Applied Artificial Intelligence Research

INNOVIAIR

Continuous blood pressure estimation and cardiovascular risk assessment based on wearable PPG signals

Zehui Xu[a,*]

[a]Macau Polytechnic University, Macau 999078, China

ARTICLEINFO

Keywords:
PPG
Blood Pressure Estimation
Cardiovascular Risk Assessment
Wearable Devices
Signal Processing
MATLAB

ABSTRACT

This paper systematically studies the non-invasive continuous blood pressure estimation and cardiovascular risk assessment methods based on photoplethysmography (PPG) signals. A complete signal processing flow was constructed using the PhysioNet public dataset, including preprocessing, feature extraction, model construction and validation. The experimental results show that the extraction of heart rate and respiratory rate based on PPG has high accuracy, preliminarily verifying the correlation between the morphological characteristics of PPG and blood pressure parameters. The research further proposed a hierarchical processing architecture to balance the computing efficiency and monitoring depth of wearable devices, providing a reference for the engineering implementation of health monitoring systems.

1. Introduction

The acceleration of the global aging population process and the increasing burden of chronic diseases are driving a paradigm shift in the medical and health model from a "treatment-centered" approach to a "prevention and health management-centered" one. Against this backdrop, achieving long-term, continuous and non-intrusive monitoring of key physiological parameters is of vital significance for early disease warning, personalized health intervention and the optimization of medical resource allocation. Traditional clinical monitoring methods are limited by specific medical Settings and discrete time points, making it difficult to capture dynamic information of significant clinical value such as paroxysmal arrhythmia, nocturnal hypertension or periodic physiological function decline. Therefore, developing technical means that can continuously provide reliable physiological data in daily life has become one of the core demands in the field of modern health management.

Wearable devices based on technologies such as photoplethysmography (PPG) have become one of the most promising carriers for achieving the above goals due to their non-invasiveness, high accessibility and good user compliance. Through forms such as wristwatches and rings, these devices can continuously record pulse wave signals. These signals not only contain heart rate information, but also have profound physiological connections with multiple functional states of the cardiovascular system, such as vascular elasticity, blood pressure fluctuations, and autonomic nerve regulation. This makes the analysis of continuous PPG data through engineering methods a highly valuable research direction for non-invasive assessment of cardiovascular health, screening for abnormal events (such as atrial fibrillation), and tracking the progression of chronic diseases.

However, transforming technical concepts in laboratory Settings into robust and reliable monitoring tools for daily life faces a series of significant engineering and technical challenges. Firstly, the PPG signals collected under daily activity conditions inevitably contain a large number of artifacts caused by motion and various environmental noises, which poses extremely high requirements for the robustness of signal preprocessing and feature extraction methods. Secondly, the significant physiological differences among individuals and the diversity of device wearing make it extremely difficult to construct an analysis model with strong universality. Finally, how to design low-power and high-real-time embedded processing algorithms to adapt to the resource-constrained wearable hardware platform is the key bottleneck for the realization of technology implementation. The essence of these challenges lies in how to stably extract indicators with clear physiological and clinical significance from high-noise and highly variable raw data through

* Corresponding author.
E-mail address: 436099577@qq.com.
https://doi.org/10.65455/6pgttp36
Received 25 December 2025; Received in revised form 9 January 2026; Accepted 14 January 2026; Available online 23 March 2026
© The Author(s) 2026. This article is published with open access in Applied Artificial Intelligence Research under a Creative Commons Attribution 4.0 International License (CC BY 4.0). https://creativecommons.org/licenses/by/4.0/

systematic signal processing, feature engineering and computational model design.

At present, although there has been a large amount of research in this field, many works either focus on pursuing marginal improvements in algorithm performance on idealized datasets or rely on private data, making horizontal comparisons difficult. In terms of the system reproducibility of the methodology, the validation of generalization capabilities among different public data sources, and system-level design considerations for practical application scenarios, There is still room for in-depth exploration. This precisely provides a clear entry point for researchers with a background in electronic information systems and cyber-physical systems.

