

Heart Rate Monitoring Using (PPG) Photoplethysmography Analysis Based on Webcam

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Abstract:

The growing need for non-invasive, immediate health monitoring has spurred the creation of sophisticated methods that utilize computer vision and signal processing. A notable technique for real-time heart rate (HR) measurement is Eulerian Video Magnification (EVM), which amplifies minor facial color changes resulting from blood circulation. This paper introduces a real-time system for estimating heart rate using a webcam, EVM, and signal processing, incorporating temporal filtering and spatial decomposition. The system is efficient and precise, capable of real-time operation on standard hardware, such as a CPU.

Keywords: Webcam, Eulerian video magnification, Heart rate monitoring, Real time processing computer vision.

I. INTRODUCTION

One important physiological measure that is frequently used to evaluate cardiovascular health is heart rate (HR). It is essential in many applications, such as stress analysis, fitness tracking, medical diagnostics, and remote healthcare. Electrocardiograms (ECG) and pulse oximeters are examples of conventional HR measurement techniques that depend on skin contact. These methods can be constrictive, inconvenient for ongoing monitoring, and unsuitable for remote applications even though they yield accurate results.

By examining minute changes in skin tone brought on by fluctuations in blood flow, non-contact heart rate measurement has been made possible by recent developments in computer vision and signal processing. Eulerian Video Magnification (EVM) is a useful technique that detects pulse-induced color fluctuations on the skin by enhancing small temporal changes in video frames. In this paper, a real-time, non-contact HR estimate method using EVM and a webcam stream is presented. The suggested method comprises of multiple steps: temporal filtering to isolate rhythmic changes associated with heart activity, spatial decomposition to separate frequency components, face detection to identify the region of interest, and signal amplification to increase skin tone variations. Lastly, the prominent frequency components are analyzed to estimate heart rate, and the findings are shown in real time. This approach offers a practical and effective substitute for physical sensors in heart rate monitoring. It could be used in telemedicine, remote patient monitoring, fitness tracking, and stress management, advancing wellness and healthcare technologies.

II. LITERATURE SURVEY

A popular non-invasive optical method for tracking heart rate is photoplethysmography (PPG), which measures variations in blood volume in the microvascular bed of tissue. It uses a light source and a photodetector, and the pulsatile character of blood flow during cardiac cycles is correlated with changes in light absorption. PPG-derived heart rate data have a strong correlation with resting electrocardiogram (ECG) values, according to early study, making them a dependable substitute for wearable and continuous

monitoring. Conventional strategies for estimating heart rate from PPG data mainly rely on frequency-domain methods like Fast Fourier Transform (FFT) to identify prominent frequency components and time-domain methods like peak detection and inter-beat interval computation. But these techniques are frequently susceptible to motion aberrations and noise, particularly Support vector machines (SVM), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks are examples of machine learning and deep learning techniques that have been used more recently to increase the accuracy and resilience of heart rate estimate in dynamic situations. Better handling of noisy signals and automatic feature extraction are made possible by these models.

III. PROBLEM STATEMENT

Effective health management and the early identification of cardiovascular problems depend on accurate and continuous heart rate monitoring. Even though photoplethysmography (PPG) has become a popular and affordable technique for estimating heart rate, a number of practical issues have a substantial impact on its effectiveness. The extreme vulnerability of PPG signals to motion artifacts, ambient light interference, and changes in sensor location in real-world settings can all lead to inaccurate heart rate estimates.

