IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 10, Issue 5, May 2023

DOI: 10.17148/IARJSET.2023.10566

Heart Rate Detection through Eulerian Video Magnification of Face Videos

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Abstract: Remotely measuring vital indicators, such as heart rate (HR), is possible using facial footage captured by a consumer-level digital camera. However, background light and bodily motions frequently have an impact on how accurately the heart rate is estimated. Therefore, we suggest an anti-disturbance strategy to measure HR at a distance, Eulerian video magnification (EVM), signal quality assessment (QA), and adaptive chirp model decomposition. The performance of the suggested method is then assessed and validated in five distinct situations, including low illumination, normal illumination, high illumination, imbalanced illumination, and head motion. The experimental findings showed a high degree of congruence between the proposed method's HR estimations in various scenarios and the related ground facts. Additionally, whether compared to techniques based on empirical mode decomposition (EMD) or variable mode decomposition (VMD).

Keywords: HR Estimation, Convolutional Neural Network, Spatial Decomposition, Temporal Filtering

I. INTRODUCTION

Resolving the shortcomings of the current contact-free heart rate measuring techniques and adding new factors to make up for these flaws. Constructing a novel technique to increase the non-contact pulse rate measurement system's robustness more difficult and realistic capture situations. A method to recover hidden temporal information from videographic data is Eulerian video magnification. In experimental and comparative physiology, where contact-based recordings cannot be made, this can be used.

Heart rate monitoring is becoming a common practise in both public and private settings, including hospitals. This portable device is small and convenient to carry. Heart rate monitors can be used in conjunction with other gadgets like microcontrollers, and other suitable hardware and software. A variety of sensory tools, including an ECG machine, a pulse oximeter, and a Doppler probe, among others, can detect heart rate. All of these pieces of equipment operate satisfactorily, but the patient finds their use to be rather painful. The subject's movement and fluctuations in lighting are the two key issues that have an impact on the accuracy of contact-free heart rate measurements. If accurately retrieved from the subject's facial imaging, the derived pulse signal may have a variety of beneficial uses, including biometric recognition, lie or stress detection, sports analysis, etc.

Limited capacity to effectively estimate heart rate through dark and tattooed skin. Not necessarily accurate in sports when you move your hands vigorously or flex the muscles and tendons near your wrist. More likely to be worn improperly either too tight or not tight enough. Internal monitoring carries the risk of infection and injury to other body parts. The project's goal is to research contact-free heart rate monitoring techniques, with a focus on the main challenges of subject motion and lighting noise in heart rate estimation from human face videos. We work to gain a thorough understanding of these issues, the technologies currently in use, how well they operate under realistic and more difficult circumstances, and what uses the contact-free pulse extraction from facial films might have. We examine the most well-liked and/or most promising methodologies, point out their shortcomings, and suggest potential upgrades.

The rest of the paper is organized as follows. The next section composes a review of similar researches that have been implemented and tested for Heart Rate Detection. In Section III, the methodology is described. In Section IV, experimental results are reported. Finally, some conclusions are given and future work is proposed.

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II. REVIEW OF OTHER METHODS

[1] The paper proposed the adaptive eulerian video magnification methods to extract bio signals is an emerging technique. methods Spatiotemporal video processing is a new method for extracting bio signals. Through thorough experimentation and analysis, this report seeks to advance previous research. Thermal and optical cameras recorded a blood flow simulation model as hot water was circulated through the apparatus. In addition, five volunteers were enlisted for two experimental trials: a facial perfusion trial and an arm blood occlusion study, in which volunteers sat still while thermal and optical cameras recorded video data. Each video underwent adaptive Eulerian video magnification (EVM), which is the iterative application of EVM. The first time, it was applied with a wide temporal bandpass filter and a low amplification factor. The second time, it was applied with a narrower, targeted temporal bandpass filter and a higher amplification factor.

