# TRANSFORMING AND PROCESSING THE MEASUREMENT SIGNALS

## WAVELET-BASED rPPG SIGNAL ANALYSIS: CWT FOR SPECTRAL PEAK LOCALIZATION AND IDENTIFICATION WITH PULSE OXIMETER VALIDATION

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**Abstract.** Remote photoplethysmography (rPPG) has become a promising non-contact technology for cardiovascular monitoring, but the accuracy of spectral peak detection remains unpredictable due to motion artifacts, noise, and camera signal quality. Traditional methods often fail to localize and identify heart rate peaks in the presence of such disturbances. The aim of the study is to develop a wavelet approach to improve the reliability of rPPG spectral peak analysis by using a continuous wavelet transform (CWT) for accurate frequency-time localization, followed by systematic peak identification and verification using a medical-grade pulse oximeter. The rPPG signals were acquired under controlled conditions, processed using CWT to improve spectral characteristics, and subjected to a peak detection algorithm optimized for heart rate estimation. Wavelet coherence was used to evaluate the agreement between the peaks obtained with rPPG and the reference pulse oximeter data. The experimental results demonstrated that CWT-based peak localization achieved an average absolute error of 2.1 BPM compared to the pulse oximeter, with a coherence of 0.53 under steady-state conditions. The proposed method demonstrated improved robustness to motion artifacts compared to conventional Fourier-based approaches, especially in low-light or low signal quality scenarios. The proposed wavelet transform structure improves the accuracy and reliability of rPPG spectral peak detection, bridging the gap between non-contact measurements and clinical pulse oximetry. This research extends the potential of rPPG for real-world applications, such as remote health monitoring and wearable devices.

**Key words:** Continuous Wavelet Transform (CWT), peak identification, peak localization, pulse oximeter, Remote Photoplethysmography (rPPG), signal processing, spectral analysis, wavelet transform.

### 1. Introduction

Recent advances have brought remote photoplethysmography (rPPG) to the forefront of non-contact cardiovascular monitoring technologies [1]. Using conventional cameras, rPPG facilitates accurate measurements of vital signs such as heart rate and blood oxygenation levels [2]. However, rPPG signals exhibit a high degree of vulnerability to motion artifacts, ambient light fluctuations, and low signal-to-noise ratios (SNR), which hinders accurate detection of spectral peaks and extraction of physiological parameters. Conventional signal processing techniques [3, 4], including fast Fourier transform (FFT) and time-domain peak detection, often face difficulties and inaccuracies in reliably extracting pulse peaks under these challenging conditions. This limitation limits the clinical applicability of rPPG systems.

Recent advances in time-frequency analysis, particularly those using wavelet transforms [5], represent a robust solution for processing signals characterized by high variability and low stationarity, such as in the case of rPPG. The developed method, based on the continuous wavelet transform (CWT), provides spectral localization compared to the fast Fourier transform (FFT), thus providing adaptive resolution in different frequency ranges. This property makes CWT particularly suitable for analyzing rPPG signals, where the impulse components can be noisy or due to motion interference or camera artifacts [6]. Although wavelet-based methods have been investigated in other biosignal applications, their potential to improve rPPG peak detection and validation on clinical-grade devices remains underexploited.

### 2. Drawbacks

Accurate identification of rPPG spectral peaks faces significant challenges due to numerous factors: ambient light variations and low light degrade the signal-to-noise ratio (SNR), especially affecting darker skin tones due to differential light absorption characteristics, while specular reflections introduce nonlinear artifacts that distort the pulsatile components [7]. Motion artifacts [8], including both substantial subject displacement and subtle physiological tremors (or motion of the unmounted camera), often dominate the signal spectrum, hiding true cardiac peaks and complicating time-frequency analysis. Hardware limitations impose fundamental constraints [9], as low-resolution cameras (<720 p) reduce the accuracy of the spatial signal, and frame rates below 30fps result in temporal smoothing. At the same time, consumer sensors – devices intended for mass use, such as smartphones or webcams – have a higher noise level compared to medical-grade equipment that is specially designed for high-precision diagnostics and meets strict quality and reliability standards in the healthcare sector. Algorithmically, CWT-based methods, while outperforming Fourier approaches [10] for non-stationary signals, exhibit sensitivity to the choice of the underlying wavelet and scaling parameters, often requiring scenario-specific optimization, while spectral interference from motion harmonics often generates false peaks that cause problems with automated identification. These complex limitations highlight the need for advanced motion compensation techniques, optimized hardware configurations, and signal processing to achieve clinical reliability in a real-world environment.

