtering

Step size change is shown in Figure 9. LMS adaptive filtering PPG signal result after smoothing is shown in Figure 10.

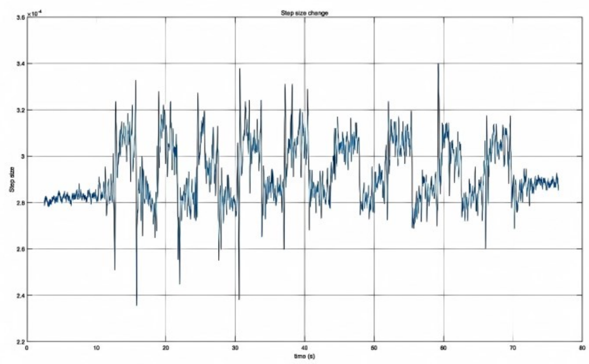

Figure 9: Step size change

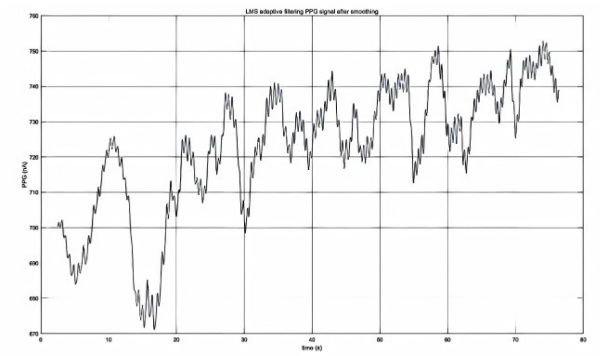

Figure 10: LMS adaptive filtering PPG signal after smoothing

This experiment uses wavelet denoising filtering technology as the control group. Referring to the method mentioned by Yang Yuliang et al. in "PPG signal processing method based on wavelet transform and adaptive filtering", the original PPG signal is filtered [15]. The results are as follows:

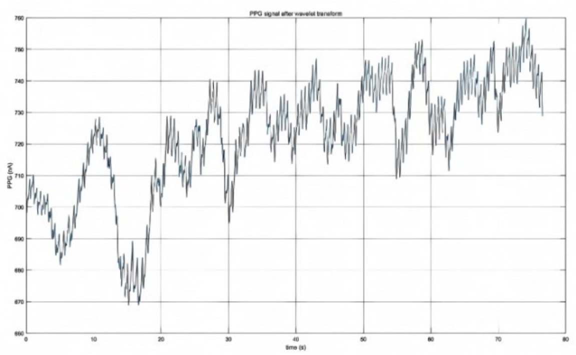

Figure 11: PPG signal after wavelet transform

4.1. Indicator analysis

The indicators of the experimental results are shown in the Table 1.

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Table 1: Results indicator analysis

Filtering algorithm	Low-pass filtering algorithm	LMS adaptive filtering	Improvement	Wavelet denoising (comparative experiment)
SNR (dB)	46.24	61.37	+15.13(↑ 32.7%)	45.82
MSE	12.3858	0.0029	-12.3829 (↓ 99.98%)	13.6510
R	0.9824	0.9849	+0.0025(↑ 0.25%)	0.9806

4.1.1. SNR analysis

The SNR obtained after low - pass filtering is 46.24 dB. This indicates that the algorithm effectively suppresses high - frequency noise, including circuit noise and ambient light fluctuations, thereby preliminarily enhancing the signal quality. Conventionally, a signal - to - noise ratio exceeding 40 dB is regarded as indicative of a high - quality signal. After LMS adaptive filtering, the SNR increased to 61.37 dB, a significant increase of about 15 dB. This clearly demonstrates that the LMS algorithm further eradicates motion artifacts and residual noise. This enhancement is primarily attributed to the capacity of adaptive filtering to dynamically adjust parameters. In particular, it compensates for motion interference in real - time via the accelerometer reference signal, rendering the effective components in the signal more conspicuous.

4.1.2. MSE analysis

The MSE following low - pass filtering is 12.3858. This relatively high MSE value implies that while low - pass filtering can eliminate high - frequency noise, it is ineffective in handling motion artifacts and low - frequency noise (e.g., baseline drift), thus leading to substantial residual errors. After using LMS adaptive filtering, the mean square error dropped to 0.0029, almost approaching zero, and the error reduction exceeded three orders of magnitude. This shows that the LMS algorithm greatly improves the consistency between the signal and the reference signal by means of the optimization strategy of minimizing the mean square error. At the same time, it is necessary to verify whether the extremely low MSE causes signal distortion due to overfitting. Given that R is close to 1, over-filtering can be ruled out, which shows that the algorithm can effectively reduce noise while retaining signal characteristics well.

