Cluster-Based Motion Artifact Filtering for Enhanced PPG Noise Reduction in Wearable Health Monitoring

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Abstract

Photoplethysmography (PPG) is widely used in wearable health monitoring but remains highly susceptible to motion artifacts, which can degrade signal quality. Traditional filtering techniques often struggle under dynamic conditions, resulting in inaccurate physiological measurements. This study introduces a novel cluster-based filtering method that leverages accelerometer data to mitigate motion artifacts in PPG signals. Data were collected from 50 patients using chest bands which recorded three PPG channels and tri-axial accelerometer data. Motion artifacts were classified into three clusters using k-means clustering on statistical features, enabling context-aware wavelet-based filtering. The proposed method significantly improved signal quality, reducing noise energy by 30.90 dB while preserving physiological information. Clustering performance was validated with a average Silhouette Index of 0.8987, confirming robust segmentation. Comparisons with second order Butterworth filter and Daubechies 4 wavelet filters demonstrated superior artifact suppression without distorting PPG morphology. This adaptive approach enhances preprocessing for continuous health monitoring and improves the reliability of wearable PPG-based applications.

1. Introduction

Photoplethysmography (PPG) is a non-invasive, cost-effective optical technique commonly employed in wearable devices to monitor key physiological parameters such as heart rate (HR), oxygen saturation (SpO_2), and blood pressure (BP) [1]. It functions by emitting light into the skin and measuring variations in absorption caused by blood volume changes [2], providing valuable insights into cardiovascular health [3]. Due to its affordability, ease of use, and capability for continuous monitoring, PPG has become a standard feature in both consumer fitness trackers and clinical-grade devices [4].

Despite its widespread use, PPG is highly vulnerable to motion artifacts and other noises, especially during physical activity [5]. These artifacts can distort the signal and mask underlying information, presenting a major obstacle to reliable health monitoring in real-world conditions [6].

Conventional filtering methods, including Butterworth filters and wavelet-based approaches, perform adequately in controlled settings but often fail under dynamic conditions due to fixed parameters and limited adaptability [7]. Additionally, many of these techniques overlook contextual data from sensors such as accelerometers, which could be leveraged to enable more adaptive filtering [8].

This study introduces a cluster-based filtering framework that utilizes accelerometer data to adaptively respond to motion context. By incorporating motion-aware wavelet filtering guided by cluster-specific information [9], this adaptive strategy represents a promising approach for effectively suppressing artifacts while preserving the morphology of the PPG signal.

2. Materials and Methods

The dataset comprised recordings from 50 participants wearing Polar Verity Sense wristbands (Polar Electro Oy, Finland), each equipped with three PPG channels and a tri-axial accelerometer. The cohort consisted of 60% women; 50% reported active lifestyles, and 40% were under cardiovascular medication, including beta-blockers or statins. Participants wore the device on the forearm for 24 h while engaging in their usual daily activities.

PPG signals were sampled at 55 Hz. Accelerometer data were resampled to the same frequency, and total acceleration was calculated as the Euclidean norm of the three

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axes. Each 24 h recording was segmented into 10-second windows, and seven statistical features were extracted per window: mean, standard deviation, maximum intensity, energy, skewness, kurtosis, and entropy. These features are commonly used in human activity recognition based on tri-axial accelerometry [10]. Outliers were removed using the interquartile range (IQR) method, and Min-Max normalization was applied.

Feature selection was guided by a correlation matrix to reduce redundancy. A custom scoring function was used to assess clustering performance, incorporating the Silhouette Mean (SM), Davies–Bouldin Index (DBI), and Dunn Index (DI), while penalizing highly correlated features:

$$S = \frac{1}{4}S_{\text{SM}} + \frac{1}{4}(1 - S_{\text{DBI}}) + \frac{1}{4}S_{\text{DI}} - \frac{1}{4}P_{\text{Corr}} \quad (1)$$

Standard deviation and skewness emerged as the optimal pair, achieving the highest score, and were selected for clustering; the remaining features were discarded. Using k-means clustering with $k = 3$, three motion-related clusters were identified, each corresponding to a characteristic level of artifact contamination. These clusters were then mapped to the synchronized PPG segments.

