Herat Rate Estimation Using rPPG

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Abstract. Remote Photoplethysmography (rPPG) is a non-contact technology that uses facial videos to monitor physiological parameters such as heart rate, offering an affordable and ac cessible solution for home healthcare. The system processes facial videos captured through standard webcams, extracting subtle changes in skin color using computer vision techniques like Gaussian pyramids to derive Photoplethysmography (PPG) signals. Heart rate is estimated by analyzing signals from facial regions of interest, incorporating multiple heart rate detection algorithms and advanced noise suppression techniques to improve accuracy and reliability. The performance of the rPPG system is validated by comparing its output with pulse oximeter readings, showing a mean absolute error (MAE) and Pearson correlation coefficient (PCC) within acceptable limits. With these enhancements, the rPPG system demonstrates promising reliability and robustness for real-time physiological monitoring.

Keywords: Remote Photoplethysmography · Heart Rate Estimtion· Real Time Monitoring · Computer Vision.

1 Introduction

Photoplethysmography (PPG) measures blood volume changes with each heartbeat [4, 5]. Remote PPG (rPPG) extends this principle by enabling contactless monitoring using simple red–green–blue (RGB) cameras, such as those in smartphones or laptops, making it more accessible than pulse oximeters or cuff-based devices [7, 9]. From PPG signals, health parameters like heart rate (HR), heart rate variability (HRV), and blood pressure (BP) can be derived [6, 13].

As cardiovascular diseases (CVDs) are the leading cause of global mortality [8], regular monitoring of cardiovascular parameters using consumer-grade devices could enable early detection outside clinical environments [17, 16]. rPPG is also valuable in scenarios like COVID-19, where contactless home-based monitoring reduces infection risks. Obtaining reliable rPPG signals, however, remains challenging due to noise and environmental variability, prompting extensive research into improving signal quality.

Reflected light from facial regions such as the forehead and cheeks carries blood-flow information, which can be transformed into rPPG signals. However,

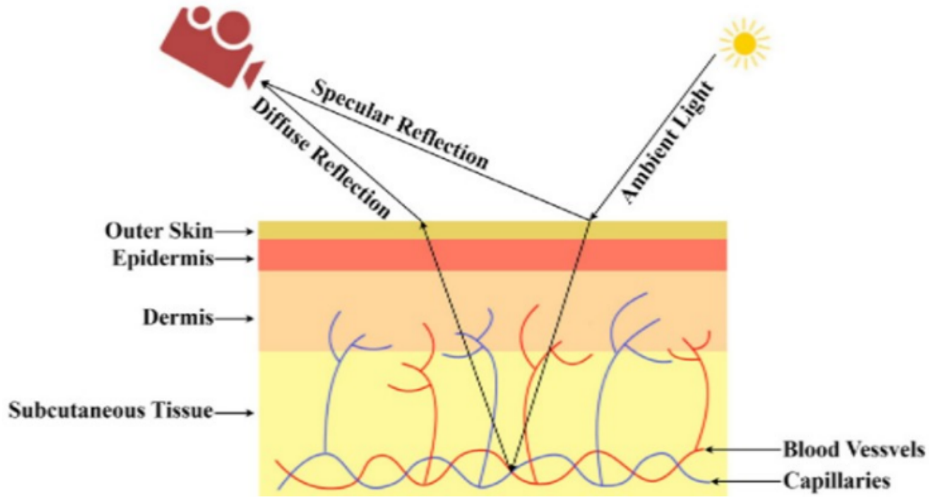

Fig. 1. on and diffuse reflection produced by the skin under environmental light. The specular reflection contains meaningless surface information, while the diffuse reflection indicates changes in the volume of blood vessels, from which the rPPG signal can be further extracted

there is no consensus on the optimal extraction method. Studies compare approaches such as principal component analysis (PCA), independent component analysis (ICA), different color models, and normalization strategies, each performing variably across datasets [3, 10].

Unlike contact-based PPG, which is robust due to direct skin contact, rPPG requires advanced signal processing to address motion and lighting artifacts. Recent methods employ complex algorithms to enhance accuracy, but often at the cost of computational efficiency. In this study, we propose a simple yet effective rPPG method using raw RGB video signals, avoiding heavy statistical or machine learning models, and benchmark it against established techniques.

