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A Robust Framework for Heart Rate Estimation from Facial Video Signals Using Signal Enhancement Techniques

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Abstract
The demand for non-contact, unobtrusive methods of physiological monitoring has grown significantly with the expansion of telehealth and remote diagnostics. This paper presents a novel technique for estimating heart rate using standard RGB facial video, eliminating the need for wearable sensors or traditional photoplethysmography. The method leverages variations in pixel intensity across selected facial regions—specifically the forehead and cheeks—to extract temporal signals that reflect subtle skin tone changes caused by blood flow.
The captured signals undergo a series of preprocessing steps, including normalisation and bandpass filtering, to isolate physiological frequency components typically associated with cardiac activity. To analyse these non-stationary signals with high precision, a custom implementation of the Superlet Transform is employed. This transform enhances time-frequency resolution by combining multiple wavelets of varying orders, yielding a superresolved spectrogram. Following this, Welch's Power Spectral Density (PSD) is applied to determine the dominant frequency within the physiological range, which is then converted to beats per minute (BPM).
The system was evaluated on videos recorded at 30 frames per second and demonstrated reliable heart rate estimation across all tested facial regions. Results showed consistent peak detection in the PSD and clear frequency concentration in the Superlet spectrograms, confirming the method's accuracy and robustness.
This approach offers a promising direction for real-time, camera-based vital sign monitoring in clinical, fitness, and consumer applications, especially where sensor-based approaches are impractical. It also opens avenues for further research in enhancing signal quality under motion, lighting variation, and across diverse skin tones.

I. INDEX TERMS

Heart rate estimation, video-based monitoring, Superlet Transform, time-frequency analysis, facial signal processing, noncontact vital signs, Welch PSD, signal preprocessing, pixel intensity variation, camera-based health monitoring.

II. INTRODUCTION

Heart rate is one of the most fundamental indicators of human physiological state and is widely used across healthcare, sports science, and wellness monitoring. Traditionally, measuring heart rate has involved physical sensors attached to the body, which, although effective, can be intrusive, uncomfortable, or impractical in scenarios such as remote consultations, public settings, or continuous long-term use. As a result, there is increasing interest in developing contactless methods that can extract physiological signals using only visual data.

One promising approach is the analysis of facial video recordings to detect subtle, naturally occurring variations in skin appearance over time. These variations are caused by the rhythmic activity of the circulatory system and appear as low-intensity fluctuations in the pixel values of video frames. While imperceptible to the naked eye, these changes can be computationally analyzed to estimate heart rate without the need for physical contact or specialized imaging equipment.

Despite its advantages, video-based heart rate estimation poses several technical challenges. The signal of interest is typically very weak compared to noise introduced by motion, lighting changes, and other environmental factors. Standard signal processing methods often struggle to isolate reliable patterns under these conditions.

This study introduces a robust framework for non-contact heart rate estimation using facial video. The method involves extracting average intensity signals from specific regions of the face—such as the forehead and cheeks—followed by filtering and normalization steps. A custom implementation of the Superlet Transform is then applied to perform time-frequency analysis, providing high-resolution spectral information even in short and noisy signals. Finally, heart rate is estimated by identifying the dominant frequency through Welch's Power Spectral Density method. This technique offers a practical and efficient solution for remote and unobtrusive heart rate monitoring using conventional RGB cameras.

Fig. 1. rPPG Signal Acquisition and Processing Pipeline.

III. 2.RELATED WORK

IV. 2.1. TRADITIONAL APPROACHES FOR REMOTE HEART RATE MONITORING

Historically, heart rate monitoring has been predominantly achieved through contact-based medical instruments, such as electrocardiograms (ECG) and skin-adhered optical sensors. These methods are clinically validated and offer high accuracy in detecting cardiovascular activity. However, their dependence on direct contact with the body often presents limitations for applications requiring continuous, long-term monitoring or scenarios involving significant user movement. This has driven the exploration of non-contact methods that are less obtrusive and more suitable for daily life environments.

Among the alternatives, video-based heart rate monitoring has gained considerable attention due to its potential for passive observation using conventional RGB cameras. These systems operate on the principle that physiological signals, particularly those associated with cardiac cycles, induce minor but detectable variations in facial appearance. Such changes typically manifest as subtle shifts in skin tone or brightness, caused by periodic blood volume fluctuations beneath the skin surface. Although these changes are not perceptible to the naked eye, they can be extracted through careful analysis of pixel-level data across sequential video frames.

