

Research on Optimized Methods for Dynamic Characteristic Retention and Artifact Removal in Blood Oxygen Signals

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Abstract: This paper presents a hybrid filtering technique combining ensemble empirical modal decomposition (EEMD) and Adaptive Kalman Filter (AKF) based on the new interest variance is proposed to realize dynamic filtering in a nonlinear environment. EEMD is used to decompose the original signals and extract the low-frequency components in order to obtain the main physiological signal features. Meanwhile, AKF dynamically adjusts the filtering parameters to optimize the performance of the algorithm through the new resting variance method. The experimental results demonstrate that in comparison with conventional Kalman Filtering (KF), the proposed method enhances the average signal-to-noise ratio from 1.80 dB to 4.38 dB, reducing the mean square error by 48.95%, and exhibits an average processing time of 1.2 mS. These improvements make the technique particularly advantageous for the processing of pulse oximetry signals with motion artifacts. By balancing noise reduction and information fidelity with low power consumption, this approach is well-suited for wearable devices, offering reliable data for daily health management and disease prevention.

Keywords: Blood oxygen signal, Innovation variance, EEMD, Adaptive Kalman Filter, Power consumption

1. Introduction

After enduring a severe epidemic, monitoring cardiovascular health has become a hot topic in today's healthcare development. Oxygen saturation, an important indicator of cardiovascular health, reflects the percentage of oxygen in the blood and plays a vital role in disease prevention and management. PPG is used to monitor oxygen saturation (SpO₂) by measuring the ratio of oxygenated to deoxygenated hemoglobin [1]. This method is favored for its simplicity, accuracy, cost-effectiveness, and non-invasive nature [1]. However, motion artifacts (MA) severely interfere with the blood oxygenation signal during daily exercise and in complex environments, leading to increased errors in oximetry monitoring. Existing filtering techniques are facing two problems: first, the signal separation effect is limited, and it is difficult to simultaneously balance the accuracy of real-time monitoring and signal fidelity. Second, the complexity of the filtering algorithm increases, which additionally increases the power consumption of the device and reduces the portability.

To address these challenges, this paper proposes a new hybrid filtering technique that combines the Adaptive Kalman Filter (AKF) with Ensemble Empirical Mode Decomposition (EEMD) based

on innovation variance. The AKF technique accurately filters out noise interference by predicting and updating motion artifacts and continuously and adaptively adjusting the parameters. The EEMD, well-suited for nonlinear and unsteady signal signals, reduces computational complexity by decomposing the original signals to provide the main signals with effective components.

Compared with the traditional single filtering technique, the hybrid filtering technique is designed to reduce the interference of motion artifacts on the processing of blood oxygenation signals while optimizing the algorithm to ensure the operation efficiency. It not only ensures high-precision filtering effect but also controls power consumption within a reasonable range, realizing the value of oximetry in daily life and preventive monitoring of diseases, and contributing effective and innovative solutions for medical and healthcare monitoring of oximetry technology.

The remainder of this paper is organized as follows. Section II reviews the technical background of related denoising algorithms and analyzes the characteristics and shortcomings of existing filters. Section III describes the algorithms of EEMD and innovation-based AKF hybrid filter in detail. Section IV analyzes the characteristics of hybrid filters through signal-to-noise ratio, mean square error, and runtime, and discusses their advantages and shortcomings. Section V summarizes the contributions and application scenarios of the filtering technique and provides directions for future research.

2. Literature Review

Motion artifacts (MA) are characterized by a spectrum greater than 0.1 Hz., which overlaps and distorts the main frequency signal of PPG (0.5-5 Hz) [2]. Due to the various complex physical motions in daily life, MA becomes one of the serious factors interfering with the oxygenation signal of PPG monitoring and reduces the accuracy of oximeter monitoring. Therefore, designing a hybrid filter to suppress MA and maintain low power consumption to improve the convenience and reliability of wearable oximeters is a major challenge in researching the monitoring of oximetry in healthcare.

