Advances in the Use of rPPG for Non-Invasive Heart Rate Estimation

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Abstract— **Despite the growing adoption of remote photoplethysmography (rPPG) for non-contact heart rate monitoring, conventional whole-face approaches face major challenges in real-world scenarios. These include sensitivity to facial movements (e.g. blinking, talking) and uneven illumination, both of which degrade measurement accuracy. To address these limitations, this article presents a comprehensive evaluation of six unsupervised rPPG algorithms (ICA, GREEN, CHROM, LGI, PBV, and POS) across 21 anatomically defined facial regions, with the objective of identifying the most robust and precise zones for heart rate estimation. Our results show that specific regions, particularly the forehead, outperform full-face analysis due to their higher vascular density and reduced susceptibility to motion artifacts. Experiments on standard datasets reveal that region-specific methods achieve mean absolute errors below 1.5 beats per minute, and certain combinations of algorithm-regions improve accuracy by up to 66% compared to conventional techniques.**

Keywords— **Heart rate estimation, contactless BPM monitoring, computer vision, signal processing.**

I. INTRODUÇÃO

The use of physiological signals for disease diagnosis has become increasingly relevant in modern medicine, especially with technological advances that allow precise and non-invasive patient monitoring [1]. Among these signals, heart rate, often represented by beats per minute (BPM), stands out as a crucial indicator of health conditions. Traditionally, BPM monitoring is carried out using specific equipment such as electrocardiograms (ECG) or photoplethysmography (PPG) with physical sensors, offering real-time insights into cardiovascular function.

However, capturing and interpreting these signals presents significant technical challenges [2]. Detection accuracy depends on several factors, such as sensor quality, position of the equipment on the body, and interference from external noise. In addition, collecting and analyzing these signals often demands a controlled environment and is dependent on invasive or high-cost equipment, which is not always feasible in more dynamic clinical contexts, such as home care, telemedicine consultations, or emergency situations. The high cost of precision monitoring equipment can further restrict accessibility, especially in low-resource settings, creating disparities in cardiovascular care. Invasiveness and discomfort caused by traditional methods, combined with financial barriers, can also pose challenges to continuous patient monitoring, limiting the ability to perform regular exams and detect early signs of cardiovascular problems.

Recently, an innovative approach has emerged: the use of cameras to estimate BPM non-invasively, without the need for physical contact with the patient. This technique, known as remote photoplethysmography (rPPG), has been gaining attention since initial studies around 2008 [3]. It is based on the detection of subtle changes in skin color caused by blood circulation, observed through real-time videos or photographs. The principle behind rPPG is that heartbeats create small fluctuations in blood flow, which are reflected as changes in skin tone, visible even without physical sensors [4].

This non-invasive approach offers several advantages over traditional methods. The main advantage is the elimination of the need for physical contact with the patient, which can increase acceptance of the technique, particularly among individuals who are averse to invasive tests. Furthermore, the use of cameras allows for continuous remote monitoring, making it ideal for telemedicine and remote diagnostics, expanding access to healthcare, especially in underserved regions or during situations such as pandemics.

However, the use of rPPG presents some technical challenges, such as image quality, the influence of lighting conditions, patient movement, and the presence of artifacts in the images. The accuracy of BPM estimation depends on the ability to efficiently process this information and apply advanced machine learning algorithms to interpret the signals in a robust and precise manner. The evolution of image processing technologies and artificial intelligence has been crucial in overcoming these obstacles, enabling greater reliability in using rPPG for real-time BPM estimation.