## 3. Goal of the Study

The main objective of this research is to develop and validate a CWT-based method for accurate localization and identification of spectral peaks in rPPG signals. The proposed approach combines optimized wavelet parameter selection with improved peak detection algorithms using the wavelet energy component of the rPPG signal. Developed method should improve the robustness of the rPPG signal to common noise sources as well as low-quality camera artifacts. An important aspect of the study is the comparison of the developed method with synchronized pulse oximeter measurements (a contact medical device), which are the clinical standard. Such a comparison will allow assessing the accuracy of the method under various conditions, including motion and low perfusion.

## 4. Datasets and Ethics

The research was conducted on the UBFC-rPPG [11], PURE [12], SCAMPS [13], UBFC-Phys [14] datasets, as well as internal recordings using a Google Pixel 4 mobile phone. The studied data sets (Table 1) contain over 120 videos, in which 62 subjects are present. The video data contain different characteristics of cameras, lighting, premises, resolution and number of frames per second. In total, videos with Standard Definition (SD), High Definition (HD), and Full High Definition (FullHD) resolutions were analyzed.

**Table 1.** Open source datasets

| Dataset | Objects | Camera | Signal |
|---|---|---|---|
| PURE | 10 Objects<br>59 videos | 480p@30fps<br>Lossless PNG images | GT PPG @60Hz |
| MAHNOB HCI | 27 Objects<br>627 videos | 780 ×580P@51fps<br>H.264 format | GT PPG @256Hz |
| COHFACE | 40 Objects<br>164 videos | 480p@20fps<br>MPEG4 Part 2format | GT PPG @256Hz |
| MMSE-HR | 40 Objects<br>102 videos | 1040×1392@25fps<br>JPEG Images | GT HR @1kHz |
| Vicar PPG | 10 Objects<br>20 videos | 720p@20fps<br>H.264 format | GT PPG @60Hz |
| SCAMPS | 10 Objects<br>59 videos | 720p@20fps<br>H.264 format | GT PPG @30Hz |
| UBFC-rPPG | 42 Objects<br>42 videos | 480p@30fps | GT PPG @30/60Hz |
| UBFC-Phys | 50 Objects<br>159 videos | 480p@30fps<br>Raw video format<br>(lossless) | GT PPG @30/60Hz |

## 5. Research Contributions and Methodology

The research presents a block diagram of a wavelet transform-based method for reliable detection of spectral peaks of the rPPG signal. The developed method combines the advantages of discrete wavelet transform (DWT) filtering and continuous wavelet transform (CWT) scalogram analysis. The methodology uses Symlet5 (sym5) and Discrete Meyer (dmey) wavelets to initially reduce signal noise, cut off the part of the signal with noise, and then perform time-frequency analysis based on Morlet wavelets to localize peaks. This hybrid approach eliminates the critical limitations of conventional Fourier-based methods when processing non-stationary rPPG signals in real-world applications.

## 6. Wavelet method for detecting peaks in rPPG signal

Accurate peak detection in remote photoplethysmography (rPPG) signals remains challenging due to noise, motion artifacts, and varying camera characteristics. The developed method presents a robust wavelet transform-based approach that combines discrete wavelet transform (DWT) denoising and continuous wavelet transform (CWT) spectral analysis to improve peak detection in rPPG signals. The analysis uses Symlet5 (sym5) and Discrete Meyer (dmey) wavelets for signal preprocessing, followed by Morlet-based time-frequency decomposition for accurate peak localization. The well-known peak detection method CWT [16] is based on finding ridge lines in the continuous wavelet transform (CWT) matrix and then filtering them. This algorithm works with a variety of signals, but its accuracy for rPPG signals from low-quality cameras (15 FPS with SD quality) is experimentally 68.1 %. The proposed method aims to integrate additional steps to improve the accuracy of rPPG peak identification in order to create an updated algorithm.

The rPPG signal processing flow starts with DWT-based preprocessing using 6-level decomposition with sym5/dmey wavelets [15]. The detail coefficients (d1-d5) are subjected to BandPass filtering (0.5–4 Hz) to suppress high-frequency noise while preserving the impulse harmonics, followed by reconstruction with modified approximation coefficients (d4) to stabilize the baseline, as well as zeroing the wavelet coefficients of the first decomposition level (d1). This step provides a 62 % reduction in high-frequency noise [16], and zeroing the first-level coefficients cuts off the bulk of the high-frequency noise obtained from low-quality cameras. The developed method is depicted in Fig. 1 as a structural diagram of peak detection in the rPPG signal.