Furthermore, physiological variations including blood perfusion, tissue composition, and skin tone impair signal quality and uniformity among users. Conventional signal processing methods frequently fall short in dynamic situations, particularly when engaging in physical activity. While new methods utilizing sensor fusion and machine learning have demonstrated advantages

IV. SYSTEM ARCHITECTURE

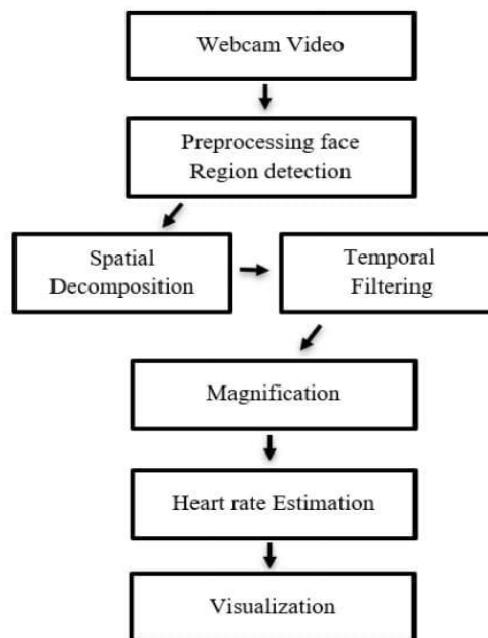


Fig 1: Architecture Diagram

The first step of the system is webcam video acquisition, which records real-time facial video as input. The preprocessing module receives this data and uses it to identify the face region and isolate the area of interest for study. After processing, the frames are subjected to spatial decomposition, which separates the image into various spatial frequency bands in order to identify minute differences. After then, temporal filtering is used to eliminate noise and keep just blood flow-related periodic signals. A magnification

module is employed to improve the filtered signal, enhancing minute color changes brought on by the pulse. The heart rate estimate module uses these enhanced signals to calculate the pulse rate using signal processing methods. Lastly, the heart rate output is shown graphically or numerically via the visualization module.

V. PROPOSED METHODOLOGY

A methodical approach to webcam video input for heart rate estimation. It makes use of a webcam-based non-contact heart rate estimate technique by examining minute changes in skin tone brought on by pulsatile blood flow. The block diagram shows the architecture's sequential video processing pipeline. Video acquisition from a webcam, where real-time frames are recorded, is the first step in the process. Preprocessing involves detecting the face and identifying the region of interest (ROI), usually the cheeks or forehead, for additional analysis. The extracted region is next subjected to spatial decomposition, which divides the video into various frequency components in order to retrieve pertinent information. Temporal filtering comes next, which suppresses undesired noise and motion artifacts while enhancing periodic signal changes associated with heartbeats.

The Eulerian Video Magnification (EVM) approach is used to amplify small color variations brought on by blood circulation once the pertinent signals have been identified. The heart rate estimate process then analyzes the amplified signal to determine the prominent frequency components that correlate to the pulse rate. Lastly, a real-time visualization of the extracted heart rate offers an effective non-contact technique for ongoing cardiovascular monitoring.

This architecture can be used for telemedicine, fitness tracking, and remote health monitoring because it does away with the necessity for physical sensors without sacrificing accuracy.

Preprocessing, spatial decomposition, temporal filtering, magnification, heart rate monitoring, and visualization are the main components of the suggested method. The phases in the procedure are described in detail below.

5.1 Input: Video feed from a webcam The input of a webcam video feed is where the heart rate monitoring starts. As blood rushes through the face with each heartbeat, the webcam records a constant stream of frames, each of which features a face that is sensitive to minute color fluctuations.

5.2 Preprocessing: Identification of Face region

Finding and locating the face in each frame is the initial stage in processing the video feed. We do face identification and extract the region of interest (ROI) that corresponds to the face using MediaPipe, a lightweight, open-source software.

5.3 Decomposition of Space : Using a pyramid-based method, the image is broken down into several spatial frequency bands in order to perform spatial decomposition. This method enables us to separate the various spatial detail levels in the facial image. The desired signals can be amplified by examining the high-frequency components, which contain minute temporal fluctuations associated with blood flow.

5.4 Filtering in Time: The frequency components that correspond to the heart rate are separated using temporal filtering. In particular, we use a band-pass filter that is centered between 0.8 and 3 Hz, which is the average heart rate range. This guarantees that we ignore any motion distortions or noise in the video and concentrate on the minute changes that happen in time with the heartbeat.