Researchers have investigated various methods to suppress the effect of MA. Joseph et al. filtered MA at low frequencies by high pass filter [3], while other scholars who used traditional filtering techniques such as FIR/IR, moving average filtering, etc. [4], whereas a single filter's cutoff frequency often leads to distortion of the signal and loss of critical information. However, these single-filter approaches often distort signals due to fixed cutoff frequencies, leading to the loss of critical information. To address this, Wood and Asada combined FIR with Adaptive Noise Cancellation (ANC) to filter MA for linear models [5] to enhance the universality of the filter. The actual noise is mostly nonlinear, making this hybrid filtering model of limited effectiveness.

Independent Component Analysis (ICA) has also been employed to statistically separate signals for nonlinear scenarios. For instance, Kim and Sun's predecessors used Independent Component Analysis (ICA) to filter the noise signal by effectively separating the PPG from the MA signal [6]. However, ICA's effectiveness is conditional on the spectra of the signals being independent of each other, and the noise signal and the target signal will overlap and the effect is unstable in practical monitoring. Therefore, Pankaj et al. proposed a Fourier Decomposition Method (FDM) based on Fast Fourier Transform (FFT) [7], whose band function can effectively differentiate the noise without relying on the accelerometer signals and improve the stability. Despite its benefits, the FDM's fixed threshold selection limits its adaptability to dynamic signal changes. In order to enhance the sensitivity of signal processing, the adaptive filter improves the filter gain by dynamically adjusting the measurement noise and the system noise to reduce the error and improve the filtering effect [8], which effectively overcomes the fixity of the traditional filtering technique. The multi-channel adaptive filtering technique proposed by Christopher et al. based on the integrated IMU to realize the localized motion data acquisition [9], addressing the limitations of traditional methods that rely on a single motion reference signal. Han et al. used a fourth-order Normalized Least Mean Square (NLMS)

adaptive filtering technique to effectively reduce the distortion rate from 52.3% to 3.53% [10]. Based on a comprehensive comparison of the various techniques currently available [5], adaptive filters show excellent advantages in denoising in physiological signal processing. However, these filters often require high-quality input signals, are dependent on initial parameters, and consume significant computational resources, making them less suitable for daily wearable medical devices.

Emerging approaches leveraging advanced technologies have also been explored. CH et al. utilized a 1-D CNN network to monitor and analyze interference signals in PPG [11], while J et al. developed a method to separate MA using multiple wavelength channels and varying light wave penetrations in the human body [2]. These filtering techniques add extra power consumption due to large-scale datasets, complex computational power. Consequently, the development of a filtering algorithm that integrates the suppression of MA interference with the control of power consumption within a reasonable range has become a major research direction for wearable oximetry devices.

In summary, single filters lack flexibility and are prone to signal distortion. Techniques such as Low-pass, High-pass, and Band-pass Filters are difficult to quickly distinguish between target and noise signals, resulting in a higher possibility of signal distortion. While adaptive filters excel in real-time denoising, their dependency on signal quality and initial parameters, along with increased computational complexity, limits their practicality in wearable devices. Similarly, Kalman Filter (KF) provides a dynamic recursive filtering algorithm for linear signals, which can quickly track and analyze the changing physiological parameters, but it will reduce the filtering effect in nonlinear situations.

This paper introduces a hybrid filtering technique that combines Adaptive Kalman Filter (AKF) with Ensemble Empirical Mode Decomposition (EEMD) through adaptive parameter tuning based on innovation covariance. Firstly, the EEMD algorithm initially decomposes the blood oxygen signal into Intrinsic Modal Functions (IMFs) of different frequencies, selects the low-frequency IMFs containing the components of the blood oxygen signal, and filters out the high-frequency noises, which realizes the effective separation of the target signal from the noise signal. Next, the AKF processes the IMF components with main physiological parameters and reconstructed the filtered PPG signal. The noise covariance is dynamically adjusted by the innovation covariance, and the state is continuously and iteratively predicted and updated to dynamically optimize the filtering algorithm, which enhances the flexibility and robustness of removing artifacts and improves the stability and real-time monitoring.

Compared to Empirical Modal Decomposition (EMD), EEMD can effectively reduce modal aliasing [12], preprocess complex and nonlinear signals. AKF excels in dealing with the linear case, requiring only the filtered IMFs post-EEMD decomposition. By integrating these two methods, the proposed approach addresses their individual limitations, improving dynamic filtering accuracy, reducing signal distortion, controlling algorithmic power consumption, and increasing practicality for real-world applications.