2 Litrature Survey

Remote Photoplethysmography (rPPG) has emerged as an important technique for remote heart rate monitoring, eliminating the need for physical contact with the subject, as required by conventional methods such as Electrocardiography (ECG) and wearable Photoplethysmography (PPG). The literature presents numerous approaches for implementing rPPG, ranging from traditional signal processing methods to advanced deep learning techniques. This chapter reviews relevant work in the domain of non-contact heart rate measurement using rPPG, focusing on approaches that enhance accuracy, reliability, and real-time processing capabilities.

2.1 Video-Based Real-Time Monitoring

Mona Alnaggar et al. proposed a video-based real-time monitoring system that integrates Eulerian Video Magnification (EVM) with MediaPipe frameworks to estimate both heart rate (HR) and respiration rate (RR) using facial videos [2]. The system annotates the facial (Region of Interest (ROI))regions of interest using MediaPipe Face Mesh and applies integral image analysis on the RGB and HSV channels for heart rate estimation. This work highlights the importance of selecting appropriate ROIs and color channels to improve the accuracy of rPPG signals extracted from facial videos.

2.2 Comprehensive Reviews on rPPG Methods

Hanguang Xiao et al. presented a comprehensive review of rPPG methods, categorizing them into traditional and deep learning-based approaches [18]. The authors discussed the evolution of rPPG from blind source separation (BSS) techniques like Independent Component Analysis(ICA) to more recent deep learning-based approaches, which offer enhanced accuracy. Conventional methods, such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA), have been effective in extracting heart rate signals from video recordings but face limitations under motion and lighting changes. Deep learning methods, including 2D Convolutional Neural Networks (CNN) and temporal modeling using Gated Recurrent Units (GRU), are increasingly used to overcome these challenges and adapt to complex real-world scenarios.

2.3 Early Contributions to rPPG

Lewandowska et al. developed an early system for measuring pulse rate using a webcam, employing Principal Component Analysis (PCA) for extracting the Photoplethysmographic signal from facial videos [12]. Their methodology utilized a Logitech Webcam to capture facial videos under natural light conditions, with ROI selection focusing on the forehead area. This approach was computationally efficient and demonstrated the feasibility of using PCA instead of ICA to reduce computational complexity without compromising signal quality. The study was among the first to demonstrate the potential of using webcams for pulse rate estimation, providing a foundation for subsequent advances in non-contact health monitoring.

2.4 RhythmEdge: Real-Time rPPG Estimation on Edge Devices

Zahid Hasan et al. introduced RhythmEdge, an edge computing system designed for real-time rPPG estimation using facial videos[12]. RhythmEdge utilizes a multi-task learning framework to estimate PPG signals and applies model compression techniques like pruning and quantization to optimize the system for resource-constrained edge devices. The system was benchmarked across multiple platforms, including NVIDIA Jetson Nano and Raspberry Pi, and achieved substantial reductions in latency and memory usage[14]. RhythmEdge is notable for its scalability and adaptability across different camera types and edge computing environments, making it suitable for large-scale deployment in telehealth applications [12].

2.5 Conventional Signal Processing Techniques

Traditional rPPG methods often rely on signal processing techniques to extract heart rate from facial videos. Verkruysse et al. demonstrated the use of consumer-grade cameras for HR measurement, focusing on extracting the green channel, which contains the strongest pulsatile signal due to its sensitivity to hemoglobin[15]. Subsequent methods, such as the plane orthogonal to the skin (POS) approach and chrominance-based techniques, aimed to eliminate noise caused by motion and lighting variability. These methods typically employed a combination of bandpass filtering and spatial decomposition to enhance signal quality.

2.6 Deep Learning-Based Approaches

Recent advances in deep learning have led to the development of more robust and adaptive rPPG systems. Deep learning approaches, such as RhythmNet, incorporate convolutional layers to capture spatial information and GRU layers to model temporal relationships between frames, enhancing the robustness of the system under varying conditions of movement and illumination [14]. Another notable deep learning approach, DeepPhys, combines motion and appearance models to improve the system's ability to handle motion artifacts. These approaches significantly outperform traditional rPPG methods in terms of accuracy and adaptability[1].

