Technologies for Safe & Efficient Transportation

THE NATIONAL USDOT UNIVERSITY TRANSPORTATION CENTER FOR SAFETY

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Driver Status Monitoring in Autonomous Vehicles Using In-Seat Inertia Sensors

FINAL RESEARCH REPORT

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Contract No. DTRT12GUTG11

DISCLAIMER

#101 Driver Status Monitoring in Autonomous Vehicles Using In-Seat Inertia Sensors
Project Period: 01/01/2015 - 12/31/2015

1. Problem

Autonomous vehicles are becoming a reality. Many car companies are already incorporating advanced cruise control systems (such as active lane-keep, automatic braking, etc.) into current generation of vehicular systems. As cars become more autonomous, incidences that require human driver involvement will become less [1-3]. However, this will likely result in less attentiveness in the drivers when driver involvement is required. In order for the car to safely give control to the driver, the system must be able to understand the attention level of the driver.

Prior work has explored on-body sensors to maintain attention level of the driver [4-7]. These works often have sensing requirements that require direct contact with the driver, making them unsuitable for casual drivers. Another approach utilizes camera based systems that monitor the driver [5, 7]. These systems are often sensitive to different lighting and line-of-sight limitations. Furthermore, these works focuses on maintaining the driver's attention, as oppose to understand the level of inattention due to the current driver state.

In order to address the challenge of understanding attention level, we developed a non-intrusive sensing system embedded in the car seats to infer driver physiological states in two levels: 1) posture and motion (macro-motion) and 2) muscular and cardiovascular states (micro-motion).

2. Our Approach

Our driver monitoring system consists of three-tiers: 1) an inertial sensor node network to sense motion and muscle vibration, 2) a mobile data aggregator to collect and transmit data, and 3) a backend server to process transmitted sensor data. Each tier has different processing and communication capabilities that must be dynamically optimized over different sensing applications. A brief overview of these three main components is shown in Figure 1, and their details are provided below.

Sensor Node Network The sensor network of the system is made up of a set of small unobtrusive inertial sensor nodes that enable fine-grained activity monitoring by detecting body motion as well as the skeletal muscle vibrations. The network consists of inertial sensor nodes, a microcontroller chip, and three triaxial sensors: accelerometers, gyroscopes, and magnetometers. The main challenge in sensing is that since the sensor nodes are designed to be small and to collect data as fast as possible to capture small amplitude transient vibrations, they are relatively resource constrained. To this end, we included a mobile data aggregator, to coordinate their sampling and data transmission to the backend server.

Mobile Data Aggregator Since the sensor nodes are resource constrained, the monitoring system uses a mobile data aggregator to coordinate the sensor sampling, error correction, and wireless data transfer to the backend server. In other words, this component is in charge of driving the sensor network, as the master on the node system. We used a wired connection to communicate with the other sensors on the same suit and Wi-Fi to communicate with the base station. Although the network is extremely bandwidth limited due to the high number of sensors, the processing on the aggregator is less constrained compared to the sensors. Thus we used a differential compression running on the aggregator to reduce the wifi load to the back-end server. This significantly reduced the processing needed for the aggregator to run the wifi system due to the reduced clutter on the wireless transmission.

Backend Server The backend server receives inertial data to create human motion and vibration
signatures to infer muscle identity as well as stress level. The back end server contains two modules: 1) posture and motion recognition (macro-motion), and 2) muscular and cardiovascular activity inferencing (micro-motion) module. The first module involves detecting large amplitude low frequency motions, while the latter one focuses on small amplitude high frequency signals.