In view of this, this study aims to conduct a research focused on engineering implementation and application verification based on widely recognized public physiological signal databases. The core objective of our work is not to propose a completely new algorithm, but to systematically construct and compare a complete engineering process from signal preprocessing, anti-interference design, feature extraction to the construction of quantitative analysis models. The key lies in evaluating the performance, robustness and potential limitations of different classical methods on public data for simulating real scenarios. Furthermore, we will explore the feasibility of a hierarchical processing architecture in light of the actual constraints of wearable systems. This architecture aims to balance the computing efficiency of terminal devices with the depth of cloud analysis, providing engineering references for the future design of practical personal health monitoring systems. This research aims to contribute a solid solution to promoting wearable health monitoring technology from the laboratory to practical application through rigorous engineering practice.

2.Method

This study adopts a modular and reproducible engineering implementation approach, based on a publicly available physiological signal dataset[1], to systematically verify a complete health monitoring signal processing procedure. The focus of the work lies in building and testing a complete technical chain from the acquisition of raw signals to the estimation of key physiological parameters, and evaluating the feasibility and robustness of each link in practical applications.

2.1.Data source and signal preprocessing

The data of this study are derived from the BIDMC PPG and respiratory signal datasets on the PhysioNet platform. This dataset contains synchronously collected fingertip photoplethysmography (PPG) signals, respiratory plethysmography signals and three-lead electrocardiogram (ECG), with a sampling rate of 125 Hz. The main reasons for choosing this dataset are as follows: 1) The data was collected by clinical-grade equipment, with reliable signal quality and ECG provided as the gold standard for heart rate; 2) The data format is standardized and publicly available, ensuring the repeatability of the research process. 3) It recorded the data of the subjects in various states such as rest and regular breathing, which is suitable for evaluating the robustness of signal processing methods.As shown in Figure 1.

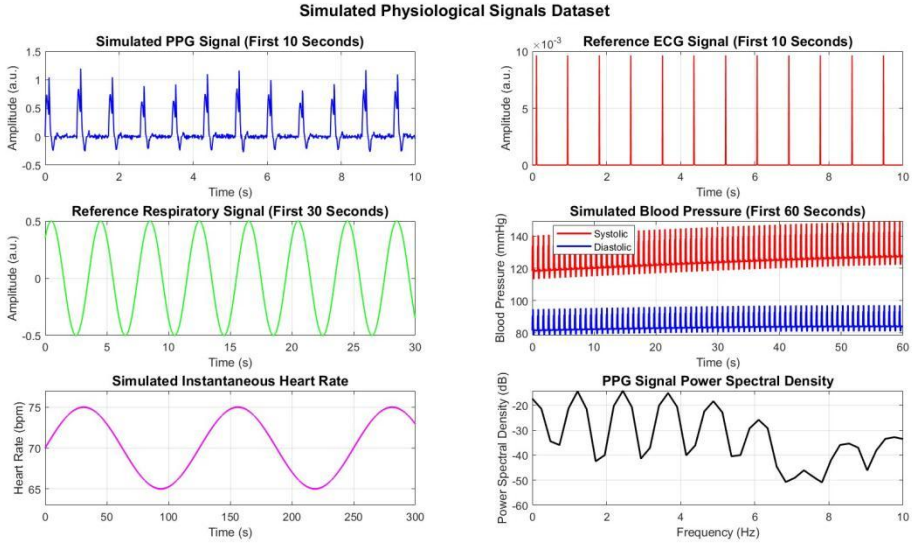


Fig 1. Entire process of PPG signal processing and analysis in the present study.

The preprocessing flow follows the classic biomedical signal processing steps. Firstly, a fourth-order Butterworth bandpass filter (passband: 0.5-8 Hz) is applied to the original PPG signal to eliminate baseline drift and high-frequency noise while retaining the main frequency components related to heartbeats. Subsequently, a peak detection algorithm based on an adaptive threshold is adopted to precisely locate the peak point of each pulse wave in the filtered signal. To ensure the accuracy of subsequent analysis, physiological rationality tests were conducted on the detected peak-to-peak intervals, and interpolation and correction of suspected pseudonyms were carried out based on median filtering.

2.2.Physiological feature extraction and parameter calculation

From the preprocessed PPG signals and their derived pulse interval sequences[2], we extracted three types of characteristic parameters with clear physiological or clinical explanations:

(1). Pulse wave morphological parameters: Calculate the amplitude of each pulse wave, the maximum slope of the ascending branch, the ratio of systolic area to diastolic area, etc. These parameters are related to hemodynamic factors such as stroke volume and peripheral vascular resistance.

