Non-Contact In-Car Monitoring of Heart Rate: Evaluating the Eulerian Video Magnification Algorithm in a Driving Simulator Study

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ABSTRACT

Monitoring drivers' health is crucial for saving lives in emergencies and enabling in-car health applications. The state of the art in pulse monitoring is contact-based sensors which impair the driving experience and have to be applied manually before driving. This paper focuses on automated hyper parameter optimizing the Eulerian Video Magnification (EVM) algorithm, which detects heart rates through non-contact facial camera images, for use in driving scenarios. We conducted a user study where 21 participants performed a driving simulation while their heart rates were recorded by a wearable fitness tracker (serving as ground truth) and facial images with an RGB camera. Our findings indicate that, despite using the optuna library for hyper parameter tuning, the Eulerian Video Magnification algorithm is insufficient for accurate pulse detection in a driving simulator environment.

CCS CONCEPTS

• **Applied computing → Health informatics**.

KEYWORDS

Automotive Health, Heart Rate, Eulerian Video Magnification, User Study, Driving Simulator

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1 INTRODUCTION

In the European Union, the implementation of attention monitoring systems for newly approved cars becomes mandatory in 2024. In this context, some automotive manufacturers utilize camera systems to monitor the behavior of vehicle drivers. The image data captured by these camera systems enable new applications and opportunities for the car's infotainment system to communicate more effectively, informatively, and adapted to the driver's state. Furthermore, tracking one's own health is becoming increasingly important for many individuals. The number of wearable devices sold in Germany, which are able to monitor vital signs, has more than doubled over the last 10 years [5]. While driving, using external devices to view one's vital signs, such as smartphones or smartwatches, can be distracting and thus increase the risk of accidents. Due to the short release cycles of these devices, it is difficult to connect them to in-car systems and keep the system up-to-date. Some approaches to integrate driver vital sign monitoring directly into the car use special sensors, such as chest straps [10] or in-seat sensors [7], which are either inconvenient for drivers or expensive for car manufacturers.

Nevertheless, tracking vital signs in an automotive environment can have many advantages. After an accident, for example, the emergency call system (e-call) could transmit additional information, such as the driver's pulse. Furthermore, the vehicle could stop autonomously and call for help if it detects that the driver is experiencing a heart attack. The ability of the system to react to different driver states, such as an increased stress level [3], can result in a different communication of the infotainment system with the driver. For example, it can make the suggestion for breaks or try to reduce the driver's stress level through audio or light settings.

In this paper, we address the question if it is possible to use the available driver camera for non-contact heart rate monitoring in a controlled driving simulator environment. We extend the work by [6] using state of the art automated hyperparameter tuning to optimize the Eulerian Video Magnification (EVM) algorithm processing facial image data.

2 RELATED WORK

The detection of heart rate based on captured RGB images was already achieved in 2012 by a research team in Harvard [6]. The proposed algorithm is called Eulerian Video Magnification (EVM) and makes subtle movements or colour changes visible to the human eye. The EVM algorithm amplifies changes of the pixel intensities over time. By filtering specific frequency bands within the time range of interest, the human pulse can be visualized and detected. After the magnification the blood flow is clearly visible in the facial region of the filmed participant. The amplification results in varying red colorations of the depicted skin surface.

Miljković and Trifunović [8] conducted a study demonstrating that the pulse detected using EVM deviates by less than 5 % from

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baseline measurements obtained via electrocardiogram (ECG). However, they evaluated their results with only two healthy volunteers in a laboratory setting with controlled illumination and showed that modifications to the EVM are necessary for heart rates corresponding to cardio-vascular diseases.

For home users the main type of pulse rate monitoring sensor available are wearable fitness trackers. These devices can be worn like a watch on the wrist or as a ring on the finger. These affordable sensors determine the pulse by measuring the different absorption rates of light when it hits oxygenated and deoxygenated blood [2]. However, these sensor types have a common disadvantage: they require direct contact to the skin in order to function, and despite their popularity, not everyone owns one of these devices. In the context of integrating such systems into the vehicle environment, this means that the user must manually attach the sensor in order to access its functions, which is an obstacle to user-friendliness and makes the system less attractive.

Our aim is therefore to develop a system that records the driver's vital signs without contact. This integration would allow all drivers of a vehicle to use the system without the need to attach a single sensor. Based on the experiences from Miljković and Trifunović [8], we use state-of-the-art hyper parameter tuning to optimize the EVM in a driving simulator setting.

3 DRIVING SIMULATOR STUDY TO ASSESS HEART RATE DURING DRIVING

To evaluate the suitability of the EVM algorithm in a simulated automotive environment, a study was conducted. The results were quantitatively assessed by comparing the outputs of the optimized EVM algorithm with a fitness tracker.

