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Automatic Peak-to-Peak Detection and Segmentation of Radial Pulse Waveforms

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Abstract: Accurate identification of systolic peaks and individual pulse cycles is important for reliable analysis of radial pulse waveforms. This study presents an automated peak-to-peak based method for systolic peak detection and pulse-cycle segmentation from real-time radial pulse signals. Radial pulse recordings were acquired using a Nellcor SpO_2 probe at a sampling frequency of 500 Hz, with three-minute real-time PPG recordings obtained from 25 samples. The acquired signals were subjected to baseline correction, smoothing, Savitzky–Golay filtering, and normalization to reduce signal variations while retaining relevant waveform characteristics. Systolic peaks were identified using a prominence-based detection approach incorporating signal-dependent amplitude characteristics and minimum peak-distance criteria. Consecutive detected peaks were used to determine peak-to-peak intervals and adaptive boundaries for pulse-cycle segmentation, followed by valley-based refinement of the segment boundaries. The peak-detection performance was quantitatively assessed using true-positive, false-positive, and false-negative detections together with sensitivity, precision, detection error rate, and F1-score. Additionally, 25 impedance plethysmography (IPG) samples representing five drug conditions were used to compare the peak-detection results obtained using the proposed method with those obtained using BARC software as the reference method**.** The proposed method provides an automated approach for consistent peak identification and segmentation of radial pulse waveforms.

Keywords: Radial Pulse Waveform, Peak-to-Peak Detection, Pulse Segmentation, Savitzky-Golay Filtering, Pulse Cycle Extraction, Real-time Pulse Analysis.

I. INTRODUCTION

Radial pulse waveform analysis is an important area of biomedical signal processing because the waveform contains information related to cardiovascular activity and arterial characteristics [1],[2]. The radial pulse can be acquired non-invasively and analyzed to identify characteristic features of individual cardiac cycles. Reliable identification of these features is particularly important when pulse waveforms are subsequently used for morphological or physiological analysis.

For automated radial pulse analysis, accurate detection of the systolic peak is a fundamental processing step. The detected peak provides a temporal reference for determining consecutive pulse cycles and calculating the peak-to-peak interval. However, radial pulse recordings can exhibit baseline variations, amplitude fluctuations, noise, and waveform distortions arising from sensor placement and recording conditions [3],[4]. These variations may lead to missed peaks or false detections if fixed detection criteria are applied.

Several signal-processing approaches have been reported for identifying characteristic points in photoplethysmographic and peripheral pulse signals [5],[6],[7]. Conventional techniques include amplitude thresholding, derivative-based methods, filtering, and local extrema detection. Although these approaches can be effective under stable recording conditions, variations in waveform morphology and signal amplitude can affect their performance. Therefore, an appropriate combination of preprocessing and adaptive peak-detection criteria is required for reliable analysis of real-time radial pulse signals.

In the present work, a peak-to-peak based method is developed for automatic systolic peak detection and segmentation of radial pulse waveforms. The acquired signal is first subjected to preprocessing to reduce baseline variation and unwanted fluctuations while preserving the relevant waveform morphology. Systolic peaks are then identified using prominence-based detection criteria together with minimum peak-distance constraints. The locations of consecutive detected peaks are used to determine the peak-to-peak interval, which provides the basis for adaptive pulse-cycle segmentation. Previous studies have also used pulse waveform analysis for heart-rate extraction and assessment of arterial waveform properties [8],[9].

The proposed method is evaluated quantitatively using radial pulse recordings from 25 samples. Peak-detection performance is assessed using true-positive, false-positive, and false-negative detections, followed by calculation of sensitivity, precision, detection error rate, and F1-score. In addition, 25 impedance plethysmography (IPG) samples representing five drug conditions are used to compare the peak-detection results obtained using the proposed method with those obtained using the reference method. Representative results from 10 PPG recordings and 15 IPG samples are reported in this study.

The main contribution of this work is the development and quantitative evaluation of a peak-to-peak based approach that combines signal preprocessing, systolic peak detection, adaptive interval estimation, and valley-refined pulse segmentation for real-time radial pulse waveform analysis.