Cluster-based filtering was implemented using a 5-level Discrete Wavelet Transform (DWT) with the Symlet 4 wavelet. High-frequency noise and abrupt fluctuations were captured at lower decomposition levels, while baseline drift appeared at higher levels.

Wavelet coefficients were selectively suppressed based on the assigned motion cluster: (i) in the first cluster, A_5 and D_1 were zeroed to eliminate baseline drift and high-frequency noise while preserving the core pulsatile signal; (ii) in the second cluster, A_5, D_1, and D_3 were suppressed to further reduce motion artifacts while retaining the main PPG band (0.5–3 Hz); (iii) in the third cluster, A_5, D_1, D_2, and D_3 were removed to maximize suppression of noise and drift, preserving key components in D_4 and D_5.

Filtering was applied independently to each segment to prevent variable motion conditions. Segments were reconstructed using inverse DWT and combined using 30% overlapping windows to minimize boundary artifacts.

The proposed method was compared against a second-order Butterworth bandpass filter (0.5–3 Hz) and a 5-level DWT using the Daubechies 4 wavelet. Performance was evaluated using signal-to-noise ratio (SNR), computed with MATLAB's built-in function to quantify signal preservation and noise reduction.

3. Results

Clustering performance was evaluated across 10 sessions per recording using the selected feature pair (standard deviation and skewness). Results confirmed that this combination yielded compact, well-separated clusters with high internal consistency. Three standard clustering metrics were employed to assess performance. The average Silhouette Index was 0.898 ± 0.012, indicating strong intra-cluster cohesion. The mean Davies–Bouldin Index was 0.003 ± 0.0002, suggesting excellent inter-cluster separation. The mean Dunn Index was 0.442 ± 0.031, reflecting well-defined and tight clusters. The low standard deviations across all metrics demonstrate high repeatability and robustness across sessions.

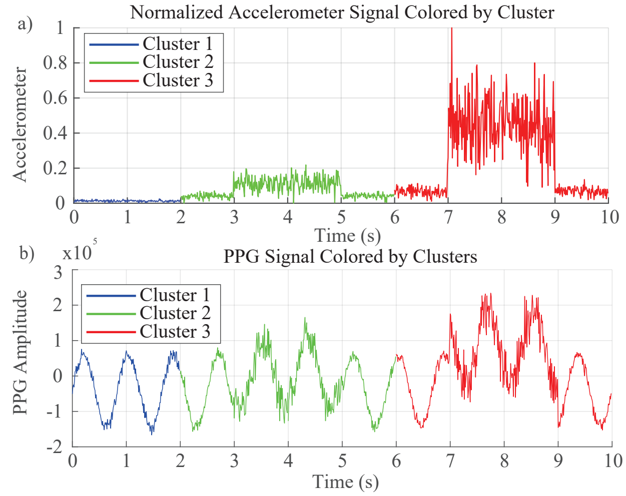

Figure 1: Example of cluster-based segmentation of a PPG signal. (a) The acceleration norm is classified into three motion-related clusters using reference centroids. (b) These cluster labels are mapped onto the corresponding PPG signal, illustrating segments with different levels of motion-induced noise.

An example of cluster-based segmentation is shown in Fig. 1, where the acceleration norm is clustered and mapped onto the corresponding PPG signal.

The proposed filtering method significantly improved PPG signal quality. As illustrated in Fig. 2, the cluster-based filter effectively suppresses baseline drift and high-frequency noise while visually preserving the morphology of the PPG waveform. Moreover, Figure 3 compares the proposed method with two baseline approaches: Butterworth band-pass filtering (0.5–3 Hz) and wavelet filtering using Daubechies 4. The clustering-based filter produced cleaner outputs with better retention of PPG morphology compared to both alternatives.