3.1 Hypothesis

The hypothesis of this study is that non-contact measurement of heart rates within a driving simulator, using an RGB camera and hyper parameter tuned EVM data analysis, is as reliable as using a wearable sensor.

3.2 Study Design

For the user study we received an ethical approval from the GHEBa committee (GEHBa-202312-V-152-R). Within this study, a dataset is established to serve as a foundation for this research. Participants completed a predefined route within the "CARLA" driving simulator. CARLA (Car Learning to Act) [1] is an open-source simulator designed for driving research. It provides a platform for developing, training, and validating driver assistance systems in realistic urban environments, using high-fidelity simulations. All participants had to be of legal age and in possession of a driving license to participate in the study.

Indipendent Variables: The study consists of two different driving segments, highway and inner-city environment, and two breaks for physical activity. The driving segments lasted for approximately 20 minutes in total. The control mechanism of the driving simulator is similar to an automatic car. The driver only needs to accelerate and brake, shifting gears is not required. No other simulated road users are added to the scenario. During the drive two breaks are planned where the participant needs to be physically active. With these activities we aim to raise the pulse of the participant. To achieve this, the participants do squats, which are carried out over a one-minute period. The number or speed of squats is not specified, allowing participants to gauge their own physical limits and health considerations.

Dependent Variables: The study uses a wearable fitness tracker "FitBit Charge 6" and an RGB camera to record data during the driving segments. The wearable device monitors the participants heart rate and is used as ground truth data. According to a study published in 2018, FitBit brand fitness trackers have a deviation of ±3 percentage points from the baseline [4].. The RGB camera records facial video data, similar to in-car driver cameras. Images are captured using a Logitch camera with a resolution of 640 x 480 pixels, matching the resolution used in the EVM paper to visualize the pulse within the facial region. The camera provides a framerate of 30 fps, resulting in a sampling rate of 30 Hz. According to the Nyquist-Shannon sampling theorem, which requires a sampling rate of more than twice the highest frequency to be measured, this setup is sufficient to capture a pulse up to 180 beats per minute (i.e., 3 Hz). This heart rate is unlikely to be reached within this study.

Aparatus: The camera is positioned like the rearview mirror inside an automotive interior. Figure 1 illustrates the chosen position of the camera relative to the driver's position. The participant is directly placed in front of a 24" Monitor with a resolution of 1920x1200. The steering wheel in use is a Logitech G29. The windows are covered with blinds to ensure consistent, controlled lighting.

Figure 1: Positioning of the used camera during the study
Camera position relative to the test person following numbers define the objects inside the Figure 1:Test Person, 2:Camera, 3:Monitor, 4:Steering wheel

3.3 Data processing

To analyze the study's data, the results of the optimized EVM algorithm are compared with the ground truth data from the fitness tracker to assess the algorithm's suitability within the study's context. The EVM algorithm predicts the pulse in beats per minute (BPM) based on a 4-second time window. This window length ensures the minimum pulse of 1 Hz can be detected, fulfilling the

Shannon sampling condition. A 4-second window provides additional safety without excessively averaging the mean value. The ground truth is derived from the average pulse recorded by the fitness tracker during the 4-second time window. The deviation between the EVM-calculated heart rates and the ground truth data is represented as the mean absolute error (MAE).

Various meta-parameter settings for the EVM algorithm can significantly influence the results. These parameters include the gain (alpha) and the attenuation of the I and Q components within the YIQ color space, where the algorithm operates. Additionally, the cut-off frequencies for the applied ideal bandpass filter are adjustable. In this study, the filter limits were set to 1 Hz (lower frequency limit) and 2.7 Hz (upper frequency limit), enabling the detection of pulses between 60 BPM and 162 BPM. This range is sufficient to capture both resting heart rates while driving and slightly elevated heart rates after physical activity. Consistent with the original EVM paper, the two deepest layers of the constructed Gaussian pyramid are not amplified by the alpha factor. This configuration was maintained in this evaluation, using a four-level pyramid structure as described in the EVM paper.

To determine the optimal combination of the two parameters (alpha and chromatic attenuation), an automated meta parameter optimization is performed. This method, which has gained popularity primarily through hyper parameter tuning in deep learning, is also suitable for the optimization problem described. For the optimization in this study, the optuna library (Version 3.6.1) [11] is used, which specifies the two parameters and adjusts them according to the MAE between the detected frequency and the ground truth. The optuna library utilizes a TPESampler (Tree-Structured Parzen Estimator) a bayesian optimization algorithm for its hyper parameter tuning. For the used setup the optuna library runs 50 trials with different settings for alpha and the chromatic attenuation. In every trial the deviation of the calculated heartbeat to the ground truth heartbeat is calculated for a subset of five randomly assigned participants. The hyper parameter setting with the smallest deviation from the ground truth will be used to calculate the heartbeat for all participants.