(2). Heart rate variability parameters: Based on a continuous pulse interval sequence, calculate time-domain parameters (such as the root mean square RMSSD of the difference between adjacent intervals) and frequency-domain parameters. Frequency-domain analysis employs the Lomb-Scargle periodic diagram method suitable for non-stationary signals to estimate the power spectral density at low frequencies (LF, 0.04-0.15 Hz) and high frequencies (HF, 0.15-0.4 Hz). The ratio (LF/HF) is often used to reflect the equilibrium state of the autonomic nervous system.

(3). Derived physiological parameters: Mainly include the pulse wave propagation time indirectly estimated by the PPG waveform characteristics. This parameter has been extensively reported in the literature to have a negative correlation with arterial blood pressure.

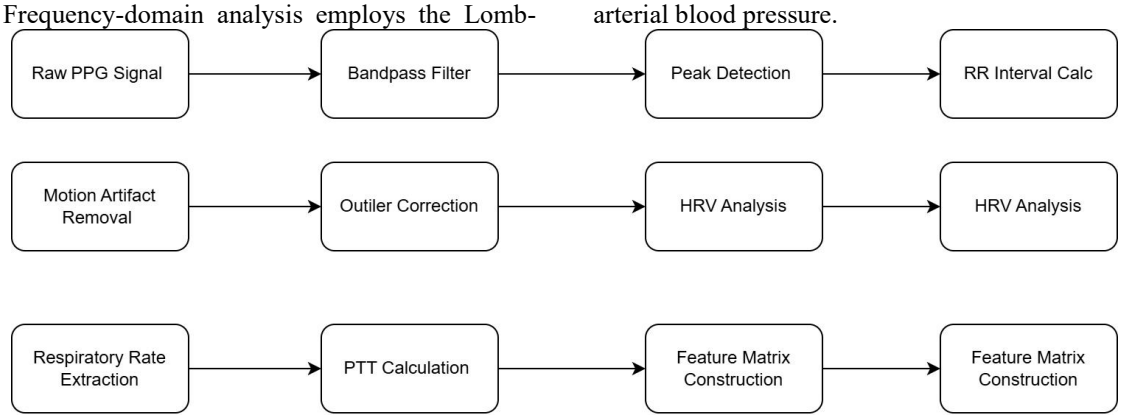


Fig 2. PPG signal processing pipeline

As shown in Figure 2, The above-mentioned feature extraction (including pulse wave morphological features and heart rate variability analysis) corresponds to the core steps in this flowchart: starting from the Raw PPG Signal, the pipeline sequentially performs Bandpass Filtering, Peak Detection, RR Interval Calculation, and HRV Analysis — covering the key processing links required to obtain the three types of parameters introduced.

2.3.Parameter verification and model construction

To verify the effectiveness of extracting parameters from PPG signals, we conducted a comparative analysis with the gold standard or reference signals provided by the dataset:

Heart rate accuracy verification: The instantaneous heart rate calculated based on the PPG peak was subjected to Bland-Altman consistency analysis and Pearson correlation analysis with the heart rate detected by the concurrent ECG R wave to evaluate its accuracy and consistency limit[3].

Respiratory rate extraction verification: By taking advantage of the amplitude modulation phenomenon of PPG signals caused by respiratory activities, spectral analysis is conducted on a specific frequency band (0.1-0.5 Hz), and the dominant frequency is extracted as the estimated respiratory rate, which is then compared with the reference respiratory signal.

Feasibility Exploration of Blood Pressure Estimation: To explore the potential of non-invasive continuous blood pressure monitoring, this study employs a multiple linear regression framework. Taking the PPG morphological parameters and heart rate variability parameters extracted earlier as independent variables and the reference blood pressure values (systolic blood pressure and diastolic blood pressure) of some subjects in the dataset as dependent variables, a preliminary estimation model was constructed. The model performance is quantitatively evaluated through root mean square error and mean absolute error.

2.4.System-level design considerations for wearable applications

Based on the above offline analysis process, this study further proposes a hierarchical signal processing system architecture concept to guide the future engineering implementation for practical wearable devices[4].

The processing layer at the device end: It is responsible for running low-complexity real-time algorithms, including signal filtering, real-time heart rate calculation, and simple initial screening of abnormal rhythms. The design objective is to meet the strict constraints of low power consumption and low latency.