3. Methodology

3.1. A mathematical model of the KF

KF is a recursive filter for linear systems and is used to estimate different states of a dynamic system [13]. Its basic principle is divided into two steps: prediction and updating. In real-time filtering of signals, it is mainly used to filter out motion artifacts and suppress noise. The assumptions are as follows:

- The system is a linear dynamic model.
- The noise signal satisfies Gaussian distribution.

The dynamic noise of the system is independent of the measurement noise and has an initial unbiased estimate with a known covariance matrix [14].

The state transfer equation with measurement noise is given in (1):

$$\begin{aligned} x_k &= Fx_{k-1} + Bu_k + w \\ z_k &= Hx_k + v \end{aligned} \quad (1)$$

x_k is the current estimate of the oximetry PPG, F is the state transfer matrix representing the change in state of the PPG from the previous moment to the current moment, B is the control input matrix representing the effect of external inputs on the oximetry signal, and w is the process noise modeling the uncertainty in the change of the dynamic signal. z_k is the signal value at the current sampling point, and H is the observation matrix, and v is the measurement noise representing the introduction of the random noise.

Prediction step: predict the current signal amplitude $\hat{x}_k^-$ and the prediction error covariance matrix P_k^- as in equation (2):

$$\begin{aligned} \hat{x}_k^- &= F\hat{x}_{k-1}^- + Bu_{k-1} \\ P_k^- &= FP_{k-1}^- F^T + Q_k \end{aligned} \quad (2)$$

$\hat{x}_{k-1}^-$ is the predicted value of the signal state at the previous moment and u_{k-1} is the control input. Larger values of P_k^- represent lower confidence in the prediction and Q_k is the process noise covariance matrix.

Updating step: the observations of the previous moment are combined with the a priori estimates to update the estimates. The Kalman gain K_k obtained from the update and the update error covariance P_k are expressed as in (3):

$$\begin{aligned} K_k &= \frac{P_k^- H^T}{HP_k^- H^T + R_k} \\ P_k &= (I - K_k H)P_k^- \end{aligned} \quad (3)$$

H is the observation matrix, which represents the mapping relationship between the measured and predicted values of PPG, R_k is the measurement noise covariance matrix, which is used to quantify the error value of the sensor when measuring PPG, and $HP_k^- H^T + R_k$ is used to adjust the Kalman gain so that the filter is biased towards the measured values. When R_k is small and K_k increases, and vice versa for the predicted values. And P_k denotes the amplitude update after the uncertainty.

The result of the correction estimation, $\hat{x}_k$, is the final filter result. The expression is represented as (4):

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (4)$$

The fomula shows the processing logic for KF filtering noise from linear dynamic systems, where the two steps of prediction and updating are constantly alternating and cycling to form a recursive algorithm that provides a more accurate estimate for the next motion state. However, KF's reliance on linear systems, the assumption of Gaussian-distributed noise, and its sensitivity to initial values limit its applicability and robustness in practical scenarios.

3.2. Design and mathematical modeling of hybrid filtering techniques

In order to solve the limitation of independent filters to process the signal, a hybrid filter of EEMD and AKF is proposed and the main processing is analyzed as follows.

3.2.1. EEMD Decomposition Signal

First white noise is introduced. White noise of suitable amplitude is introduced into the original signal $x(t)$ to form a noise-bearing signal $x_i(t)$. The expression is as in (5):

$$x_i(t) = x(t) + w_i(t) \quad (5)$$

$x_i(t)$ represents the value of the i th PPG signal at moment t , and $w_i(t)$ is the i th randomly generated white noise.

Signal decomposition of $x_i(t)$ is performed based on EMD. EMD is used to decompose a number of different IMFs through a screening process [15]. The IMFs should satisfy two conditions, one is that the number of extreme points and the number of over-zero points of the signal are the same or do not differ by more than one, and the other is that, at any point, the signal has a local mean value of zero [16]. The expression for the screening process is given in (6):

$$x_i(t) = \sum_{j=1}^n c_{i,j}(t) + r_{i,n}(t) \quad (6)$$

Where $c_{i,j}(t)$ is the IMF generated during screening. The corresponding residual low-frequency portion is $r_{i,n}(t)$, which can also be referred to as the residual, and is typically a smooth, low-frequency signal.