II. LITERATURE REVIEW

Radial and peripheral pulse waveforms have been widely investigated for non-invasive assessment of cardiovascular activity. The morphology of a pulse waveform reflects changes associated with arterial blood flow and the cardiac cycle, making accurate identification of characteristic waveform points important for subsequent signal analysis. Photoplethysmography (PPG) is also widely used for physiological signal monitoring because it provides a non-invasive representation of blood-volume changes [10]. Automatic beat detection has also been investigated in physiological pressure signals [11].

Various techniques have been developed for detecting characteristic points in physiological waveforms. Conventional peak-detection approaches include amplitude thresholding, derivative-based techniques, and zero-crossing methods. Specific approaches for detecting pulse-wave onset and systolic peaks have also been reported, including Hilbert-transform-based detection and systematic analysis of PPG waveform features [12],[13]. Although these techniques can identify prominent waveform features, their performance may be affected by baseline drift, noise, amplitude variation, and changes in waveform morphology. These limitations become more relevant when signals are acquired continuously under real-time conditions.

Signal preprocessing is therefore commonly applied before characteristic-point detection. Filtering and smoothing techniques can suppress unwanted fluctuations while retaining important features of the original waveform. The Savitzky–Golay filtering approach is particularly useful for biomedical signals because it performs smoothing while maintaining the shape of important waveform characteristics.

Peak-based segmentation approaches use detected systolic peaks as temporal reference points for separating continuous pulse recordings into individual cardiac cycles [12],[13]. Standardized terminology is also important when describing characteristic points and waveform features in PPG analysis [14]. Fixed-window segmentation can be affected by variations in pulse duration because a constant window may not represent every cardiac cycle equally. In contrast, segmentation based on the interval between consecutive detected peaks can adapt the extraction window according to changes in pulse-cycle duration [15].

Previous research has also examined radial pulse morphology and characteristic pulse patterns for physiological assessment. Such analysis requires reliable extraction of individual pulse cycles before morphological characteristics can be compared or classified [16],[17],[18]. Previous PPG peak-detection research, including wavelet-based approaches, further demonstrates the importance of robust peak identification under varying signal conditions [19].Therefore, accurate peak detection and segmentation remain important preprocessing stages for automated pulse waveform analysis.

Based on the limitations identified in existing approaches, the present work focuses on a peak-to-peak based method that combines signal preprocessing, prominence-based systolic peak detection, adaptive peak-to-peak interval estimation, and valley-based boundary refinement. The method is quantitatively evaluated using true-positive, false-positive, and false-negative detections and the resulting performance measures. A separate IPG dataset is also used to compare the detected peak counts with the reference method, providing an additional benchmark for the proposed approach.

III. MATERIALS AND METHODS

The proposed method was developed for automatic detection of systolic peaks and segmentation of individual pulse cycles from real-time radial pulse waveforms. The overall processing procedure consists of signal acquisition, preprocessing, systolic peak detection, peak-to-peak interval estimation, adaptive pulse segmentation, and boundary refinement. The detected peaks were subsequently evaluated using quantitative performance measures. A separate IPG dataset was used for comparative evaluation against a reference method.

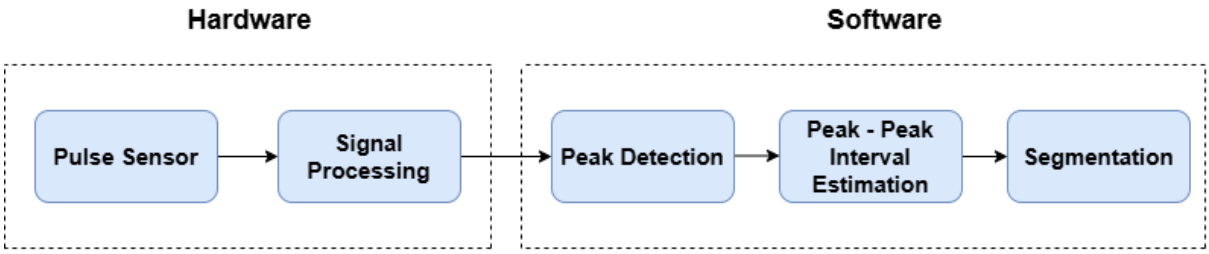

Fig. 1. Overall workflow of the proposed radial pulse peak detection and segmentation method.