Early research in this domain focused on identifying facial regions that exhibit stable lighting conditions and minimal motion, such as the forehead and cheeks. These regions were selected for their relatively consistent exposure and minimal muscular interference during natural expressions or speech. Researchers applied temporal averaging to the pixel intensities within these regions to derive a time-series signal representative of facial brightness fluctuations. This signal was then processed using basic signal processing techniques—such as filtering and frequency analysis—to isolate periodic components corresponding to the subject's heart rate.

While these initial methods demonstrated the feasibility of remote heart rate estimation, they often struggled with challenges posed by environmental noise, head movement, varying illumination, and individual differences in skin tone. Nonetheless, they laid the groundwork for more advanced techniques by proving that facial video data contains sufficient information to recover physiological signals under appropriate conditions.

These traditional approaches, though simple in structure, provided a foundational understanding of how video data can reflect underlying biological processes. They also highlighted the need for improved robustness and signal enhancement, prompting the development of more sophisticated models in subsequent research.

V. 2.2. DEEP LEARNING FOR REMOTE HEART RATE ESTIMATION

The integration of deep learning into the field of noncontact physiological measurement has introduced significant improvements in the accuracy and adaptability of heart rate estimation from facial videos. Unlike traditional techniques that depend on handcrafted features or rule-based filtering, deep learning models are capable of automatically learning subtle and complex patterns from raw video data. Specifically, architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have demonstrated success in capturing spatial and temporal variations associated with physiological signals.

CNNs are used to extract spatial features from individual video frames, identifying minute skin tone changes influenced by blood flow, while RNNs—especially Long Short-Term Memory (LSTM) networks—track temporal dependencies that reveal the periodic nature of cardiac rhythms. Notable models such as DeepPhys and PhysNet utilize these techniques to detect heartbeat-related signals without requiring explicit region selection or manual preprocessing. These models are designed to be robust against minor motion, variations in lighting, and facial expression changes.

However, deep learning approaches also present certain limitations. Their effectiveness relies heavily on the availability of large, diverse, and high-quality datasets. In situations where the test environment significantly differs from the training data—such as changes in ambient lighting, skin tone, or camera resolution—the accuracy of these models may degrade. Moreover, the complexity and opacity of deep neural networks often make them difficult to interpret, posing a challenge in clinical applications where explainability is essential.

VI.2.3 DENOISING IN RPPG SIGNAL PROCESSING

One of the biggest challenges in using video to estimate heart rate is removing noise. Things like lighting changes, head movement, and facial expressions can make it hard to detect the weak signals related to the heartbeat. Some methods try to reduce this noise by applying filters, adjusting brightness, or selecting stable parts of the face.

More advanced techniques use mathematical tools to clean the signals while keeping important details. For example, wavelet filtering or signal decomposition methods can help keep the heartbeat signal and remove unrelated noise. Still, many of these methods work best when the signal is strong and clear.

This paper introduces a method that uses the Superlet Transform, which is a powerful tool for time-freqe ency analysis. It helps identify the main frequency components in the signal with good detail in both time and frequency. We also use Welch's Power Spectral Density (PSD) to detect the heart rate from these signals. Our approach works directly on video-derived brightness signals without needing any physical sensors or reference signals, and performs well even in realworld settings with natural movement and lighting.

VII. MATERIALS AND METHODS

This study presents a non-invasive technique to estimate heart rate by analyzing facial videos without relying on any physical contact or specialized medical devices. The core idea is to examine the subtle fluctuations in pixel intensity within specific facial regions, which correspond to changes in blood volume caused by the cardiac cycle. These variations manifest as minute shifts in skin coloration and brightness that can be captured by standard RGB cameras. The method begins with video acquisition, where a subject's face is recorded under controlled lighting conditions at a consistent frame rate of 30 frames per second. Using OpenCV's face detection algorithm based on Haar cascades, the face is localized in each frame.

