

Research Progress of Noise Removal Techniques for Oximeters Based on Signal Processing Algorithms

Yuxuan Wang

*School of Information Engineering, Wuhan University of Technology, Wuhan, China
253174012@qq.com*

Abstract. Blood oxygen saturation (SpO_2) is a crucial physiological index that can be affected by baseline drift, motion artifacts, and high-frequency noise, affecting clinical diagnosis accuracy. This paper focuses on noise reduction techniques for oximeters using signal processing algorithms, analyzing traditional methods like adaptive filtering and wavelet transform and modern deep learning models like CNN, LSTM, and GAN. The study reveals challenges such as insufficient generalization ability in complex noise environments, contradiction between real-time performance and computational efficiency, significant influence of individual differences, and scarcity of high-quality labeled data. Traditional methods offer advantages in specific noise environments but have limitations when dealing with complex and changeable scenes. Deep learning technology has made breakthroughs in noise reduction performance but is limited by model complexity and data requirements. Future interdisciplinary innovation and integration, combining biomedical engineering, artificial intelligence, and signal processing technologies, are expected to provide new solutions for oximeter noise removal and promote non-invasive oxygen monitoring technology.

Keywords: Oximeter, Signal noise removal, Adaptive filtering, Wavelet transform, Deep learning

1. Introduction

Blood oxygen saturation (SpO_2) is a core physiological indicator for assessing the function of the human respiratory and circulatory systems, with non-invasive monitoring primarily relying on oximetry. Based on the optical principles, such devices emit red light (approximately 660nm) and infrared light (around 940nm) to penetrate human tissues. By leveraging the differential absorption of oxyhemoglobin and deoxyhemoglobin at these distinct wavelengths, combined with the Lambert-Beer law, the SpO_2 value is calculated. However, photoelectric signals are prone to interference from baseline drift (low-frequency physiological noise), motion artifacts (resulting from relative displacement), and high-frequency electromagnetic interference. These factors can introduce measurement errors, thereby compromising the accuracy of clinical diagnoses. In recent years, some progress has been made in noise reduction techniques. In traditional methods, adaptive filtering suppresses motion artifacts through real-time parameter adjustment of closed-loop structure, and wavelet transform separates different frequency bands noise by multi-scale decomposition. In the

deep learning technology, CNN can capture the time domain characteristics of the signal, and LSTM can parse the time dependence relationship. Nevertheless, significant research gaps remain: the lack of generalization ability of the algorithm in complex noise environment, the contradiction between real-time performance and computational efficiency, and the poor model adaptation caused by individual differences and data scarcity. This paper focuses on noise removal technologies for oximeters based on signal processing algorithms, exploring how to balance performance and efficiency by optimizing the algorithm through interdisciplinary methods. Through literature review and technical analysis, this study systematically combs the principles and applications of traditional and modern noise reduction techniques. The significance of this research lies in identifying the bottlenecks of existing technologies, providing directions for interdisciplinary innovation that integrates biomedical engineering, artificial intelligence, and signal processing, promoting the clinical application of non-invasive blood oxygen monitoring in complex scenarios, and laying a theoretical foundation for addressing noise-induced measurement errors.

2. Principle and noise analysis of oximeter

As a non-invasive medical device, the oximeter is widely used to measure blood oxygen saturation (SpO_2) in the medical field. At present, the mainstream oximeter uses the optical principle to emit red light (about 660nm) and infrared light (about 940nm), so that it penetrates human tissues [1]. Due to the differences in absorption characteristics between oxyhemoglobin and deoxyhemoglobin for light of different wavelengths, the SpO_2 value can be calculated in accordance with the Lambert-Beer law—which states that when a beam of parallel monochromatic light passes vertically through a uniform, non-scattering absorber, the absorbance is proportional to the concentration of the absorber and the thickness of the absorbing layer, while being inversely proportional to the transmittance [2]. The photoelectric sensor in the oximeter is responsible for receiving the reflected and transmitted light signals, and the oxygen content in the blood is estimated with the help of signal processing algorithms. However, in the actual use scenario, the oximeter is vulnerable to a variety of noise interference, resulting in measurement errors. These noises mainly include baseline drift, motion artifacts, and high-frequency noise [3]. Baseline drift originates from the physiological activities of the measured subject and falls into the category of low-frequency noise. Motion artifacts are caused by the relative displacement between the measurement object and the device caused by its own motion. High-frequency noise is mostly electromagnetic interference during measurement. In view of the serious impact of noise on measurement accuracy, many noise reduction methods based on signal processing have been proposed.