Energy-based analysis validated the method's performance, and the proposed filter achieved very good noise reduction (30.90 dB) while preserving signal integrity (Fig. 4). Butterworth filtering provided higher attenuation (34.88 dB) at the cost of waveform distortion. Wavelet filtering better preserved signal shape but achieved poorer noise reduction (22.58 dB), leaving residual artifacts.

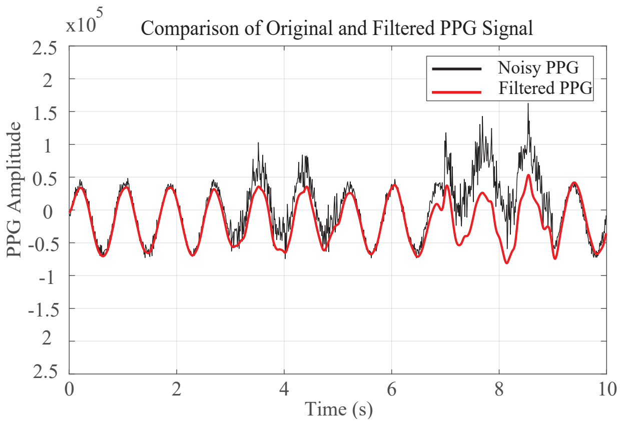

Figure 2: Comparison of original PPG signal affected by varying levels of noise (black) and the filtered signal (red) using the proposed clustering-based method. Motion and baseline artifacts are effectively removed, while the underlying morphology of the PPG signal is preserved.

4. Discussion

In wearable health monitoring systems, PPG signal preprocessing must strike a balance between effective noise suppression and preservation of waveform integrity. Traditional methods, such as Butterworth filtering and wavelet denoising, often exhibit limitations—Butterworth filters can introduce phase distortion and attenuate physiologically relevant features, while wavelet-based methods typically rely on fixed thresholds that may fail to eliminate high-frequency noise and motion artifacts [11, 12].

The proposed filtering approach addresses these shortcomings by adaptively suppressing noise based on motion-derived features. In contrast to conventional filters, it selectively targets noisy segments while preserving cleaner signal regions, thereby maintaining the morphological fidelity of the PPG waveform. Visual analysis demonstrates improved signal clarity, while quantitative evaluation confirms higher signal energy retention and superior noise attenuation. Moreover, clustering performance was consistent across sessions, indicating robustness and reliability in real-world, motion-rich wearable scenarios.

Unlike previous approaches relying on PPG-based clustering to discard noisy segments entirely [13], our method uses accelerometer features to guide the filtering process. This enables artifact suppression without removing entire portions of the PPG signal, preserving more usable data.

Nevertheless, the approach has limitations. It may be sensitive to the choice of clustering parameters and the initialization of centroid positions [14], which could impact filtering consistency under different conditions.

Future work should include a more detailed assessment of computational efficiency and investigate how the number of clusters and window size influence performance. Testing on more diverse and larger-scale PPG datasets will also be essential to evaluate the method's robustness and generalizability.