A. Data Acquisition

Radial pulse waveforms were acquired using a Nellcor SpO_2 probe positioned at the radial site for non-invasive pulse signal measurement. The signals were sampled at 500 Hz**,**and each recording was obtained for approximately 3 min**.** A total of 25 real-time PPG recordings were considered for evaluation of the proposed peak-detection method. The recordings were obtained from healthy subjects and subsequently processed using the proposed signal-processing workflow.

For comparative evaluation, a separate dataset comprising 25 IPG samples was considered. The IPG dataset included samples representing five drug conditions and was used to compare the peak-detection results obtained using the proposed method with those obtained using a reference method**.** The complete datasets were used for the respective analyses. Representative results from 10 PPG recordings and 15 IPG samples are reported in this study.

The data used in this study were collected through the Department of Biomedical Engineering, MGM's College of Engineering and Technology, Navi Mumbai, Maharashtra, India, and Father Muller Medical College and Hospital, Mangaluru, Karnataka, India**.**

B. Signal Preprocessing

The acquired radial pulse signals may contain baseline variations, amplitude fluctuations, and unwanted noise resulting from recording conditions and sensor placement. Preprocessing was therefore performed before peak detection to improve signal quality while preserving the relevant characteristics of the pulse waveform.

Initially, baseline correction was applied to reduce slow variations and the DC component of the acquired signal. Smoothing was then performed to suppress small fluctuations present in the waveform. A Savitzky-Golay filter was applied to reduce high-frequency noise while maintaining the shape and important characteristics of the radial pulse waveform. Additional smoothing was applied to minimize residual fluctuations. Finally, the processed signal was normalized to reduce amplitude differences between recordings and provide a consistent signal range for subsequent peak detection and segmentation.

C. Systolic Peak Detection

Following preprocessing, systolic peaks were identified as the major local maxima corresponding to individual pulse cycles. A prominence-based peak-detection approach was employed to distinguish significant systolic peaks from minor fluctuations and noise.

The detection process considered peak prominence, peak amplitude, and minimum distance between successive peaks**.** The prominence criterion was selected according to the characteristics of the processed signal to accommodate variations in waveform amplitude. The minimum peak-distance constraint was used to prevent multiple detections within a single pulse cycle.

The detected systolic peak locations were stored as sample indices and marked on the processed waveform. These locations were subsequently used for peak-to-peak interval estimation, pulse-rate calculation, and adaptive segmentation of individual pulse cycles.

D. Peak-to-Peak Interval Estimation

After detecting the systolic peaks, the distance between consecutive peaks is calculated to determine the duration of each pulse cycle. The peak-to-peak interval represents the time difference between two successive systolic peaks and provides information about the cardiac cycle period. Fig. 2 shows the real-time radial pulse waveform with the detected systolic peaks and the corresponding heart rate, peak amplitude, and peak-to-peak interval.

The interval between adjacent detected peaks is calculated as:

$$CC = median(p_{\{i+1\}} - p_i)$$

where $P_i$represents the position of the current systolic peak, P_{i+1}represents the next detected peak, and CCindicates the estimated pulse cycle interval. Instead of using a fixed segmentation window, the proposed method calculates the cycle duration based on detected peak locations. The median value of consecutive peak differences is considered to reduce

the effect of irregular peaks and small variations in pulse rhythm [13]. This provides a stable reference interval for extracting individual pulse cycles from the continuous radial pulse waveform.

The detected peak positions are also used for pulse rate estimation. The time interval between successive peaks is calculated using the sampling frequency of the acquired signal. The pulse rate is obtained as:

$$Pulse\ Rate(BPM) = \frac{60}{Peak\ Interval}$$

where the peak interval represents the time duration between two consecutive systolic peaks in seconds.