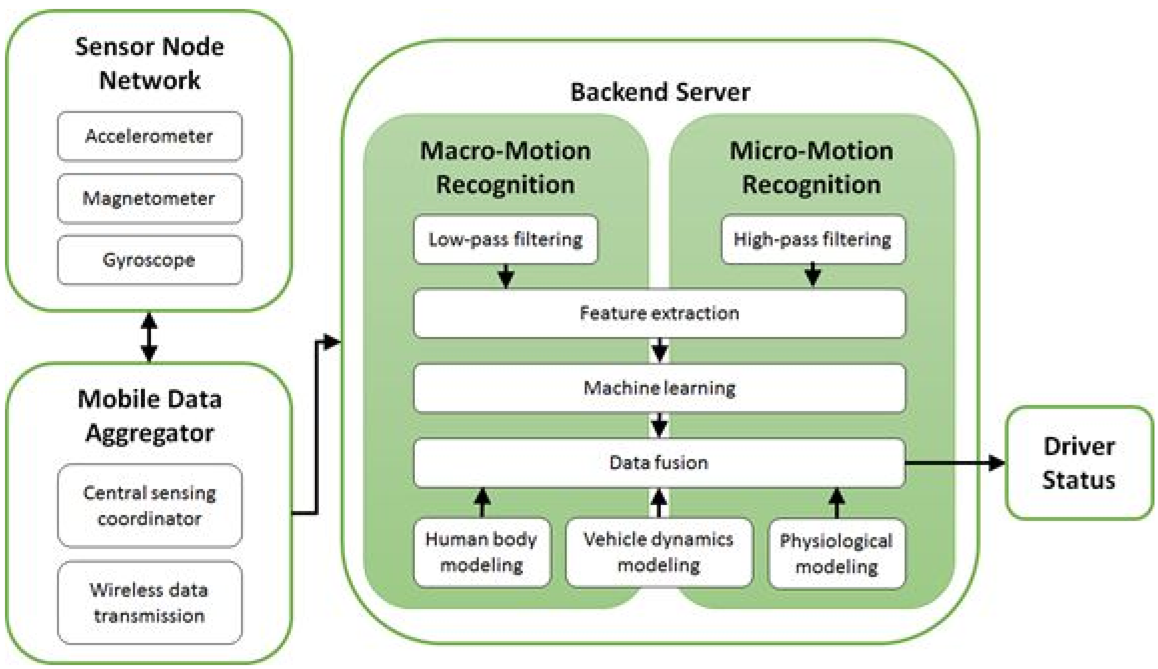

Figure 1. System Overview

3. Methodology

The posture and motion recognition module extracts the overall activities of the driver through human body modeling and inertial data mining. The main challenge of this module is to deduce those information using limited sensing ranges (i.e., only through the contacts). To overcome this limitation, we combined data from multiple sources and utilize a physical model of human body to compensate for unobserved body posture and motion.

The muscular and cardiovascular activity inferencing module identifies activated muscles and measures muscle tension and cardiac muscle activities (heart rate, blood flow, etc.), which in turn are used to infer stress and fatigue level of the driver. This fine-grained activity recognition is achieved by combining feature selection and machine-learning techniques to achieve muscle group identification. We then use the change in the data to determine states of the muscle, namely to differentiate between a fresh and fatigued muscle. The human heartbeat generates a rather sizable vibration, which can also be detected using our sensors. The key challenges in obtaining finer granularity body data, such as inferring muscle fatigue, resides in low signal to noise ratio, where the signal of interest is very low amplitude, while others such as motion and vehicle dynamics result in large amplitude signals. In fact, the muscular vibrations have overlapping ranges as motion and vehicle dynamics. We infer this information only when detected motion is low combining motion tracking and activity information to determine when the lower frequency component.

4. Results

The results are in two aspects. The hardware sensor network and the algorithm.

Hardware:

We first developed a hardware system described above that consists of a network of accelerometers, gyroscopes, and magnetometers embedded inside car seats and seat belts. Pictured in Figure 2.

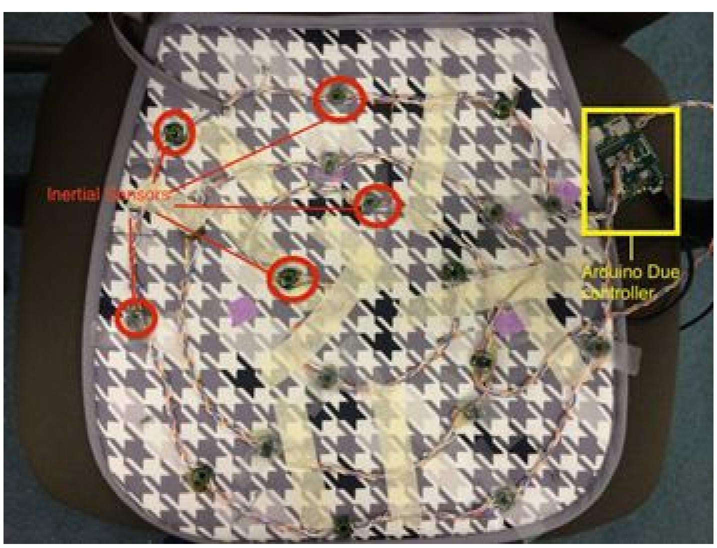

Figure 2: Back of the seat cushion on which the network of sensors and controller are mounted is shown. Marked in red circles, are the sensors. The Arduino Due controller is marked in yellow.

Algorithm:

The algorithm is used to detect a number of features. The drivers presence is shown in Figure 2. Each pair of vertical blue lines with labels [A1, A2], …, [F1, F2] are the time of a pair of stand-up and sit-down of the driver on the seat. As can be seen from the spectrogram, the times at which the drivers stand up and sit down produce a banding effect (high energy across all frequencies, which is closely related to the singularity in signal). The system was able to identify the driver's presence using this feature and will potentially detect/identify other detailed movements.