Multiple Repeat Decomposition. Each individual EMD decomposition may result in results with subtle gaps due to the addition of multiple different white noises [17]. Therefore, EEMD repeats the EMD decomposition process several times to obtain multiple decomposition results.

Averaging IMFs. In order to counteract the interference of white noise, several IMFs need to be averaged. When averaged over enough multiple decomposition results, the white noises cancel each other out due to randomness [18], outputting IMFs with higher stability. Expression as in (7):

$$\text{IMF}_j(t) = \frac{1}{m} \sum_{i=1}^m c_{i,j}(t) \quad (7)$$

Where $\text{IMF}_j(t)$ represents the component of the j th blood oxygenation signal, and m is the number of decompositions of $x_i(t)$ after the introduction of white noise.

By adding white noise with the ensemble mean of IMFs, EEMD overcomes the shortcomings of modal aliasing in EMD and is suitable for processing non-smooth and non-linear signals. The low-frequency IMFs output by EEMD decomposition contain the main blood oxygenation signal features, while the high-frequency IMFs are usually noise such as motion artifacts.

3.2.2. AKF based on innovation covariance to filter out motion artifacts

The AKF requires only noise filtering of the low-frequency IMF output from the EEMD decomposition, which greatly reduces the operation scale. In this paper, the measurement noise covariance and process noise covariance are adaptively adjusted using the innovation variance to establish a mathematical model:

·New-interest and new-interest covariance

Firstly, according to the state transfer equation of the KF with the measurement equation (Eq. (1)), the new interest v_k is established. expression as (8):

$$v_k = z_k - \hat{v}x_k^- \quad (8)$$

Where the innovation v_k is the difference between the signal of the blood sample to be measured and the predicted signal.

From this, the innovation covariance S_k is established and the expression is given in (9):

$$S_k = \widehat{H}\widehat{K}_k H^T + R_k \quad (9)$$

The core of the AKF is to dynamically adjust the gain K_k to ensure that the selected parameter values have the highest probability of occurring, so the maximum likelihood estimation of S_k is selected as the criterion for adjusting the noise covariance to achieve the purpose of efficiently adjusting the gain and improve the robustness and accuracy of the filtering [19]. The sequence length of the new innovation v_k is denoted as N , and the maximum likelihood estimate of S_k is denoted as $\widehat{S}_k$, and the expression is shown in (10):

$$\widehat{S}_k = \frac{1}{N} \sum_{i=0}^{N-1} v_{k-i} v_{k-i}^T \quad (10)$$

·Dynamic adjustment of noise covariance

Assuming that the process noise covariance is known, the updated measurement noise covariance $\widehat{R}_k$ is obtained as (11):

$$\widehat{R}_k = \widehat{S}_k - \widehat{H} P_k^{-1} H^T \quad (11)$$

Similarly, assuming that the measurement noise covariance is known, the updated process noise covariance $\widehat{Q}_k$ is shown in Equation (12):

$$\widehat{Q}_k = K_k \widehat{S}_k K_k^T \quad (12)$$

·Calculation of updated Kalman gain and system state

Based on the adjusted noise covariance of $\widehat{S}_k$, the updated adaptive Kalman gain $\widehat{K}_k$ is obtained with the updated estimated resultant state $\widehat{X}_k$, the expression is shown in (13):

$$\begin{aligned} \widehat{K}_k &= P_k^{-1} H^T \widehat{S}_k^{-1} \\ \widehat{X}_k &= \widehat{x}_k^- + \widehat{K}_k v_k \end{aligned} \quad (13)$$

The above is the algorithm of the AKF based on the innovation variance. Figure 1 shows the filtering model and decomposition method of this paper.