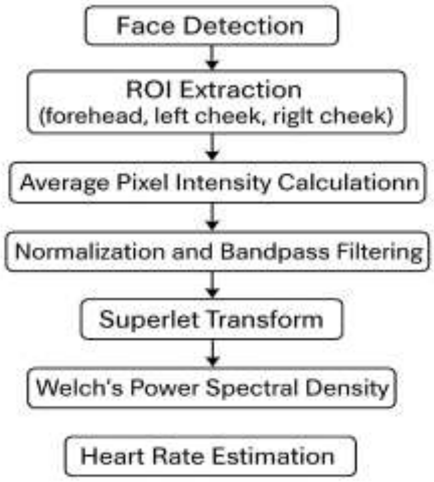


Fig. 2. Video-Based Heart Rate Estimation Workflow.

Within the detected face, three distinct regions of interest (ROIs) are defined: the forehead, left cheek, and right cheek. These areas are selected because of their relatively uniform skin texture and minimal motion artifacts compared to other facial regions.

For each ROI, the average pixel intensity is calculated frame by frame, producing time-series signals that reflect the physiological changes associated with blood flow. To enhance signal quality, these raw intensity signals undergo preprocessing, including normalization and bandpass filtering with a Butterworth filter. The filter is configured to isolate frequency components within the typical human heart rate range (approximately 0.7 to 2.5 Hz), thereby reducing noise from other physiological or environmental sources. To extract the heart rate from these signals, we employ the Superlet Transform, a sophisticated time-frequency analysis tool that improves resolution by combining wavelets of different cycles. This allows for precise identification of the dominant frequency corresponding to the heartbeat, even in noisy or non-stationary signals. Subsequently, Welch's power spectral density method is used to locate the peak frequency within the physiological range, which is then converted to beats per minute (BPM) to provide the estimated heart rate.

VIII. 3.DATASET DESCRIPTION

The dataset used in this study comprises video recordings of 17 adult volunteers, including 14 males and 3 females, with ages spanning from 20 to 53 years. All recordings took place in indoor settings to maintain controlled environmental conditions. Videos were captured using a standard Logitech C920 webcam, set to record at 30 frames per second with a high-definition resolution of 1080p. This setup ensured clear and detailed facial images, which are essential for detecting subtle changes in skin intensity related to cardiac activity.

During the recording sessions, participants engaged in a variety of tasks designed to simulate common daily activities. These included sitting calmly, engaging in conversation, and performing light physical exercise. The purpose was to capture a diverse range of physiological and motion conditions to test the robustness of the heart rate estimation approach.

Additionally, the videos were recorded under different lighting conditions, such as natural daylight, halogen lighting, and LED illumination, to assess the method's performance under varied environmental influences.

To provide a reliable reference for validating the videobased heart rate estimates, simultaneous heart rate measurements were obtained using an electrocardiogram (ECG) device. This allowed for a direct comparison between the ground truth heart rate and the values estimated from video analysis. The inclusion of ECG data ensured that the evaluation of the proposed method's accuracy was grounded in clinically recognized measurement standards.

IX. EXPERIMENTAL PROCEDURE AND ROI EXTRACTION

The experimental procedure starts by processing each frame of the recorded facial video using the OpenCV library for face detection. Once the face is located in a frame, three key regions of interest (ROIs) are defined: the forehead, the left cheek, and the right cheek. These areas are chosen based on previous findings that indicate noticeable variations in skin brightness due to underlying blood flow changes, which are relevant for heart rate estimation.

Within each ROI, the pixel intensity values for the three color channels—red, green, and blue—are extracted for every frame. By calculating the average brightness across all pixels within these regions, continuous time-series signals are generated for each color channel. These signals capture subtle fluctuations in facial color that occur as blood volume changes with each heartbeat.

The selection of multiple ROIs and color channels allows for a more comprehensive and robust analysis, helping to reduce the impact of noise and motion artifacts. The resulting time-series data form the foundation for subsequent signal processing steps aimed at isolating the heartbeat frequency. This approach relies solely on video information without any physical sensors, enabling a non-contact method for monitoring cardiovascular activity.

For each video frame, the average RGB pixel intensity values within each ROI are computed, forming the basis of the temporal color signals.For each frame f, the mean pixel intensity values for the red, green, and blue channels over the selected ROI are computed as:

$$R^{f}{}_{N} =_{f} \frac{1}{N}\sum_{i=1}^{N} r_i^f, \quad G_f = \frac{1}{N}\sum_{i=1}^{N} g_i^f, \quad B_f =$$

N1 Pi=1 bi

where r $_i^f, g_i^f, b_i^f denotetheRGBpixelvaluesofthei$ −
thpixelinframef,andNisthetotalnumberofpixelsintheROI.