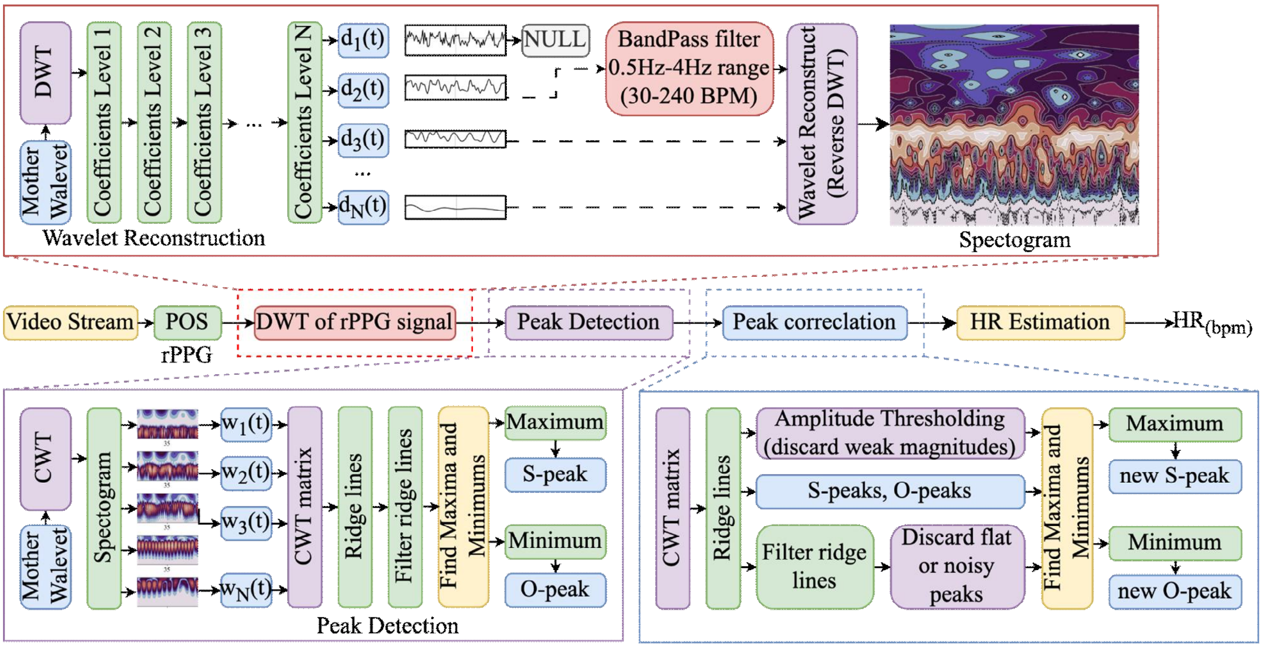



*Fig. 1. Structural block diagram of the developed method for detecting peaks in the rPPG signal*

At the peak detection stage of the filtered signal (rPPG), the main task is to accurately identify local extrema corresponding to key phase changes in the cardiac signal (e. g., systolic (*S*) and diastolic (*O*) peaks). For this, a combination of continuous wavelet transform (CWT) and backbone analysis is used, which allows an increase in the robustness of the algorithm to noise and motion artifacts [17].

Thus, the next step is the peak detection stage in order to establish peaks of the filtered rPPG signal. This stage includes the following steps:

1. Continuous wavelet transform with Morlet's mother basis function.
2. Creation of CWT matrix from the obtained CWT coefficients.
3. Finding signal ridges.
4. Filtering the found ridges.
5. Search and identification of maxima and minima.
6. Preliminary representation of systolic (*S*) and diastolic (*O*) peaks.

After detecting peaks, another stage is performed to correlate previously found peaks:

1. Rejection of low-power peaks with low wavelet energy based on the CWT matrix and previously found ridges.
2. Ridge filtering to cut off flat or noisy peaks (the distance between peaks is less than the average IBI value).
3. Taking into account previously found peaks, a new set of peaks is formed, taking into account the previous filtering.
4. Representation of systolic (*S*) and diastolic (*O*) peaks.