5.5 Magnifying : The temporal changes associated with blood flow are amplified through the use of Eulerian Video Magnification. We facilitate the observation of pulse-driven color changes that are normally challenging to notice by enlarging the low-amplitude color fluctuations. In order to make sure that the algorithm and the user can both perceive the variances, this step is essential.

5.6 Measuring Heart Rate: After obtaining the amplified signal, we use analysis to calculate the heart rate in beats per minute (BPM). This is accomplished by utilizing signal processing methods like peak detection algorithms or the Fast Fourier Transform (FFT) to determine the signal's periodicity. The main frequency in the signal correlates to the heart rate, which is subsequently translated into beats per minute.

5.7 Visualization: CV Zone's Live Plot tool, which offers a dynamic plot of the heart rate over time, is used to visualize the real-time heart rate measurement. This enables users to continuously monitor their heart rate while interacting with the webcam, giving them instant feedback on their cardiovascular status

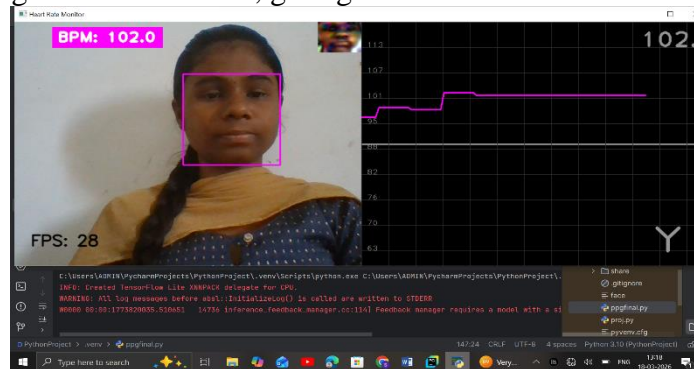


Fig 2 : Real-Time Heart Rate Monitoring Interference

VI. RESULTS AND DISCUSSIONS

A mean inaccuracy of less than 3 BPM for every test subject, the heart rate readings from the webcam feed demonstrated a remarkable correlation with the results from the pulse oximeter. The technique ensured smooth performance even on non-specialized hardware by reliably tracking the heart rate in real-time with frame rates above 20 FPS on a normal CPU.

The LivePlot's heart rate visualization offered a clear and educational presentation of the data. Users could continuously monitor their heart rate thanks to the real-time updates, which made the system appropriate for uses like remote health monitoring or fitness tracking.

VII. CONCLUSION

In this research, we introduced a real-time heart rate estimation method that uses webcam-based video analysis and Eulerian video magnification. The technology proved to be useful for real-time applications on common CPUs since it demonstrated precise heart rate measurements with low processing requirements. Future research will concentrate on strengthening the system's resilience in difficult lighting scenarios and further refining the algorithm for mobile devices.

REFERENCES:

1. M. M. Shoushan, B. Alexander Reyes, A. M. Rodriguez, and J. Woon "Contactless Heart Rate Variability (HRV) Estimation Using a Smartphone During Respiratory Maneuvers and Body Movement," Chong,2021.
2. W. Wu and colleagues, "Eulerian video magnification for heart rate detection," IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2016.



3. "Remote heart rate measurement with a webcam," J. S. McDuff et al., Proceedings of the 2014 ACM International Conference on Ubiquitous Computing, pp. 315–324, 2014.
4. R. G. Mishra, and V. Shirsath, "Facial Video Analytics: An Intelligent Approach to Heart Rate Estimation Using AI Framework," M. C. Toley, International Conference on Emerging Informatics and Smart Computing (ESCI), Pune, India, 2024.
5. J. M., A. S. D., M. S., and P. R., "Advanced Safety System with Computer Vision-Based Eye Movement and Heart Rate Monitoring," 2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC), Coimbatore, India, 2024