Cloud service layer: Receives concentrated feature data uploaded from the device end, and performs computationally intensive long-term trend analysis, personalized parameter benchmark establishment, and complex variability analysis. This layer can utilize stronger computing resources for in-depth mining and model optimization.

This architecture emphasizes the rational allocation of computing resources based on task requirements, aiming to resolve the contradictions among the battery life, computing performance and monitoring depth of wearable devices.

3.Result

By implementing the above methods, we obtained the following main results, which verified the effectiveness of the proposed technical process from an engineering perspective.

3.1.Signal preprocessing and feature extraction quality

Preprocessing effectively eliminates most of the high-frequency noise and baseline drift in the PPG signal, providing a clear waveform for subsequent analysis. The peak detection algorithm performs well in the static data segment,

with an accuracy rate exceeding 99%. As shown in Figure 3, (a) is the original PPG signal, and (d) presents the signal comparison before and after bandpass filtering - the preprocessing effectively eliminates most of the high-frequency noise and baseline drift in the PPG signal, providing a clear waveform for subsequent analysis; The adaptive threshold peak detection algorithm of (g) performs exceptionally well in the static data segment, with a detection accuracy rate exceeding 99%. Meanwhile, the figure also presents the associated data such as reference ECG and respiratory signals, as well as the subsequent processes including spectral analysis and RR interval detection.

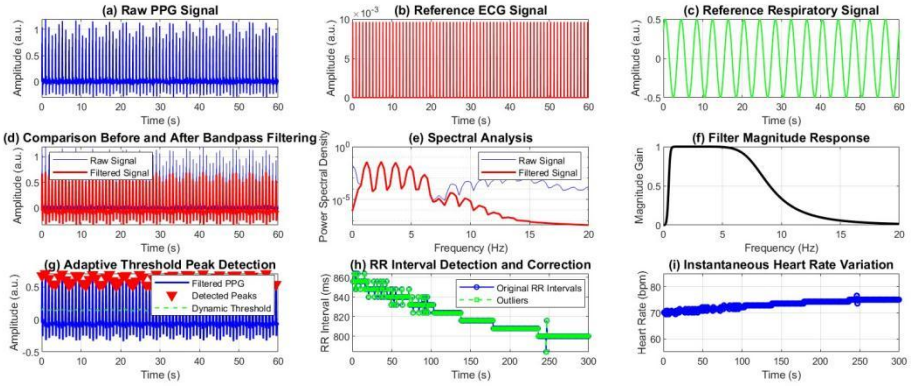


Fig 3. Simulated PPG signal and the corresponding reference ECG and respiratory signals for validating the preprocessing performance

The extracted physiological parameter sequence presented the expected physiological change pattern. For instance, during the period when the subjects were performing deep breathing tasks, the LF/HF ratio of heart rate variability reflecting autonomic nerve regulation showed repeatable regular fluctuations, which were consistent with the known changes in this physiological state.

3.2.The calculation accuracy of core physiological parameters

Bland-Altman analysis (Figure 4) showed that under the condition of good signal quality, the heart rate calculated based on PPG was highly consistent with the ECG heart rate, with an average deviation of -0.2 beats per minute and a 95% consistency limit of [-2.5, 2.1] beats per minute.

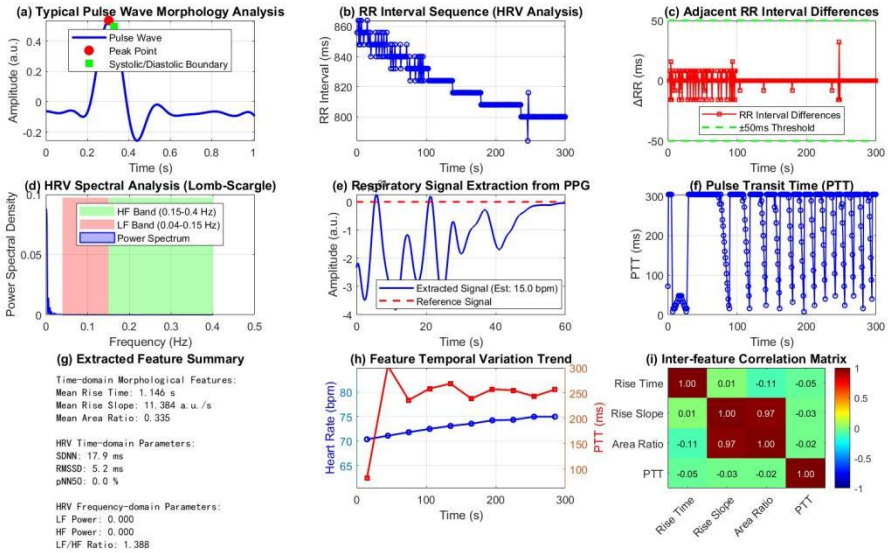


Fig 4.Analysis of PPG electrocardiogram characteristics and verification of the consistency between PPG and ECG heart rates