This study investigates the feasibility and effectiveness of using rPPG for accurate BPM estimation, highlighting the technological advances that enable the effective capture of these signals and the precise interpretation of the data, even in scenarios outside controlled environments. The primary contributions of this work lie in advancing the understanding of spatial dynamics in rPPG and demonstrating the benefits of region-specific signal extraction. By systematically evaluating six unsupervised algorithms in multiple facial regions, the study provides both practical insight and methodological tools to improve heart rate estimation in real world scenarios. The main contributions are as follows:

- Facial Segmentation into Anatomically Defined ROIs: The study introduces a detailed segmentation of the face into 21 anatomically grounded regions of interest (ROIs), allowing localized and targeted rPPG signal extraction. This approach allows for a more granular understanding

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of spatial signal quality variations across the face.
- Analysis between ROIs and rPPG Algorithms: A comprehensive evaluation was conducted to explore the interaction between specific ROIs and six unsupervised rPPG methods. The results reveal that certain region-method combinations significantly outperform full-face approaches, emphasizing the importance of region-algorithm compatibility.
- Identification of Optimal Regions for Robust Heart Rate Estimation: The study highlights that the flatter, more illuminated and less mobile facial regions, particularly the forehead, produce higher accuracy in the estimation of heart rate due to the favorable anatomical and environmental properties. These insights provide actionable guidance for improving rPPG systems in real-world settings.

The article is structured as follows. Section II presents a review of relevant and related works in the literature. Section III describes the materials and methods used to develop the technology. Section IV presents the results obtained throughout the study, along with a detailed discussion. Finally, Section V concludes the study and outlines potential directions for future work.

II. Related Works

Numerous studies have explored non-invasive methods for measuring vital signs, with a particular focus on rPPG as a promising alternative. Several classical methods adopt unsupervised mathematical or statistical techniques to extract the rPPG signal from video frames. These include approaches such as Remote plethysmographic imaging using ambient light (GREEN) [3], Advancements in noncontact multiparameter physiological measurements using a webcam (ICA) [5], Robust pulse rate from chrominance-based rPPG (CHROM) [6], Local group invariance for heart rate estimation from face videos in the wild (LGI) [7], Improved motion robustness of rPPG by using the blood volume pulse signature (PBV) [8] and Algorithmic principles of rPPG (POS) [9]. These methods rely on decomposing the video signal captured through the Red, Green, and Blue (RGB) color channels to design a synthetic signal capable of representing the individual's PPG. They show that rPPG signals can be reliably extracted using relatively simple mathematical models.

However, challenges remain, particularly with regard to noise and artifacts. For example, the GREEN method leverages the predominance of the green channel, based on the higher absorption of green light by hemoglobin. However, the ICA method further improves signal quality by exploiting all RGB channels, considering the absorption characteristics of hemoglobin in both visible and near-infrared spectra.

Motion and environmental changes are also significant obstacles. The CHROM method addresses this by modeling the influence of illumination changes on color perception, proposing chrominance-based signals to mitigate the impact of specular reflections. LGI extends this idea by refining motion-robust signal extraction.

To enhance motion robustness, de Haan and van Leest [8] proposed to derive a unique physiological signature of the pulse of blood volume, based on average pixel values from the skin regions. Their method suppresses non-conforming signals through a new linear combination of the skin's RGB values. Building upon physiological and optical models, the POS algorithm [9] introduces a temporally normalized RGB space and defines a plane orthogonal to the skin tone to isolate the cardiac signal more effectively.

In contrast to previous studies that focus on a single method or signal property, this work proposes a hybrid approach that combines and evaluates multiple rPPG techniques across different facial regions. Specifically, the face is segmented into ROIs and various combinations of methods are tested in each region, such as chrominance-based filtering, color normalization, physiological signatures, and mathematical decomposition. The goal is to identify optimal strategies to mitigate artifacts and improve signal quality, leading to BPM estimates that are more accurate and robust, especially in unconstrained environments.

III. Materials and Methods

The main tool used in this study is the rPPG Toolbox, a platform that combines various extraction techniques in one place [10]. The rPPG Toolbox serves as a comprehensive platform for rPPG, integrating various extraction techniques and algorithms for efficient physiological signal measurement. It supports both traditional unsupervised algorithms and advanced supervised neural methods, making it flexible for researchers and developers to benchmark existing methods and create their own algorithms and deep learning models.

