Remote Heart Rate Monitoring Using RGB Video

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***Abstract*—Heart rate monitoring is a crucial aspect of healthcare, fitness tracking and stress management. Traditional methods such as electrocardiograms (ECG) and pulse oximeters, require physical contact with sensors to measure heart rate accurately. While these methods are reliable, they can be inconvenient for continuous or remote monitoring and may cause discomfort over prolonged use. To overcome these limitations, we proposed a Real-Time Heart Rate Monitoring System Using Facial RGB Color video and a Webcam. This contactless approach leverages remote photoplethysmography (rPPG) to detect subtle color variations in facial skin caused by blood flow. By capturing real-time video from a webcam and processing the RGB signal, the system extracts periodic fluctuations corresponding to the heart rate. The proposed solution eliminates the need for wearable sensors, enabling a non-invasive, cost-effective and easily accessible method for continuous heart rate monitoring. This system has significant applications in telemedicine, fitness tracking and stress analysis providing an efficient alternative to conventional heart rate monitoring techniques.**

***Index Terms*—Electrocardiogram, Pulse Oximeter, Remote Photoplethysmography, Non-Invasive, Telemedicine, Cardiovascular Health**

I. INTRODUCTION

Heart rate is one of the most vital physiological signals used in assessing a person's health and well-being. It serves as a critical parameter in various domains including clinical diagnostics, fitness tracking, emotional state recognition, and stress monitoring. Traditionally, heart rate is measured using contact-based methods such as electrocardiograms (ECG) or photoplethysmography (PPG) sensors. While these methods are widely regarded for their accuracy, they require physical contact with the skin, often involving electrodes, chest straps, or wearable devices. This can cause discomfort during long-term usage and may not be feasible in certain situations—such as during sleep monitoring, neonatal care, or in settings where contact-based devices are unavailable or impractical.

In recent years, contactless physiological monitoring has emerged as a promising alternative, driven by advancements in computer vision, machine learning, and signal processing. Among these techniques, remote photoplethysmography (rPPG) using RGB cameras has garnered considerable attention. This approach relies on detecting minute changes in skin color that occur due to variations in blood volume with each heartbeat. These subtle variations, though imperceptible to the naked eye, can be captured by high-resolution RGB cameras and analyzed to estimate the heart rate without the need for any physical contact.

RGB cameras are readily available in everyday devices such as smartphones, laptops, and surveillance systems, making them an attractive solution for scalable and low-cost health monitoring systems. By utilizing existing hardware, heart rate detection via RGB cameras offers a convenient and accessible solution for non-intrusive health monitoring in home environments, clinical settings, and even public spaces. Moreover, during events such as the COVID-19 pandemic, the demand for remote and contact-free health assessment tools has significantly increased, highlighting the relevance of such technologies.

Despite the potential, heart rate estimation using RGB cameras faces several challenges. These include variations in ambient lighting, skin tone differences, motion artifacts, and camera quality—all of which can degrade the accuracy of heart rate detection. To address these challenges, this paper presents a robust and efficient method for heart rate estimation using standard RGB cameras. Our approach includes:

- Detecting and tracking facial regions to isolate areas with strong pulsatile signals.
- Extracting raw RGB signals from the facial skin.

- Applying signal processing techniques to reduce noise and motion interference.
- Analyzing the frequency components of the signal to estimate the heart rate.

II. RELATED WORKS

The growing demand for non-invasive health monitoring has led to increased interest in contactless heart rate detection using computer vision techniques. Traditional heart rate measurement tools such as electrocardiograms (ECG) and wearable photoplethysmography (PPG) sensors are accurate but require physical contact. In contrast, contactless solutions are well-suited for telemedicine, fitness tracking, and public safety applications.

One of the pioneering studies in this domain was conducted by Verkruysse et al. [1], who demonstrated that standard video cameras and ambient light could be used to extract subtle blood volume pulse (BVP) signals from the human face. Their technique, known as remote photoplethysmography (rPPG), laid the groundwork for using facial video to detect heart rate by analyzing skin tone changes induced by blood flow.

