PulseVision: A Real-Time Heart-Rate Monitoring System Using Computer Vision and Signal Processing Techniques

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Abstract - In the dynamic landscape of technology and healthcare, the quest for real-time physiological monitoring solutions has sparked innovation. This study proposes a method that leverages computer vision and signal processing to create a cutting-edge system for monitoring heart rates in real-time. The script employs OpenCV for face detection and incorporates custom modules for real-time plotting, offering a comprehensive and instantaneous assessment of cardiovascular activity. The Python script unveils a real-time heart rate monitoring system that harnesses the synergy of computer vision and signal processing. Utilizing OpenCV for precise face detection and custom modules for dynamic plotting, the script processes video frames from a webcam to analyze the facial region for heart rate monitoring. Employing color magnification, Gaussian pyramid construction, and bandpass filtering, the script extracts the pulse signal's frequency content. Heart rate, calculated in beats per minute (BPM), provides a valuable metric for physiological assessment. This system, with its innovative approach, has the potential to redefine real-time physiological monitoring applications, offering insights for healthcare and personal well-being.

Key Words: Heart Rate Monitoring, Computer Vision, Signal Processing, OpenCV, Real-time Plotting, Face Detection, Frequency Analysis, Pulse Signal, Gaussian Pyramid, Bandpass Filtering.

1.INTRODUCTION

Monitoring heart rate has traditionally relied on methods that require direct contact with the body, such as electrocardiograms (ECGs) and photoplethysmography (PPG). While accurate, these methods can be restrictive, uncomfortable, and susceptible to errors caused by movement. This has sparked a quest for non-contact, remote heart rate monitoring techniques. Exciting advancements in computer vision offer a promising solution: using facial video analysis to estimate heart rate without any physical sensors. This technique, known as remote photoplethysmography (rPPG), captures subtle colour changes in the facial skin caused by blood flow. It holds the potential to provide continuous, unobtrusive heart rate monitoring in various settings, from healthcare to fitness and human-computer interaction.

However, rPPG faces challenges. The signals it relies on are delicate and easily affected by factors like changes in lighting, head movements, and facial expressions. To extract reliable heart rate measurements, researchers are developing sophisticated signal processing techniques and face detection algorithms to overcome these challenges and ensure accurate heart rate estimation.

This review delves into the recent progress in face-based heart rate monitoring using vision-based approaches. It explores the theoretical foundations of rPPG, analyzes the common challenges and existing solutions, and highlights promising research directions aimed at further refining the technology and expanding its real-world applications. The goal is to provide a comprehensive understanding of this emerging field and inspire further research to unlock the full potential of face-based heart rate monitoring across diverse domains.

2. METHODOLOGY

Growing interest in remote heart rate measurement via camera and image processing is fueling research in deep learning methods. This paper reviews publicly available deep learning methods and compares their performance using the UBFC dataset. PhysNet emerges as the top performer, with mean absolute error of 2.57 bpm and mean square error of 7.56 bpm. While vision-based heart rate measurement holds promise, noise and motion artifacts have hindered its accuracy. This research proposes a novel method using unsupervised clustering on ballistocardiographic head movements captured by a camera. Unlike traditional methods relying on peak detection and Fourier transform, which are sensitive to noise, this approach extracts a robust signal and builds a model for accurate heart rate estimation. Tests demonstrate its superiority in handling facial expressions and head movements, opening the door for reliable non-contact heart rate monitoring in daily life. This innovative approach paves the way for more comfortable and accessible cardiovascular health tracking in diverse settings.

This paper presents a method for extracting heart rate signals from facial videos that effectively addresses motion artifacts and ambient light interference. By separating the face from the background, removing motion artifacts in the ROI, and employing normalized adaptive filtering, the technique accurately extracts heart rate values even under varying illumination conditions, demonstrating its robustness and potential for real-world applications.This paper presents the development and validation of a noninvasive point-of-care method for monitoring heart rate and respiratory rate from video of a user's face. This paper explores the potential of remotely measuring heart rate via video analysis during drone-captured in-flight activities. Using facial and forearm skin detection, pose estimation, and various VPG methods, it demonstrates promising accuracy in estimating heart rate even outdoors and during movement. This opens doors for future applications in diverse scenarios.

3. PROPOSED SYSTEM

Webcam Access: OpenCV's 'VideoCapture(0)' function accesses the default webcam for continuous video capture. This provides a real-time stream of frames for heart rate analysis.

