Driver State Monitoring with Computational Fabrics for Safer Driving

Krithika Subramanian[1], Jiting Liu[2], Qijia Shao[2], Xia Zhou[2]
1: College of Information Sciences and Technology, The Pennsylvania State University, State College, PA
2: Fu Foundation School of Engineering and Applied Science, Columbia University, New York City, NY

Introduction: In recent years, cars have become increasingly intelligent. However, drivers remain as the main risk factor for road accidents. By monitoring the physiological state of a driver, our system aims to detect driver drowsiness which can provide an additional layer of safety. Previous methods to track a driver's physiological states include computer vision, driver sonar, and rigid wearable sensors. Our proposed method uses conductive fabrics as sensing electrodes embedded into the steering wheel for physiological sensing. Unlike the previous methods, fabric-based sensing is a form of unobtrusive monitoring, which allows for long-term monitoring without discomfort or distraction. Additionally, they're easily scalable and customizable to different vehicle types and driver preferences. Over the course of the summer, we focused on creating a steering wheel prototype to test the viability of electrocardiogram (ECG) signals in different driving environments.

Methods: An echocardiogram uses electrodes (leads) to capture the electrical activity of a heart by creating an electrode path that passes through the heart with positive and negative electrodes on the left and right hands, respectively. Thus using the Lead I of the standard 12-lead system. First, we took an ECG recording using gel electrodes to generate a ground truth ECG recording to create a comparison to data from fabric-based electrodes. The fabric-based electrodes are made from conductive fabrics that work as electrodes which allow for an ECG signal to be generated. Through the comparison, we viewed that a ground electrode was not necessary to produce reliable ECG signals, as it is only used to cancel out common noise. Then, we created and tested a steering wheel prototype with attached fabric electrodes to test different driving motions to understand how driving affects ECG signal readability.

Figure 1. Steering Wheel Prototype & Different Driving Motions For Testing

Additionally, the gel electrode ECG data we developed an algorithm to calculate HRV data. R Peaks were found for the data and specific time domain HRV measurements were calculated with the criteria of being accurate for ultra short recordings (<5 min of data).

Results: By simulating different driving movements and tracking ECG signals for five minutes, we are able to understand that two points of contact are needed to visualize a clear ECG signal.

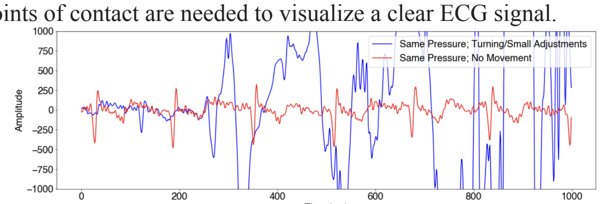

Figure 2. ECG Detection using Fabric Electrodes Attached to the Prototype Steering Wheel while Demonstrating Different Driving Techniques

Using a thousand frame sample in milliseconds, we can visualize the no movement ECG and the turning/slight adjustments ECG data. As the driver adjusts and turns the wheel by moving their hands, as seen in blue, the ECG becomes unreadable.

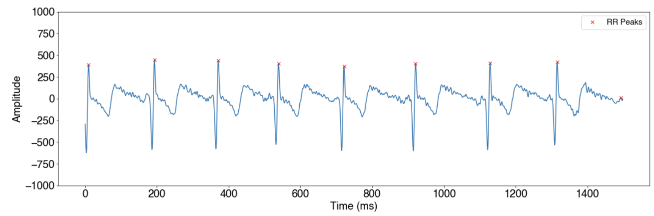

Figure 3. R Peak Detection Using a Ground Truth Gel Electrodes

This ECG signal data from gel electrodes after filtrations, has been used for R peak detection with the Pan-Tompkins algorithm, the highest amplitude of the R wave. These data points are then used to calculate different types of HRV.

Table 1. Time Domain Calculations of HRV using Minutes of Data

Time Domain Calculations of HRV

RMSSD	Root mean square of successive differences: relevant and accurate measure of Autonomic Nervous System activity over the short term	190.2451 (ms)
SDRR	Standard deviation of the R to R intervals but includes abnormal or false beats	12.55927 (ms)
SDNN	Standard deviation of the R to R intervals	0.616741 (ms)

Time Domain Measurements allow for the calculation of the variability of Interbeat Intervals, which allows us to see quick changes in HRV due to physiological changes like drowsiness.

Discussion and Next Steps: Continuing this research, an HRV association with a driver's physiological states is required. This can be done by using an objective rating scale (Kundinger) and computing more features from the time and frequency domain of HRV. This could lead to developing a classifier like SVM or a neural network using these features. Additionally, another next step is enhancing system reliability. This will allow for tracking of ECG when hands are moving and not on the wheel. This could be done by implanting electrodes into areas that will have constant contact with the driver.

References:

1. Kundinger, T.; Sofra, N.; Riener, A. Assessment of the Potential of Wrist-Worn Wearable Sensors for Driver Drowsiness Detection. *Sensors* **2020**, *20*, 1029. https://doi.org/10.3390/s20041029

Acknowledgements: Thank you to the Amazon SURE Program, Professor Zhou for working in her lab and all the lab mentors for helping me