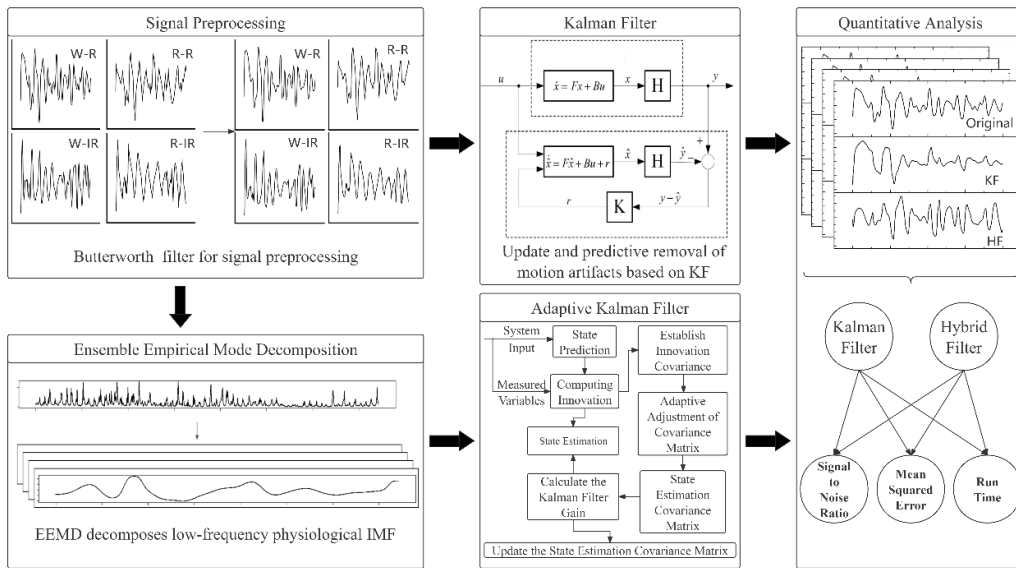


Figure 1: Filtering model and decomposition method in this paper

3.3. Experimental design

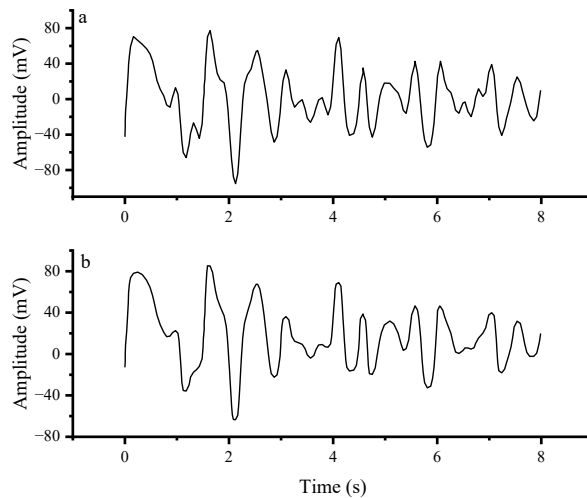
The aim of this paper is to remove motion artifacts from blood oxygen signals using hybrid filters. Based on the visualization of signal processing and the efficiency of program running, the software experimental simulation experiments were conducted using MATLAB. The experimental data included real red-light and infrared-light PPG signals obtained in two states of walking (speed of 1.0m/s-1.5m/s) and riding (4m/s-6m/s) [20], and the sampling frequency is 256Hz to enhance the reliability and universality of the experiment.

The noise standard deviation (NSTD) that controls the added noise amplitude is required to take the value range of $0.2 \leq \text{NSTD} \leq 0.3$ in order to meet the requirements of the EEMD decomposition signals, i.e., the standard deviation of the signals is 20%-30%. In the KF, according to the signal smoothness, the process noise covariance Q value coefficient is adjusted in the range of 10^{-6} - 10^{-3} , and the Q value can be appropriately increased when the signal changes strongly. Based on the noise magnitude in the blood oxygenation samples, the measurement noise covariance (R) ranges from $10^{-4} \leq R \leq 10^{-2}$, and the R value can be appropriately increased when the motion artifacts are severe or the motion amplitude is large.

4. Results

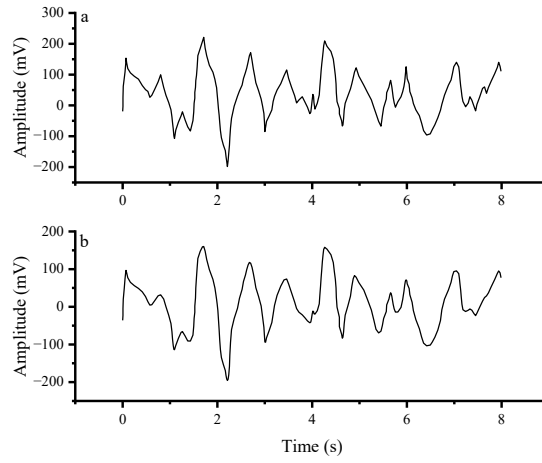
4.1. Artifact removal results

The two states of PPG signals are firstly preprocessed based on the Butterworth Bandpass Filter, and the results are respectively shown in Fig. 2, 3, 4 and 5.



