Heart Rate Measurement Using Face Detection in Video

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***Abstract*—Measuring the heart-rate (HR) of people has multiple applications in telemedicine, Internet-of-Things (IoT), sports, security, etc. However, sometimes it is difficult to use a classic method for measuring HR or the classical method does not scale. This paper presents a solution that works on live video streams and can measure the HR of multiple people at the same time. Face detection combined with object tracking is used to produce a set of face rectangles, which are sampled in the later stages of the pipeline for color variations. The average of the color, in a region of interest (ROI) chosen on the face, represents a signal which corresponds to the heart rate. Using signal processing, a heart rate frequency can be extracted from this signal. The method is quite precise and stable. With this algorithm, four people's faces were detected and their heart rates were measured at the same time, and an error rate of 3-5% can be obtained for the HR. By utilizing object tracking combined with face detection, our method reduces the processing power needed and allows better scaling.**

Keywords—heart rate; Internet-of-Things; face detection; object tracking.

I. INTRODUCTION

The heart rate (HR) of a person represents the number of heart beats per minute. It is an essential physiological parameter, a source of information related to the entire cardiovascular system and has great importance in diagnosis or assessment of the stress levels experienced by the person. The heart rate normal values differ depending on the age, medical history or usual physical activity [1]. For example, people who are less physically active are expected to have a higher heart rate, as their heart muscle has to work harder to maintain a constant cardiac rhythm. It has been well-known for decades that any unusual variations of the cardiac pulse have to be taken into consideration for further investigation and diagnosis [2].

As a consequence of society becoming more health conscious, various concepts of remote health monitoring platforms are developed [3], [4]. Among others, these also include supervising elderly people or chronic diseases patients from residential environments. Also, there are situations in which continuous heart rate monitoring is required but skin contact is problematic, and the patient feels uncomfortable to be continuously connected to a pulse measuring apparatus. In addition to this, any contact device is only able to monitor a single patient at a time, which does not help when needing neither a fast nor a permanent examination of people from a specific location – for example an office or a metro station.

We present a new approach to contact-free methods for measuring heart rate using video processing. This technique requires the subject to be relaxed and to be placed near a webcam. The distance between the camera and the patient can vary between 1 and 3 meters, and the illumination conditions have to be constant during the process.

In order to measure the heart rate in real time, image processing will be performed using OpenCV and implemented in Python programming language. Unlike other existing solutions, it aims at simultaneously measuring the pulse for multiple people, using object tracking in conjunction with face detection. This optimization will reduce the computational requirements and makes implementation feasible on more types of devices.

The remaining paper has been divided into three sections: Section II provides related work, and Section III presents our approach. Finally, the conclusion is dealt with in Section V of the paper.

II. RELATED WORK

As this non-contact method for measuring the pulse can be easily implemented in platforms for health monitoring, there are several studies regarding the measurement of the heart rate using image processing.

In [5] the authors present a non-contact method for measuring HR. It is described as being helpful for people suffering from different skin conditions. The pulse-detection algorithm is implemented while taking into consideration different ways for choosing the region of interest (ROI), which is then used for calculating the mean pixel values. In addition to this, the method is tested while the subject is moving and also when encountering signal disturbances. The errors encountered are quite low: about 3.4 ± 0.6 beats per minute (bpm) in normal video and 2.0 ± 1.6 bpm when the subject is moving.

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Also, this [6] paper describes a video-based heart rate detection algorithm which is implemented to determine the subject's physiological changes under the relaxed condition and while moving. The ROI selected is divided into 3 parts and for each of them, the pixels' mean values are calculated. To obtain a clear signal, the Independent Component Analysis (ICA) is implemented, after which peak detection is used to determine the heart rate value out of the video processed. As the authors mention, the algorithm does not provide "real-time" results, but the values obtained are as expected when compared to other HR measuring methods.

In this [7] article the HR measuring method is presented as being "real-time" and is based on the implementation of three different methods for signal-processing: ICA, Principal Component Analysis (PCA) and Fast Fourier Transform (FFT). The image acquisition is made using a laptop camera, and the HR calculation method is also based on the skin color variation. The results obtained are similar to other methods.