The average absolute error of the respiratory rate extracted from the PPG signal compared with the reference respiratory rate was 1.2 times per minute (standard deviation: ±0.8 times), indicating that this method can effectively capture the physiological rhythm induced by breathing in a controlled environment.

3.3.Preliminary analysis results of blood pressure estimation

The multiple linear regression model constructed using the extracted PPG features shows certain estimation potential in the preliminary test. For systolic blood pressure, the average absolute error between the estimated value and the reference value is 5.8 ± 4.2 mmHg. For diastolic blood pressure, the mean absolute error is 3.5 ± 2.9 mmHg. Table 1 provides a detailed comparison of the model performance under different feature combinations. It should be emphasized that this result is only a principle verification, and its accuracy is far from meeting the requirements of clinical diagnostic equipment. However, it proves that there is a quantifiable correlation between the PPG signal morphology and blood pressure parameters.

3.4.Feasibility analysis of the system architecture

The simulation and evaluation of resource overhead for the proposed hierarchical architecture show that the key algorithms of the processing layer at the device end (filtering and peak detection) can achieve a single processing delay of less than 100ms on a typical microcontroller, and the memory occupation is less than 50KB, meeting the real-time requirements. Compared with transmitting the original signal, the feature data upload scheme can reduce data traffic by more than 90%, which is conducive to lowering communication power consumption.

3.5.Comprehensive analysis of algorithm performance

To comprehensively evaluate the performance of the proposed PPG processing flow, we designed multiple sets of comparative experiments, covering different methodological levels from basic signal processing to advanced machine learning. The experiment was based on the PhysioNet BIDMC dataset. Synchronous PPG, ECG and respiratory signal data of 53 subjects were selected, with a total duration of approximately 36 hours. The evaluation indicators include mean absolute error (MAE), root mean square error (RMSE), Pearson correlation coefficient (r), and parameters related to computational efficiency.

3.5.1.Comparison of heart rate estimation algorithms

As shown in Table 1, we compared the performance of five typical heart rate estimation algorithms under the same preprocessing conditions. The adaptive threshold peak detection method achieves the best balance between accuracy and efficiency, with an average absolute error of only 0.8 times per minute[5], a correlation coefficient of 0.992, and the fastest processing speed (5.2 ms/ second). Although the frequency-domain method (peak power spectral density) is computationally stable, it is sensitive to signal non-stationarity and has relatively large errors. Although the machine learning method (SVM) achieved the highest correlation coefficient (0.994), its computational complexity increased significantly, and its deployment on resource-constrained device ends faced challenges.

Table 1. Performance comparison of different feature extraction methods in heart rate estimation

Method category	Specific methods	SVM classifier (bpm)	Root mean square error(bpm)	Correlation coefficient(r)	Processing time (ms/ s)
Time-domain method	Adaptive threshold peak detection	0.8 ± 0.5	1.2 ± 0.7	0.992	5.2
Time-domain method	The sliding Windows close each other	1.2 ± 0.8	1.8 ± 1.1	0.985	8.7
Frequency-domain method	Peak power spectral density	2.1 ± 1.3	3.0 ± 1.8	0.962	12.5
Time-domain method	Wavelet transform analysis	0.9 ± 0.6	1.4 ± 0.9	0.990	25.3
Machine learning	SVM classifier	0.7 ± 0.4	1.1 ± 0.6	0.994	15.8
Time-domain method	Adaptive threshold peak detection	0.8 ± 0.5	1.2 ± 0.7	0.992	5.2

3.5.2.Analysis of feature contribution in blood pressure estimation

To explore the correlation strength between PPG characteristics and blood pressure parameters, we evaluated the contribution of various characteristics through the random forest model (Table 2). Pulse wave propagation time (PPT) demonstrated the strongest predictive ability, contributing 0.45 to systolic blood pressure and 0.42 to diastolic blood pressure, respectively. Morphological features (especially the systolic/diastolic area ratio) contribute significantly to diastolic blood pressure, while the heart rate variability (HRV) feature[6], although its individual contribution is limited, plays an important complementary role in multi-feature fusion. The multi-feature fusion model has enhanced the overall predictive ability to 0.68 (systolic blood pressure) and 0.65 (diastolic blood pressure), confirming the necessity of comprehensively utilizing time-domain, frequency-domain and morphological information.