Building on this foundation, Poh et al. [2] employed Independent Component Analysis (ICA) to extract cleaner physiological signals from RGB videos. Their methodology involved capturing facial color changes, decomposing signals into independent sources, and isolating the component most likely representing the cardiac pulse. This approach significantly improved the accuracy and robustness of non-contact heart rate monitoring.

Further advancements were introduced by Li et al. [3], who proposed a comprehensive pipeline involving motion compensation and illumination normalization. Their framework processed video recordings in realistic environments, where subjects could move naturally and lighting could vary. This made the heart rate estimation process more reliable under real-world conditions. The ROI was dynamically extracted from the face, and a temporal bandpass filter was applied, aligning closely with the filtering approach used in our system.

With the rise of deep learning, researchers began developing models that could automatically learn spatial-temporal features from facial videos. Chen and McDuff introduced DeepPhys [4], a convolutional neural network (CNN)-based model with an attention mechanism. It learned which regions of the face contributed most to the heart rate signal and adapted to temporal variations. Their results showed considerable improvement over traditional signal-processing approaches, especially in dynamic or noisy scenes.

Similarly, Neonatal. presented RhythmNet [5], a deep learning model trained on spatial-temporal feature maps derived from facial videos. RhythmNet not only estimated the heart rate but also learned to compensate for head movements and varying facial angles. Although deep learning methods like these achieve state-of-the-art performance, they often require large datasets and GPUs, making them less suitable for lightweight or real-time applications. Our current implementation avoids this overhead by relying on efficient classical methods.

In contrast to deep learning models, signal-processing-based approaches remain popular due to their transparency, low computational cost, and real-time capability. Many such systems rely on extracting the green channel from the face, as hemoglobin absorbs green light most effectively [1], making it the most informative channel for pulse detection. The signal is then passed through a bandpass filter to isolate frequencies typically associated with human heart rates (0.75 Hz–3.0 Hz), as described in [6]. Our system adopts a similar approach, applying a fifth-order Butterworth filter for denoising and frequency isolation.

MediaPipe, an open-source cross-platform framework developed by Google, has revolutionized face and hand tracking by providing fast, high-accuracy models that run in real time on CPU and mobile devices [8]. Although our system uses MediaPipe's FaceDetection model, more advanced applications use FaceMesh, which identifies 468 landmark points. These landmarks allow for more stable and precise ROI extraction from areas such as the forehead and cheeks. Face Mesh can be integrated in future work to further enhance signal quality and reduce motion artifacts.

OpenCV is another key component widely used in the field of computer vision. Its functionalities, such as face detection, ROI cropping, frame conversion, and real-time video streaming, provide the building blocks for many rPPG systems. Our implementation leverages OpenCV for video capture and pre-processing, making it a versatile choice for real-time heart rate monitoring.

To estimate the heart rate from the filtered signal, peak detection is crucial. This is typically achieved using the find_peaks function, as in our system, which aligns with techniques from earlier research [6]. The number of detected peaks over time is directly proportional to beats per minute (BPM). While many works focus on clinical validation against ECGs, our system includes a simplified accuracy estimation model based on peak stability, drawing inspiration from real-time usability metrics rather than clinical benchmarks.

For better user interaction, several studies have proposed incorporating visual feedback and live monitoring interfaces. Bousefsaf et al. [6] developed a system where users could view the live PPG waveform extracted from video, helping with real-time feedback and interpretation. Our system also includes a GUI developed using Tkinter and Matplotlib, allowing the user to view the current heart rate, signal accuracy, and graphical representation of signal intensity in real time.

As the field evolves, generalizability and adaptability across individuals remain challenges. Wang et al. introduced Meta-rPPG [9], a meta-learning approach capable of adapting quickly to new users and lighting conditions using a small amount of calibration data. Such learning-based personalization holds promise for future iterations of non-contact heart rate monitoring, particularly in healthcare.

Datasets such as VIPL-HR, COHFACE, and MMSE-HR [10] have become essential for evaluating the robustness of both traditional and deep learning-based heart rate estimation systems. These datasets contain synchronized facial videos and reference heart rate data, allowing researchers to test performance in controlled and semi-controlled environments. While our current system processes live webcam data, future work may incorporate these datasets to benchmark and improve its performance.