3. Application of signal processing algorithms in noise removal of oximeter

3.1. Traditional noise removal techniques

3.1.1. Application of adaptive filtering

The adaptive algorithm is a filtering method that can adjust the parameters and structure in real time according to the characteristics of the input signals. It possesses self-learning and dynamic adaptation, and can flexibly deal with the non-stationary characteristics of the signal [4]. The core of the adaptive algorithm is to minimize the output error by continuously optimizing the filter coefficients, so as to realize the accurate extraction of the target signals. Adaptive algorithms are primarily categorized into open-loop and closed-loop structures. In the open-loop structure, the

output is solely determined by the input signal; parameter adjustments rely on preset rules, and there is no feedback mechanism. In the closed-loop structure, the error signal feedback is introduced, and the filter parameters are dynamically modified by passing the deviation between the expected output and the actual output into the adaptive algorithm, which significantly improves the ability to suppress complex noise (as shown in Figure 1) [5].

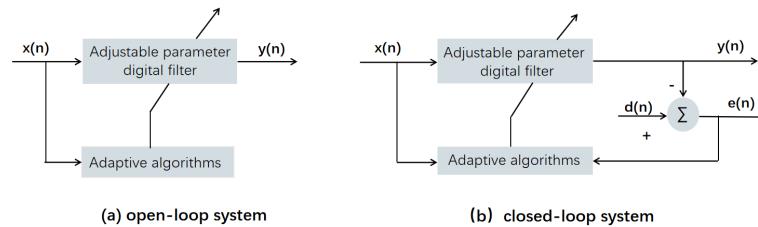


Figure 1. Two structures of adaptive filters [5]

In the signal processing of oximeters, adaptive filtering is particularly effective in suppressing motion artifacts. As a kind of noise with strong randomness and certain correlation with the effective photoelectric signals, motion artifacts have frequency characteristics of motion artifacts will change dynamically with the intensity of motion—such as slight shaking or vigorous activity—making them difficult to handle effectively with traditional fixed-parameter filters [6]. The LMS (least mean square) adaptive filtering algorithm with closed-loop structure usually takes the motion signal collected by the acceleration sensor as the reference input, and uses its strong correlation with the motion artifact to gradually cancel the motion interference component in the photoelectric signal by iteratively updating the filter coefficient. The experimental data show that the proposed method can reduce the error of blood oxygen measurement from $\pm 3.2\%$ to $\pm 1.1\%$, which greatly improves the stability of dynamic monitoring. Researchers have proposed improvement strategies for optimizing performance in complex scenarios, such as using convex combined LMS algorithms for multi-motion state switching and RLS adaptive filters for multi-channel blood oxygen monitoring systems. These improvements make adaptive filtering suitable for low-power devices, especially in dynamic monitoring scenarios like sports rehabilitation and outdoor first aid.

3.1.2. Application of wavelet transform principle in filtering

As a multi-resolution analysis tool, wavelet transform has significant advantages in removing noise from oximeter signals. The core principle is to expand the signal according to the wavelet basis, find useful signal features in the time domain and frequency domain, and decompose the signal into sub-bands of different scales by scaling and translating the signal, so as to realize the local feature extraction of the non-stationary signal [7]. Given a signal $f(t)$, its continuous wavelet transform can be expressed as follows.

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \Psi^*\left(\frac{t-b}{a}\right) dt$$

$\varphi(t)$ represents the mother wavelet function, a is the scale factor, and b is the translation factor. In the blood oxygen signal processing, the wavelet transform can effectively separate the useful signal and noise, especially for the pulse wave signal baseline drift, power frequency interference and high frequency noise have a good removal effect [8]. By selecting appropriate wavelet basis functions and decomposition levels, noise can be filtered out effectively while preserving the details of the signal. In practical applications, the threshold denoising method is usually used to remove the

wavelet coefficients corresponding to the noise by soft threshold or hard threshold processing, and then the denoised signal is obtained by wavelet reconstruction.

3.2. Modern noise removal techniques

3.2.1. Deep learning model denoising

In the field of noisy photoplethysmography (PPG) signal processing, deep learning technologies featuring multi-layer nonlinear transformations are gradually occupying a dominant position. The extraction of active components can be realized by this technology, which makes a breakthrough in the noise removal of oximetry. Commonly reported in the literature are convolutional neural network (CNN) class models, Long Short-Term memory (LSTM) network architectures, and Generative Adversarial network (GAN) frameworks [9]. CNNs utilize convolution kernels to capture local time-domain features, with one-dimensional CNNs being capable of directly processing raw signals. The training stability is improved by the introduction of skip connections in the Residual Network (ResNet). The resolution of temporal dependencies is responsible for by the LSTM gating mechanism, and the combination of the attention mechanism significantly reduces the signal reconstruction error. The mapping from noise to clean signal was realized by the adversarial training of the generator and discriminator under the GAN framework, and the optimization of the recovery accuracy in the dynamic noise environment was assisted by the introduction of Conditional GAN (cGAN) multimodal data [10].