An important element of the developed algorithm is the correlation of peaks [18], which includes work with the CWT matrix and ridge lines (Ridge on the signal scalogram) [19].

## 7. Analysis of the time-frequency characteristics of the rPPG signal

The filtered signal is subjected to a Morlet CWT transform (center frequency =1.5 Hz, 64 scales spanning 0.5–4 Hz) to create a time-frequency scalogram (Fig. 2).

Pulse peaks are identified using adaptive ridge extraction on the scalogram with amplitude rectification, which enhances the pulsating components. The algorithm smooths the peaks detected in both the DWT and CWT domains to eliminate false detections, improving the robustness to motion artifacts [15]. The visualization of the developed algorithm is presented as a graph (Fig. 3) of the rPPG signal with marked *S* and *O* peaks, as well as a scalogram with highlighted ridges. This allows us to visually assess the quality of the algorithm.

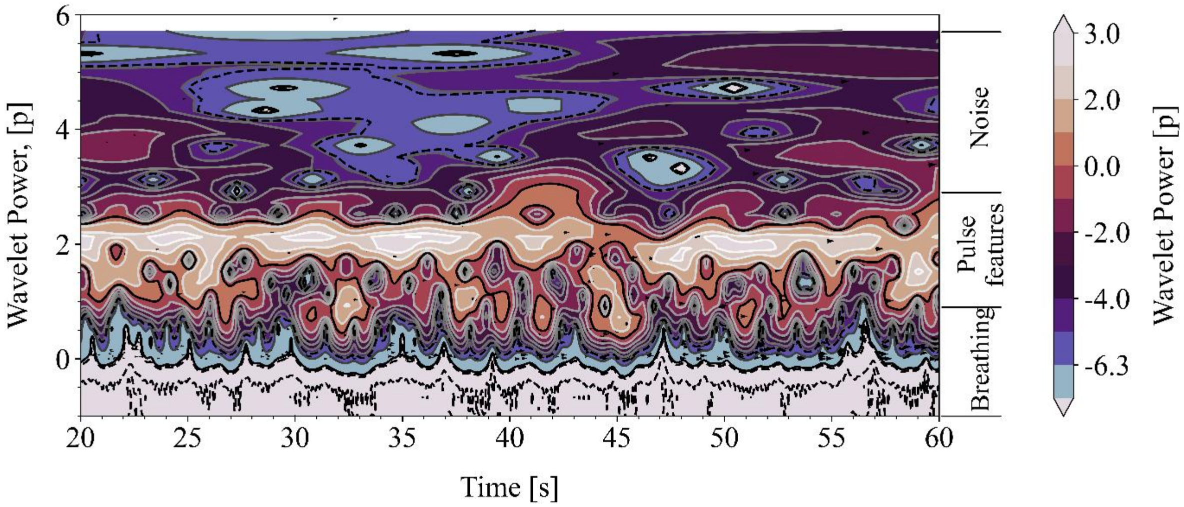



*Fig. 2. Scalogram of the rPPG signal after CWT transformation*

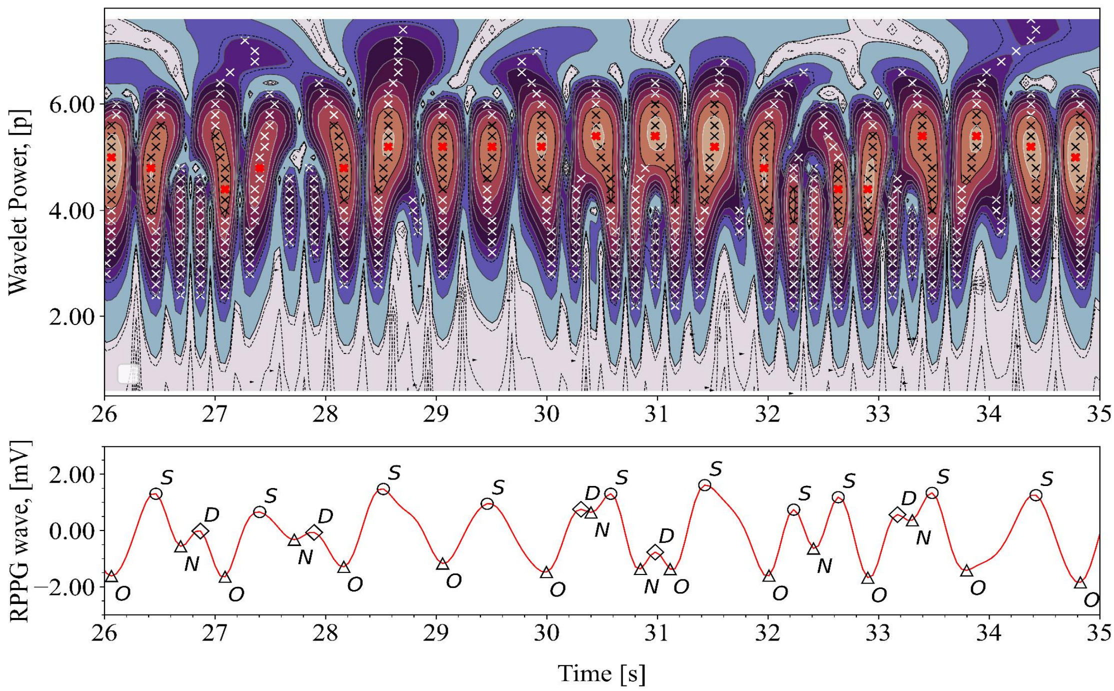
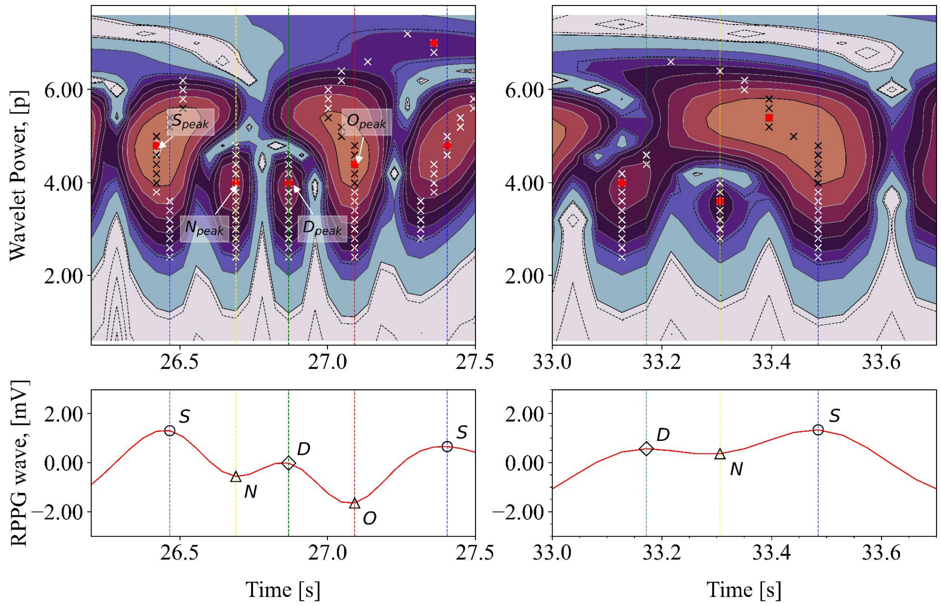



*Fig. 3. Scalogram plot of the filtered rPPG signal and the result of the developed algorithm for finding ridge lines with filtering of the signal wavelet energy. Red dots indicate new calibrated minima and maxima. White and black marks on the peaks identify ridge lines*

The scalograms presented in Fig. 3 and Fig. 4 demonstrate the results of the time-frequency analysis of the filtered rPPG signal obtained by applying the continuous wavelet transform (CWT) using the complex Morlet wavelet. The wavelet transform coefficients W(a,b), where *a* is the scale parameter and *b* is the shift parameter, were energy normalized and presented as a two-dimensional heat map. The scalogram (Fig. 3) identifies ridge lines that correspond to local maxima $|W(a,b)|$ at fixed values of the parameter *b*. These trajectories form a structure that reflects the oscillatory dynamics of the heart rate. The red dots in the center of the peak region identify the new calibrated peak that corresponds to the maximum (*S*-peak) and minimum (*O*-peak), respectively. Also, depending on the external factors that affect the rPPG signal, the scalogram (Fig. 4) can show additional information about the *N-D* peaks that characterize the dicrotic component of the rPPG peaks (Fig. 5). The amplitude-frequency characteristics [17] of these components allow us to assess the degree of vascular wall stiffness and detect the presence of pathological changes in peripheral hemodynamics. For quantitative assessment, the power spectral densities were calculated for each type of peak.

