Camera-based heart rate variability and stress measurement from facial videos: Poster Paper

Abstract

Remote measurement of physiological signals through facial videos is an emerging field of research. Through remote photoplethysmography (rPPG), RGB cameras can measure a person's heart rate variability (HRV) by analyzing subtle light variations on the skin. Fluctuations in HRV readings are caused by imbalances in the autonomic nervous system, such as experiencing a stressful event. This paper presents a novel method for HRV measurement from rPPG signals. We tested the model on 14 subjects participating in stress-inducing tasks. We compared our results against a contact-based ground truth device and demonstrated the potential for an off-the-shelf webcam to provide robust HRV measurement and subsequent stress estimation.

Keywords

Remote Photoplethysmography, SDNN, RMSSD, Baevsky Stress Index

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1 Introduction

Photoplethysmography (PPG) is an optical technique to measure human vital signs. In the last decade, remote PPG (rPPG) methods have garnered a lot of attention in the research community due to its advantage in capturing physiological measurements by utilising a digital camera and ambient light.

Heart rate variability (HRV), the variation in time between heartbeats, is a measurement that can be extracted from the rPPG signal. As HRV is dependent on the balance between the sympathetic and parasympathetic nervous system. Changes in HRV readings can indicate stress, cognitive processes and mental load.

In this work, we present a novel method for measuring HRV from rPPG signals extracted from facial videos, which was used to further estimate a person's stress level.

2 Method

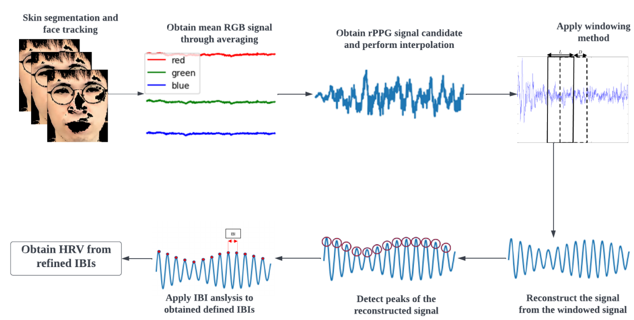

Figure 1: Software Pipeline to Extract Heart Rate Variability Metrics from Video

Figure 1 shows the pipeline for extracting HRV metrics from facial video. For each video, the subject's face was detected and tracked throughout the frames, followed by skin segmentation to enhance signal quality by removing non-skin regions, such as hair. The mean RGB signal was obtained by a spatial average of the red, green, and blue channels. Finally, the Plane Orthogonal to Skin (POS) algorithm [3] was applied to obtain the rPPG signal candidate.

The rPPG signal candidate was interpolated to ensure equal spacing between data points. A windowing method was applied to the interpolated signal, where parts (windows) of the signal were cleaned with a narrow bandpass filter at around heartbeat frequency. The signals from each window were combined in an overlapping, mean-zero way to reconstruct a clean rPPG signal. Finally, peaks of the cleaned rPPG signal were detected, and the inter-beat interval (IBI) between each successive peak was calculated. IBI values were further filtered by removing physiologically impossible regions.

For this paper, the following four HRV metrics were calculated: Standard Deviation of Normal Intervals (SDNN), Root

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Mean Square of Successive Differences (RMSSD), Low Frequency/High Frequency (LF/HF) and Baevsky Stress Index.

SDNN represents both the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). An SDNN has average values between 30-90 ms. RMSSD is more closely tied to the PNS. Typical RMSSD values range from 20 to 75 ms [2].

LF/HF represents an estimate of the ratio between the SNS and PNS and is regarded as a metric of equilibrium of the Autonomous Nervous System. Normal values range between 1 and 5.5 [2]. The Baevsky SI is a good estimation of stress levels. High values of the Baevsky SI indicate high stress and vice versa. Normal values range between 50 and 150. Baevsky SI is given by:

$$BaevskySI = \frac{AMo(IBI)}{2 * Mo(IBI) * MxDMn(IBI)} \quad (1)$$

where *Mo(IBI)* is the mode of IBI, *MxDMn(IBI)* is the difference between the maximum and minimum IBI, and *AMo(IBI)* is a relative number of the mode of IBI to the total number of IBIs.

3 Data Collection

Fourteen adults (age 18-33) with different skin colors were seated 1m in front of a Logitech Brio camera. Videos were recorded at 60 fps in ambient room lighting, and the ground truth PPG signal was recorded by a CONTEC CMS-60C pulse oximeter at a frequency of 60 Hz. Each participant was recorded for 11 minutes while they were taking the Stroop test[1]. The test was designed to induce cognitive stress and enable HRV measurement under different circumstances. The test consisted of 3 parts: Rest Stage (1 min), Stroop test with sound stimulus (3 mins), and Stroop test without sound stimulus (3 mins). Subjects rested for 2 minutes between each stage. During the Stroop Test with sound stimulus, participants would experience a positive or negative audio cue based on whether they gave the correct answer.

4 Analysis and Results

Table 1: Performance of our method against HRV metrics calculated from the ground truth signal.

	MAE ± std	PCC
SDNN	4.89 ± 3.95	0.9
RMSSD	11.2 ± 9.0	0.45
LF/HF	0.65± 0.65	0.4
BaevskySI	30 ± 35	0.85

Table 1 indicates the performance of our method compared against the HRV metrics calculated from the ground truth pulse oximeter signal. We evaluated the performance of our method using the mean absolute error (MAE) with standard deviation (sd) and Pearson correlation coefficient (PCC).

The MAE of RMSSD, SDNN, LF/HF and Baevsky Stress Index during each stage of the Stroop test are shown in Table 2. The MAE values throughout the experiment are relatively stable for all of the metrics which highlights the robustness and reliability of our method under difference stress-inducing scenarios. The highest accuracy result for SDNN was for the test 2 stage with a value of 3.97 ± 3.50. The highest accuracy results for RMSSD was also during the test 2 stage with a value of 8.9 ± 8.1. For LF/HF the highest accuracy value is also during test 2 with a value of 0.42 ± 0.31. Finally for the Baevsky Stress Index the highest accuracy value was for Test 1 with a value of 25 ± 30.

Table 2: MAE of HRV measurements under different stress conditions

	Rest	Test1	Test2
SDNN (ms)	4.88±3.69	5.82±4.37	3.97±3.50
RMSSD (ms)	13.5±8.5	11.1±9.8	8.9±8.1
LF/HF	0.83±0.78	0.70±0.70	0.42±0.31
BaevskySI	33±36	25±30	31±37

Test1 = Stroop Test with Sound
Test2 = Stroop Test without Sound

5 Conclusion

In this paper, we presented a novel method for extracting HRV metrics from facial videos. Our method extracts the rPPG signal by performing face detection, skin segmentation and applying the POS algorithm. Then, signal analysis and windowing were used to obtain IBIs and HRV metrics. Preliminary data shows that our method is robust and performs well under different stress inducing conditions.

References

[1] J Ridley Stroop. 1935. Studies of interference in serial verbal reactions. *Journal of experimental psychology* 18, 6 (1935), 643.

[2] Andreas Voss, Rico Schroeder, Andreas Heitmann, Annette Peters, and Siegfried Perz. 2015. Short-term heart rate variability—influence of gender and age in healthy subjects. *PloS one* 10, 3 (2015), e0118308.

[3] Wenjin Wang, Albertus C Den Brinker, Sander Stuijk, and Gerard De Haan. 2016. Algorithmic principles of remote PPG. *IEEE Transactions on Biomedical Engineering* 64, 7 (2016), 1479–1491.

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