The calculated peak-to-peak interval is further used to determine adaptive boundaries around each systolic peak for accurate segmentation of radial pulse cycles [14].

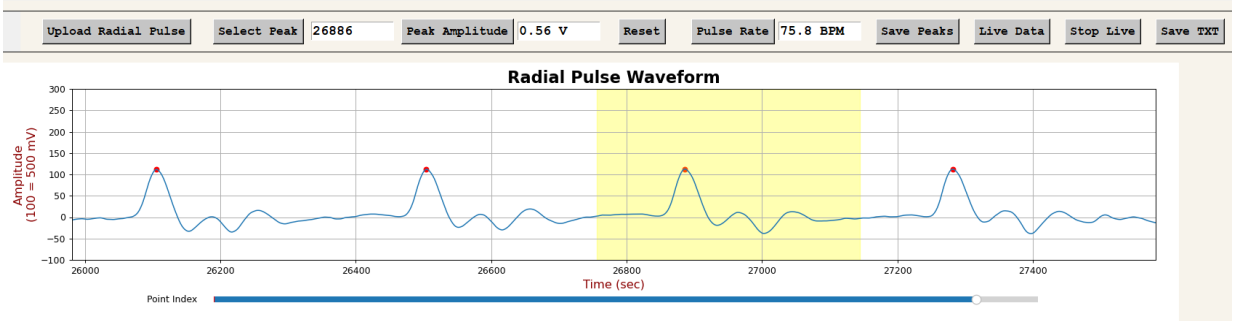

Fig. 2. Real-time radial pulse waveform showing detected systolic peaks and calculated pulse parameters.

Along with pulse rate estimation, the amplitude of the selected systolic peak is also calculated from the processed waveform. The peak amplitude represents the maximum pulse strength at the detected systolic point. It is obtained from the corresponding signal amplitude value as:

$$Peak\ Amplitude = \frac{A_p \times 0.5}{100}$$

where $A_p$represents the amplitude value of the selected peak from the acquired radial pulse waveform. The calculated peak amplitude provides additional information about the intensity variation of the recorded pulse signal.

E. Pulse Segmentation

After estimating the peak-to-peak interval, the continuous radial pulse waveform is divided into individual pulse cycles. The main objective of segmentation is to extract a complete waveform corresponding to each cardiac cycle while preserving important morphological characteristics.

For every detected systolic peak, the peak location is considered as a reference point. The calculated peak-to-peak interval is used to estimate the initial start and end boundaries of the pulse segment. The segmentation window is determined as:

$$Start = C - \frac{CC}{3}$$

$$End = C + \frac{2CC}{3}$$

where Crepresents the detected systolic peak position and CCrepresents the estimated peak-to-peak cycle interval.

This approach considers a smaller portion of the waveform before the systolic peak and a larger portion after the peak to include the complete rising and falling characteristics of the pulse cycle. Since the exact boundary points may vary due to waveform changes, additional valley-based refinement is performed.

For boundary correction, local minimum points are searched around the estimated start and end positions [15]. A smoothed valley detection approach is used to identify the nearest minimum locations between consecutive pulse cycles. These valley points provide more accurate starting and ending positions for each extracted waveform [16]. The extracted pulse segments generated using the proposed segmentation method are shown in Fig. 3.

After boundary refinement, each pulse segment is evaluated to remove incomplete or distorted cycles. The extracted segments are normalized and smoothed to maintain uniform waveform representation. Only valid pulse cycles containing a single dominant systolic peak are retained, while noisy segments are eliminated.