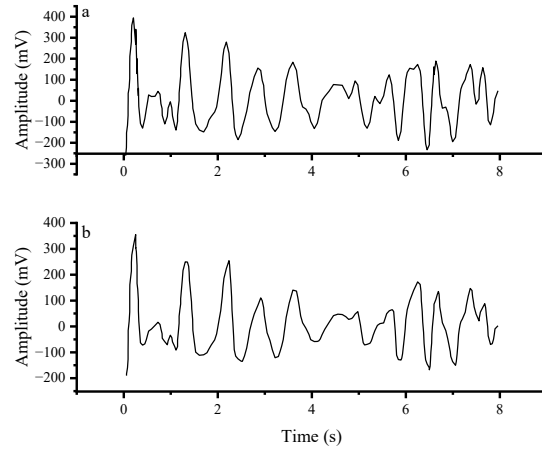
(a) Unprocessed red light signal (b) Preprocessed red light signal

Figure 2: Red light signal in walking state



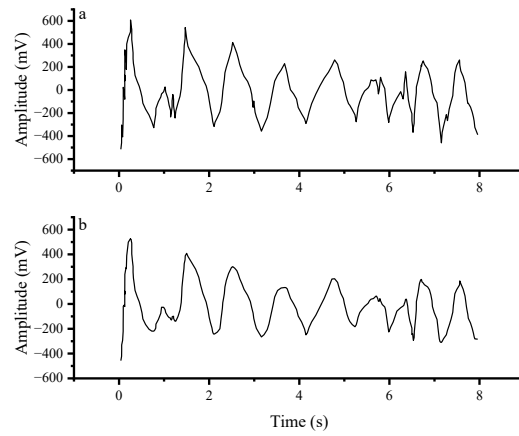
(a) Unprocessed infrared light signal (b) Preprocessed infrared light signal

Figure 3: Infrared light signal in walking state



(a) Unprocessed red light signal (b) Preprocessed red light signal

Figure 4: Red light signal in riding state



(a) Unprocessed infrared optical signal (b) Preprocessed infrared optical signal

Figure 5: Infrared optical signal in riding state

Compared to the original signal, the preprocessing result suppresses the high-frequency noise to a certain extent, effectively eliminates the burr noise, while maintaining the integrity of the waveform without noticeable distortion. This is particularly evident in the 3-6s signal with rich time-domain detail features and obvious dynamic changes. Through the data preprocessing, the accurate base signal is provided for the subsequent comparative analysis of the hybrid filter and the single KF.

After preprocessing, the motion artifacts were removed from the walking and riding numbers based on the hybrid filtering method of EEMD and AKF. Fig. 6, 7, 8 and 9 show the comparative analysis of the hybrid filter versus the standard KF for removing the motion artifacts of the PPG in both states.