[2] This paper proposed Validation of heart rate extraction using video imaging on a build-in camera system of smartphone. A smartphone demonstrates its potential as a low-cost, accurate physiological monitoring solution that can be utilised outside of the clinical environment as its popularity and performance increase quickly. because the delicate colour is led by the heart's pulse. Through the use of a digital camera to record face video, a pulsatile signal known as a photo platysma graphic (PPG) signal can be used to measure changes in the skin. In this study, we investigate the possibility of leveraging face video captured by a smartphone camera to measure a reliable heart rate remotely. First, facial footage was captured on a smartphone's front-facing camera. Face detection was used to identify the facial region on each frame's image, and the resulting raw trace signal from

[3] This paper proposed the Contact-Fee Heart Rate Measurement from Human Face Videos and its Biometric Recognition Application. The most significant muscle organ in the human body is the heart, and the rate at which it beats can be used to gauge its strength. There are several ways to remotely monitor heart rate, which is an important factor in determining how well people are doing with greater comfort and convenience. It can be made more user-friendly and used for covert surveillance by using contact-free heart rate monitoring. The effectiveness of previously created. Under controlled circumstances, touch-free techniques were found to be effective and precise.

Their performance suffers in more difficult and realistic settings since each technique has its limitations. The performance typically depends on well-calibrated lighting and minimal subject movement. More plausible circumstances are the approach that is suggested can address numerous issues with light reflection and the subject's motion is tracked as the heart rate is remotely measured on human faces using a standard camera. We track the faces from the recorded films using the Sarangi face tracker, will provides more accurate region of interest (ROI) extraction than basic face detection. To improve the assessment of skin colour in each frame and lessen the impact of facial hair, wrinkles, and illumination, we find the robust mean of the colour values of the skin pixels in the chosen ROI. Additionally, using our training dataset, we compute the least-squares error optimum filter to more precisely predict the heart rate from the observed colour changes over time.

[4] This Pre-processing Realistic Video for Contactless Heart Rate Monitoring using Video Magnification. The goal of this study is to enhance Eulerian video magnifying results in practical settings. They discuss the central Eulerian Magnification requirement that the subject in the video be perfectly still. Stabilisation and targeting. The final product is more compatible with Eulerian magnification limitations. Our technique permits the use of magnification in numerous applications where motion is present, such as tracking a treadmill user's heart rate. Our research's central goal of stabilisation was accomplished using two techniques. First, we created a stabilised video with little motion using facial tracking. Second, feature extraction, matching with skin selection, and feature detection were utilised to create a clear heart rate measurement.

[5] This paper proposed how to measure the heart rate from videos. For sensitive people, a non-contact method of detecting heart rate could be helpful. It would be helpful in telemedicine to be able to calculate the pulse using a basic webcam or phone camera. Previous research has demonstrated that a person's heart rate may be detected in a colour video of their face. The reimplementation of one such method—which employs independent component analysis on mean pixel colour values within a region of interest (ROI) around the face—is covered in this study. The notion is further developed by examining various methods for selecting the ROI, such as segmenting facial pixels using a reimplementation of Grab Cut, and evaluating the algorithm's resistance to subject movement and bounding box noise. In still footage, the heart rate was recorded with a 3.4–0.6 bpm inaccuracy.

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III. METHODOLOGY

The implementation phase's objective is to convert the system design created during the design phase into coded form in a specific computer language. The computation defined by the design can then be carried out by a machine executing the code. Well-written code can lower the cost of testing and maintenance. The coding process has a significant impact on both. Implementation is the process of turning a design into a functional system. The implementation phase entails a number of steps, including selecting the programming language, the development environment, the programming approach to employ to meet the need, and the library that could be utilised within the system and how it should be incorporated. Guido van Rossum created Python, an interpreted, object-oriented, high-level programming language with dynamic semantics. It was first made available in 1991. The name "Python" is a tribute to the British comedy group Monty Python and is meant to be both simple and entertaining. Because it manages much of the complexity for the user, Python has a reputation for being a beginner-friendly language, displacing Java as the most popular beginning language and allowing beginners to concentrate on completely understanding programming ideas rather than minute details.

Python is a popular language for Rapid Application Development and as a scripting or glue language to tie existing components together because of its high-level, built-in data structures, dynamic typing, and dynamic execution. Python is also used for server-side web development, software development, mathematics, and system programming. Anaconda Python is a free, open-source programming language that enables you to create and run programmes. Python is a programming language. It is created by continuum.io, a Python-focused business. Development. The most well-liked method for teaching and using Python for data science, machine learning, and scientific computing is the Anaconda platform. There are more than 30 million users. It is available for Windows, macOS, and Linux users everywhere. Without utilising command-line commands, Anaconda Navigator's desktop graphical user interface enables you to run programmes and effectively manage condo packages, environments, and channels. Because it makes managing and deploying packages simpler, Anaconda Python is popular. Additionally, it has a substantial collection of libraries and packages that can be used for the project.

