Measuring Heart Rate With an RGB Camera For Real-Time General Health Monitoring

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1. Motivation

Measuring a person's heart rate (HR) is important, as it is a good indicator of a person's cardiac health. Bradycardia (HR < 60 beats per minute) and Tachycardia (HR > 100 beats per minute) are considered abnormal and are often indicators of underlying conditions or diseases.

Traditional measurement devices, like the electrocardiogram or the finger pulse oximeter, require physical contact and can cause discomfort or irritation to patients. This is an impediment to consistent measurement for general health monitoring.

2. Research Question

Q: What are the impediments to non-intrusive, camera based, heart rate monitoring systems from being deployed in a general health monitoring context? How can they be addressed?
A: Reliability; Lack of real-time performance

3. Approaches

There are two main approaches:

- Photoplethysmography (PPG): Analysing the subtle changes in skin colour caused by Haemoglobin light absorption
- Imaging Ballistocardiography (iBCG): Analysing the micro movements of face landmarks due to the mechanical motion of blood pumping through the veins

PPG-based methods are more prone to signal degradation due to improper lighting conditions. iBCG is therefore more suitable for a general monitoring situation.

4. Method

For both PPG and iBCG, many methods require the subject to stand very still for accurate measurements. An approach that achieved good performance in a more natural, human-computer interaction scenario, is that presented by Haque et al.[1]. It takes into account motion caused by facial expressions and head movements, resulting in much less signal degradation due to subject motion.

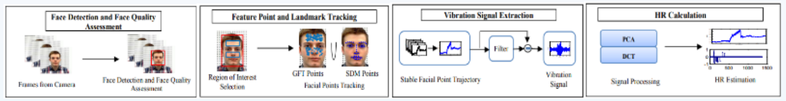


Fig 1. Filter chain presented by Haque et al.[1]

A more recent paper[2] has discovered that using anterior-posterior traces (Z-axis) instead of vertical traces (Y-axis) can lead to better results given the nature of the pulsatile motions.

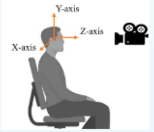


Fig 2. Axis diagram from Cheng et al.[2]

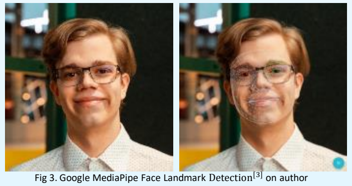
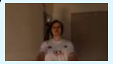


Fig 3. Google MediaPipe Face Landmark Detection[3] on author

Through their Media Pipes project, Google provides a machine-learning based model for 3-dimensional face landmark detection. This will be integrated into the filter chain proposed by Haque et al.[1] resulting in the filter chain described by the simplified diagram below:

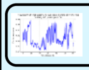
Face Landmark Detection

Video frames are passed to Face Landmark Detection CNN and face meshes are computed

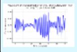


Frames with high levels of noise (due to motion, lighting, distance from camera) are identified through model confidence values and discarded

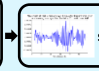
Signal Filtering



Unfiltered movement traces are obtained from face meshes



Traces are filtered to frequency range containing Heart Rate using Butterworth filter

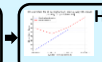


Movement traces are smoothened by applying moving average filter

Signal Processing and HR Estimation

Movement sources are separated using Principal Component Analysis

Most periodic component is identified using Discrete Cosine Transform



Heart rate estimation is made using Fast Fourier Transform

5. Results and Discussion

The proposed method was evaluated on the ECG-Fitness dataset collected by Spetlik et al.[4]. The dataset features 17 participants performing 6 activities in different lighting conditions. A comparison with state of the art methods can be seen below. The results for the other methods are from the paper where Spetlik et al. introduce their model based approach (HR – CNN[4]). The other methods, CHROM[5], Li – CVPR[6] and 2SR[7] are all based on the principles behind PPG.

	Proposed method	HR-CNN	CHROM	LiCVPR	2SR
Mean Absolute Error	37.66	14.48	21.37	63.25	43.66
Root Mean Squared Error	38.23	19.15	33.47	67.67	52.86
Pearson Correlation Coefficient	0.0545	0.50	0.33	-0.02	0.06

The proposed method performed well on activities with low and moderate head motion (talking; exercise on an elliptical trainer or stationary bike), but poorer performance on the high motion rowing activities raises concerns about robustness to challenging conditions.

The improvements to run-time performance are sufficient to make it possible to process video faster than it's duration, enabling the processing of live data, and thus the implementation of real-time applications using the proposed method.

6. Conclusions and Future Work

The proposed method develops on that introduced by Haque et al.[1], improving runtime performance. Future research should prioritize increasing robustness through targeted model training on datasets featuring challenging conditions.

The proposed method could be adapted to real-time applications, allowing for the early detection of cardiac problems. Preventative health interventions facilitated by this early detection could lead to better health outcomes for patients.

7. References

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