In addition to this, the paper [8] presents a different approach for measuring HR, which consists of using both web and thermographic cameras. All the measurements were taken in the middle of the day, and the only illumination source was the sunlight. Also, the volunteers (both men and women) stood 1 meter from the camera and did not move during the experiment. The region of interest was on the forehead, an area which seems to have a constant temperature. For reducing the complexity of the process, the ROI selected was smaller, and the experiment results state that ICA and PCA have similar accuracy when extracting the pulse.

Also, the authors of this [9] patent describe the estimation of HR variability by video processing for obtaining a time-series signal. Data is then used to extract the PPG signal and to calculate a power spectral density function in order to detect frequency components needed for the HR measurement.

III. The Experimental Method

During the heartbeats the blood is pumped throughout the body, causing skin color variations. These changes can not be observed with the naked eye but can be detected in a video stream. To implement the image processing algorithms, it is necessary to choose a region of interest, which is relevant in the sense of being able to observe how the pixels in the selected area change their intensity. By averaging the intensity of the skin color and extracting the frequencies that appear in the signal, a clear peak will appear which represents the frequency of the heart beats. In order to accomplish the project, the pixels within the selected region of interest are processed in the Spyder development environment, using OpenCV and Python.

A. Face Detection

In this paper, the primary focus is not the face detector. Because of that, we are not going to choose the best current method but instead, choose one which is readily available and it is known to have been implemented on consumer hardware and even mobile devices [10].

Face detection (FD) has been implemented using Haar cascades. It is a simple yet efficient method, which has been presented by Paul Viola and Michael Jones in their [11] paper. It is based on machine learning and is trained on a set made of both positive images (photos of faces) and negative images (pictures which don't contain any face). The Viola-Jones detector has several key-features, as follows:

1) *Converting the pixel intensity values into an Integral Image.*
2) *Haar features:* They are different rectangular images, as presented in Fig. 1.
3) *The AdaBoost learning algorithm:* it is used for selecting the best features out of the entire set.
4) *The Cascades Filter:* it discards the negative windows in order to focus the computational process on the positive ones as much as possible.

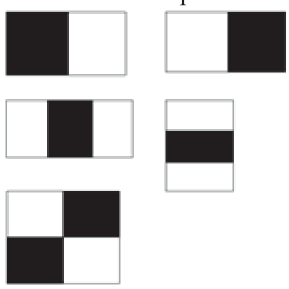

Fig. 1. Haar Features

B. The Selection of the Region of Interest (ROI)

The region of interest is an area of the image, selected on specific criteria, which is to be used during the computational process. In order to observe the skin color variation, the most suitable area is the forehead as it provides detailed changes encountered. The dimension of the rectangle placed on this area is in respect to the facial detection box, as its size changes depending on the distance between the subject and the webcam. The next step is calculating the median or the average of the pixels within the region of interest, for each frame. The ROI selection is shown in Fig. 2.

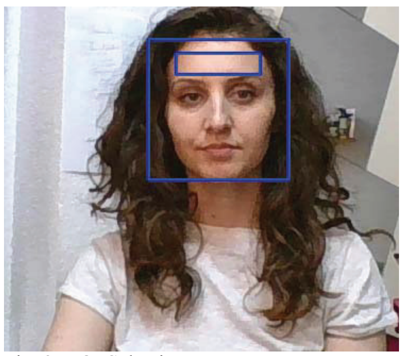

Fig. 2. ROI Selection

C. Object Tracking

In order to identify the face of the subject, two options can be implemented:

1) Applying the face detection algorithm for each frame.

2) Applying the face detection algorithm for certain frames, between which only face tracking is implemented.

We used the second method, as it is considered faster. This is because when tracking an object detected in the previous frame, there are also given details about the appearance of the object [12].

According to this [13] study, the best tracking algorithms are Boosting and Multiple Instance Learning tracker (MIL). We chose to use MIL as when testing, its average processing time is about 9 ms/face while Boosting tracker needs about 15 ms/face.

D. Measuring the Heart Rate

The FFT (Fast Fourier Transform) is applied to the window formed by the last 200 frames of the signal obtained at the previous point. Since normal heart rates are between 35 and 195 beats per minute, frequency filtering can be applied to correct false readings. The heart rate translates to a frequency between 0.5 Hz and 3 Hz. This frequency range is far away from the powerline frequency, 50 Hz or 60 Hz, so there are very few chances of interference from there. The continuous component on the other hand, will influence the spectrum, given how close the heart-rate is from 0 Hz. During the process, the sampling frequency will only take effect on the spectral density, as the algorithm will run on the web camera frequency.

First, the maximum is detected avoiding the 0 Hz component. To ensure the maximum indeed corresponds to a HR frequency, a ratio is calculated between the maximum and the median of the spectrum. We discovered that a ratio of 3:1 is a good discriminant for this case.

E. Method

The previous steps are combined to produce the final method. These can be seen as a series of blocks depicted in Fig. 3. The first block does FD on every frame until a face or more are detected. After that frame, each face is tracked using a separate object tracker and FD is not used on each frame anymore. Every 10 seconds, a new face detection is applied for up to 10 consecutive frames to verify if the object tracked is still a face or if new faces appeared in the frame.

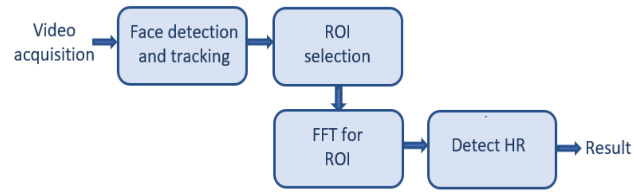

Fig. 3. The HR measuring algorithm diagram

The faces detected by the previous block are passed to another block which selects a region of interest for each face, based on geometry, that corresponds to the forehead. If the forehead is covered, one of the cheeks is chosen. For each ROI an average is computed using a mean function. These will represent the samples that are processed by the next block, which does FFT in a moving window representing the last 200 frames. This value is chosen because the algorithm should detect frequencies between 0.5 Hz and 3 Hz, in steps of ~0.01 Hz. The actual frequency is selected using the method described in section III.D.

F. Testing Environment

During development, tests were run on the following hardware:

- Processor: Intel(R) Core(TM) i5-7200U, CPU @2.50 GHz.
- RAM: 4.00 GB.
- 720p HD webcam.

After calculating the mean value of the pixels from the ROI, we compared the results obtained for people having a visible difference of the skin tone, as presented in Table I. The tests have been run under the same conditions for each of the 20 persons involved. The subjects did not wear make-up and none of them suffered any form of skin condition.

TABLE I. EXPERIMENTAL DETAILS

Subject	**Features**	
	Age	***Skin tone***
Person 1	23	Brown medium
Person 2	26	Brown medium
Person 3	23	Light

Fig. 4 shows Person 2 and Person 3 while running the test:

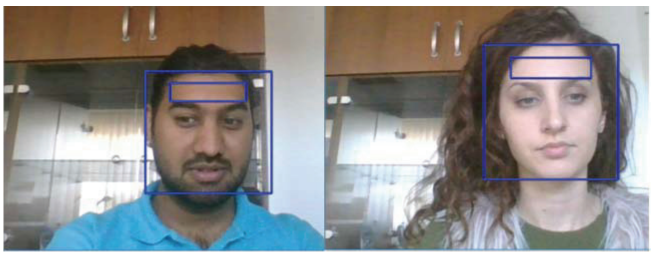

Fig.4. Running tests on different skin tones

In addition to this, HR tests were done later in parallel with two other heart-rate monitor devices to ensure the accuracy of the measurement. Errors of ~3% were detected, but it is hard to calculate the real error rate, as the monitors exhibit intrinsic errors. The tests were done using different skin tones corresponding to persons of European descent, and two persons originating from the Indian subcontinent. No significant differences were discovered in terms of HR accuracy. The devices used are:

1) Ambiotex: the smart shirt presented as having 99.1% accuracy [14].

2) Fitbit Alta HR [15]: considered to be one of the best Fitbit products as it continuously measures HR [16].

Table II shows the intervals of the HR detected, and the errors encountered for each one of them. Each error has been calculated using the mean value of the Ambiotex HR results and the Fitbit Alta HR measurement.

TABLE II. HR TESTS ACCURACY

Interval number	Experimental Results	
	Interval [bpm]	*Error [%]*
1	55 - 85	~ 5.1
2	85 - 95	~ 4.3
3	95 - 105	~ 3.8
4	105 - 115	~ 3.0
5	115 - 125	~ 2.7
6	125 - 135	~ 2.7
7	135 - 170	~ 2.5

IV. CONCLUSIONS

Heart rate monitoring is essential, as unusual changes related to the cardiovascular system help to obtain a diagnosis. Among all the pulse monitoring methods, the non-contact ones are considered to become the most useful in daily life and IoT applications. The approach we have presented is solving the problem of multiple-subjects heart rate monitoring and makes a mobile implementation to become feasible. Up to 4 people can have their HR monitored using a single webcam, as here only a low-quality laptop camera was used. The algorithm also has a reduced computational time, as it uses both face detection and object tracking.

This article represents a good proof of concept for this method, but there are areas which remain unexplored. For the future, we propose to study the influence of camera quality to the number of faces that can be detected and to the maximum distance between the camera and the subject. Also, we envision to implement the HR measuring algorithm on different platforms, such as Android and Raspberry Pi. This is in order to develop tracking of multiple persons and their HR, over multiple cameras.

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REFERENCES

[1] J. Hart, "Normal resting pulse rate ranges," Sherman College of Chiropractic, Spantanburg, South Carolina, United States, Journal of Nursing Education and Practice, vol. 5, pp. 95-98, 2015.

[2] "Why it is important to know your heart rate," http://blog.zensorium.com/why-it-is-important-to-know-your-heart-rate/.

[3] J. Evans, A. Papadopoulos, CT. Silvers et al., "Remote health monitoring for older adults and those with heart failure: adherence and system usability," Telemedicine Journal and e-Health., vol. 22, pp. 480-488, June 2016.

[4] S. Majumder, T. Mondal, MJ. Deen, "Wearable sensors for remote health monitoring," Sensors (Basel, Switzerland), vol. 17, pp. 130, January 2017.

[5] I. Bush, "Measuring heart rate from video," Standford Computer Science, in press, 2016.

[6] T. Pursche, J. Krajewski, and R. Moeller, "Video-based heart rate measurement from human faces", International Conference on Consumer Electronics, January 2012.

[7] H. Rahman, Hamidur, M. Ahmed, S. Begum, and P. Funk: "Real time heart rate monitoring from facial RGB color video using webcam," 9th Annual Workshop of the Swedish Artificial Intelligence Society, 2016.

[8] M. Lewandowska, J. Rumiński, T. Kocejko and J. Nowak, "Measuring pulse rate with a webcam — A non-contact method for evaluating cardiac activity," Federated Conference on Computer Science and Information Systems, Szczecin, pp. 405-410, 2011.

[9] L.K. Mestha, S. Kyal, B. Xu, and H.J. Madhu, "Video-based estimation of heart rate variability," US8977347, 2015.

[10] Fotonation Limited, "Digital image processing using face detection and skin tone information," https://patents.justia.com/patent/9516217, 2014.

[11] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features, "Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition," , vol.1. pp. 511-518, 2001

[12] Object Tracking using OpenCV, https://www.learnopencv.com/object-tracking-using-opencv-cpp-python/

[13] P. Janku, K. Koplik, T. Dulík, and I. Szabo, "Comparison of tracking algorithms implemented in OpenCV," MATEC Web of Conferences. vol. 76, no. 04031, 2016.

[14] Ambiotex, https://www.ambiotex.com/en/techunit/

[15] Fitbit Alta HR, https://www.fitbit.com/shop/altahr

[16] Best Fitbit 2018, https://www.wareable.com/fitbit/what-fitbit-tracker-should-you-buy