DriverWatch: Video-Based Heartrate Detection for Automotive Safety

Vasudev Nair Vishnu Nambiar Shrimoy Satpathy Dharshini Mahesh Aditya Janan
Sriram Sendhil Dr. Katherine Brown

Introduction

Decoding vital signs from video input provides a non-invasive approach to monitoring driver well-being. Heart rate is an extremely vital indicator of physiological well-being. In our work, we researched Eulerian Video Magnification (EVM) to extrapolate the heart rate from video.

This research project delves into investigating whether or not EVM was the most effective way to calculate heart rate through a non-invasive approach. By utilizing the power of spatial decomposition and video processing, we aim to assist automotive engineers and healthcare workers in monitoring driver health and performance, enhancing road safety.

Dataset and Implementation

Our dataset is the DriverMVT (Driver Monitoring dataset with Videos and Telemetry) dataset from the St. Petersburg Federal Research Center of the Russian Academy of Sciences. The data set contains videos of researchers driving combined with information about their head pose, heart rate, and driving habits. It contains a total of 1506 videos recorded by 9 different drivers (7 male and 2 female.)

- Precise tracking with a bounding box enables real-time estimation of heart rate based on facial hue changes
- Gaussian Pyramid construction and Fourier transform operations are applied within the box to extract physiological signals
- Spatial decomposition analysis presented in the upper right box provides detailed facial change insights

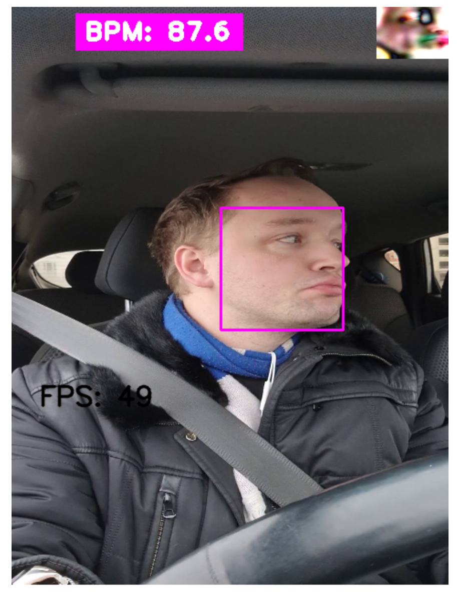

Figure 1. Feature extraction

Figure 2. Dataset presented

Computer Vision and Eulerian Video Magnification

Eulerian video magnification is a technique used to amplify subtle changes in videos that go unnoticed by the naked eye. It utilizes a fast-fourier transform to decompose the video into different frequency bands to obtain and amplify the desired frequency. This allows for the visualization of color variation on the human face, allowing researchers to determine heart rate.