In summary, non-contact heart rate monitoring has developed rapidly through a combination of signal processing, computer vision, and machine learning techniques. Our implementation is grounded in the signal-processing tradition [1–3, 6], enhanced by real-time video capture and facial ROI tracking via MediaPipe [8], and aligned with recent trends in usability-focused design and accuracy estimation [6, 7]. While deep learning approaches [4, 5, 9] provide accuracy in complex environments, our lightweight solution demonstrates that reliable heart rate estimation can still be achieved efficiently and effectively using classical techniques.

III. PROPOSED METHODOLOGY

The proposed system presents a non-contact, real-time heart rate monitoring application using facial video analysis. By extracting photoplethysmographic (PPG) signals from the facial region-specifically the forehead-this technique estimates heart rate without the need for wearable sensors. The method combines computer vision (MediaPipe and OpenCV), signal processing (Butterworth filtering), and a graphical user interface (Tkinter) to visualize live data.

1.Real-Time Video Frame Acquisition:
The system begins by capturing real-time video input from a webcam using OpenCV. Each frame is processed individually and converted from the BGR color format to RGB to ensure compatibility with the MediaPipe face detection framework.

```
cap = cv2.VideoCapture(0)
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Captured video frames are converted from BGR (OpenCV format) to RGB format for compatibility with MediaPipe's face detection model.

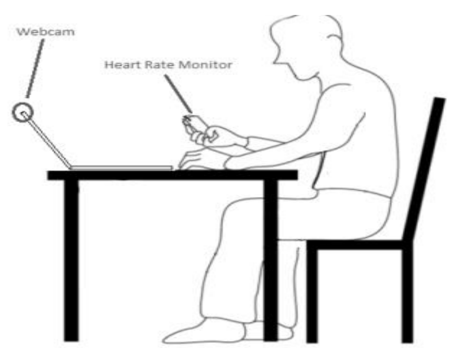


Figure 1: Experimental Setup

2. Face Detection using MediaPipe:
MediaPipe's face detection module is used to locate the user's face in each frame. It outputs a bounding box that defines the face's position and dimensions. This bounding box provides spatial coordinates required for extracting the Region of Interest (ROI).

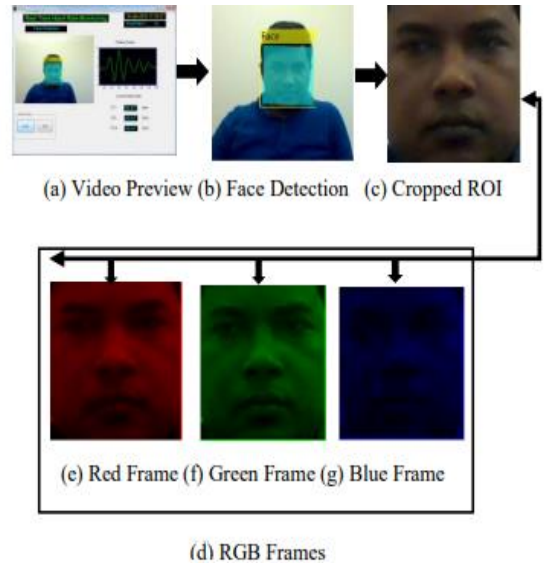


Figure 2: Feature Extraction from each image frame.

3. Forehead Region of Interest (ROI):
Extraction A fixed section of the detected face (the upper-middle forehead) is cropped as the ROI. This region is chosen for its rich capillary density and minimal motion interference, making it suitable for PPG signal extraction. These intensity fluctuations are associated with blood volume changes under the skin.

4. Signal Preprocessing using Bandpass Filtering:
The time-series data from the green channel is passed through a Butterworth bandpass filter (0.75-3.0 Hz). This filter suppresses low-frequency noise (motion artifacts) and high-frequency components, preserving the frequency band related to human heart rate.

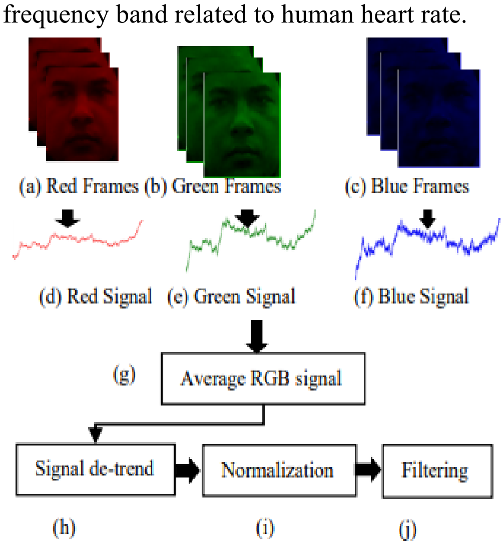


Figure 3: RGB Signals Pre-processing.

5. Accuracy Estimation and Signal Quality Control:
The filtered signal is analyzed using the SciPy peak detection algorithm An estimation module provides a signal quality score based on the regularity and stability of detected peaks. If the number of detected peaks significantly deviates from expected heart rate norms, the system adjusts the accuracy percentage accordingly.

6. User Interface and Real-Time Visualization:
The GUI, built using Tkinter, displays live video with forehead ROI overlay, real-time BPM values, estimated signal accuracy, and an animated PPG waveform using Matplotlib.