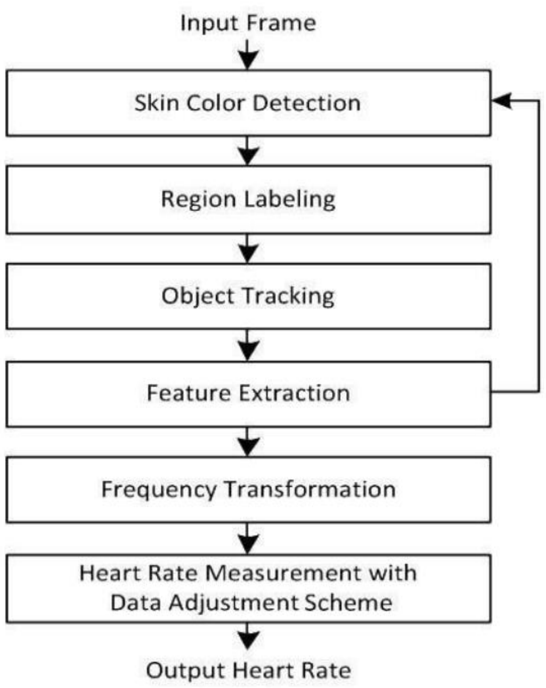

Fig. 1 Flow chart

To recognise skin tone pixels from the pictures. They annotated the skin pixels on the face with labels. used the mean-shift tracker to follow them. Discrete-time discrete-space analysis of the raw signals and calculation of the ROI's RGB values the heart rate was then determined using a Fourier transform. They presented a data counting technique that transforms a tiny quantity of data at the initial stages of video collection and measures the heart rate in a very brief amount of time. The outcomes demonstrate the potency of their suggested methodology, but they also draw attention to the issue of light effects and movement while filming videos. These two issues could possibly be resolved by colour enhancement algorithms.

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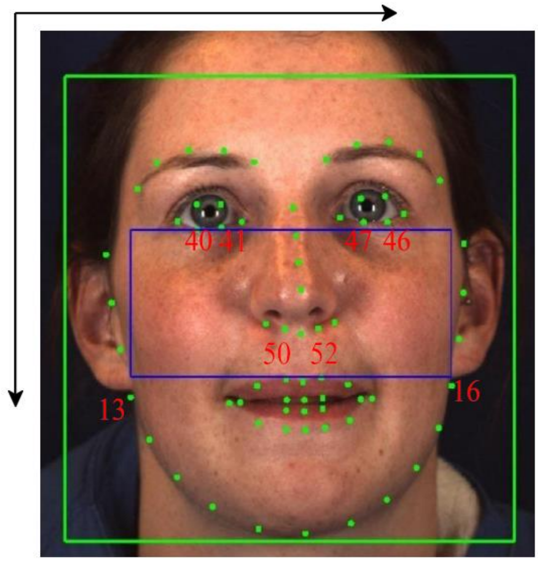

Fig. 2 Face captured in built in camera

The height of the blue rectangle, Erect, the width of the blue rectangle, XP16 and XP13, the x coordinates of Points 16 and 13, and YP50 and YP52, the y coordinates of Points 50 and 52, respectively. This definition of the blue rectangle ensures that regardless of how the subjects swivel their heads, the ROI always excludes the area around the mouth and eyes. Additionally, lip movements and eye blinking have less of an impact. In light of this, a cheek zone devoid of nonracial pixels is defined. Since the feature extraction system is used to collect the color changes of each fixed pixel over a specific period of time, a fixed-size ROI rectangle is required as the feature extraction system's input. The heart rate was calculated using a straightforward webcam and videos of human faces. They displayed a brand-new technique for blind source separation (BSS) and facial video imaging for non-contact automated heart rate assessment. This creative strategy was used using the color. Images of a human face that had been automatically tracked were used to estimate the heart rate by blind source separating the color channels into separate components.