Face Detection: To focus on relevant blood flow signals, the code employs the 'FaceDetector' module from cvzone. This efficient tool accurately locates the face within each video frame, reducing processing requirements and improving signal quality.

Facial ROI Extraction: Once the face is detected, the code extracts the region of interest (ROI) using the bounding box coordinates provided by the 'FaceDetector'. This ROI, typically the forehead, contains subtle color variations associated with blood flow pulsations, crucial for heart rate estimation.

Gaussian Pyramid Decomposition: This technique creates multiple versions of the facial ROI at progressively coarser resolutions (like a pyramid). This allows us to capture subtle color variations associated with blood flow at different spatial scales. Lower frequencies (larger variations) are visible in coarser levels, while higher frequencies (smaller variations) are seen in finer levels.

ZONE	% OF MAX HR	EXERTION LEVEL	FITNESS GOAL
5	90 - 100%	MAX	FOR FIT ATHLETES IN VERY BRIEF DURATIONS, DEVELOP FAST-TWITCH MUSCLE FIBERS TO BOOST SPRINT SPEED
4	80 - 90%	HARD	INCREASE ANAEROBIC THRESHOLD AND MAX CAPACITY FOR SHORTER EFFORTS
3	70 - 80%	MODERATE	IMPROVE AEROBIC FITNESS AND MUSCLE STRENGTH
2	60 - 70%	LIGHT	BUILD BASIC ENDURANCE, FAT BURNING, SUSTAINABLE FOR LONG PERIODS OF EXERCISE
1	50 - 60%	VERY LIGHT	WARM UP, COOL DOWN, AND ACTIVE RECOVERY
0	< 50%	REST	NO MEANINGFUL STRAIN ON THE BODY

Figure - 1: Colour Magnification

Bandpass Filtering: To isolate the heart rate signal, the code applies a filter that only allows frequencies within the typical heart rate range of 1-2 Hz to pass through. This filter suppresses noise from other sources like head movement or lighting changes, enhancing the desired signal for accurate analysis.

Signal Amplification: Multiplying the filtered signal by a factor of 170 (as defined in the code) visually amplifies the subtle color changes associated with blood flow. This amplification makes the pulsations easier to see and analyze, improving the accuracy of heart rate estimation.

Inverse Fourier Transform: This operation converts the filtered signal back from the frequency domain (where we isolated the heart rate signal) to the spatial domain (where we can see the actual color changes). This reconstructed signal visually represents the amplified heart rate pulsations on the face.

Temporal Fourier Transform: Analyzing the color changes over time in a sequence of color-magnified frames using the Fourier transform reveals the frequency components present in the signal. This includes the dominant frequency related to the heart rate.

Peak Frequency Identification: The code identifies the frequency within the 1-2 Hz range that has the highest magnitude (using 'np.argmax'). This peak frequency corresponds to the strongest pulsations visible in the color-magnified signal and, therefore, the most likely indicator of the heart rate.

BPM Calculation: The peak frequency is converted to beats per minute (BPM) using the simple formula BPM = 60 * Hz. This provides an estimated heart rate value based on the identified heart rate signal frequency.

BPM Buffering: To smooth out transient fluctuations and provide a more stable readout, the code averages recent heart rate estimates (10 values) stored in a buffer. This helps to filter out noise and produce a more reliable heart rate measurement.

Overlay of Color-Magnified Signal: The amplified color-magnified signal is superimposed onto the original video frame in the top-right corner, occupying half the frame's width and height. This allows users to visualize the pulsations associated with the heart rate in real-time, providing immediate feedback on blood flow changes.

BPM Display: The estimated heart rate value (BPM) is prominently displayed on the video output, positioned in the center of the top region of the frame. During the initial calculation period, a "Calculating BPM..." message is displayed instead. This ensures users are informed when the displayed value might not be fully accurate.

Live Plot Generation: The 'LivePlot' module from cvzone dynamically generates a plot of heart rate values over time, displayed alongside the video frame. This provides users with a visual representation of heart rate trends and variations beyond the current instant, offering additional insights into their cardiovascular activity.