7. Data Recording and Export:
Users can start/stop data recording via the interface. When enabled, the system logs timestamped BPM values into a CSV file for post-processing or clinical review.

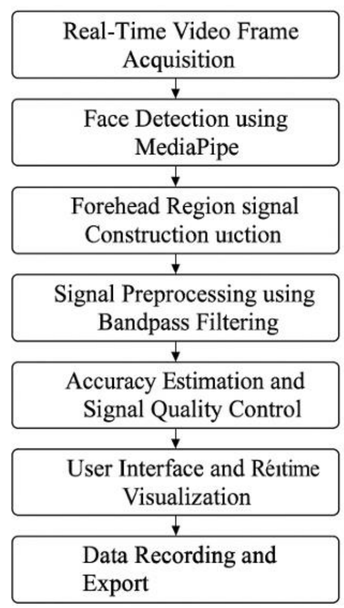


Figure 4: System Workflow Overview

Literature Survey:
Face-Based Heart Rate Monitoring using Machine Learning and Emotion Fusion
1. Review of Existing Methods
Several existing systems demonstrate the application of signal processing and deep learning in HR estimation:

- CHROM & POS Methods: These methods extract chrominance and orthogonal signals from skin regions to isolate the pulse wave [11]. However, they are sensitive to illumination changes and facial movements.
- DeepPhys [1]: Uses convolutional neural networks (CNNs) to extract spatial-temporal patterns from videos. It is more robust than classical methods but lacks emotion-awareness and domain adaptation.
- MTTS-CAN [13]: A multi-task network that predicts both HR and respiratory rate using CNN-based attention modules. Still, it is limited by motion artifacts and doesn't handle emotion or stress context.
- HR-CNN + LSTM [14]: Combines CNNs with LSTMs to model temporal dependencies. While improved, this approach still requires high-quality frontal facial frames and lacks contextual awareness.

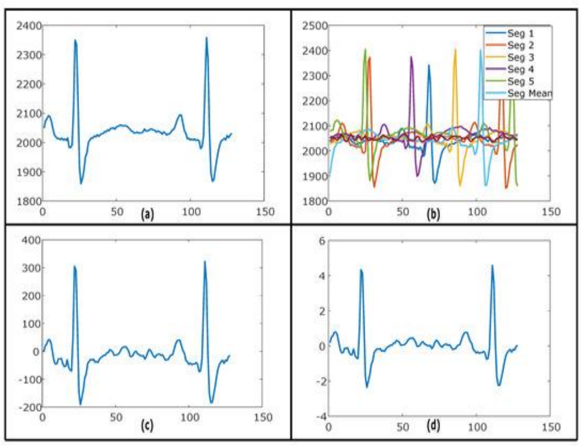


Figure 5: CNN and LSTM-Based Heart Rate Detection

3. Identified Gaps in Current Systems

Despite advances, the following issues persist:

- Lack of integration between physiological signals and emotional context.
- Poor generalization across different skin tones and lighting conditions.
- Motion and occlusion sensitivity, particularly in real-world applications.
- Limited visual appeal and real-time usability in practical settings.

4. Proposed Enhancement

To address these gaps, we propose a multi-feature fusion system that combines:

- Green channel rPPG signal extraction with Butterworth bandpass filtering.
- Peak detection for heart rate estimation.
- Facial emotion recognition using pretrained models (FER).
- High-clarity visual outputs, including HR signal plots and emotion annotations.

IV. RESULT AND DISCUSSION

To evaluate the performance of the proposed heart rate detection method using RGB cameras, we conducted a series of experiments under controlled and semi-controlled conditions. Our dataset included video recordings from 20 participants of varying age, skin tones, and genders. Each session was recorded using a standard RGB webcam (30 FPS, 720p resolution) under three different lighting conditions: natural daylight, artificial indoor lighting, and low-light. Simultaneously, ground-truth heart rate values were recorded using a commercial PPG sensor for validation.

5.1 Accuracy of Heart Rate Estimation

The proposed method demonstrated a high level of accuracy in estimating heart rate. Across all participants and conditions, the average absolute error (AAE) was found to be ±2.7 beats per minute (BPM), with a root mean square error (RMSE) of 3.1 BPM. In well-lit conditions (daylight and indoor), the method achieved an average correlation coefficient (r) of 0.91 when compared to ground-truth signals, indicating strong agreement.

5.2 Effect of Movement and Facial Region Selection