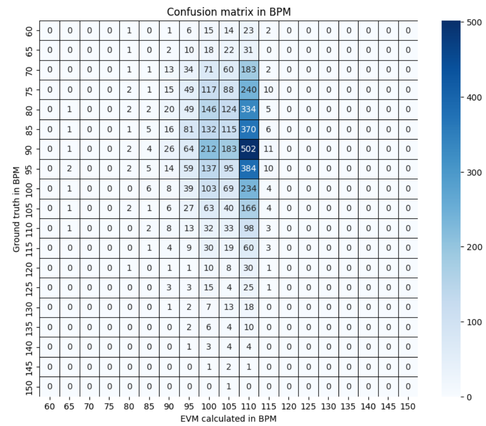

Figure 2: Ground truth over EVM calculated heart rate
The results of the EVM calculation shows no clear indication of correlation to the ground truth heart rate.

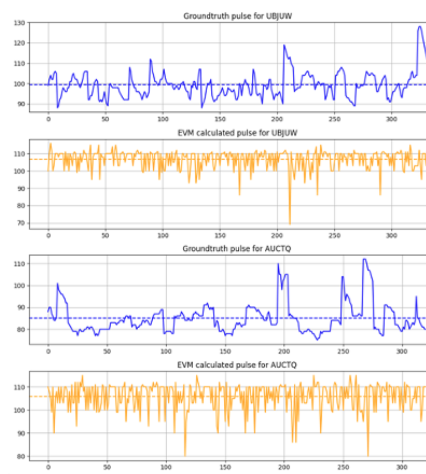

Figure 3: Groundtruth heartbeat and detected heartbeat over time for two participants with aliases AUCTQ and UBJUW
The heartbeat over time shows two different participants with different mean groundtruth heartbeats. The EVM detects more or less the same mean Heartbeat irrespective of the actual heart rate.

4 RESULTS AND DISCUSSION

We analyzed the data from 21 participants (self identified as 8m/14f/0d). Meta-parameter optimization using the optuna library indicated that an alpha value of 174 and a chromatic attenuation of 0.6 were most suitable for the test setup. Utilizing these parameters, the entire dataset of video material was evaluated against the heart rates of the participants as measured by the fitness tracker. The evaluation results are presented in the confusion matrix in Figure 2. In this matrix, the x-axis represents the heart rate calculated by the EVM in beats per minute (BPM), while the y-axis represents the ground truth heart rates in BPM. The data are quantized in steps of five BPM for easier interpretation.

The matrix indicates no discernible correlation between the heart rate calculated by the EVM algorithm and the heart rate measured by the wearable fitness tracker. Ideally, a strong correlation would be represented by an accumulation of values from the upper left corner to the bottom right corner of the matrix. A subsequent t-test, yielding a t-value of 75 and a p-value of 0.0, further supports the hypothesis that the participants' baseline heart rates do not correlate with the heart rates calculated by the EVM algorithm. Figure 3 illustrates the heartbeat over time for two participants with the aliases AUCTQ and UBJUW. The data presented demonstrate that the EVM algorithm produces circa the same heart rate estimations irrespective of the actual heart rates of the participants. This indicates that, within the parameters of our test setup, the current implementation of the EVM algorithm is inadequate for accurately measuring an individual's heart rate from video recordings of their skin surface. Consequently, the hypothesis that non-contact heart rate measurements using camera images and the EVM algorithm within a vehicle simulation can achieve accuracy comparable to that of wearable devices was not supported by our findings.

5 CONCLUSION AND FUTURE WORK

Within the conducted study, important results for the development of RGB image-based heart rate detection are gathered. The initial approach to substantiate the hypothesis that the heart rate of subjects can be detected using the EVM algorithm, and that this detection is comparably accurate to that of a wearable fitness tracker, could not be confirmed, even while using state-of-the-art hyper parameter tuning. The deviation shows that a different approach has to be pursued in order to be able to reliably integrate the non-contact heart rate detection into in-car systems. One possibility for this would be the use of deep learning methods. Particularly with regard to the success of AI models in computer vision applications, it can be assumed that deep learning is also a promising approach for video sequences detecting heart rates. Pulkit et al. [9] uses a regression CNN (Convolutional Neural Network) to extract the relevant information out of a EVM magnified video and estimates the heart rate . Based on the gained experiences, our dataset, and results from Pulkit et al. [9], we are in the process to develop an AI aided algorithm to detect the heart rate in a driving scenario reliably to adapt the human-car-interaction to the user's state.

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