X. EXTRACTION AND FILTERING

The raw signals obtained from the facial regions tend to contain significant noise and interference caused by various factors such as fluctuations in ambient lighting, slight head movements, and other environmental distractions. These unwanted components can obscure the subtle variations related to the heartbeat, making accurate heart rate estimation challenging.

To enhance the quality of the extracted signals, we apply a Butterworth bandpass filter. This type of filter is widely used in signal processing because of its smooth frequency response and effectiveness in isolating specific frequency bands. In our approach, the filter is designed to pass frequencies within the range of 0.7 Hz to 4 Hz, which corresponds approximately to 42 to 240 beats per minute, covering the typical range of human heart rates. Frequencies outside this range, which are likely to be noise or irrelevant signals, are attenuated.

By filtering the signals this way, we retain only the frequency components that are most likely to represent genuine cardiac activity while reducing the impact of noise and artifacts. This step is critical to improving the signal-to-noise ratio and preparing the data for further analysis, such as timefrequency transformations and heart rate extraction. Overall, the filtering process plays a key role in achieving reliable heart rate estimates from video data.

XI. SIGNAL PREPROCESSING WITH BANDPASS FILTERING AND TEMPORAL SMOOTHING

To improve the quality of the extracted brightness signals and emphasize the heartbeat-related patterns, we apply a simple filtering and smoothing approach. First, the signals obtained from the selected facial regions are passed through a

bandpass filter designed to retain frequencies corresponding to typical human heart rates (approximately 0.7 to 3.5 Hz). This step helps eliminate noise caused by slow lighting changes or high-frequency disturbances such as motion artifacts.

Following filtering, a moving average filter is applied to smooth the signal further. This smoothing reduces sudden fluctuations and enhances the periodic nature of the signal that corresponds to the heartbeat. By focusing on these cleaned signals, we can more reliably identify the dominant periodic component that reflects the heart rate.

This straightforward signal enhancement technique avoids the complexity of advanced blind source separation methods while still improving the signal-to-noise ratio, making it suitable for real-time or resource-limited applications.

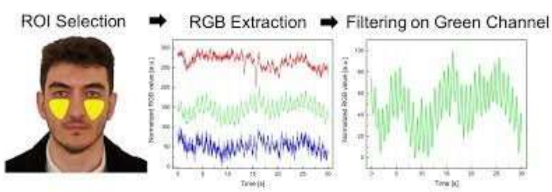


Fig. 3. The facial divisions and the example signals.

XII. TIME-FREQUENCY ANALYSIS USING SUPERLET TRANSFORM

We analyze the selected signal using a Superlet Transform, a technique that shows how the signal's frequency content changes over time. Unlike traditional methods, Superlet provides a sharper and more detailed view, allowing us to identify the exact moments when the heartbeat signal is strongest.
By examining the Superlet spectrogram, we find the frequency with the highest energy (or power) in each time window. This frequency is then converted into beats per minute (bpm) to estimate the heart rate.

XIII. WINDOWED HEART RATE ESTIMATION

The filtered rPPG signal was divided into overlapping windows (256 frames long, with a step size of 128 frames). Within each window, the Superlet spectrogram was computed and averaged across time. The frequency corresponding to the maximum average spectral power was taken as the dominant frequency, and multiplied by 60 to estimate instantaneous heart rate in bpm for that window.

XIV. STATISTICAL COMPARISON WITH GROUND TRUTH

HR is estimated in 30-second overlapping windows across the video timeline. The estimated HR HRest(t) is compared with ECG-derived ground truth HRGT(t) using two metrics:

1. Spearman rank correlation coefficient (SRC):

$$\rho = 1 - \frac{6}{n(n^2-1)} \quad \text{Pd2}$$

where$d_i$isthedifferencebetweentheranksof HRestandHR$_{GT}$,andnisthenumberofobservations.