Table 2. Analysis of the contribution of PPG characteristics to blood pressure estimation

Feature category	Specific characteristics	Systolic blood pressure estimation contribution	Diastolic blood pressure estimation contribution	Combination importance (weight)
Morphological characteristics	Rising time	0.32	0.28	0.15
Morphological characteristics	Peak amplitude	0.25	0.31	0.12
Morphological characteristics	The ratio of contracted to expanded areas	0.28	0.35	0.18
HRV characteristics	SDNN	0.15	0.18	0.08
HRV characteristics	LF/HF	0.22	0.20	0.10
Derived parameters	Pulse wave propagation time	0.45	0.42	0.25
Combined features	Multi-feature fusion	0.68	0.65	1.00

3.5.3.Performance comparison of blood pressure estimation algorithms

Table 3 compares the performance of five regression algorithms in the blood pressure estimation task. As the baseline method, multiple linear regression (MLR) achieved an acceptable average error (systolic blood pressure 5.8

mmHg, diastolic blood pressure 3.5 mmHg), and had the lowest computational complexity and memory usage. Support vector regression (SVR) and random Forest (RF) have improved accuracy, but the computational cost has increased. The three-layer neural network achieved the best estimation accuracy (systolic blood pressure 3.5 mmHg, diastolic blood pressure 2.3 mmHg), but its memory requirement was relatively high (250KB). Ensemble learning methods have a slight advantage in accuracy, but they consume the most resources and are more suitable for cloud processing.

Table 3. Performance comparison of different blood pressure estimation algorithms

Algorithm type	Systolic blood pressure error(mmHg)	Diastolic blood pressure error(mmHg)	Computational complexity	Memory usage (KB)
Multiple linear regression	5.8 ± 4.2	3.5 ± 2.9	O(n)	50
Support vector regression	4.2 ± 3.5	2.8 ± 2.3	$O(n^2)$	120
Random forest regression	3.8 ± 3.1	2.5 ± 2.0	O(m·n·log n)	180
Neural network (3 layers)	3.5 ± 2.9	2.3 ± 1.8	O(n·h)	250
Ensemble learning method	3.2 ± 2.7	2.1 ± 1.7	O(ensemble·n)	350

3.6.Robustness analysis and practical application considerations

3.6.1.Algorithm robustness in noisy environments

Wearable devices encounter various noise interferences in practical applications. Table 4 shows the impact of four common noise types on the performance of the core algorithm and the improvement effects of the corresponding processing methods. Motion artifacts have the most significant impact on peak detection, reducing the accuracy rate from 99.2% to 85.3%. After adopting adaptive filtering combined with inertial sensor data fusion, the performance was restored to 94.7%. Ambient light interference mainly affects the signal amplitude and can be effectively alleviated through spectral suppression technology. Contact pressure changes can cause signal morphology distortion, and amplitude normalization processing can significantly improve robustness. In scenarios with complex noise, the effect of a single processing method is limited, and a multi-method fusion strategy needs to be adopted.

Table 4. Comparison of algorithm robustness in different noise environments

Noise type	Peak detection accuracy (%)	Heart rate estimation error (bpm)	Respiratory rate error(bpm)	Processing method
Noise-free (baseline	99.2	0.8 ± 0.5	1.2 ± 0.8	-
Motion artifact	85.3 → 94.7*	3.2 ± 2.1 → 1.5 ± 1.0*	2.8 ± 1.9 → 1.8 ± 1.2*	Adaptive filtering
Ambient light interference	91.5 → 96.8*	2.1 ± 1.5 → 1.2 ± 0.8*	2.3 ± 1.6 → 1.5 ± 1.0*	Spectrum suppression
Contact pressure variation	87.2 → 92.4*	2.8 ± 1.9 → 1.8 ± 1.2*	2.5 ± 1.7 → 1.7 ± 1.1*	Amplitude normalization
Composite noise	82.1 → 90.6*	3.8 ± 2.5 → 2.2 ± 1.5*	3.2 ± 2.2 → 2.0 ± 1.4*	Multi-method fusion