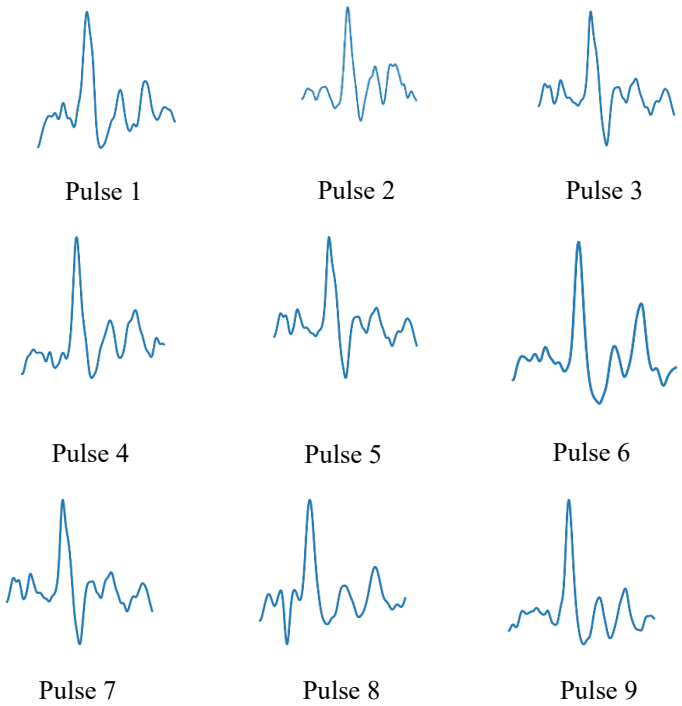

Fig. 3. Extracted pulse segments (Pulse 1-Pulse 9) obtained using peak-to-peak based segmentation.

Finally, the processed pulse cycles are stored individually as segmented waveform images. These extracted pulse segments provide a structured dataset suitable for further radial pulse waveform analysis.

F. Peak-Detection Performance Evaluation

The automatic peak-detection results were evaluated against the reference peak annotations. Seven performance parameters approved for this study were considered:

True Positive (TP): number of correctly detected reference peaks.

False Positive (FP): number of detected peaks that do not correspond to reference peaks.

False Negative (FN): number of reference peaks that were not detected.

Sensitivity/Recall: proportion of reference peaks correctly detected.

$$\frac{TP}{TP + FN} \times 100$$

Precision (Positive Predictive Value): proportion of detected peaks that correspond to reference peaks.

$$\frac{TP}{TP + FP} \times 100$$

Detection Error Rate (DER):

$$\frac{(FP + FN)}{(TP + FP + FN)} \times 100$$

F1-score: harmonic mean of precision and sensitivity.

$$\frac{2 \times (Precision \times Sensitivity)}{Precision + Sensitivity}$$

Accuracy was additionally reported as a summary measure of the proportion of correctly classified peak detections among the total detected and missed peak events.
These measures were used to quantify the ability of the proposed method to identify the reference systolic peaks while minimizing missed and incorrectly detected peaks.

G. Comparative Evaluation

A comparative evaluation was performed using 25 IPG samples representing five drug conditions. The peak-detection results obtained using the proposed method were compared with those obtained using the reference method. For each sample, the number of detected peaks from both methods was recorded and compared to assess the consistency of peak detection across the dataset. Results from 15 representative samples are presented in the comparative table, while the complete set of 25 samples was considered for the overall comparison. The comparison provides an additional evaluation of the proposed peak-detection approach under different IPG signal conditions.

IV. RESULTS AND DISCUSSION

The proposed peak-detection and segmentation method was evaluated using the radial pulse recordings collected for this study. The performance assessment was based on the detected systolic peaks and their correspondence with the reference peak annotations. In addition, a separate IPG dataset was used to compare the peak-detection results obtained using the proposed method with those obtained using the reference method.

The preprocessing procedure reduced baseline variations and unwanted fluctuations while retaining the characteristic morphology of the radial pulse waveform. The prominence-based detection approach identified the major systolic peaks from the processed signals, and the detected peak locations were subsequently used for peak-to-peak interval estimation and pulse-cycle segmentation. The adaptive segmentation procedure enabled the segment boundaries to vary according to the detected pulse-cycle duration, while valley-based refinement was used to obtain more appropriate boundaries between consecutive cycles.

The quantitative performance of the proposed peak-detection method was assessed using TP, FP, FN, sensitivity, precision, detection error rate, and F1-score. The results obtained from the complete PPG dataset were used for the performance assessment, while 10 representative samples are presented in the corresponding table to illustrate the sample-wise detection performance.