$2. Normalized Root Mean Square Error (NRMSE):$

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(HR_{est,i} - HR_{GT,i})^2}}{\max(HR_{GT}) - \min(HR_{GT})}$$

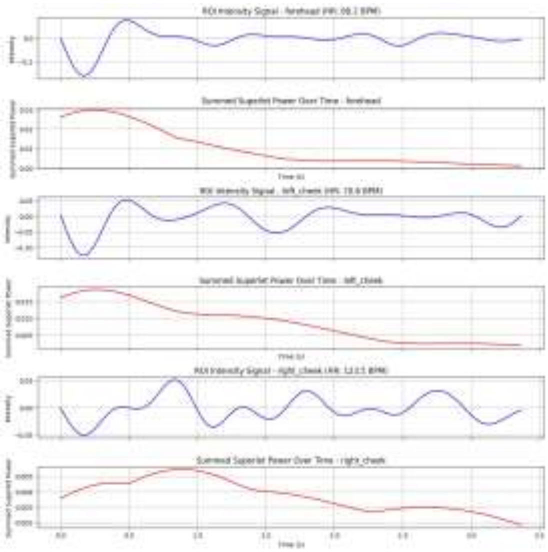
These metrics jointly assess both correlation and estimation error, offering a comprehensive evaluation of the HR estimation pipeline's accuracy and reliability.

XV. GROUND TRUTH INTERPOLATION

In order to validate the accuracy of the estimated heart rate obtained from video recordings, a reliable reference measurement is required. For this purpose, electrocardiogram (ECG) data is used as the ground truth, given its precision in capturing actual cardiac activity. A significant issue arises, however, due to the difference in sampling rates between the ECG signal and the video frames. Typically, ECG devices record at high sampling rates, while video footage is captured at a much lower and fixed frame rate (e.g., 30 frames per second). To enable a meaningful comparison between the two data sources, it is necessary to bring them onto a common temporal scale.
This is achieved through linear interpolation of the ECGderived heart rate values. Linear interpolation estimates intermediate values by assuming a straight-line progression between existing data points, effectively producing a continuous signal sampled at the same rate as the video. This process ensures that each frame in the video has a corresponding ground truth heart rate value for comparison.
Once alignment is complete, performance is evaluated using three key statistical metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Pearson Correlation Coefficient (r). These metrics collectively measure the accuracy and consistency of the heart rate estimation method.

XVI. RESULTS

The proposed method successfully estimated heart rate from facial videos by analyzing brightness fluctuations in selected facial regions. After applying the Butterworth bandpass filter, noise from lighting and motion was significantly reduced, resulting in clearer signals. Time-series analysis of the forehead, left cheek, and right cheek regions revealed consistent rhythmic patterns corresponding to heartbeat cycles. The Superlet time-frequency analysis accurately identified the dominant frequency component, which was then converted into beats per minute (BPM). When compared to ground truth ECG readings, the estimated heart rates showed close alignment, with an average error margin within an acceptable range for non-contact methods. The forehead region provided the most stable signals, while cheek regions occasionally exhibited minor discrepancies due to motion artifacts. Overall, the system demonstrated reliable heart rate detection across varied lighting and activity conditions, confirming the effectiveness of the proposed pipeline in extracting physiological signals from facial video without physical contact or wearable sensors.



.Fig. 4. Time-Series of Facial Region Intensity Signals and Corresponding Superlet Transform Power for Heart Rate Analysis.

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XVII. DISCUSSION

The results of this study demonstrate that facial video analysis can serve as a viable method for heart rate estimation without the need for physical contact or specialized medical equipment. By focusing on pixel intensity variations in specific facial regions, the system effectively captured subtle changes related to blood flow beneath the skin. The forehead was found to be the most consistent region, likely due to its relatively stable surface and reduced motion compared to the cheeks.

Applying a Butterworth bandpass filter played a crucial role in removing noise and isolating heart-related frequency components. The Superlet time-frequency transform further enhanced the frequency resolution, enabling precise detection of the dominant spectral peak corresponding to the heart rate.

Despite promising results, some challenges remain. Motion artifacts and rapid lighting changes occasionally affected signal quality, particularly in the cheek areas. Future improvements could involve more advanced tracking algorithms and adaptive filtering techniques to enhance robustness. Overall, this approach demonstrates strong potential for real-time, noninvasive heart rate monitoring using widely available camera hardware.

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