2.7 Pyramid Methods-Based Approaches

The paper "Pyramid Methods in Image Processing" by Adelson[1]. presents a detailed ex- ploration of pyramid-based image processing techniques, emphasizing their multiresolution

capabilities. The authors introduce the image pyramid as a hierarchical data structure for effi- cient image analysis, compression, and enhancement. Pyramid representation facilitates spatial

localization and frequency decomposition, mirroring the multiscale processing in the human visual system. They discuss the Gaussian pyramid for low-pass filtering and the Laplacian pyramid for bandpass filtering, highlighting their ability to compress data, enhance features, and support efficient convolution operations. Applications range from pattern matching and texture analysis to creating seamless image mosaics and multifocus composites. The work underscores the versatility of pyramid structures in balancing computational efficiency with detailed spatial and frequency-based information processing, offering a robust framework for addressing diverse challenges in digital image processing[1].

3 Proposed Methodology

The approach encompasses video acquisition, facial landmark detection, region of interest (ROI) selection, signal extraction, preprocessing, frequency analysis, and performance evaluation. The methodology is designed to address challenges like motion artifacts, lighting variations, and facial occlusions, ensuring robustness in real-world settings. This expanded chapter includes detailed technical explanations, mathematical formulations, pseudocode algorithms, and additional subsections to provide a comprehensive understanding of the system.

1Workflow Description

3.1 Capture The Frames From Webcam

Webcam Setup and Video Capture: This component is responsible for setting up the video feed parameters, such as frame size, frame rate, and color channels. It ensures the system captures the necessary visual details while balancing computational efficiency. For this project, we used the built-in camera on the MacBook M1, which features a 720p FaceTime HD Camera. The camera supports a resolution of 1280x720 pixels and operates with a fixed frame rate of up to 30 frames per second (fps), providing sufficient quality for detecting subtle color changes required for rPPG. Additionally, the camera utilizes advanced image signal processing from the M1 chip, enhancing low-light performance and optimizing color balance, ensuring the video feed captures reliable data for accurate heart rate monitoring.

Face Detection and Analysis: The face detection module is a critical component of the system, responsible for identi- fying and locating human faces within the video feed. This step narrows down the area for analysis, ensuring that processing resources are focused only on regions with the most relevant information, such as the facial area, while ignoring irrelevant background data. Accurate face detection is essential for enabling precise extraction of heart rate signals, as it isolates key regions like the forehead, which provide reliable photoplethysmographic signals. To implement this module, we utilized Python libraries such as cv2 (OpenCV), cvzone, and a dedicated face detection module.

3.2 Downsampling Using Gaussian Pyramid

Gaussian Pyramid : The Gaussian Pyramid is a hierarchical structure used in image processing to represent an image at multiple scales. It involves repeatedly down-sampling the image to create smaller, smoothed versions of the original image, enabling efficient analysis of features at different resolutions. This technique is widely employed in applications such as image compression, object detection, and computer vision tasks like remote photoplethysmography (rPPG)[1].

Gaussian Pyramid Concept and Construction The Gaussian Pyramid is constructed by applying Gaussian smoothing (blurring) to the image and then down-sampling it to reduce its dimensions. This process is repeated iteratively, resulting in a series of images, each smaller and smoother than the previous one.