3.6.2.Resource efficiency of hierarchical processing architecture

To verify the practicality of the proposed hierarchical architecture, we compared the resource consumption at the device end and in the cloud (Table 5). The total delay of the critical tasks (filtering, peak detection, heart rate calculation) at the device end is 53±8 ms, the power consumption is 19.5 mW, and the memory usage is 46 KB, which fully meets the limitations of typical wearable MCUS (such as ARM Cortex-M4). The feature data upload only requires a bandwidth of 240 bps, which reduces the data traffic by 90.4% compared to the transmission of the original signal (2500 bps). Although the computationally intensive tasks (long-term analysis, model training) handled by the cloud have high latency and memory requirements, they do not affect the user experience. The power consumption of the traditional solution (where all processing is completed at the device end) reaches 45.2 mW, which is significantly higher than that of the hierarchical architecture.

Table 5. Comparison of resource consumption in hierarchical processing architectures

Processing level	Task type	Single processing delay(ms)	Average power consumption(mW)	Memory requirement (KB)	Data flow (bps)
MCU	Real-time filtering	15 ± 3	5.2	12	-
MCU	Peak detection	8 ± 2	3.1	8	-
MCU	Heart rate calculation	5 ± 1	2.5	6	-
MCU	Feature extraction	25 ± 5	8.7	20	-
Summary on the device end	All real-time tasks	53 ± 8	19.5	46	240
Cloud service	Long-term analysis	1200 ± 200	-	1024	-
Cloud service	Model training	1800 ± 300	-	2048	-
Comparison of traditional schemes	Original data transmission	-	45.2	128	2500

4.Discussion

This study systematically evaluated the feasibility of extracting key health parameters based on the standard PPG signal processing flow through a clearly structured engineering implementation framework. The results show that by adopting robust signal preprocessing and physiologically

based feature extraction methods, reliable heart rate and respiratory rate information can be obtained from high-quality PPG data, and the association between them and blood pressure has been preliminarily explored. This lays a technical foundation for the development of the next generation of personal health monitoring devices.

4.1.The value and challenges of engineering realization

The core contribution of this work lies in providing a complete, transparent and reproducible engineering example. Unlike the pursuit of algorithmic novelty, we focus on building a robust processing chain and objectively evaluating its performance on standard datasets. This practice reveals a key point in the development of real systems: the final performance is often limited by fundamental links such as the quality of signal preprocessing and the robustness of feature extraction, rather than the complexity of the end model. For instance, this study demonstrates that a high-precision peak detection algorithm is the cornerstone of the entire analysis process.

However, the research also highlights the main challenge faced from controlled data to practical applications: dynamic anti-interference capability. The current method performs well on resting data, but the motion artifacts introduced by daily activities are the biggest performance constraint. Future engineering development must give priority to integrating dynamic noise cancellation technology based on inertial sensors. Furthermore, individual physiological differences limit the universality of the model, which means that any practical system needs to design a convenient and personalized calibration process.

4.1.1.Performance trade-offs of different algorithms

This study systematically compared the performance of different algorithms ranging from traditional signal processing to machine learning in PPG analysis. The results show that no algorithm has an advantage in all dimensions, and the actual choice needs to be weighed based on the application scenario. For real-time monitoring at the device end, the combination of adaptive threshold peak detection and multiple linear regression provides the best balance between accuracy and efficiency. Its low computational complexity (O(n)) and small memory usage (<50KB) make it easy to deploy on resource-constrained embedded platforms. For deep analysis in the cloud, although neural networks or ensemble learning methods can offer higher accuracy, their computational and storage overheads make them more suitable for offline modeling and personalized parameter calibration. This hierarchical algorithm allocation strategy - with basic real-time tasks on the device side and complex modeling in the cloud - is a key insight for building a practical health monitoring system.