The enhancement of a model's generalization ability strongly relies on optimized design in the data preprocessing stage, among which data augmentation techniques are a key link. Specifically, synthetic noise injection significantly improves the model's ability to adapt to complex noise by simulating the interference types in real scenes. Firstly, Gaussian white noise is introduced to simulate circuit thermal noise, whose mean is zero and variance is dynamically adjusted according to the target Signal-to-Noise Ratio (SNR). The second is to introduce 1/f noise (pink noise) to simulate low-frequency wave interference in physiological signals (e.g., baseline drift) by adjusting parameters of the power spectral density function to match their characteristics. Thirdly, the motion artifact simulation uses acceleration data from a motion sensor, reproducing distortion under motion states. Noise injection intensity is controlled within 5-20 dB to maintain performance in extreme noise environments. Signal segmentation and Z-score standardization improve feature learning consistency by eliminating amplitude differences.

3.2.2. PPG signal noise reduction application

At the software level, the multi-level joint optimization strategy for PPG signal noise reduction at the software level constructs a hierarchical architecture of "preprocessing-feature learning-parameter optimization" by fusing traditional signal processing and deep learning algorithms. First of all, maximum overlap discrete wavelet transform is applied for multi-scale decomposition of the signal, and a hierarchical thresholding strategy is employed to separate high-frequency noise and baseline drift. Its translational invariance and boundary optimization characteristics can reduce phase distortion while preserving the physical properties of the signal [11]. Subsequently, the lightweight convolutional neural network learns noise features through a bottleneck structure and atrous convolution, and combines the contrast loss function to force the similar physiological state signals to cluster in the feature space, so as to realize efficient noise reconstruction and feature extraction. The attention mechanism and intelligent optimization algorithm are the key to improve performance.

The Transformer-based model dynamically focuses on the heart rate frequency band through the temporal attention module, suppresses the motion interference frequency band, and enhances the adaptability to non-stationary noise. The whale optimization algorithm simulates the whale predation behavior, automatically searches for the best parameters of variational mode decomposition, and combines adaptive wavelet threshold post-processing to achieve accurate separation of signal components [12]. Cascade type RLS adaptive filter through multi-channel reference signal filtering step by step motion artifact, fast convergence by using the recursive least squares algorithm, improve robustness under complicated motion scene. Through the combination of domain prior knowledge and data-driven capabilities, these strategies achieve low delay and high signal-to-noise ratio noise reduction effects without relying on hardware improvements.

4. Current research status and challenges

At present, oximeter denoising technology based on signal processing algorithms has become one of the research hotspot, attracting in-depth investigations from numerous researchers both domestically and internationally. Among them, the most common algorithms are wavelet transform denoising method, Fourier transform denoising method, cyclostationary filter denoising method and other kinds of denoising methods. Among these, cyclostationary filtering denoising method and wavelet transform denoising method have obvious advantages in denoising effect and stability, thus finding widespread application in oximeter denoising. Fourier transform denoising and wavelet transform denoising which are based on digital signal processing technology, offer improved denoising effect is improved compared to traditional filtering method, but they require high data sampling frequency [13]. Because of its simple principle and no need for the support of sampling frequency, wavelet transform denoising method is more suitable when other methods can not complete the filtering process of small data. In the photoelectric pulse wave volume (PPG) signal processing domain, the signal processing algorithm based oximetry denoising technique to solve the problem of the noise of the PPG signal provides an important train of thought. Nevertheless, when these algorithms are applied to practical PPG signal denoising, they still face multiple challenges in the transformation from theory to practice. Specifically, although wavelet transform and cyclostationary filtering algorithms have shown certain advantages in oximeter denoising, when they are extended to the more complex physiological signal scene of PPG signals, the research on joint optimization strategy has made progress, but there are still multiple challenges to be solved as follows.

In the photoelectric pulse wave volume (PPG) signal noise reduction algorithms study, although progress has been made in joint optimization strategies, it still faces multiple challenges. Firstly, the generalization ability of complex noise environment is insufficient. Noise in real-world scenarios is non-stationary and diverse, making it difficult for traditional algorithms to adapt to its time-varying characteristics. Secondly, there is a contradiction between real-time performance and computational efficiency. Modern intelligent models have high latency on low-power hardware, and traditional algorithms have limited ability to suppress complex noise. In addition, the cross-individual error of the general model can reach $\pm 2.5\%$ due to individual physiological differences, which is far beyond the clinical requirement of $\pm 1\%$. Finally, the scarcity of high-quality labeled noise data sets and the unclear nonlinear coupling mechanism between noise and signal lead to difficult modeling and easy damage features. These challenges require interdisciplinary technical innovation breakthroughs.