TABLE I Peak-detection results for 10 representative PPG samples.

Subject	Reference Peaks	Detected Peaks	TP	FP	FN	Accuracy %
1	252	250	250	0	2	99.21
2	163	163	161	2	2	97.58
3	200	200	196	4	4	96.08
4	151	151	150	1	1	98.68
5	230	226	226	0	4	98.26
6	179	179	179	0	0	100
7	247	247	242	5	5	96.03
8	214	214	212	2	2	98.15
9	221	221	221	0	0	100
10	210	206	204	2	6	96.23

The representative sample-wise results show that the proposed method detected the majority of reference systolic peaks with a limited number of false-positive and false-negative detections. The accuracy values across the 10 representative recordings ranged from 96.03% to 100%, demonstrating consistent peak-detection performance across the selected recordings.
The TP, FP, and FN values provide a direct measure of correctly detected, incorrectly detected, and missed systolic peaks, respectively. The corresponding sensitivity, precision, detection error rate, and F1-score further characterize the detection performance and provide a balanced assessment of the proposed method.

TABLE II Overall peak-detection performance of the proposed method.

Performance Parameter	Overall Value
Accuracy	97.98%
Sensitivity	98.74%
Precision	99.22%
F1 score	98.98%
Detection Error Rate (DER)	2.02%
TP	2041
FP	16
FN	26

The overall results obtained from the evaluated PPG recordings indicate a sensitivity of 98.74% and a precision of 99.22%, with an F1-score of 98.98%. The detection error rate was 2.02%. The evaluation resulted in 2041 true-positive detections, 16 false-positive detections, and 26 false-negative detections. These results indicate that the proposed method can detect systolic peaks with a high level of consistency while maintaining a low detection error.

For comparative evaluation, the proposed method was also applied to the 25 IPG samples representing five drug conditions. The detected peak counts were compared with those obtained using the reference method. Fifteen representative IPG samples are presented in the comparative table, while the complete set of 25 samples was considered for the comparison.

TABLE III Comparison of peak counts between the proposed method and the reference method

Sample No.	Drug Name	Proposed Method- No. of Peaks Detected	Reference Method- No. of Peaks Detected	Difference
1	Apis mel	306	310	4
2	Apis mel	300	304	4
3	Apis mel	290	295	5
4	Calcarea carb	388	391	3
5	Calcarea carb	351	354	3
6	Calcarea carb	270	268	2
7	Cocculus	250	248	2
8	Cocculus	209	206	3
9	Cocculus	303	301	2
10	Lycopodium	312	311	1
11	Lycopodium	312	310	2
12	Lycopodium	246	248	2
13	Sulphur	366	362	4
14	Sulphur	347	342	5
15	Sulphur	234	235	1

The comparative results provide an additional assessment of the peak-detection behaviour of the proposed method across different IPG signal conditions. Differences in detected peak counts between the two approaches are reported directly without assuming that a higher or lower peak count alone indicates superior performance.

V. CONCLUSION

This study presented an automated peak-to-peak based approach for systolic peak detection and segmentation of real-time radial pulse waveforms. The proposed processing pipeline combines signal preprocessing, prominence-based

systolic peak detection, peak-to-peak interval estimation, adaptive pulse-cycle segmentation, and valley-based boundary refinement. The detected systolic peaks provide temporal reference points for identifying individual pulse cycles and extracting consistent pulse segments.

The proposed method was quantitatively evaluated using 25 real-time PPG recordings. The overall evaluation yielded an accuracy of 97.98%, sensitivity of 98.74%, precision of 99.22%, and F1-score of 98.98%, with a detection error rate of 2.02%. The evaluation resulted in 2041 true-positive detections, 16 false-positive detections, and 26 false-negative detections. In addition, 25 IPG samples representing five drug conditions were used for comparative evaluation with a reference method.

The extracted pulse cycles provide a structured signal representation that can support subsequent radial pulse morphology analysis and related biomedical signal-processing applications. Future work will focus on further validation using larger and more diverse datasets and evaluation under a wider range of signal-quality and physiological conditions.

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