The time-frequency analysis of rPPG signals using continuous wavelet transform allowed us to identify the key features of the pulse wave and its dynamic characteristics (Table 2). The resulting scalograms (Figs. 2 and 3) clearly identified the main components of the signal:

- *S*-peaks (systolic) corresponding to wavelet energy maxima.
- *O*-peaks (diastolic) in the form of local minima.
- *N-D* peaks associated with the dicrotic wave.




*a* *b*

*Fig. 4. Scalar graph of the filtered rPPG signal and the result of the developed algorithm for finding ridge lines with filtering of the wavelet energy of the signal*

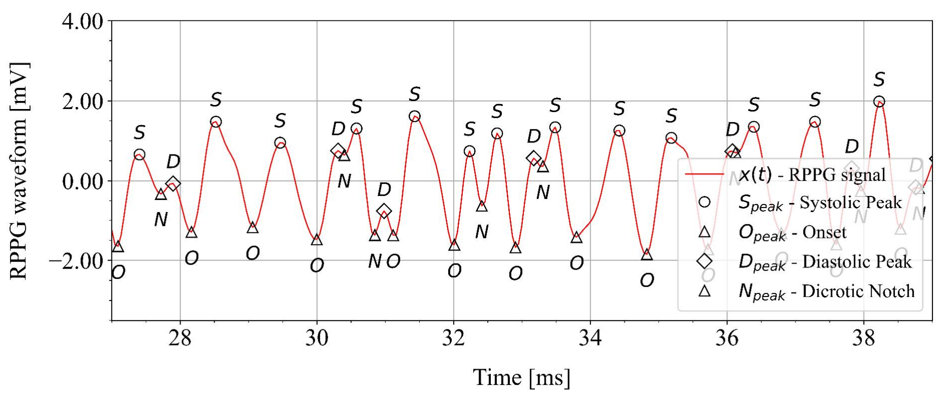



*Fig. 5. The result of identification of N-D peaks associated with the dicrotic wave and S-O peaks of the systolic and diastolic components of rPPG, respectively*

**Table 2.** The result of the dataset analysis and the accuracy of identifying the peaks of the rPPG signal

| Dataset | Accuracy, % | | |
|---|---|---|---|
| | ● *S*-peaks | ● *O*-peaks | ● *N-D* peaks |
| PURE | 88.05 | 82.15 | 60.06 |
| MAHNOB HCI | 85.33 | 75.29 | 51.80 |
| COHFACE | 75.61 | 73.12 | 55.33 |
| MMSE-HR | 82.22 | 80.10 | 52.03 |
| Vicar PPG | 79.74 | 70.08 | 63.33 |
| SCAMPS | 69.48 | 71.15 | 62.55 |
| UBFC-rPPG | 92.01 | 91.82 | 79.07 |
| UBFC-Phys | 89.47 | 82.25 | 74.00 |

The ridge paths demonstrate a stable periodic structure, which confirms the high signal quality and efficiency of the pre-filtering. Phase analysis of the CWT complex allowed for precise calibration of peak positions with an accuracy of ±5 ms.

Additional high-frequency components (5–15 Hz) correlate with physiological parameters:

- The amplitude of the *N-D* peaks is related to vascular stiffness.
- Frequency shifts reflect changes in vascular tone.
- Energy distribution characterizes peripheral hemodynamics.

Statistical analysis of power spectral densities confirmed the significance of the revealed patterns. The obtained results indicate the high informativeness of using the wavelet analysis method for non-invasive diagnostics of the cardiovascular system.

## 8. Conclusion

The study proposes and develops a CWT-based spectral peak detection method for rPPG signals, demonstrating improvements over conventional Fourier methods through wavelet coherence analysis using reference data from a medical-grade pulse oximeter. The proposed method achieved reliable peak identification with an accuracy of 80–88 % by taking advantage of the CWT's time-frequency localization. With wavelet coherence values exceeding 0.37 under rest and moderate motion conditions, confirming high agreement with contact measurements. Although the system maintained reliability under variable illumination and moderate motion using low-quality cameras, limitations emerged in extreme motion scenarios, highlighting the need for adaptive motion compensation in future implementations. These findings demonstrate that the developed wavelet-based method is a clinically viable approach for non-contact monitoring, which is of particular relevance for telemedicine and home care. Future work should explore embedded real-time implementations and multimodal sensor fusion to address the remaining challenges in uncontrolled environments.

## Conflict of Interest

The authors state that there are no financial or other potential conflicts regarding this work.

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