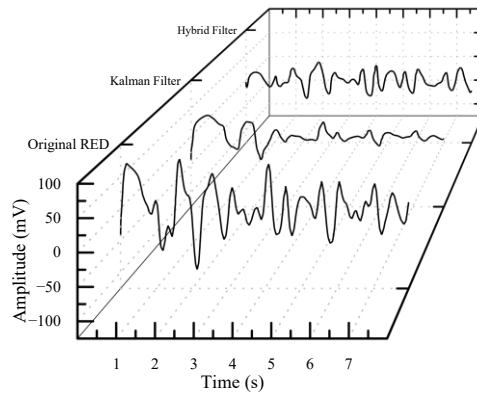


Figure 6: Denoising results of red light signal for walking

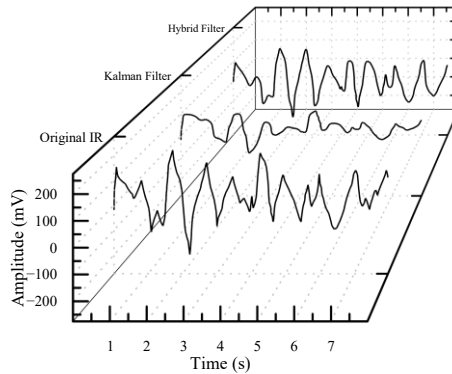


Figure 7: Denoising results of infrared light signals for walking

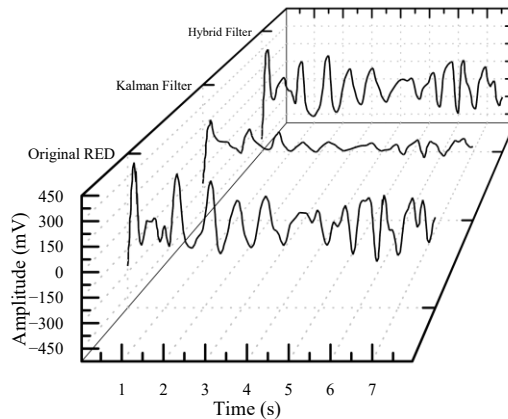


Figure 8: Denoising results of red light signal for riding

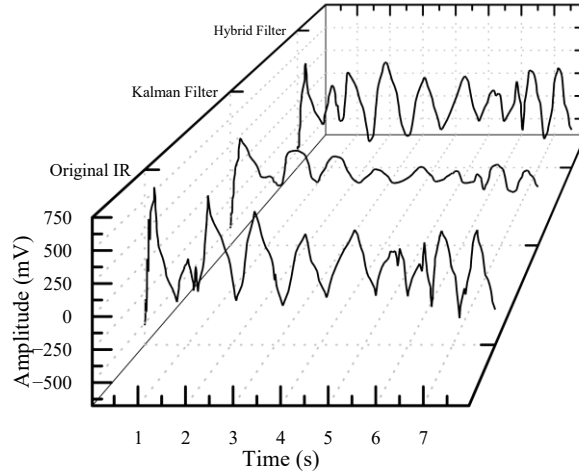


Figure 9: Denoising results of infrared light signals for riding

As a result, the hybrid filter effectively suppresses motion artifacts, the signal amplitude is stabilized, and the baseline drift is significantly reduced. At the same time, the dynamic characteristics of the signal are preserved to a greater extent. In the time domain within 2-6s, the fluctuations of the red and infrared light signals are clearer, with less interference from motion artifacts. The standard KF suppresses motion artifacts to some extent, but some of the signal dynamic characteristics are weakened. The amplitude variation range of the signal is small, and excessive smoothing occurs especially at the critical peaks and valleys within 1-3s. The noise suppression effect is significantly weaker than that of the hybrid filter in the initial and middle segments of the time domain.

Due to the fixed covariance of the standard KF, it is highly likely to cause distortion and excessive smoothing of the signal, which face difficulties in dealing with more complex blood oxygenation signals. The hybrid filter adaptively adjusts the noise covariance matrix based on the innovation covariance and adapts to the dynamic changes of the oximetry signal, which has the advantage of efficiently filtering out motion artifacts and ensuring that the signal is not distorted. Quantitative metrics will be introduced in the next section for analysis.

4.2. Quantitative analysis of filtering results

The filtering results were analyzed based on Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE). SNR was calculated as expression (15) and MSE was calculated as expression (16). The quantitative analysis results are shown in Table 1, 2.

$$\text{SNR} = 10\log_{10}(P_s/P_n) \quad (15)$$

Where P_s and P_n are signal power and noise power respectively.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (S_i - \hat{S}_i)^2 \quad (16)$$

Where S_i and $\hat{S}_i$ represent the signal after filtering and the real signal before filtering respectively, and N is the total number of sampling points.

Table 1: Quantitative analysis of walking state filtering results

Signal type	Index	Kalman Filter	Hybrid Filter
Infrared Light (IR)	SNR (dB)	2.29	4.52
	MSE	0.0334	0.0106

Table 1: (continued).