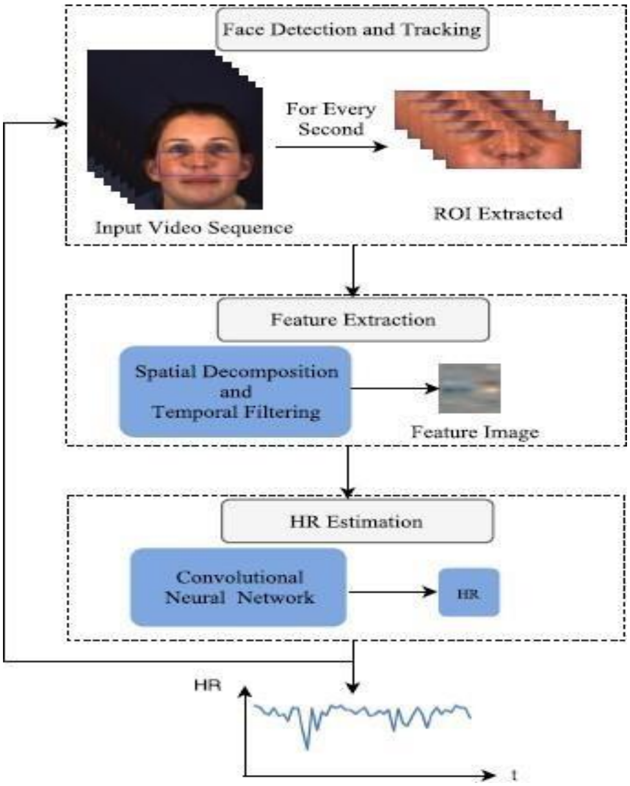

Fig. 3 System Architecture

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A temporal image that was extracted during the preceding phase is used to estimate the HR.A regression convolutional neural network is used to do this. The network receives a feature picture as input and returns an HR in response. The input image's size is specified as due to the feature extraction module's output, 25253. The RGB video sequence input has three channels, as was previously indicated. The extracted ROI is converted to one column for each channel in the feature extraction module, and the three channels are then combined to create the feature picture by concatenating all of the converted frames within one second. A RGB image with the same number of columns as the frame rate serves as the feature image.

IV. EXERIMENTAL RESULTS

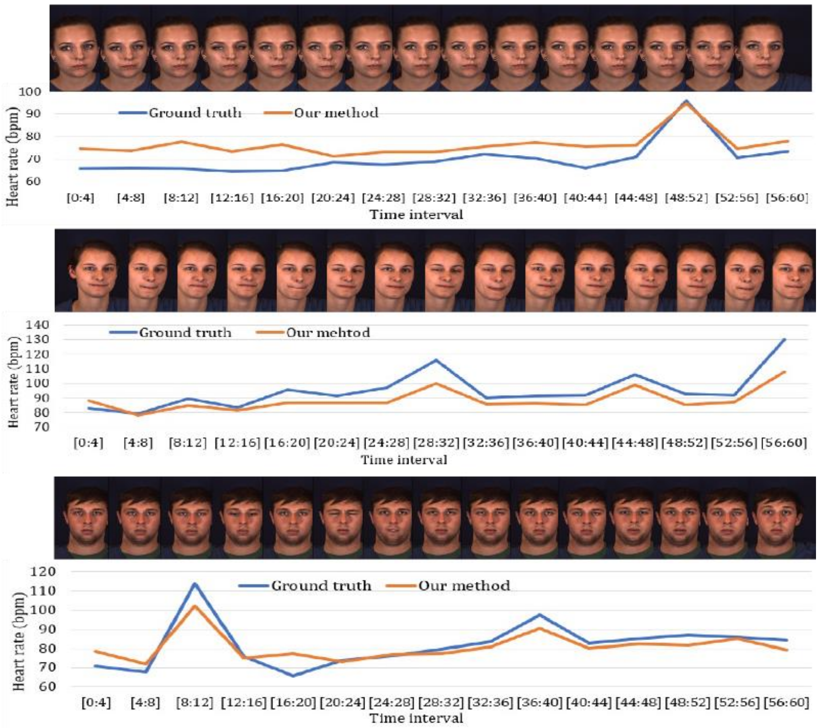

Fig. 1 Captured face in different directions

Three sequences of HR were estimated using a 4 s frame. The orange line represents the outcome predicted by our technique, whereas the blue line represents the actual data. The HR that corresponds to each frame is displayed below. The frames indicate the subject's face expression. A demonstration of the processing of three difficult sequences with a window size of 4 s is visualized in order to highlight the effectiveness of the suggested approach for short-term HR estimate. The final ground truth for each video series is determined using the mean of the ground truth within 4 seconds, and one frame is chosen from each 4 s video sequence to represent the subject's facial expression during that time period, as illustrated in where the horizontal axis represents time.The ground truth displays a low-frequency H