The proposed methodology aims to extract and validate BPM from videos and PPG signals using image and signal processing techniques. The input of the system consists of a video and a traditionally collected PPG file, obtained from the Pulse Rate Detection Dataset [11], which contains sequences of PNG-format images (video frames) of individuals along with a file that includes the PPG signal measured during the recording. Initially, the video goes through a face detection process using the dlib library, the first modification compared to the rPPG Toolbox which ends up using HaarCascade and Retina Face. The intention is to locate the face throughout the video and then segment it into ROIs, which are specific areas for analyzing the signal. Each ROI is extracted and saved as a sequence of frames, with each frame being resized to 72x72 pixels. In addition, the PPG value corresponding to that ROI is saved next to the frame in an .npy file.

For each pair of data generated in this pipeline (containing an ROI and its respective PPG value), the signal is processed using different blood volume pulse (BVP) extraction methods. The BVP signal and the label value are then passed to a function that calculates the BPM, using specific filters on the BVP signal to generate the rPPG. Once the rPPG has been obtained, both signals (rPPG and PPG) are analyzed using the fast Fourier transform (FFT) in Algorithm 1 or peak detection (PD) in Algorithm 2 functions, which make it possible to calculate the bpm generated by the video and the PPG provided.

The system is validated by comparing the BPM values obtained from the rPPG with the BPM values of the provided

Algorithm 1 Heart Rate Calculation using FFT

Require: ppg_signal, $fs = 60\text{Hz}$, $low\_pass = 0.75\text{Hz}$, $high\_pass = 2.5\text{Hz}$
Ensure: Estimated heart rate fft_hr in BPM
Preprocess signal:
$ppg\_signal \leftarrow \text{expand\_dims}(ppg\_signal, 0)$
Compute FFT parameters:
$N \leftarrow \text{next\_power\_of\_2}(\text{len}(ppg\_signal))$
$(f\_ppg, pxx\_ppg) \leftarrow \text{periodogram}(ppg\_signal, fs, N)$
Apply frequency bandpass:
$fmask\_ppg \leftarrow \text{where}((f\_ppg \geq low\_pass) \wedge (f\_ppg \leq high\_pass))$
$mask\_ppg \leftarrow f\_ppg[fmask\_ppg]$
$mask\_pxx \leftarrow pxx\_ppg[fmask\_ppg]$
Find dominant frequency:
$peak\_idx \leftarrow \text{argmax}(mask\_pxx)$
$hr\_hz \leftarrow mask\_ppg[peak\_idx]$
$fft\_hr \leftarrow hr\_hz \times 60$
return fft_hr

Algorithm 2 Heart Rate Calculation using Peak Detection

Require: ppg_signal, sampling rate fs in Hz
Ensure: Estimated heart rate hr_peak in BPM
Peak Detection:
$ppg\_peaks \leftarrow \text{find\_peaks}(ppg\_signal)$
Calculate Intervals:
$peak\_intervals \leftarrow \text{diff}(ppg\_peaks)$
$mean\_interval \leftarrow \text{mean}(peak\_intervals)$
Convert to Heart Rate:
$hr\_peak \leftarrow \frac{60 \times fs}{mean\_interval}$
return hr_peak

PPG signal. For this comparison, performance metrics are generated, such as the mean absolute error (MAE) described in Equation 1 and the mean absolute percentage error (MAPE) as follows in Equation 2. These metrics are calculated individually for each ROI and for each BVP extraction method, allowing a detailed assessment of the system's accuracy and reliability under different conditions and for different facial regions. This approach aims to provide a robust and accurate analysis of heartbeats from the combination of videos and PPG signals, with quantitative validation through error metrics.

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

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

Figure 1 illustrates the mapping of the facial ROIs used to extract the BVP signal. Segmentation is performed based on facial reference points, forming colored polygons superimposed on the original image. Each ROI is identified by a distinct color, with a side legend that facilitates visual identification.