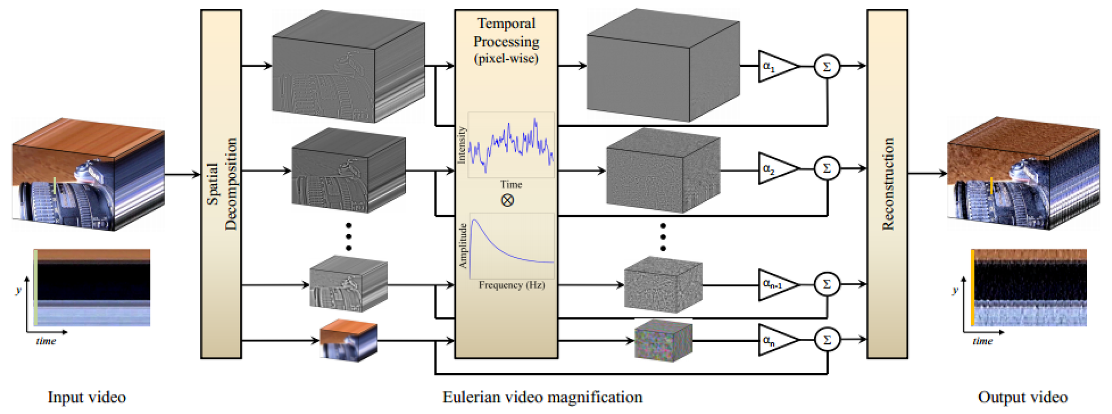

Figure 3. Model Architecture

Results

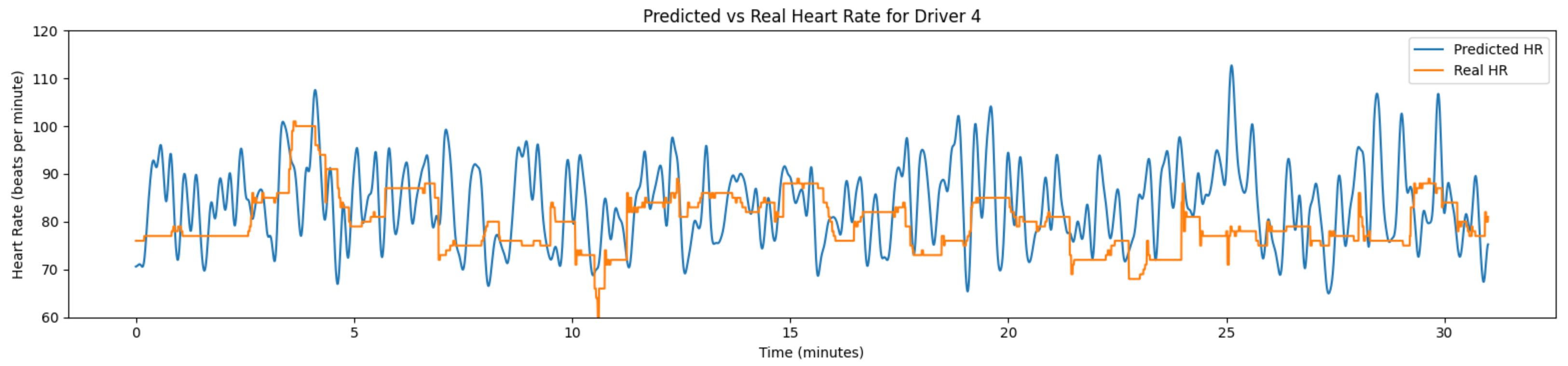

Figure 4. Driver 4 comparison of real heart rate to predicted

Correlation Coefficient: 0.1202236. ANOVA (p-value): 5.30163e-51. Mean Predicted HR: 83.8623. Mean Real HR: 79.8131.

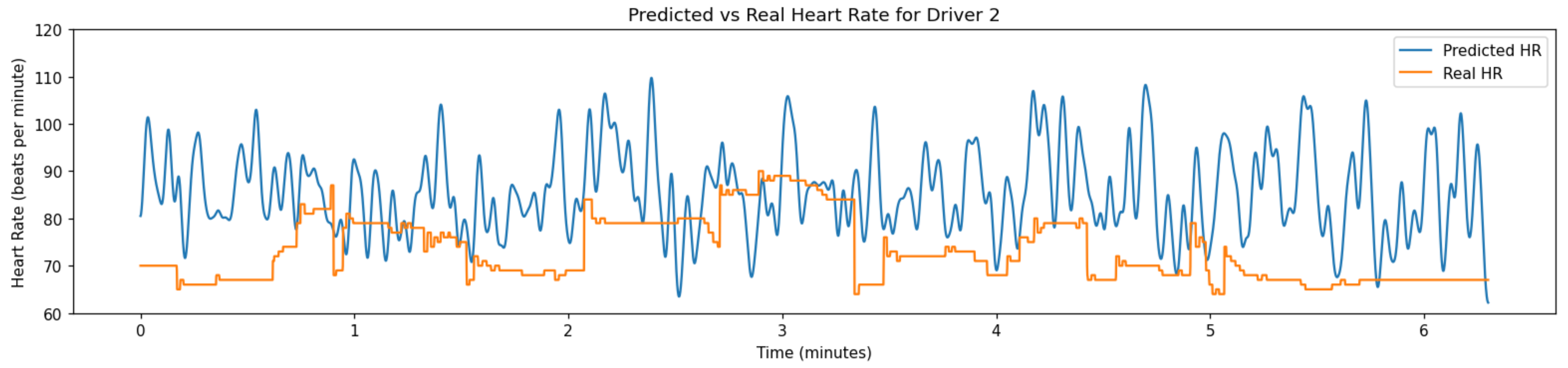

Figure 5. Driver 2 comparison of real heart rate to predicted

Correlation Coefficient: 0.0897076. ANOVA (p-value): 0. Mean Predicted HR: 85.6096. Mean Real HR: 73.1080.

Analysis

The analysis of heart rate values derived from the Eulerian Video Magnification (EVM) technique compared to actual heart rate measurements revealed significant discrepancies. We employed an Analysis of Variance (ANOVA) to assess the differences between the two datasets, which returned extremely low p-values (5e-51 for Figure 4 and 0 for Figure 5), allowing us to confidently reject the null hypothesis that the predicted and actual heart rates are equivalent. Furthermore, the correlation coefficients (0.1202 for Figure 4 and 0.0897 for Figure 5) suggest a weak positive relationship, indicating that the EVM predictions do not closely align with the actual measurements. This weak correlation is further supported by the differences in mean heart rate values, where the EVM predicted heart rate is approximately 4 bpm higher in Figure 4 and about 12.5 bpm higher in Figure 5 than the measured rates. These results highlight substantial inaccuracies in the EVM technique for predicting actual heart rate values, the trend seen in the other videos within the dataset.

Conclusion

EVM may not be the most viable approach to monitoring a driver's physiological state. It might be accurate when the driver is still in place - however, this isn't a realistic scenario in a driving context due to vibrations from the engine, bumps in the road, air conditioning, etc. For future applications, our work introduces the idea of validating Convolutional Neural Networks (CNNs) for a driving setting. A limitation of CNNs is that they require a significant amount of training time and computing power - especially with a large dataset, like DriverMVT.

References

- Othman, W., Kashevnik, A., Ali, A., & Shilov, N. (2022). DRIVERMVT: In-cabin dataset for driver monitoring including video and vehicle telemetry information. Data, 7(5), 62. https://doi.org/10.3390/data7050062
- Othman, W., Kashevnik, A., Ryabchikov, I., & Shilov, N. (2022). Contactless camera-based approach for driver respiratory rate estimation in vehicle cabin. Lecture Notes in Networks and Systems, 429–442. https://doi.org/10.1007/978-3-031-16078-3_29
- Wu, H.-Y., Rubinstein, M., Shih, E., Guttag, J., Durand, F., & Freeman, W. (2012). Eulerian video magnification for revealing subtle changes in the world. ACM Transactions on Graphics, 31(4), 1–8. https://doi.org/10.1145/2185520.2185561
- Abbas, G., Khan, M. J., Qureshi, R., & Khurshid, K. (2017). Scope of video magnification in Human Pulse Rate Estimation. 2017 International Conference on Machine Vision and Information Technology (CMVIT). https://doi.org/10.1109/cmvit.2017.28