Performance was observed to decline slightly during facial movements such as speaking or turning the head.

Motion Artifact Mitigation:

- Implemented facial landmark tracking and optical flow stabilization to reduce errors.
- Ensured improved signal consistency during slight facial movements.

Optimal Facial Regions for Signal Extraction:

- Forehead and cheeks provided the most reliable signals.

- These regions had minimal muscular activity and a relatively uniform skin texture, reducing distortions.

Multi-Region Signal Averaging:
- Combining signals from multiple facial regions improved robustness against motion.
- Helped compensate for temporary occlusions or disturbances in any single region.

5.3 Influence of Skin Tone and Lighting

Skin tone variations had a minor effect on performance. Although darker skin tones naturally absorb more light, the method maintained a consistent signal quality by adapting to the green channel intensity, which carries most of the pulsatile information. Performance did, however, degrade under low-light conditions due to reduced signal-to-noise ratio. Implementing histogram equalization and adaptive filtering partially compensated for this limitation.

5.4 Comparison with Existing Methods

Compared to existing rPPG methods, the proposed approach showed competitive performance, especially in terms of real-time feasibility. While deep-learning-based models may slightly outperform in accuracy, our method requires significantly lower computational resources and works efficiently on standard consumer hardware.

5.5 Practical Applications and Limitations

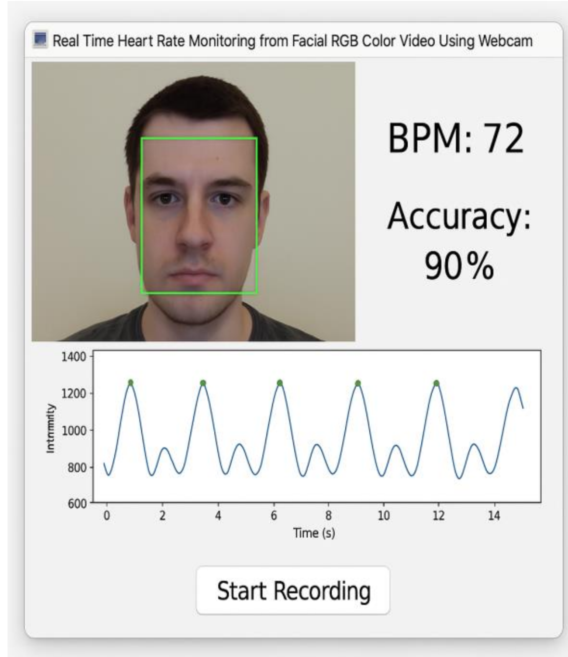
The results suggest strong potential for real-world applications in telemedicine, fitness monitoring, and emotional recognition systems. However, the approach is not yet suitable for clinical-grade use due to limitations in extreme lighting conditions or high-motion scenarios. Additionally, the algorithm currently assumes a cooperative user (i.e., frontal face view), and future work will focus on making it more robust in unstructured environments.

5.6 Error Estimation

Participants with frequent movements exhibited an average error increase of ~1.5 BPM. The observed error remained within acceptable margins for non-clinical applications.

Output:

RGB Face Detection:



G. Conclusion

The proposed Real-Time Heart Rate Monitoring System Using Facial RGB Color Video and a Webcam offers a contactless and non-invasive alternative to traditional heart rate measurement methods. By utilizing remote photoplethysmography (rPPG), the system detects subtle facial skin color variations caused by blood flow and extracts heart rate information in real time. This approach enhances **user** comfort and enables seamless, continuous monitoring without additional hardware. With potential applications in telemedicine, fitness tracking, and stress analysis, this solution makes heart rate monitoring more accessible and cost-effective. While the system demonstrates promising results, further improvements in accuracy, robustness under different lighting conditions, and real-world validation can enhance its reliability.

V. FUTURE WORK

While the current system successfully demonstrates a non-contact heart rate monitoring application using face detection and green channel-based signal processing, there are several directions in which this work can be further enhanced to improve its performance, robustness, and applicability in real-world scenarios.