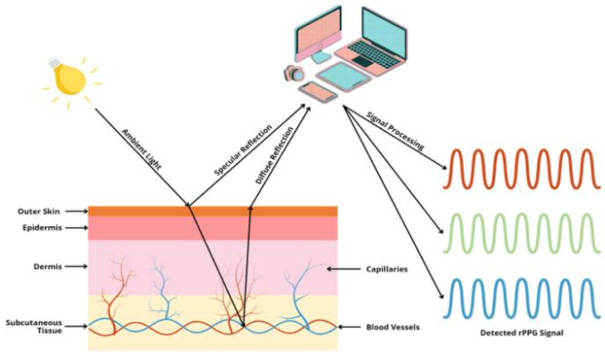


Figure -2 : Vizualisation and Display

Video and ROI Resolution: The code configures a video resolution of 640x480 pixels and resizes the extracted facial ROI to 160x120 pixels. This balance offers good video quality with efficient processing suitable for real-time analysis.

Gaussian Pyramid and Amplification: Setting the Gaussian pyramid to 3 levels and the amplification factor to 170 provides a good balance between effective signal enhancement and computational demands. Higher levels or amplification could improve accuracy but increase processing time, while lower values might not sufficiently amplify the heart rate signal for reliable estimation.

Bandpass Filter Range: Restricting the filter range to 1-2 Hz ensures isolation of the desired heart rate signals while rejecting noise from other sources. This range can be adjusted slightly based on individual heart rate variability, but too wide a range might introduce unwanted noise, and too narrow might miss the actual heart rate signal.

4. ABBREVIATIONS AND ACRONYMS

BPM - beats per minute

HR - heart rate

PPG - photoplethysmography

ECG - electrocardiograms

rPPG - remote photoplethysmography

ROI - region of interest

DFT - discrete fourier transform

IDFT - inverse discrete fourier transform

5 . RESULT

The following graph shows the variation of HR with time(s).

Key points to be considered – variation of environmental lighting, resolution, sensitivity, dynamic range, color accuracy, lens quality and video quality of camera play a key role and results can vary when these parameters are affected.

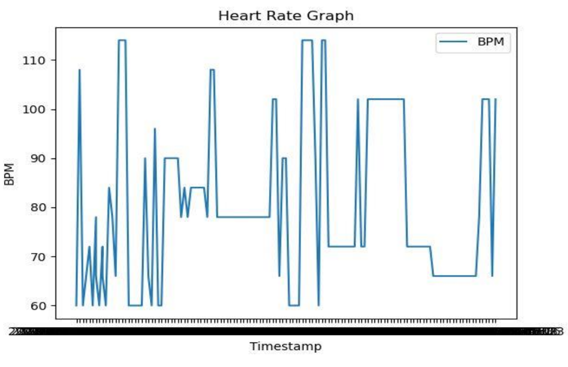
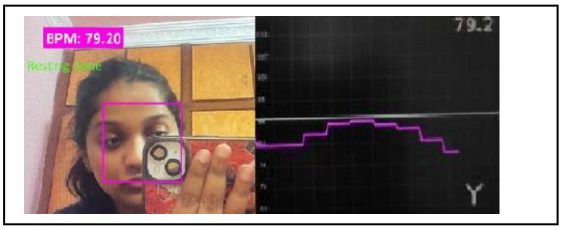


Figure - 3: Variation of HR with time(s)

The following image is a demonstration of the output obtained.



6 . CONCLUSION

This paper presented a novel system for real-time heart rate monitoring utilizing computer vision and signal processing techniques. The proposed method extracts pulse information from webcam video frames by combining face detection, color magnification, Gaussian pyramid construction, and bandpass filtering. By analyzing the frequency content of the extracted signal, the system estimates heart rate in beats per minute, providing a valuable metric for physiological assessment. Utilizing readily available tools like OpenCV and custom-developed modules for real-time data visualization, this script offers a user-friendly and comprehensive solution for heart rate monitoring.

Future research directions include:

Improving accuracy: Exploring advanced signal processing techniques and adapting parameters to individual variations in skin tone and lighting conditions.

Building a comprehensive database: Collecting data from diverse populations to refine the system's generalizability and accuracy.

Integration with wearable devices: Combining the proposed system with other modalities like pulse oximetry or electrocardiography for enhanced physiological monitoring.

The innovative approach presented in this paper paves the way for more accessible and real-time physiological monitoring solutions, holding significant potential for applications in healthcare, fitness, and personal well-being. Ongoing research and development will further refine the system's accuracy and broaden its scope, empowering individuals to proactively track their cardiovascular health in real-time.