5. Conclusion

This paper focuses on the noise removal technology of oximeter based on signal processing algorithms, and systematically reviews the principles, applications, and challenges of traditional methods and modern deep learning models. Oximeter measurements are susceptible to baseline drift, motion artifacts, and high-frequency noise, while existing technologies suffer from issues such as insufficient generalization ability, conflicts between real-time performance and computational efficiency, significant impacts from individual differences, and scarcity of labeled data in complex scenarios.

The research shows that the traditional method has advantages in specific noise environment, but it is limited in changing scenes. Although deep learning technology has breakthrough performance, it is restricted by model complexity and data demand. Aiming at the three research gaps proposed in the introduction, namely, the insufficient generalization ability of the algorithm under complex noise, the contradiction between real-time performance and efficiency, and the model adaptation problem caused by individual differences and data scarcity, this paper analyzes the existing technical progress, and reveals that interdisciplinary integration is the key direction to solve the above problems. However, this paper still has certain limitations. At the technical analysis level, discussions on some emerging algorithms is not deep enough, and the latest research trends are not fully covered. In terms of experimental verification, there is a lack of horizontal comparison of different algorithms under a unified data set, and it is difficult to intuitively reflect the advantages and disadvantages of each method. In the specific path of interdisciplinary integration, only the direction is proposed without giving a detailed technical implementation framework, and the operability of theoretical guidance needs to be strengthened.

Future research should explore the application of deep learning architecture in blood oxygen signal denoising, improve model adaptability to non-stationary noise, construct a standardized noise dataset, design a unified evaluation index, and refine interdisciplinary technology integration. This includes embedding physiological characteristics knowledge into deep learning models, developing lightweight hybrid noise reduction algorithms, and promoting accurate non-invasive blood oxygen monitoring in clinical scenarios.

References

- [1] Ye J M. (2005). Principle and measurement performance of pulse oximetry monitor. *Measurement and Measurement Technology*, 32(8), 9-10. (2005).
- [2] Xu W. (2012). Reflection pulse oxygen saturation signal detection and analysis system. Lanzhou University of Technology, Lanzhou, China.
- [3] Han Qingyang, Wang Xiaodong, Li Bingyu, & Zhou Pengji. (2015). Application of EEMD to simultaneously eliminate high-frequency noise and baseline drift of pulse wave signals in pulse oximetry. *Journal of Electronics and Information Technology*, 37(6), 1384-1388.
- [4] He LM, & Yang F. (2018). Application of LMS adaptive filtering in airborne transient electromagnetic signal denoising. *Internet of Things Technology*, 8(1), 30-32.
- [5] Yuan Y H. (2018). Research and hardware implementation of anti-exercise blood oxygen extraction algorithm based on adaptive filtering. Huazhong University of Science and Technology, Wuhan.
- [6] Zhang Linjia, Yu Xiaomin, Lin Jian, Qiu Chengen, & Wang Zhengxian. (2024). Research on dynamic blood oxygen saturation detection based on motion noise construction and convex combination least mean square adaptive filtering algorithm. *Journal of Biomedical Engineering*, 41(4), 818-825.
- [7] Shan J Y, & Li J. (2016). Blood oxygen saturation signal processing based on wavelet transform and FFT transform. *Industrial Control Computer*, 29(8), 95-96.
- [8] Xu P P. (2015). Development of pulse oximeter based on smart phone. China Jiliang University, Hangzhou.

- [9] Song Tingting, Han Yang, & Shi Meiling. (2024). Mixed noise removal for remote sensing images based on deep learning. *Computer Knowledge and Technology*, 20(13), 37-38.
- [10] Zhang S L. (2021). Application of multimodal fusion method based on deep learning in medical treatment and environment. University of Science and Technology of China, Hefei.
- [11] Xia D D. (2020). Research on pulse signal denoising and detection based on stack autoencoder. Hubei University of Technology, Wuhan.
- [12] Feng Zengxi, Li Jiale, Ge Xun, & Zhou Yaojia. (2025). Improved whale optimization algorithm based on multi-strategy fusion and its application. *Computer Integrated Manufacturing Systems*, 31(2), 590-603.
- [13] Wang Qi. (2008). Sub-health state recognition based on electrocardiogram pulse information fusion. Lanzhou University of Technology, Lanzhou. (2008).