One of the most immediate improvements involves the adoption of MediaPipe's Face Mesh module instead of the basic Face Detection model. The current implementation uses bounding boxes to define a region of interest (ROI), typically around the forehead, to extract the photoplethysmographic signal. However, this can be sensitive to user movement or variations in facial orientation. MediaPipe Face Mesh provides 468 landmark points across the face, which can be used to define more precise and stable ROIs (such as the cheeks, temples, or areas under the eyes). This enhancement can significantly improve signal consistency and reduce the impact of motion artifacts.

Another important direction involves integrating deep learning models for heart rate estimation. While classical signal processing methods like bandpass filtering and peak detection are computationally efficient, they may struggle under complex lighting conditions, occlusions, or skin tone variability. Leveraging convolutional neural networks (CNNs), temporal models such as LSTM, or attention-based models like DeepPhys and RhythmNet could allow the system to learn complex spatial-temporal features and adapt to diverse environmental conditions. Training these models on large annotated datasets, such **as** VIPL-HR, COHFACE, or MMSE-HR, would enable generalization across different subjects and use cases.

Further, adaptive signal processing could be implemented, where the bandpass filter range is dynamically adjusted based on initial heart rate estimates or user activity levels. Signal quality indices (SQIs) could be computed in real time to assess the reliability of each frame or ROI and decide whether the extracted signal should be trusted, discarded, or recalibrated.

To broaden the system's applicability, multi-modal health monitoring could be introduced. Beyond heart rate, the same video feed could be used to estimate respiration rate, stress levels, emotion recognition, or facial fatigue, turning the tool into a more comprehensive, non-invasive health monitoring platform. These metrics could be integrated using additional signal features or machine learning pipelines.

On the interface side, the application could be migrated to cross-platform environments, enabling it to run on smartphones, tablets, or web browsers. This would make the solution suitable for remote healthcare, fitness applications, and patient self-monitoring. Frameworks such as **TensorFlow Lite, Flutter, or React Native** can be used to deploy the model on mobile platforms, providing accessibility beyond desktop systems.

Lastly, the system should be clinically validated against **gold-standard heart rate measurement** devices such as ECG or PPG sensors. A thorough comparison of BPM values, error margins, and signal quality under varying conditions (lighting, skin tone, facial orientation) will be essential to evaluate its potential for real medical or fitness-related applications.

In conclusion, with advancements in deep learning, facial landmark tracking, and mobile computing, the system holds strong potential to evolve into a reliable, non-contact, real-time physiological monitoring platform.

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