4.1.3. R analysis

The correlation coefficient R after low - pass filtering is 0.9824. This value, being close to 1, indicates that the signal post low - pass filtering is highly linearly correlated with the reference signal, effectively preserving the primary features of physiological signals, such as the heart rate and blood oxygen waveform. Correlation coefficient R: after LMS adaptive filtering, the R value is increased to 0.9849. The further increase in the R value shows that the LMS algorithm can more finely retain the dynamic details of the signal, such as the instantaneous contraction characteristics of blood vessels, in the process of removing noise.

4.2. Advantages and disadvantages of filters

The low-pass filter can effectively suppress high-frequency noise. High-frequency interference such as circuit noise and ambient light fluctuations can significantly improve signal stability after processing. Moreover, its calculation is simple, the algorithm complexity is low, and the hardware

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resource requirements are not high, which is suitable for real-time processing. Taking the Butterworth low-pass filter used in this experiment as an example, the response in the passband is flat, which can well preserve the integrity of the low-frequency components of the signal. The disadvantage is that its fixed cutoff frequency cannot be adaptively adjusted in dynamic scenes, which may cause the high-frequency components of the effective signal, such as instantaneous vasoconstriction characteristics, to be filtered out, causing signal distortion, and its MSE is 12.3858. At the same time, it is difficult to effectively eliminate low-frequency noise that overlaps with the effective signal frequency band, such as motion artifacts. In addition, traditional low-pass filtering may also introduce phase offset, which needs to be compensated by zero-phase filtering (such as filtfilt).

The advantages of the LMS adaptive filter are evident. It can adjust the filter coefficients in real - time using the accelerometer reference signal, which exerts a remarkable suppression effect on motion artifacts, increasing the SNR to 61.37 dB and reducing the MSE to 0.0029. Its step size factor can be dynamically adjusted with the intensity of exercise, accelerating convergence during high-intensity exercise and maintaining stability during low-intensity exercise, and has strong adaptability. In addition, the filter has high signal fidelity, with a correlation coefficient of R=0.9849, indicating that the signal waveform details are fully preserved. However, its disadvantage is that its computational complexity is high, the filter order is L=900, and the amount of calculation increases significantly, which may affect real-time performance. In addition, its initial step size (μ=0.0005) is very sensitive to parameters and requires fine tuning, otherwise it is easy to have slow convergence or large steady-state errors. It is undeniable that for nonlinear noise, such as complex artifacts caused by intense exercise, the processing capability is limited [16].

However, due to the often complex frequency characteristics of motion artifacts, especially their low - frequency components, the wavelet transform is unable to achieve complete and accurate suppression during the denoising process, particularly when removing low - frequency motion artifacts. Although it can effectively eliminate some noise components, the accuracy of its signal reconstruction is far less than that of the LMS adaptive filter. In addition, the wavelet transform decomposes the signal based on a set of predetermined wavelet basis functions. This method has a good removal effect on high-frequency noise, but when facing non-stationary or strong frequency overlapping signals, its effect seems to be inadequate. Finally, although wavelet denoising successfully removes high-frequency noise through multi-resolution analysis, it shows certain limitations in the removal of motion artifacts, especially for those low-frequency noises that overlap with the signal frequency band in the spectrum, it cannot be accurately separated, resulting in its relatively poor recovery effect.

5. Conclusion

This study innovatively proposed a hybrid filtering technology combining low - pass filtering and LMS adaptive filtering to address PPG signal processing issues in dynamic environments. Traditional low - pass filtering has limitations due to its fixed cutoff frequency, and wavelet denoising struggles with low - frequency motion artifacts. In contrast, the hybrid filtering technology can dynamically adjust the low - pass filter's cutoff frequency and use LMS adaptive filtering for real - time artifact compensation. Experimental data show it outperforms traditional methods in SNR, MSE, and R, demonstrating great potential for wearable device monitoring.

The hybrid filtering technology paves the way for overcoming motion artifact problems in oximeter detection and enables high - precision health monitoring for wearable devices under dynamic conditions. Although there is room for optimization, like improving the real - time performance of LMS adaptive filtering and strengthening its ability against extreme nonlinear noise, it will play a crucial role in health monitoring with the development of wearable technology.

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