Red light (RED)	SNR	1.46	3.04
	MSE	0.0340	0.0228

Table 2: Quantitative analysis of riding state filtering results

Signal type	Index	Kalman Filter	Hybrid Filter
IR	SNR (dB)	1.80	5.08
	MSE	0.0466	0.0220
RED	SNR	1.66	4.86
	MSE	0.0573	0.0334

For the filtered red and infrared light signals under walking conditions, the SNRs of the hybrid filter are improved by 108.2% and 97.4%, and the MSEs are reduced by 32.99% and 68.12%, respectively. This indicates that the hybrid filter can efficiently filter out motion artifacts and high-frequency noise, maintain the true characteristics of the original signal to a greater extent, and reduce the risk of signal distortion. In the riding state, objective factors such as large motion amplitude lead to fast signal change amplitude and high frequency noise interference. At this time, after analyzing the filtered red light and infrared light signals, compared with the KF, the SNR of the hybrid filter is improved by 192.8% and 182.2%, which more fully demonstrates the superior adaptability and robustness of the hybrid filter for dynamically changing signals. The MSE is reduced by 41.77% and 52.92% respectively. The MSE is reduced by 41.77% and 52.77%, respectively, which demonstrates that the EEMD and AKF are able to maintain the key information of the original signal in complex situations, highlighting their excellent fidelity.

Overall, the hybrid filter improves the mean SNR from 1.80 dB to 4.38 dB and reduces the mean square error by 48.95% on average. As a result, the SNR of the hybrid filter is significantly improved: more than 90% when walking and nearly 200% when riding, so the hybrid filter technology has a more excellent noise suppression ability. Significantly reduced MSE: The signal processed by the hybrid filter in both states reduces the MSE, which has the ability of signal fidelity. Adaptability to complex signals: the hybrid filter in response to the riding state performs particularly well in dealing with high interference artifacts, balancing signal denoising and fidelity based on the dual characteristics of multi-component decomposition and dynamic tracking. Therefore, hybrid filtering techniques applied to highly dynamic signals will give more accurate results.

Finally, the efficiency of the filtering technique is analyzed and the running time is shown in Table 3 and Table 4.

Table 3: Filtered Walk Signal Runtime (ms)

Filter Type	Signal Type	First	Second	Third	Average
Kalman Filter	IR	1.4	0.3	0.3	0.7
	RED	1.4	0.7	0.6	0.9
Hybrid Filter	IR	1.5	0.8	0.9	1.1
	RED	1.8	1.0	1.1	1.3

Table 4: Running time of filtered riding signal (ms)

Filter Type	Signal Type	First	Second	Third	Average
Kalman Filter	IR	1.6	0.6	0.5	0.9

Table 4: (continued).

Hybrid Filter	RED	1.4	0.4	0.4	0.7
	IR	1.7	0.8	0.8	1.1
	RED	1.8	0.8	0.7	1.1

Hybrid filters have overall longer running times, mainly due to dynamic adjustment of the computation of the innovation variance, etc., increasing the complexity of the algorithm. It is usually about 22% to 58% higher than the KF, but the running time is under 2 ms, with an average of 1.2 ms. Both filters have high efficiency, but have different application scenarios., The KF is more suitable for signals with high utility and low interference, and the hybrid filter is more suitable for scenarios with high artifact interference or high signal quality requirements.

5. Conclusion

Based on the experimental results, this study summarizes the characteristics and application scenarios of the two filtering techniques, providing guidance for users to customize the filtering method corresponding to their needs in practical application situations.

The Kalman Filter(KF) has the advantage of being able to smoothly filter most of the high-frequency noise in the signal. Similar to walking and other low motion artifacts, it has strong noise suppression capability. However, its reliance on fixed parameter models makes it less adaptable to signals with dynamic variations, reducing its denoising effectiveness in such cases. In contrast, the hybrid filter has a significant effect on the retention of key information of the signal and the suppression of high-frequency artifacts, and is more targeted to dynamically changing signals. However, the increased complexity of the hybrid filter algorithm limits its applicability in real-time scenarios where rapid processing is essential. For continuous monitoring tasks requiring high real-time performance, such as blood oxygen monitoring during daily activities, an optimized KF with fine-tuned parameters is recommended. Conversely, for tasks demanding high measurement accuracy, such as medical research, the hybrid filter is the preferred choice due to its superior signal quality enhancement. Although the operating efficiency of the hybrid filter is within a reasonable range, it does not sufficiently reduce the power consumption, and it is difficult to meet the requirements of high real-time in multiple scenarios. Future research could focus on incorporating intelligent algorithms to optimize the adaptive adjustment or use fast EEMD algorithms, etc. to improve the efficiency, and design the hardware module of the embedded system for the efficient combination of the algorithm.

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