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8. REFERENCES

[1] Ni, A.; Azarang, A.; Kehtarnavaz, N. A Review of Deep Learning-Based Contactless Heart Rate Measurement Methods. Sensors 2021, 21, 3719.

[2] Lee H, Cho A, Lee S, Whang M. Vision-Based Measurement of Heart Rate from Ballistocardiographic Head Movements Using Unsupervised Clustering. Sensors (Basel). 2019 Jul 24;19(15):3263. doi:

10.3390/s19153263. PMID: 31344939; PMCID: PMC6695981

[3] W. Liu, Y. Shen and Q. Wei, "Research on Non-contact Heart Rate Signal Detection Based on Video Image," 2018 IEEE International Conference on Automation, Electronics and Electrical Engineering (AUTEEE), Shenyang, China, 2018, pp. 181-183, doi: 10.1109/AUTEEE.2018.8720755.

[4] Sanyal S, Nundy KK. Algorithms for Monitoring Heart Rate and Respiratory Rate From the Video of a User's Face. IEEE J Transl Eng Health Med. 2018 Apr 12;6:2700111. doi: 10.1109/JTEHM.2018.2818687. PMID: 29805920; PMCID: PMC5957265.

[5] Pająk A, Przybyło J, Augustyniak P. Touchless Heart Rate Monitoring from an Unmanned Aerial Vehicle Using Videoplethysmography. Sensors (Basel). 2023 Aug 21;23(16):7297. doi: 10.3390/s23167297. PMID: 37631834; PMCID: PMC10459503.

[6] Jia M, Li Z, Yang X, Xu M, Zhao L, Yang B. [A Light Adaptive Heart Rate Detection Method Based on Webcam]. Zhongguo Yi Liao Qi Xie Za Zhi. 2020 Oct 8;44(5):377-383. Chinese. doi: 10.3969/j.issn.1671-7104.2020.05.001. PMID: 33047557.

[7] X. Guo, S. Guo, Y. Zhao and J. Shi, "Research on the Key Technology of Non-contact Vital Signs Monitoring," 2023 6th International Conference on Computer Network, Electronic and Automation (ICCNEA), Xi'an, China, 2023, pp. 249-253, doi: 10.1109/ICCNEA60107.2023.00060.

[8] A. H. M. Zadidul Karim, M. S. Miah, G. R. Ahmed Jamal, R. A. Fahima and M. T. Rahman, "Application of Chrominance Based rPPG in Estimation of Heart Rate from Video Signal," 2021 24th International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ICCIT54785.2021.9689811.

[9] S. A. Alhammad, "Face Detection for Pulse Rate Measurement," 2018 1st International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia, 2018, pp. 1-5, doi: 10.1109/CAIS.2018.8442034.

[10] A. D. Mehta and H. Sharma, "Heart Rate Estimation from RGB Facial Videos Using Robust Face Demarcation and VMD," 2021 National Conference on Communications (NCC), Kanpur, India, 2021, pp. 1-6, doi: 10.1109/NCC52529.2021.9530067.

[11] E. Gonultas, O. Demirbasci and E. Mendi, "A novel method and mobile system for accurate heart rate measurement from finger and face," 2016 24th Signal Processing and Communication Application Conference (SIU), Zonguldak, Turkey, 2016, pp. 649-652, doi: 10.1109/SIU.2016.7495824.

[12] N. A. Akbar, A. Muneer, S. M. Taib and S. Mohamed Fati, "Measuring Accuracy Towards Facial Video Heart-Rate Estimation Using Haar-Cascade and CNN Method," 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 2022, pp. 1607-1611, doi: 10.1109/DASA54658.2022.9764992.

[13] Y. -P. Yu, P. Raveendran and C. -L. Lim, "Heart rate estimation from facial images using filter bank," 2014 6th International Symposium on Communications, Control and Signal Processing (ISCCSP), Athens, Greece, 2014, pp. 69-72, doi: 10.1109/ISCCSP.2014.6877818.

[14] Tang, Chuanxiang, Jiwu Lu, and Jie Liu. "Non-contact heart rate monitoring by combining convolutional neural network skin detection and remote photoplethysmography via a low-cost camera." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2018.

Ibrahim, Norwahidah, et al. "Non-contact heart rate monitoring analysis from various distances with different face regions." International Journal of Electrical and Computer Engineering 7.6 (2017): 3030.