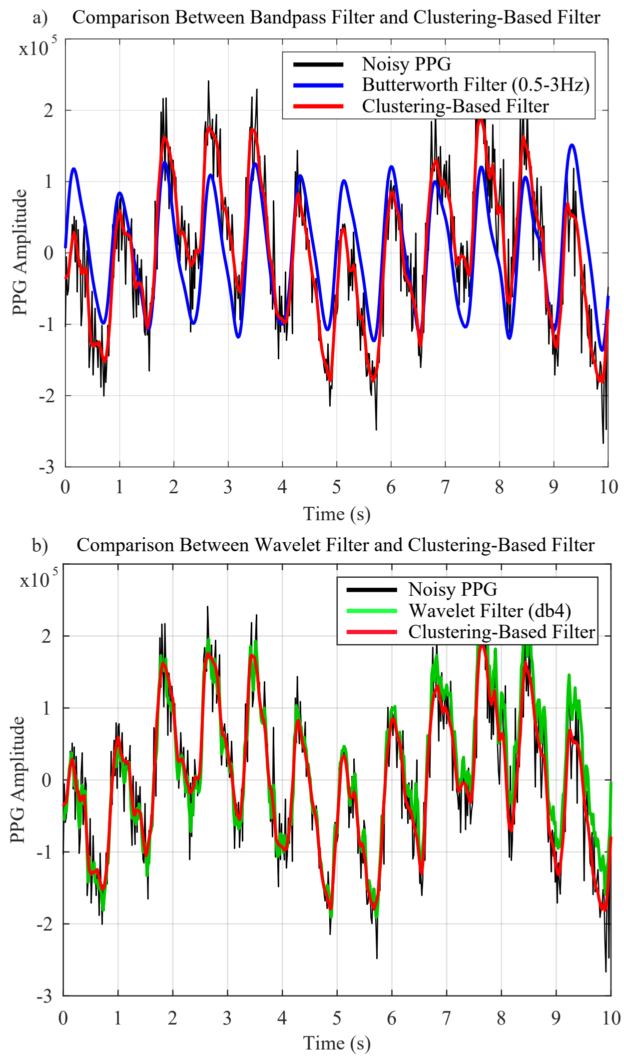

Figure 3: Comparison of filtering methods on a representative PPG segment. (a) Butterworth band-pass filter (0.5–3 Hz) vs. clustering-based filtering. (b) Wavelet filtering (Daubechies 4) vs. clustering-based filtering.

5. Conclusions

This study proposed a cluster-based filtering method that uses accelerometer data to adaptively reduce motion artifacts in PPG signals. By adjusting filtering based on motion intensity, the approach preserves signal morphology while improving noise suppression. Results show superior performance over traditional filters, highlighting its potential for reliable wearable health monitoring.

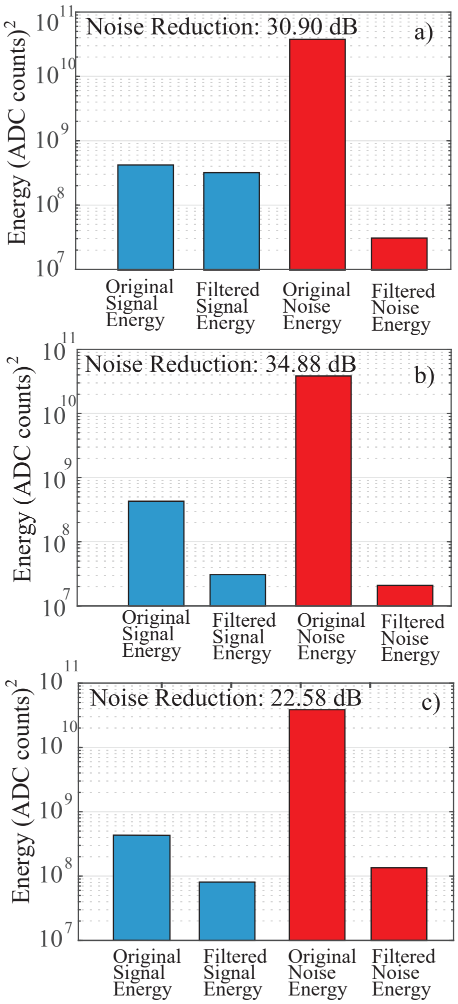

Figure 4: Average energy of signal and noise components before and after filtering. (a) Proposed clustering-based filter achieves substantial noise suppression with minimal signal loss. (b) Butterworth filter attenuates both noise and desired signal. (c) Daubechies 4 wavelet filter preserves more signal content but is less effective in noise reduction.

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