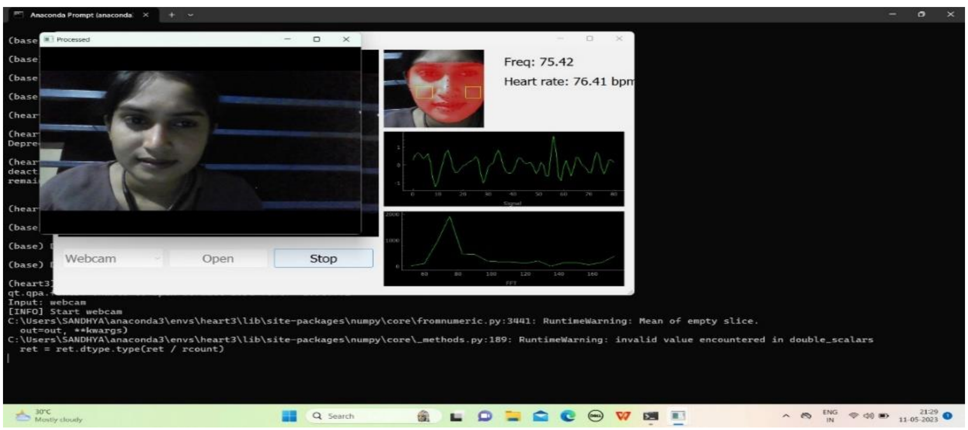

Fig. 2 Using the Webcam to gauge the heart rate and frequency

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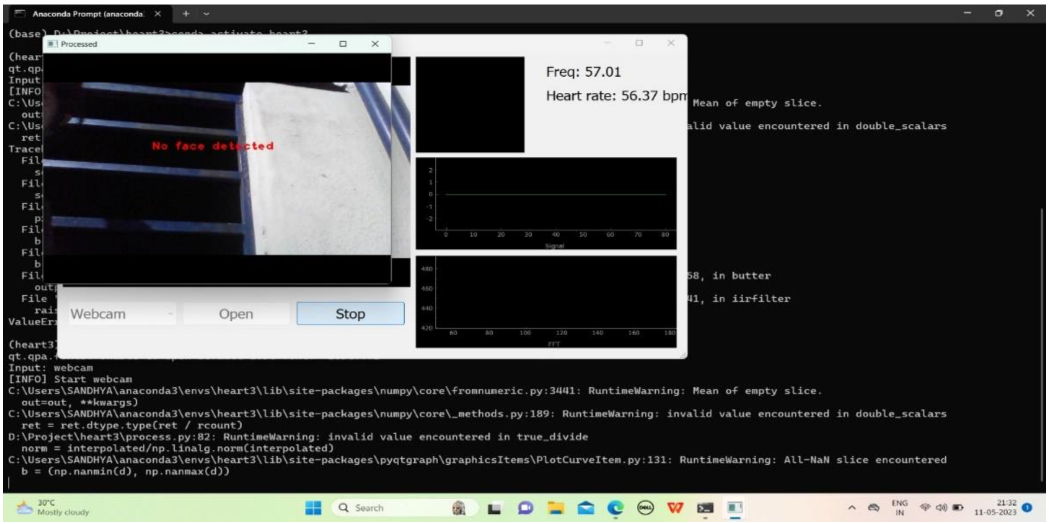

Fig. 3 No face can be seen

V CONCLUSION

This presents a novel framework for contactless HR estimate from realistic facial videos. The suggested approach uses a convolutional neural network to estimate the HR as opposed to the conventional HR estimation approach, which typically extracts a signal associated with an HR and performs power spectrum density analysis to estimate the average HR. The HR is immediately estimated from a feature image that is obtained by employing spatial decomposition and temporal filtering, which reduces both the computational complexity and the processing time. This method avoids using a series of filters to clean the underlying signal.74.13% of the variables in the testing dataset are well approximated, according to the results of testing the trained model on that dataset.