In the work by [10], the MAE and MAPE metrics were described and are used in Table I, where we present the results

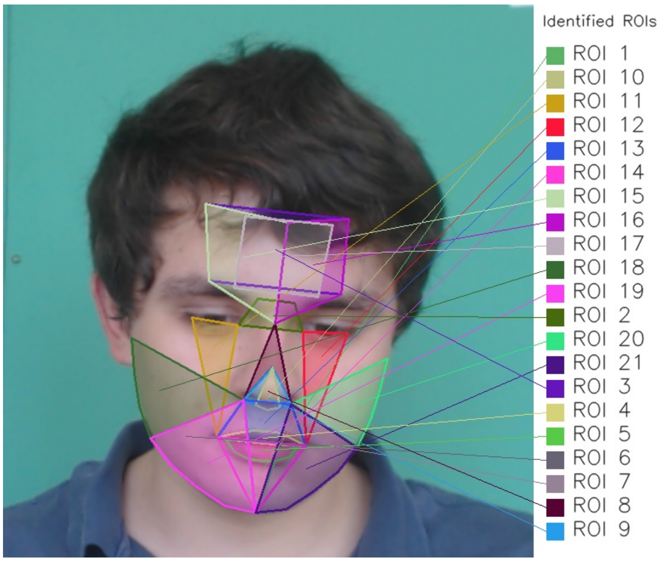

Fig. 1. Facial ROI mapping used for BVP extraction. The face is segmented into specific ROIs, which are individually analyzed to extract physiological signals. Image extracted from the UBFC-rPPG dataset [12].

obtained for different methods. The ICA method showed the best performance in terms of MAE, while the PBV method obtained the lowest MAPE value considering the complete face. However, by using segmentation in ROIs along the face, it was possible to achieve even lower values for both metrics in certain methods.

Taking into account the data set used, the ICA method, applied to ROI 3, was found to show the best results in both MAE and MAPE, which is in line with several previous studies in the literature [13]. In addition, other methods also showed significant improvements when applied to specific regions. The CHROM method, for example, reduced MAE by 3.46 in ROI 17, while POS showed an MAE reduction of 2.38 when applied to ROI 16. These results suggest that segmenting the image into more homogeneous regions that are less susceptible to variations in lighting and movement contributes to greater robustness of rPPG algorithms.

On the other hand, the PBV method had the best MAPE performance in the full-face approach, with a value of 4.82. However, it underperformed when applied to ROI 16, achieving a MAPE value of 5.85. This behavior may be related to the method's sensitivity to the specific characteristics of the selected region, indicating that not all algorithms benefit equally from ROI segmentation.

In summary, the results reinforce the effectiveness of using ROIs in rPPG algorithms, especially the ICA method, which proved to be the most accurate in this context. However, the choice of method and ideal ROI can vary according to the capture conditions and the physiological characteristics of the individual, reinforcing the importance of careful evaluation in different scenarios.

The results presented in Table I show that ROI 3 performed with the lowest MAE and MAPE values when used with the ICA method [5], corroborating previous studies on the effectiveness of this region [13]. Although ROIs such as cheeks

TABLE I
MEAN ABSOLUTE ERROR (MAE) AND MEAN ABSOLUTE PERCENTAGE ERROR (MAPE) FOR EACH ROI AND METHOD.

ROI	POS	ICA	OMIT	LGI	PBV	CHROM	GREEN
1	12.22 ǀ 19.28	12.58 ǀ 15.99	8.65 ǀ 10.21	8.69 ǀ 10.36	11.14 ǀ 13.01	11.48 ǀ 15.96	13.42 ǀ 18.75
2	4.31 ǀ 7.16	3.37 ǀ 3.05	2.78 ǀ 2.95	2.78 ǀ 2.95	5.59 ǀ 7.35	6.25 ǀ 9.79	9.65 ǀ 11.43
3	2.21 ǀ 4.22	**1.25 ǀ 1.57**	**1.33 ǀ 1.72**	**1.33 ǀ 1.72**	11.31 ǀ 12.11	2.33 ǀ 4.60	10.69 ǀ 13.66
4	19.65 ǀ 30.14	19.65 ǀ 28.32	15.40 ǀ 22.19	15.72 ǀ 22.77	18.97 ǀ 28.76	19.43 ǀ 28.67	18.86 ǀ 26.76
5	19.40 ǀ 29.65	16.52 ǀ 23.37	13.81 ǀ 18.70	13.61 ǀ 18.41	15.32 ǀ 21.53	19.60 ǀ 29.68	16.06 ǀ 22.26
6	6.46 ǀ 11.68	6.60 ǀ 6.82	6.31 ǀ 9.23	6.31 ǀ 9.23	5.70 ǀ 8.07	8.15 ǀ 14.68	12.92 ǀ 15.21
7	6.04 ǀ 10.93	4.86 ǀ 4.63	4.91 ǀ 7.26	4.88 ǀ 7.21	8.31 ǀ 8.98	6.55 ǀ 11.89	10.82 ǀ 13.16
8	7.44 ǀ 11.42	7.24 ǀ 8.12	4.54 ǀ 5.09	4.52 ǀ 5.06	9.29 ǀ 10.78	8.50 ǀ 12.36	7.92 ǀ 8.43
9	7.52 ǀ 10.43	7.48 ǀ 9.02	5.76 ǀ 5.26	5.76 ǀ 5.26	9.05 ǀ 9.39	9.87 ǀ 13.82	7.97 ǀ 8.46
10	9.22 ǀ 13.14	8.22 ǀ 9.84	7.28 ǀ 6.71	7.29 ǀ 6.73	9.05 ǀ 10.17	13.43 ǀ 20.45	7.47 ǀ 8.43
11	5.33 ǀ 10.21	5.67 ǀ 6.48	5.77 ǀ 8.13	5.75 ǀ 8.09	9.54 ǀ 11.73	6.98 ǀ 11.19	9.86 ǀ 11.31
12	5.78 ǀ 10.59	6.01 ǀ 7.01	3.55 ǀ 5.44	3.55 ǀ 5.44	10.21 ǀ 11.62	6.14 ǀ 9.69	9.32 ǀ 10.89
13	8.46 ǀ 13.17	8.43 ǀ 11.48	5.11 ǀ 6.96	5.05 ǀ 6.88	10.04 ǀ 12.08	8.51 ǀ 13.46	10.39 ǀ 11.81
14	9.87 ǀ 15.33	9.27 ǀ 11.60	5.25 ǀ 7.10	5.59 ǀ 8.01	10.17 ǀ 11.83	11.99 ǀ 17.21	13.02 ǀ 15.57
15	2.09 ǀ 3.97	1.38 ǀ 2.24	1.42 ǀ 2.20	1.42 ǀ 2.20	7.00 ǀ 7.88	2.76 ǀ 4.54	8.62 ǀ 10.76
16	**1.40** ǀ 2.76	4.03 ǀ 3.73	2.78 ǀ 3.46	2.78 ǀ 3.46	**4.95 ǀ 6.45**	3.33 ǀ 4.95	8.64 ǀ 10.32
17	1.48 ǀ **2.69**	2.39 ǀ 2.47	2.49 ǀ 2.83	2.49 ǀ 2.83	8.16 ǀ 9.90	**2.32 ǀ 3.71**	**7.18 ǀ 8.55**
18	6.12 ǀ 10.84	6.05 ǀ 7.67	5.71 ǀ 7.70	5.71 ǀ 7.70	9.60 ǀ 11.04	6.86 ǀ 11.04	14.47 ǀ 16.21
19	4.19 ǀ 7.09	8.91 ǀ 11.14	6.55 ǀ 7.60	6.48 ǀ 7.51	7.03 ǀ 7.98	5.85 ǀ 9.19	12.92 ǀ 15.29
20	4.72 ǀ 7.61	6.58 ǀ 9.10	2.97 ǀ 4.45	3.00 ǀ 4.49	8.82 ǀ 10.77	5.11 ǀ 7.95	10.11 ǀ 12.69
21	6.30 ǀ 10.11	7.93 ǀ 10.80	4.11 ǀ 6.32	4.30 ǀ 6.61	9.50 ǀ 11.87	8.55 ǀ 13.37	11.57 ǀ 14.50
FullFace	**3.63** ǀ 7.18	4.81 ǀ **4.53**	4.65 ǀ 4.96	4.56 ǀ 4.90	4.64 ǀ 5.35	5.72 ǀ 11.45	10.13 ǀ 10.34

tend to introduce noise due to facial movements [14], regions such as the forehead preserve greater stability even in dynamic environments.

IV. DISCUSSION

Results reveal that region-specific analysis can significantly improve heart rate estimation over traditional whole-face approaches. In particular, regions such as the forehead consistently demonstrated superior performance due to their anatomical advantages,namely higher vascular density, as well as their flatter surface geometry and relative uniformity in illumination and motion. These characteristics contribute to reduced susceptibility to motion artifacts and lighting variations, common challenges in real-world rPPG applications.

Although several algorithms-ROI combinations achieved MAEs below 1.5 BPM, some results were notably poor. These lower-performing cases can be partially attributed to the inherent simplicity of certain unsupervised methods, which lack sophisticated mechanisms to compensate for motion, lighting fluctuations, or intersubject variability. The forehead, for instance, showed robust results across multiple algorithms, whereas more dynamic or irregular regions (e.g., the lips or chin) performed inconsistently, emphasizing the importance of careful spatial selection in rPPG signal extraction.

Nonetheless, several limitations must be acknowledged. The study relied exclusively on a single benchmark dataset, which, although commonly used, contains a limited number of subjects and recordings under constrained conditions: a static single-camera setup with fixed angle and no environmental variability. In addition, reference heart rate values were obtained from oximeter readings provided by the dataset, without independent verification of their accuracy. Only unsupervised methods from the rPPG toolbox were evaluated, and performance was assessed solely using BPM as the output metric, excluding signal quality measures or temporal coherence analyses.

Another significant challenge lies in managing the high dimensionality of the data. Each frame provides 21 ROIs, each of which is processed by six algorithms, leading to a large number of signal permutations. Establishing correlations between subjects, methods, and regions becomes complex, limiting interpretability and requiring advanced visualization techniques. Moreover, from a computational perspective, the use of multiple independent ROIs, rather than a single full-face region, substantially increases processing time, as each method must perform inference per region per frame, which could hinder real-time deployment.

Despite these constraints, the results suggest that region-specific approaches offer a promising pathway for enhancing the robustness and accuracy of non-contact heart rate monitoring. Future work should explore multi-metric evaluation, inclusion of supervised methods, and adaptive models capable of selecting optimal ROIs dynamically. Expanding the dataset to include more subjects, variable lighting, and different camera configurations will also be essential to validate generalizability and support real-world applications.

V. Conclusion

This work proposed and evaluated a methodology for extracting heart rate from videos, combining rPPG algorithms with facial segmentation in ROIs. Different signal extraction methods were tested, applied both to the complete face and to specific ROIs, and the results were evaluated based on quantitative metrics such as MAE and MAPE.

The experiments showed that the right choice of ROI, combined with the most appropriate method, can significantly improve the accuracy of the estimates of BPM. In particular, ROI 3, combined with the ICA method, showed the best results for the dataset used, outperforming traditional approaches based on the full face. These findings show that simpler, more targeted solutions can improve the performance of more complex strategies, which is especially relevant for applications on devices with limited computing resources.

As a direction for future work, we propose investigating approaches that combine multiple ROIs and signal extraction methods to enhance robustness and introduce redundancy in heart rate estimation. Fusion strategies that integrate signals from distinct facial regions could improve stability under varying conditions of motion, lighting, and individual physiological differences. Additionally, future research should explore the use of supervised and deep learning-based rPPG algorithms to overcome the limitations observed with unsupervised methods, particularly in handling complex motion artifacts and illumination changes. Expanding the evaluations to larger and more diverse datasets, with multiple camera angles, mobile scenarios, and varied skin tones, performing comparison with other relevant literature works in addition to the results from the tool box, and calculating a statistical validation of the results would further support the generalizability of the findings. Moreover, incorporating alternative evaluation metrics beyond BPM, such as the signal-to-noise ratio (SNR) and temporal coherence, could provide a more comprehensive assessment of signal quality. Finally, addressing the computational burden of region-specific inference remains a critical challenge, and future solutions may benefit from real-time optimization techniques or hardware acceleration to support practical deployment.

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