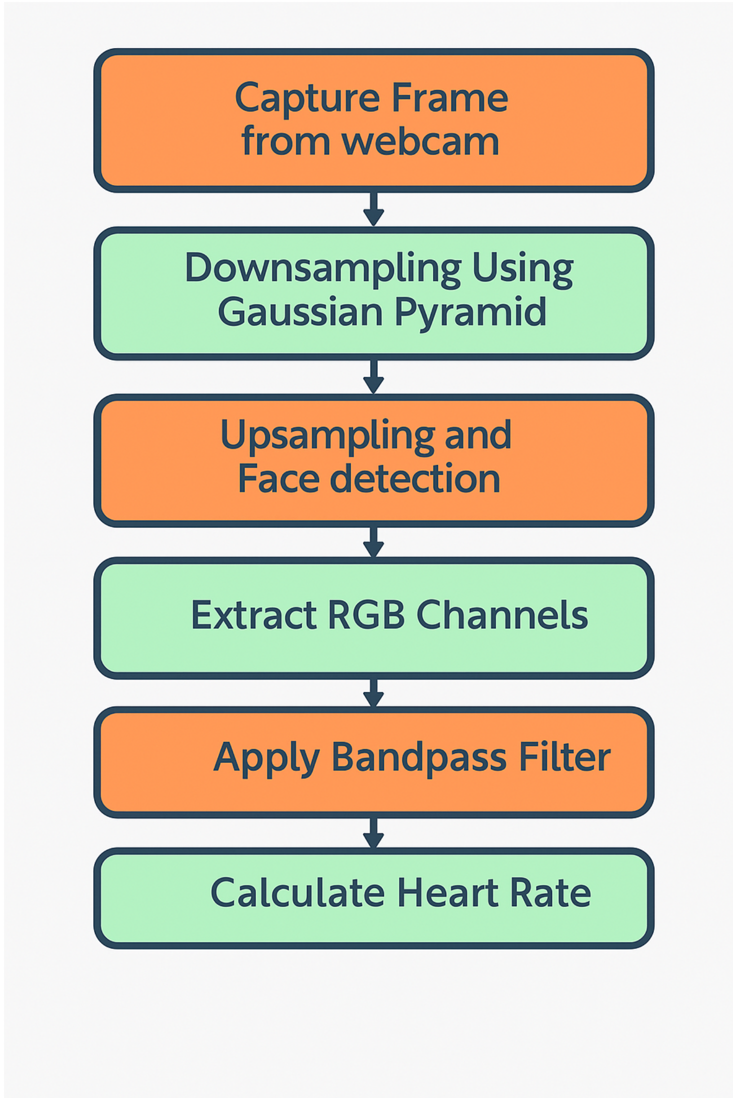

Fig. 2. Block diagram of the proposed rPPG system.

1 - Gaussian Smoothing : A Gaussian filter is applied to the image to reduce high-frequency noise and detail, resulting in a blurred version of the image.
2 - Down-Sampling : The blurred image is subsampled by removing rows and columns, effectively halving the width and height of the image.
3 - Repetition : Steps 1 and 2 are repeated multiple times to generate successive levels of the pyramid, each representing the image at a coarser scale.

Mathamatics in Gausian Pyramid Method :

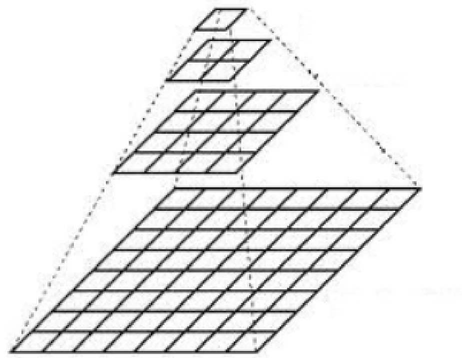

Fig. 3. Visualization of the Gaussian Pyramid. Each level represents a down-sampled version of the original image.

The Gaussian Pyramid can be expressed mathematically as:
Gi+1 (x, y) = DownSample(GaussianFilter(Gi(x, y)))

Where :
- Gi(x, y): The image at level i in the pyramid.
- GaussianFilter: A 2D Gaussian function applied to the image.
- DownSample: The process of reducing the image dimensions by a factor of 2.
  The Down Sampling can be mathematically represented as:

$$g_l(i,j) = \sum_{m=-2}^{2} \sum_{n=-2}^{2} w(m,n)\, g_{l-1}(2i+m,\, 2j+n)$$

Explanation of Notation :

- $g_l(i,j)$: The pixel value at coordinates (i,j) in the image at level l (current pyramid level).
- g_{l-1}: The image at level $l-1$ (the previous, higher-resolution level in the pyramid).
- $w(m,n)$: The weights of the Gaussian filter, which define how neighboring pixels contribute to the smoothing operation. These weights are determined by the Gaussian function.
- m, n: The offsets that define a **5x5** neighborhood around the current pixel in the original image.