Future efforts can enhance our strategy. For instance, the dataset's HR diversity can be increased. As can be seen, only around 30% of the data is made up of the low-frequency and high-frequency components, which has an impact on how well these two parts can be estimated. Therefore, next research should collect a larger dataset with proportionate HR data. Second, a similar process cube used to estimate some additional physiological data, and a combination analysis can be applied to make emotion prediction easier.

Heart rate variability, or HRV, is also required for emotion analysis in order to identify emotion changes and the potential emotions that a subject may be aroused by. The neural network is another component that can be improved. In this thesis, a convolutional neural network is used; nonetheless.

ACKNOWLEDGEMENT

We would like to thank **Mrs Asha Rani M (**Dept. of CSE, GSSSIETW, Mysuru) for their valuable guidance, feedback and encouragement to complete the project.

REFERENCES

[1]. Asthana, Asthana, Zafira, Cheng, and Pantic, "Robust discriminative learning, “fitting a response map using restrained local models." Within: the IEEE Proceedings conference on pattern recognition and computer vision. IEEE, pp. 3444–3451, 2013

[2]. "Robust heart rate measurement from video using select random patches," A. Lam and Y. Kuno. 2015, pp. 3640–3648 in Proceedings of the IEEE International Conference on Computer Vision.

[3]. "Power spectrum analysis of heart rate variability: a tool to explore neural regulatory mechanisms," A. Malliani, F. Lombardi, and M. Pagani. p. 1 of British Heart Journal 71.1 (1994).

[4]. R. Laganiere, J. Lang, and A. S. Montero. With Sparse Feature Integration, Scalable Kernel Correlation Filter. International Proceedings of the IEEE

[5]. C. Li, C. Xu, C. Gui, and M. Fox, "Distance regularised level set evolution and its application to image segmentation." IEEE Transactions on Image Processing, Volume 19, Number 12, 2010, Pages 3243–3254.

C. Liu, A. Torralba, W. T. Freeman, F. Durand, and E. H. Adelson. "Motion magnification" 519-526 in ACM

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DOI: 10.17148/IARJSET.2023.10566

[6]. C. Tomasi and T. Kanade, Tracking and Detection of Point Features. Technical report from the 1991 International Journal of Computer Vision.
[7]. L. Rothkrantz, D. Datcu, M. Cidota, S. Lukosch, and D. Datcu. "Automatic heart rate measurement without physical contact using selected facial regions in the visible spectrum." Journal of the 14th International Conference on Computer Systems and Technologies. ACM. 2013, pp. 120-127.
[8]. S. Arora and J. Bhattacharjee, "Modulation of Immune Responses in Stress by Yoga". (2008), p. 45 of International Journal of Yoga, 1.2
[9]. S. Bakhtiari, T. W. Elmer, N. M. Cox, N. Gopalsami, A. C. Raptis, S. Liao, I. Mikhelson, and A. V. Sahakian are among those who contributed to this article. "Sensor for remote monitoring of vital signs using a compact millimetre wave." Pages 830–841 of IEEE Transactions on Instrumentation and Measurement 61.3 (2012).
[10]. Segerstrom, S. C., and Miller, G. E. The human immune system and psychological stress: a meta-analysis of 30 years of research. p. 601 of psychological bulletin 130.4 (2004).
[11]. Y. Yamamoto, S. Cerutti, and A. L. Goldberger. "Recent developments in heart rate variability signal interpretation and processing." on IEEE Transactions
[12]. S. Mallat Third Edition of A Wavelet Tour of Signal Processing: The Sparse Approach, Academic Press, 2008.
[13]. S. Prakash and C. S. Tucker, in [12]. The phrase "Bounded Kalman filter method for motion-robust, non-contact heart rate estimation" is used. 873–897 in Biomedical Optics Express 9.2 (2018).
[14]. S. Ren, X. Cao, Y. Wei, and J. Sun [13]. Face alignment using local binary regressing features at 3000 frames per second. 2014, pp. 1685–1692 in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.
[15].] "Self-adaptive matrix completion for heart rate estimation from face videos under realistic conditions", S. Tulyakov, X. Alameda-Pineda, E. Ricci, L. Yin, J. Cohn, and N. Sebe. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition