Remote Detection of Heart Beat and Heart Rate from Video Sequences

A. T. M. Lima, D. B. Gusmão, and M. V. C. Costa

Abstract

The article presents a proposal to detect the heart beat and an estimation of the instantaneous heart rate based on a video, using the variation of skin tone as a function of the blood flow, which are imperceptible to the human eye. This method of data acquisition does not require a sensor to be in contact with the user's skin, so it is a non-invasive method, easy to acquire and can be performed from a certain distance. Using computer vision, it was possible to track the face over time using the KTL classifier to increase tracking accuracy and decrease the processing time. With the detection performed over time it was possible to visualize the variation of skin tone as a function of blood flow through a temporal filter and an equalization of the histogram. The final result was obtained by evaluating the histogram resulting from each processed frame of the video.

Keywords

Heart rate • Computer vision • Remote detection

1 Introduction

The heart rate variability (HRV) has several applications ranging from the study of the modulation of autonomic nervous system (ANS) on the organism, disease verification utilizing the changes in the pattern of the HRV, stress detection and others applications [1–3]. Thus, there is a great need to study this physiological variable of the human body.

The HRV indicates the ability of the heart to respond to different physiological stimulus from the environment, and changes in the HRV pattern provide sensitive markers of heart disease such as coronary heart disease, hypertension or others cardiac events and can represent one marker to detect stress [3–5].

The heart rate has some methods of acquisition such as the electrocardiogram (ECG), since it is a non-invasive method with easy data acquisition and has a great variety of algorithms for analysis, where the QRT complex is used to calculate the heart rate. The photoplethysmography (PPG), where an optical sensor directly illuminates the skin to perform the measurement, is another extremely widespread method for acquisition of the heart rate [5, 6]. However, these two methods require that the measurement be performed with the sensors in contact with the patient's skin.

HRV can be measured from the heart beat. Thus, a method is necessary to collect the heartbeats over time in a fast and non-invasive way.

The flow of blood that passes through a person's skin subtly modifies the way light is reflected. This subtle variation of radiation can be captured and monitored by a video camera and used to estimate a person's heart rate in a non-invasive mode and without contact with the skin [7].

The signal captured in the video corresponds to a wave corresponding to the variation of skin tone over time, which obeys the same frequency at which the heart beats. Therefore, the video is a time-varying signal that can be used to measure a person's heart rate [7, 8].

McDuff et al. [6] used a digital camera in 2006 to evaluate Remote Detection of photoplethysmographic systolic and diastolic peaks at a distance of up to 3 meters. The system presented good results, but at a cost of calculating the second order derivative to carry out the signal evaluation, which depending on the hardware used can consume great computational power and a lot of energy.

A. T. M. Lima (✉) · D. B. Gusmão · M. V. C. Costa
Electronic Engineering, University of Brasília at Gama, Brasília, DF 72444-240, Brazil
e-mail: arnoldo.thiago@gmail.com

D. B. Gusmão
e-mail: davi.b.gusmao@gmail.com

M. V. C. Costa
e-mail: chaffim@unb.br

D. B. Gusmão · M. V. C. Costa
Graduate Program in Biomedical Engineering, University of Brasília at Gama, Brasília, DF 72444-240, Brazil

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Sandri et al. [8] used video sequences for the mensuration of heart rate where two algorithms were proposed for the measurement. The first algorithm applies an adaptive filter that imposes the temporal coherence on the signal and the second algorithm performs the estimation through the tracking of microregions which increases the performance adding robustness to movement artifacts. However, both algorithms are complex and require a lot of processing power.

In this work a simple algorithm is proposed, one that performs the measurement of the heart rate through a video using facial tracking, temporal filtering and tone evaluation by evaluating the histogram of a human face.

2 Materials and Methods

The entire processing of this work was performed in a personal computer environment. The videos used in this work were acquired in [9] and provided by [7]. The pre-processing consists of three steps: face detection, identification of traceable characteristics and face tracking.

For the first step, face detection, the Viola-Jones detection algorithm [10] is used. By default, this algorithm performs face detection, but can be used to detect other patterns such as eyes, nose etc.

After the initial detection of the face it is necessary to track it over time. The tracking could be performed using Viola-Jones frame per frame, however it would be a very computationally expensive process and can fail to detect if the face rotates. This limitation in the detection is generated by the type of training that was used in the classifier [10]. Thus, the Kanade-Lucas-Tomasi (KLT) algorithm is used. This algorithm speeds up the face tracking process because the KLT finds a set of characteristic points in the first frame and traces it through the different frames of the video, requiring less computational power [11]. At this point it is used the maximum bidirectional error with module equal to 2. This turns the process of tracking the face more robust to noise and movement.

With face detection performed, the face is cut out from the rest of the image and stored in a new time variable, however the result obtained is doubled with its excursion, ranging from 0 to 1. Thus, a rescheduling is performed in this signal block to the excursion of an integer variable of 8 bits (0–255). This rescheduling was performed using a contrast adjustment, which performs the equalization of the histogram of a signal, in this case an image.

The penultimate process is the filtering of the signal in the time dimension in each pixel, as suggested by [7]. For this, an ideal digital bandpass filter with $\omega_L = 0.06$, $\omega_H = 0.13$ and a sampling frequency of 60 Hz is used to show changes in the skin tone as a function of cardiac output. The result of this filtering is added to the original video [7].

Finally, the histogram of each frame of the image is evaluated to obtain the HRV. However, the obtained signal is a bit noisy, requiring a filtering in the VFC signal with a lowpass IIR filter with a cutoff frequency $\omega_C = 0.16$ After filtering, the maximum signal locations are identified and the difference between two adjacent peaks is the estimate of the instantaneous heart rate.

3 Results

The facial detection algorithm of Viola-Jones presented a good result for facial recognition in the first frame of the video, where it was possible to remove much of the image that did not contain useful information, as can be seen in Fig. 1.

Using the Viola-Jones model and algorithm could be done tracing individual features like eyes, nose, upper body. But, among all the characteristics that generated a more satisfactory result was the face detection.

The characteristic points for the face tracing were obtained using the algorithm of detecting the minimum eigenvalues of an object, which provide us the corners points

Fig. 1 1st frame of the video with a yellow box around the face recognized by the Viola-Jones algorithm

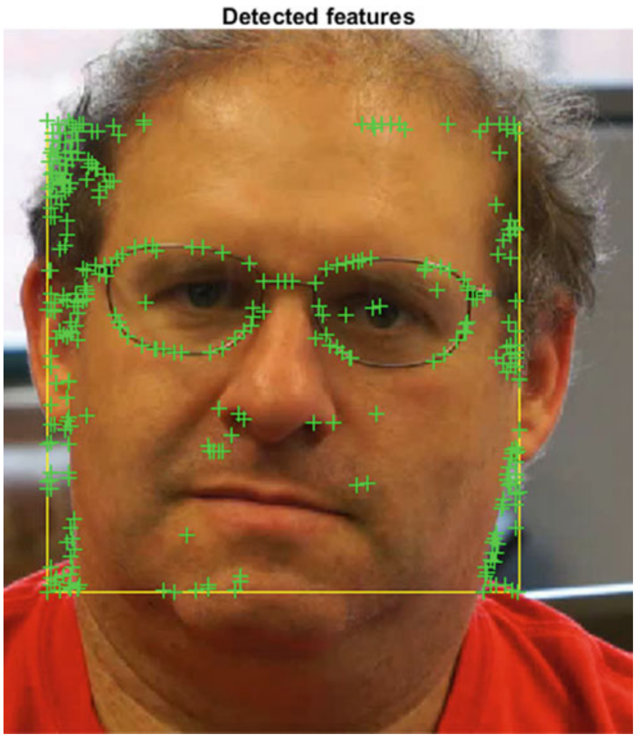


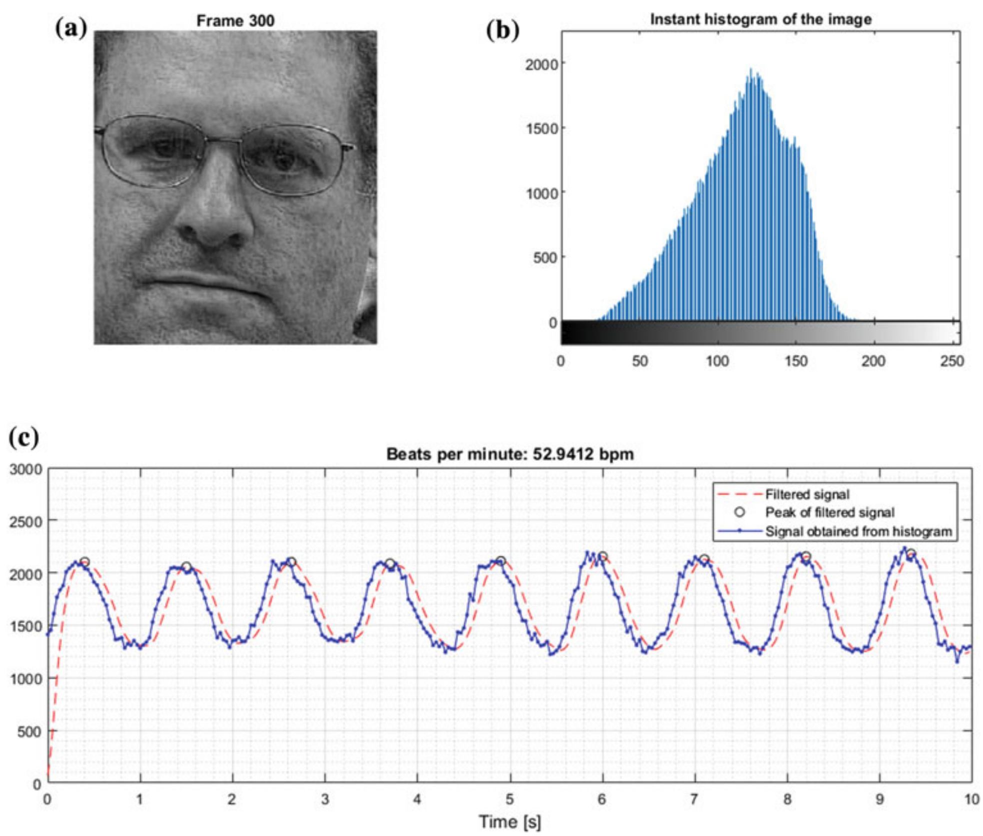
Fig. 2 Features points around the recognized face

of the image. This result can be seen in Fig. 2. This procedure causes a considerably decrease in the processing time for face tracking allowing an increase in the number of frames processed per second in the video, which brings the application closer to real-time implementation.

Using the procedure described above each image was equalized to achieve a greater excursion in the pixels values. Subsequently, the temporal filtering was performed on each pixel of the image so that the tone variation becomes more evident. The RGB image was transformed to grayscale to facilitate the processing of the evaluation step. Thus, it was possible to perform the histogram analysis to verify the heart rate over the time series of the video. The result obtained from the algorithm described above can be seen in Fig. 3.

The Fig. 3a shows the last frame processed and in Fig. 3b the histogram corresponding to that frame. It is possible to verify in Fig. 3c the wave-forms obtained by the analysis of the video signal. The blue signal, solid line, is the result of analyzing the central value of the histogram over time. However, the result is very noisy, so it would not be possible to establish a metric to estimate the instantaneous heart rate. In this way it is necessary to filter the obtained signal. The applied filter is a second-order Butterworth digital filter with cutoff frequency ω = 0.16. After this filtering the red signal,

Fig. 3 The image shows the video segment used to evaluate the heart rate together with the histogram produced by the algorithm and the time result with the heart beat in a time series. **a** Shows the analyzed frame. **b** Shows the histogram corresponding to the analyzed frame. **c** Shows the result of the analysis over time, in seconds. The blue signal, solid line, corresponds to the result obtained directly from the histogram analysis and the red signal, dashed line, is the filtered result. The circular markers correspond to the peak moment, which are used to estimate the heart rate



dashed line, is obtained, which is used to estimate the heart rate. The heart rate estimation is per-formed by taking the red signal peaks. The difference between two adjacent peaks provides the heart rate at that time.

The article presents that the proposed algorithm was able to identify the heart beat from a video using a simple algorithm such as the evaluation of the histogram of an image preceded by some pre-processing steps.

The algorithm test was performed in the videos acquired in [9] and made available by [7]. For this video sample the processing performed lasted a few minutes per video using the complete algorithm of [7]. With the pro-posed algorithm, the average execution time is 21.9 s per video. The algorithm has a simpler implementation. This is done since a histogram analysis is performed, in gray scales, over time, replacing the Eulerian motion magnification and multiscale analysis.

4 Conclusion

In this work, a simple algorithm was proposed to obtain heart rate variability and to estimate the instantaneous heart rate of a person based only on videos acquired remotely.

The algorithm presented a slowness in processing at the moment of temporal filtering. This occurred because the algorithm for temporal filtering was not optimized. This algorithm could be worked on in a hardware implementation which would allow a low power consumption as well as a parallel processing of the images, increasing the frame rate.

As McDuff et al. [6] found, it is possible to implement a heart rate detection algorithm using digital cameras, but the evaluation processing used in this work is simpler because it does not need to calculate the second order derivative of photoplethysmographic obtained by the camera. However, there is a loss of scale since it is not possible to visualize the systolic and diastolic peaks of the signal.

Taking into account the proposed problem we have that the simple algorithm was able to satisfy accurately the proposal of both capturing the HRV by a video and estimating the instantaneous heart rate.

The study in this field of signal processing continues with the intention of using an high parallel and less power consumptive platform to perform the real-time processing of this application with low energy consume.

5 Future Works

The studies continue with the comparison of the results of the proposed algorithm with the currently used gold standard, electrocardiography (ECG).

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