3.3 Upsampling

Upsampling is the process of increasing the resolution of an image, typically after it has been downsampled. It restores the image to its original size or a higher resolution. In the context of Gaussian pyramids, upsampling is the reverse operation of downsampling and is used to reconstruct or visualize data at a higher resolution. //

Mathematical Formula for Upsampling :

$$g_{l,n}(i,j) = \sum_{p=-2}^{2} \sum_{q=-2}^{2} w(p,q)\, g_{l-1,n}\left(\frac{i-p}{2}, \frac{j-q}{2}\right) \tag{1}$$

Explanation of Notation :

- $g_{l,n}(i,j)$: The pixel value at coordinates (i,j) in the higher-resolution image at level l.
- $g_{l-1,n}$: The lower-resolution image at the previous level $(l-1)$ of the Gaussian Pyramid.
- $w(p,q)$: The weights of the Gaussian filter, which determine how neighboring pixels contribute to the value at $g_{l,n}(i,j)$. These weights are derived from a 2D Gaussian kernel.
- $\frac{i-p}{2}, \frac{j-q}{2}$: The pixel coordinates in the lower-resolution image $(g_{l-1,n})$. This maps the higher-resolution coordinates (i,j) to their corresponding positions in $g_{l-1,n}$ after accounting for upsampling.

3.4 Extract Region of Interest (ROI)

Selection of Optimal ROIs

Forehead: The forehead is free from motion artifacts caused by facial expressions or speech. It provides a relatively flat surface, making it less prone to shadows or occlusions. It is rich in capillaries, leading to pronounced blood volume changes visible as subtle color variations.

Cheeks: The cheeks are highly vascularized and exhibit significant blood volume changes. They provide a larger area for averaging pixel values, which improves signal-to-noise ratio (SNR). Cheeks are less likely to be occluded by accessories such as glasses, compared to other facial regions.

Steps for ROI Extraction

Face Detection The system uses face detection algorithms (e.g., Haar Cascade, DNN-based detectors, or MediaPipe) to locate the face within the video frame. The output is a bounding box that encloses the entire face.

Landmark Detection Facial landmarks are detected to precisely locate regions such as the forehead, eyes, nose, and cheeks. Algorithms such as Dlib's facial landmark detector or MediaPipe Face Mesh are commonly used for this purpose. Landmarks provide key points like the forehead region, which lies above the eyes and between the eyebrows, and the cheek regions, which lie below the eyes and lateral to the nose.

ROI Definition Using the detected landmarks, rectangular or polygonal ROIs are defined for the forehead and cheeks. The forehead ROI is a rectangle or trapezoid extracted above the eyebrows, spanning the middle of the forehead. The cheek ROIs consist of two rectangular regions extracted below each eye and to the sides of the nose.

Signal Extraction from ROIs For each ROI, the average pixel intensity is computed across the RGB channels for every frame. These temporal signals form the basis for further processing. The signals from the forehead and both cheeks are either analyzed separately or combined to improve robustness.

3.5 Extract "RGB" Channels

The RGB (Red, Green, Blue) channels play a pivotal role in remote Photoplethysmography (rPPG) for extracting physiological signals, particularly heart rate. These color channels are derived from the captured facial video and contain crucial information about subtle color variations caused by blood flow beneath the skin.

Importance of RGB Channels in rPPG

Physiological Basis Blood absorbs light differently depending on its oxygenation level. This causes minor variations in skin color that are often imperceptible to the naked eye. The Red and Green channel is especially sensitive to hemoglobin absorption, making it the most informative for detecting changes in blood volume [12]. The Blue channel, while less dominant, provides complementary information that can improve robustness and noise suppression when combined with the Green channel [12].

Signal Composition The temporal changes in the intensity of the RGB channels correlate with the cardiac cycle, allowing the extraction of periodic signals that represent the heart rate.

Noise Resilience By analyzing all three channels, rPPG systems can mitigate noise caused by lighting conditions, movement artifacts, and skin tone variations, thereby improving the accuracy and robustness of the heart rate estimation.

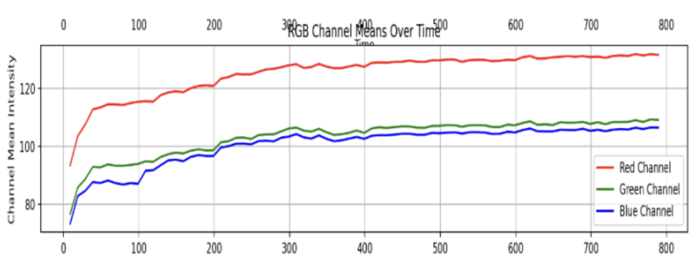

Fig. 4. Diagram showing the RGB Channels

3.6 Apply Fourier Transformation

The Fourier Transform is a mathematical technique that converts a time-domain signal into its frequency-domain representation. In the context of heart rate signal processing, this step is critical for identifying the periodic components associated with the heart's rhythm. The process involves decomposing the signal into sinusoidal components, each characterized by a unique frequency and amplitude.

3.7 Purpose of Fourier Transform in Heart Rate Analysis

1. **Purpose of Fourier Transform in Heart Rate Analysis:**
   - Heart rate signals often contain noise and irrelevant information, making it difficult to interpret them directly from the time domain. By transforming the signal into the frequency domain, the dominant frequencies corresponding to the heartbeats can be easily identified.
   - It highlights periodic patterns that are otherwise obscured in the time domain. For instance, the heart rate, which is typically between 60 to 120 beats per minute, corresponds to frequencies between 1 and 2 Hz.
2. **Steps to Perform Fourier Transform:**
   - **Signal Preprocessing:** Before applying the Fourier Transform, the raw signal is usually detrended and smoothed to eliminate baseline wander and abrupt spikes.
   - **Discrete Fourier Transform (DFT):** The actual transformation can be performed using algorithms like the Fast Fourier Transform (FFT), which efficiently computes the frequency spectrum of the signal.
   - **Interpretation of Results:** The transformed data is visualized as a frequency spectrum. Peaks in this spectrum represent dominant frequencies in the signal, which correspond to the heart rate and other physiological phenomena.

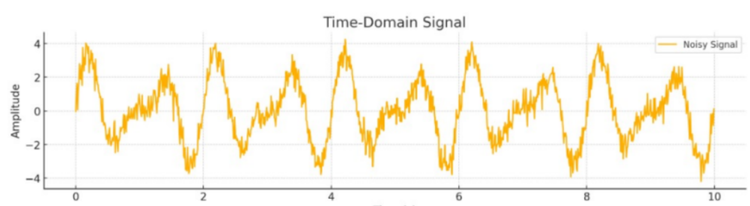

Fig. 5. Time-Domain Signal: A noisy periodic signal plotted as amplitude vs. time. This represents how the raw signal (e.g., rPPG or PPG) fluctuates with physiological changes and external noise.

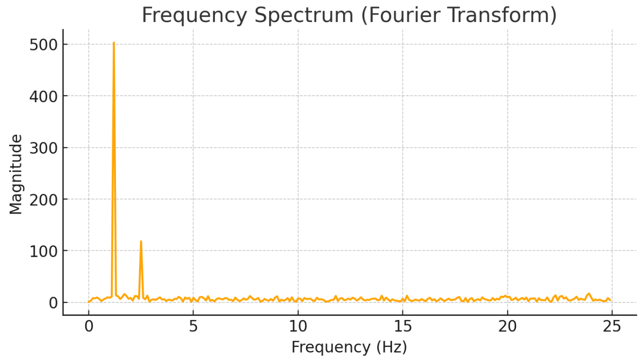

Fig. 6. Frequency Domain Signal obtained using Fourier Transform. The two peaks represent the fundamental heartbeat frequency and its harmonic.

3.8 Applying Bandpass Filter

Bandpass filtering [11] is an essential step in heart rate monitoring, used to isolate the frequency range where cardiac signals are present while removing noise. Since the heart rate signal typically lies between 1–2 Hz (60–120 beats per minute in adults), the filter allows only this range to pass, eliminating low-frequency components such as baseline drift from respiration or movement, and high-frequency noise from electrical interference or sensor artifacts.

The process starts with acquiring the raw signal, often from a photoplethysmogram (PPG) sensor. The Fast Fourier Transform (FFT) is then applied to convert the signal into the frequency domain, revealing peaks around the 1–2 Hz range. A bandpass filter, commonly designed using Butterworth or Chebyshev techniques, is applied to isolate these frequencies. In real-time applications, IIR or FIR filters are implemented for efficient processing, often using tools like MATLAB, Python (SciPy), or specialized DSP hardware.

Once filtering is complete, the signal is transformed back to the time domain, producing a cleaner waveform that highlights the heartbeat components. Combining Fourier analysis with bandpass filtering ensures the signal retains only the most relevant frequency components, enabling accurate and reliable detection of heart rate and further analysis such as heart rate variability (HRV).

3.9 Calculate Heart Rate :

Peak Detection

To calculate heart rate, the algorithm identifies the peaks in the filtered signal. Peaks represent periodic changes in blood volume and are used to determine the heart rate. The steps include:

- **Find Local Maxima:** A point s_i is considered a peak if:

$$s_i > s_{i-1} \quad \textit{and} \quad s_i > s_{i+1}$$

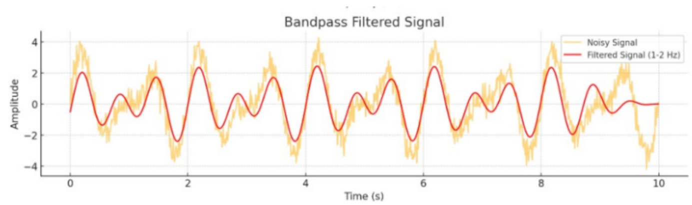

Fig. 7. Band-pass Filtered Signal

This can be implemented programmatically using libraries such as `scipy.signal.find_peaks`.

- **Filter Peaks by Amplitude:** A threshold is applied to exclude smaller peaks caused by noise or motion artifacts, ensuring only physiologically relevant peaks are considered.

Heart Rate Calculation

Once peaks are identified, the heart rate is calculated by analyzing the intervals between consecutive peaks:

- **Time Intervals Between Peaks:** Let t_i represent the time of the i^{th} peak. The intervals between peaks are:

$$\Delta t_i = t_{i+1} - t_i$$

- **Heart Rate Formula:** The heart rate in beats per minute (BPM) is given by:

$$HeartRate = \frac{60}{Mean(\Delta t)}$$

Alternatively, using the dominant frequency f_{peak} from the signal's frequency spectrum:

$$HeartRate = f_{peak} \times 60$$

This approach provides an accurate estimation of heart rate based on the periodicity of the filtered signal.

3.10 Results

The system was tested in real time using a webcam, and estimated heart rates were compared with a pulse oximeter. The Mean Absolute Error (MAE) was within acceptable limits, confirming the reliability of the proposed rPPG method.

Mean Absolute Error (MAE) The MAE is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

where y_i is the actual value, $\hat{y}_i$ the predicted value, and n the number of samples.

Actual HR	rPPG	Actual HR	rPPG	Actual HR	rPPG
97	101.2	100	101.0	86	96.3
96	103.6	100	102.3	88	99.2
97	100.2	99	103.7	88	93.2
88	86.2	98	104.2	87	94.3
89	87.6	99	104.1	85	88.9
88	82.1	98	105.7	86	91.3
87	81.2	99	110.0	86	85.4
89	82.5	99	110.7	87	83.8
87	85.7	98	109.8	86	90.0
86	89.9	87	94.2	84	87.9
101	94.1	87	93.6	83	88.1
101	97.0	86	96.3	84	85.6
100	101.1	88	99.2	76	73.4
100	101.5	88	93.2	76	75.1
101	101.0	87	94.3	76	80.1
83	83.8	85	88.9	77	81.1
77	76.1	86	91.3	78	80.9
77	74.7	86	85.4		

Table 1. Heart rate results comparison between pulse oximeter (Actual HR) and rPPG model (Calculated Results).

Pearson Correlation Coefficient (PCC) The PCC is defined as:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

where x_i and y_i are the sample points, $\bar{x}$ and $\bar{y}$ are their means, and $r \in [-1, 1]$.

Table 2. Summary of Mean Absolute Error and Pearson Correlation Coefficient

Mean Absolute Error	Pearson Correlation Coefficient
4.745	0.877

4 Conclusion

The proposed rPPG system successfully detects heart rate from facial videos. The use of PCA for dimensionality reduction made the system computationally efficient, allowing for real-time processing. Results indicate that rPPG can be a viable method for non-contact heart rate monitoring, especially in home care environments.

5 Future Work

Future work will focus on enhancing the robustness of the system to handle varying lighting

conditions and subject movements. Additionally, expanding the system's capabilities to accu- rately detect heart rate under various lighting conditions, as well as handling moving subjects

and detecting heart rates from multiple individuals simultaneously, could further improve its practical application in real-world scenarios.

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