Peakwise Correlation Pulse Detector: A Novel Method for Noise-Resilient Peak Detection in PPG signals

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Abstract

Photoplethysmography (PPG) is a non-invasive technique widely used in health monitoring, yet its reliability is often compromised by noise and motion artifacts. This study presents the Peakwise Correlation Pulse Detector (PCPD), a novel algorithm for accurate, stand-alone heartbeat detection in PPG signals without relying on external references. PCPD integrates signal segmentation, cross-correlation with ideal waveform templates, a Minimum Correlation Curve (MCC) for refined peak localization, and a machine learning classifier to validate detected peaks. The algorithm was evaluated in two controlled scenarios: a clean signal condition using high-quality PPG segments selected by expert annotation from a custom 24-hour dataset and the BIDMC database; and a noisy signal condition, where synthetic pulse-free segments were added to simulate motion artifacts and assess specificity. PCPD achieved high precision, recall, and F1 scores, exceeding 99.3% accuracy on the custom dataset and 97.1% on BIDMC under noisy conditions. Comparative analysis against eleven benchmark algorithms demonstrated that PCPD outperforms all competitors in noisy environments while maintaining comparable accuracy in clean settings. Its robustness stems from the integration of morphological analysis and physiological constraints, enabling reliable, self-contained peak detection.

1. Introduction

Photoplethysmography (PPG) is a widely used, non-invasive technique for cardiovascular monitoring in wearable devices. PPG waveforms typically display a prominent systolic peak followed by a lower-amplitude diastolic peak. However, their reliability is frequently compromised by motion artifacts (MAs), which distort the signal and hinder accurate physiological interpretation. These issues are especially pronounced under low perfusion conditions, where weakened pulse waves and reduced systolic-diastolic separation further degrade signal clarity [1].

MAs are a leading cause of false alarms in both clinical and home-based monitoring. They account for 70–71% of false-positive alerts in pulse oximetry and up to 85% in apnea monitoring systems [2]. In addition to motion, other factors such as skin tone, sensor placement, and ambient lighting can significantly affect signal quality, posing challenges for the development of reliable automated analysis algorithms [3].

Accurate heartbeat detection from PPG signals without reliance on external references, such as electrocardiography (ECG), is essential for enabling fully autonomous wearable systems [4]. Many peak detection algorithms have been proposed, often incorporating auxiliary signals like synchronized ECG or accelerometer data to enhance performance [5]. However, this dependence on external references limits the standalone utility of PPG.

Benchmarking studies have shown that algorithm performance varies by context: some detectors perform well under stationary conditions, while others are more robust to motion [6]. A key limitation of many evaluations is the reliance on ECG as the reference, which can penalize PPG-based algorithms for missing ECG-labeled peaks that are not visible in the PPG waveform.

To address these limitations, this paper introduces the Peakwise Correlation Pulse Detector (PCPD), a novel algorithm designed for standalone heartbeat detection in PPG signals. PCPD is engineered to be resilient to noise and motion artifacts by leveraging morphological analysis and physiological constraints to enhance peak detection accuracy. The approach aims to improve the reliability and autonomy of PPG-based health monitoring systems across both clinical and real-world settings.

2. Materials and Methods

To evaluate the performance of the proposed PCPD algorithm, two experimental conditions were established: a high-quality signal setting and a noisy signal setting with artificially introduced noise.

In the high-quality condition, two datasets were used. The first was a custom dataset developed for this study, consisting of 12 hours of high-quality PPG segments extracted from 24-hour recordings of 50 patients. The participants had an average age of 54 years; 80% had hypertension, 60% were overweight or obese, 60% were women, and 50% reported regular physical activity. Signals were acquired using the Polar Verity Sense device (Polar Electro Oy, Finland) at a sampling rate of 55 Hz. A total of 8,640 10-second segments [7] were graded by three experts using a four-level quality scale: 21.75% showed no visible peaks, 12.26% had fewer than 50% visible peaks, 14.35% had more than 50%, and 51.64% had fully visible peaks. Only grade 4 segments were selected for the high-quality evaluation to ensure clean PPG morphology.

The second dataset was the publicly available BIDMC dataset [8], part of the MIMIC II Matched Waveform Database. It included 53 recordings from critically ill patients, with ECG and PPG signals sampled at 125 Hz. All signals underwent preprocessing using a Butterworth band-pass filter (0.5–8 Hz), following standard practices in PPG signal processing [9].

For the noisy signal setting, artificial noise was introduced into high-quality segments from both datasets. This setup was used to assess the PCPD's specificity in distinguishing valid pulse waves from pulse-free sub-segments [10]. The resulting dataset included 4,462 segments from the custom dataset and 2,544 from BIDMC. Noisy sub-segments of varying duration (mean: 2.5 s, SD: 0.75 s, range: 0.5–4 s) were generated using zero-mean, unit-variance Gaussian noise. Each was scaled relative to the segment's standard deviation and filtered between 0.5–8 Hz [9]. This approach introduced diverse signal degradation scenarios and prevented overrepresentation of false peaks. Figure 1 illustrates a segment containing both high-quality and artificially corrupted sub-segments.

Unlike prior approaches that rely on ECG data [11], the evaluation here was conducted entirely using PPG data. Although ECG is frequently used for benchmarking, it can be misleading, as it may mark peaks that are not observable in the PPG. To create a robust validation framework, true positives (TPs) in both datasets were defined as peaks identified by a standard peak detector and manually verified in clean segments. True negatives (TNs) were obtained from noisy segments by detecting all local maxima. The final evaluation set, combining clean and noisy data, comprised 139,953 total peaks, with 47% labeled as TPs and 53% as TNs, thus ensuring a balanced classification benchmark.

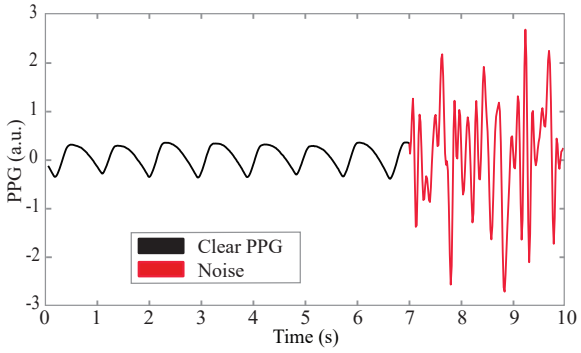

Figure 1: Example of a PPG signal segment containing a high-quality informative portion and a manually added pulse-free noisy sub-segment (highlighted in red).

The PCPD algorithm consists of five key stages. First, the PPG signal is segmented into overlapping 10-second windows with a 1-second shift to ensure that edge-adjacent peaks are captured, accommodating heart rates ranging from 40 to 220 bpm [12].

In the second stage, cross-correlation is performed between each segment and a set of precomputed ideal beat templates. These templates were generated from 50 manually selected, high-quality signal segments. For each, the average waveform of all detected beats was computed. The mean duration of these ideal beats was 854 ± 127 ms, corresponding to heart rates of 61–83 bpm, reflecting plausible resting conditions. Pearson's correlation coefficient was calculated at each time point across templates. To improve computational efficiency, the template set was reduced from 50 to 16 with negligible loss in performance.

The third stage involves computing the Minimum Correlation Curve (MCC), defined as the pointwise minimum across all template correlations. The MCC provides a smoothed, symmetric similarity representation that facilitates robust peak localization.

In the fourth stage, machine learning-based validation is applied. A quadratic linear discriminant classifier, trained on seven hours of labeled PPG data, is used to validate detected peaks. The classifier employs two features: waveform skewness and the Ratio of Area (RoA), which quantifies the compactness of the peak relative to its baseline. Five-fold cross-validation yielded a classification accuracy of 97.2%. Figure 2 illustrates the MCC and peak validation process.

In the final stage, validated peaks are realigned to the original PPG waveform using a 180 ms tolerance window to correct for time shifts caused by noise or waveform distortion. Physiological constraints are enforced to remove implausible detections, such as heart rates outside the 40–220 bpm range or highly asymmetric waveforms [12]. The complete PCPD pipeline—comprising

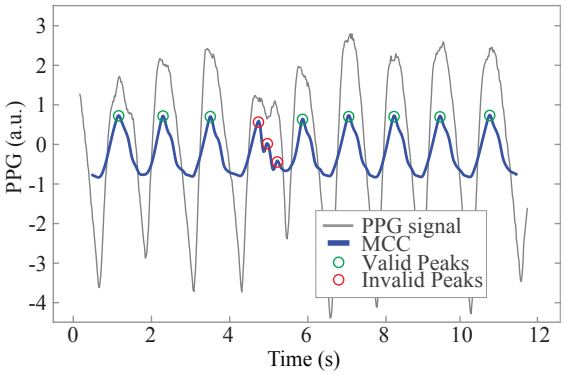

Figure 2: PPG segment overlaid with the Minimum Correlation Curve (MCC), showing the peak validation process.

Table 1: Performance of PCPD on clean and noisy datasets.

Dataset	Acc.	Prec.	Rec.	F1
Custom (Clean)	99.13	99.90	98.37	99.12
BIDMC (Clean)	97.04	95.97	98.11	96.92
Custom + Noise	99.30	99.30	99.03	99.17
BIDMC + Noise	97.16	96.82	97.31	97.06

segmentation, cross-correlation, MCC extraction, machine learning classification, and physiological constraint validation—is illustrated in Figure 3. This architecture supports robust systolic peak detection across both clean and noise-corrupted PPG signals.

2.1. Statistical Performance Metrics

To evaluate PCPD performance, standard classification metrics were computed. For datasets with noisy signals, the number of true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN) enabled calculation of accuracy, precision, recall, and F1 score. In the clean datasets, where true negatives do not apply, only TP, FP, and FN were used. Accuracy was defined as the average of precision and recall in these cases.

3. Results

The proposed PCPD algorithm was evaluated on a cohort of 103 subjects using the two previously described datasets, encompassing approximately 140,000 peaks, including both true systolic peaks and noise-induced maxima. Table 1 summarizes the performance across clean and noisy conditions, demonstrating the algorithm's effectiveness in detecting true peaks while minimizing false detections.

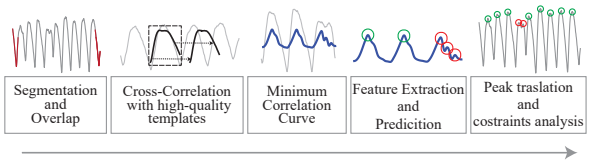

Figure 3: Overview of the PCPD algorithm pipeline.

In clean signal conditions, PCPD achieved an accuracy of 99.13% on the custom dataset and 97.04% on the BIDMC dataset. Under noisy conditions, performance remained strong, with accuracies of 99.30% and 97.16% on the custom and BIDMC datasets, respectively. These results confirm that PCPD consistently maintains high accuracy across both clean and noise-degraded environments.

4. Discussion

In a comparative evaluation against eleven established beat detection algorithms [11], including AMPD [6], MSPTD [13], and ERMA [14], the proposed PCPD method demonstrated consistently high accuracy across both clean and noisy datasets. Figure 4 summarizes the comparative results, showing that PCPD outperformed all competing methods, particularly under noise-augmented conditions.

Among the competing algorithms, MSPTD and AMPD exhibited relatively strong performance due to their multi-scale detection frameworks. However, both exhibited more pronounced accuracy degradation in the presence of noise compared to PCPD.

The superior noise robustness of PCPD is attributed to its integration of morphological analysis, the design of the Minimum Correlation Curve (MCC), and the use of a classifier-based peak validation strategy. Even under clean conditions, where most algorithms performed well, PCPD retained a slight advantage in both accuracy and F1 score, demonstrating not only resilience in challenging conditions but also high precision in ideal signal environments.

5. Conclusions

The Peakwise Correlation Pulse Detector is a robust and accurate algorithm for heartbeat detection in PPG signals. Its five-stage processing pipeline—comprising segmentation, cross-correlation with ideal templates, MCC extraction, machine learning-based classification, and physiological constraint enforcement—enables reliable peak detection even in the presence of noise and signal variability. PCPD achieved high accuracy across both clean and noisy datasets, consistently outperforming established benchmark methods. Its standalone design and resilience to ambient artifacts make it well-suited for real-world de-

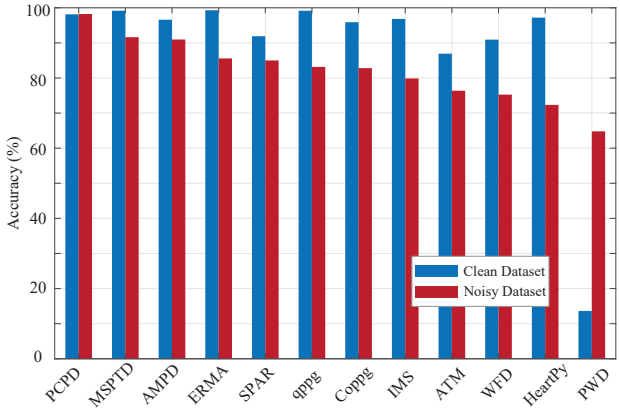

Figure 4: Comparative analysis of eleven beat detection methods and the proposed PCPD function.

ployment in wearable health monitoring systems, supporting both heartbeat detection and signal quality assessment.

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