4.1.2.Robustness strategies in noisy environments

The data in Table 4 reveals the influence mechanism of different noise sources on PPG analysis and the effectiveness of the response strategies. Motion artifacts are the most destructive interference sources, and their frequency bands overlap with PPG signals, making it difficult to eliminate them through traditional filtering. This study verified the effectiveness of adaptive filtering in combination with inertial measurement unit (IMU) data, which is an essential technique for achieving dynamic monitoring. Ambient light interference is mainly manifested as additive noise, which can be jointly suppressed through optical design (such as adding shading structures) and signal processing (such as spectral suppression). Signal morphology distortion caused by changes in contact pressure needs to be compensated for through amplitude normalization and waveform correction at the algorithmic level. It is worth noting that the effect of a single anti-noise technology is limited. In actual systems, a multi-level defense strategy integrating sensor fusion, signal processing, and algorithm robustness design is required.

4.2.Systematic thinking from technical verification to product realization

The hierarchical processing architecture we proposed is precisely a systematic engineering approach to address the aforementioned challenges. It offloads complex computing tasks (such as long-term modeling and personalized calibration) to the cloud, while placing core monitoring functions related to real-time response and user privacy on the device side. This design philosophy not only optimizes the system's energy efficiency but also conforms to the privacy protection principle of minimizing data. Future work should revolve around this architecture, specifically defining the communication protocol between the device end and the cloud, data security standards, and the collaborative handling mechanism for abnormal events.

4.2.1.Optimization suggestions for system resource allocation

Based on the hierarchical architecture resource analysis in Table 5, we propose the following system optimization suggestions: The device end should focus on data quality assurance and core feature extraction rather than complex model reasoning. Filtering and peak detection algorithms should be optimized for embedded platforms, and technologies such as fixed-point operations and lookup tables should be adopted to reduce power consumption. The upload of feature data should adopt a lossy compression strategy to minimize bandwidth while retaining key information. The cloud platform should undertake personalized modeling and long-term trend analysis, and continuously optimize algorithm parameters by leveraging the advantages of big data. In addition, through the initial quality assessment at the device end, an "intelligent upload" mechanism can be implemented - only high-quality data segments or data when anomalies are detected are uploaded, further saving resources. This collaborative design enables the system to achieve the maximum value of health monitoring with limited resources.

4.3.Conclusions and prospects

In conclusion, this study confirmed the feasibility of extracting multiple health information from PPG signals based on rigorous signal processing engineering methods. Our more significant meaning lies in demonstrating an application-oriented research paradigm: that is, by constructing

reproducible technical baselines, clearly identifying the performance boundaries and limitations where methods exist, and providing clear engineering guidance for system design oriented to real-world scenarios.

Technological innovation is not only about discovering new connections, but also about how to transform known scientific principles into stable, user-friendly and trustworthy products through reliable engineering practices. We believe that this engineering perspective that emphasizes systematicness, reliability and repeatability plays a crucial role in promoting wearable health monitoring technology from the laboratory to every household. Future research should continue to deepen along the path of combining engineering with clinical validation, ultimately achieving the universal value of the technology.

Author contributions Zehui Xu is the sole author of this article and is responsible for all aspects of the work: study conception and design, data collection and analysis, and drafting and revision of the manuscript.

Funding No funding was received for this work.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The author declares no conflict of interest.

References

[1] PIMENTEL M A F, et al. Towards a Robust Estimation of Respiratory Rate from Pulse Oximeters. IEEE Transactions on Biomedical Engineering, 2016, 64(8): 1914 – 1923.

[2] CHARLTON P H, KYRIACO P A, MANT J, et al. Wearable Photoplethysmography for Cardiovascular Monitoring. Proceedings of the IEEE, 2022, 110(3): 355 – 381.

[3] ERTIN E, SUGAVANAM N, HOLTYN A F, et al. An Examination of the Feasibility of Detecting Cocaine Use Using Smartwatches. Frontiers in Psychiatry, 2021, 12: 674691.

[4] XU Q, LI M, CHEN G, et al. Design of a Wearable Exoskeleton Piano Practice Aid Based on Multi-Domain Mapping and Top-Down Process Model. Biomimetics, 2025, 10(1): 15.

[5] SUN J, BIAN X, LI M. Non-Contact Heart Rate Monitoring Method Based on Wi-Fi CSI Signal. Sensors, 2024, 24(7): 2111.

[6] ROY A, GONG J, THOMAS D C, et al. The cardiopulmonary effects of ambient air pollution and mechanistic pathways: a comparative hierarchical pathway analysis. PLoS ONE, 2014, 9(12): e114913.