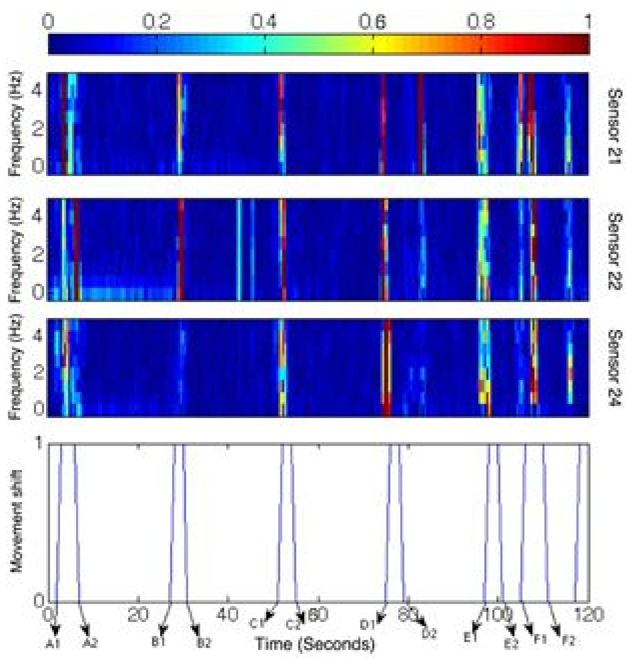

Figure 2: Driver's presence detection results.

Figure 3 shows the energy of the person sitting on the seat with the leg crossed. The dark blue represents low energy value while red and orange represent high signal energy value. Note that vibration energy is higher when the body does not touch the seat because the body adds an additional mass the system needs to vibration and slows down the sensor movement. These features are used for detection of the person sitting position.

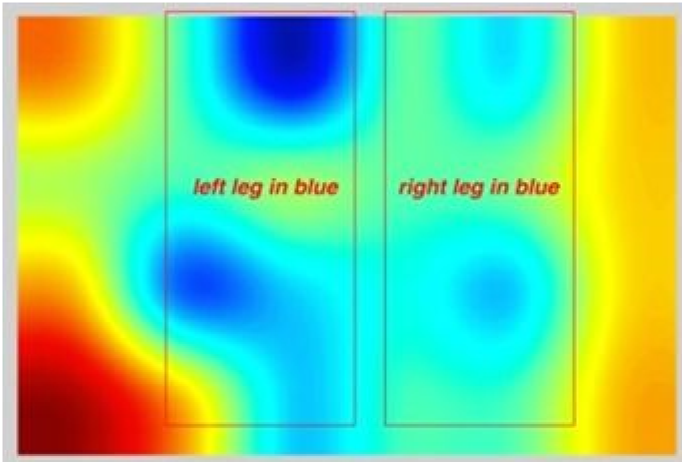

Figure 3: Spatial distribution of signal energy as the driver crosses the right leg.

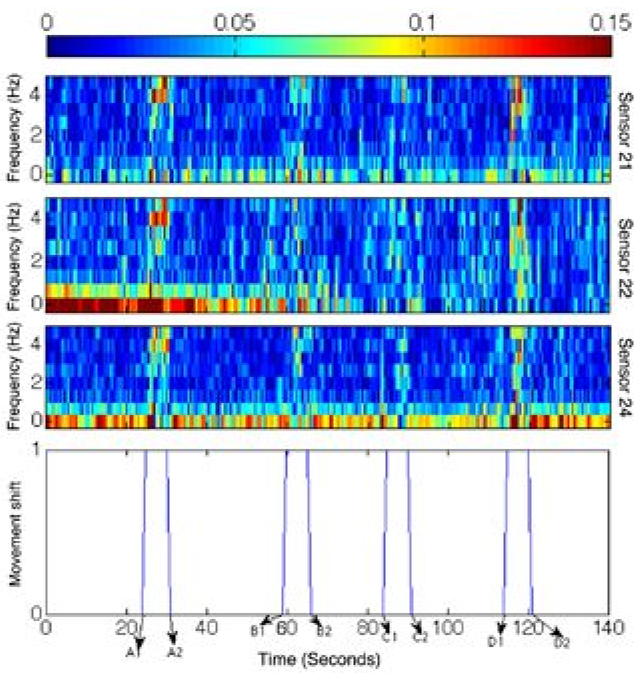

Figure 4. Time-frequency analysis of in-seat accelerometer data as the driver changes breathing rate.

Figure 4 shows the result from driver breathing while sitting in the seat. The vertical blue lines with labels [A1, A2], …, [D1, D2] indicate periods of rapid breathing. These periods are well correlated the times of high energy (red and yellow color) around 4Hz in the time-frequency plots. The plot shows the breathing can be detected from the users while sitting in the seat without motion.

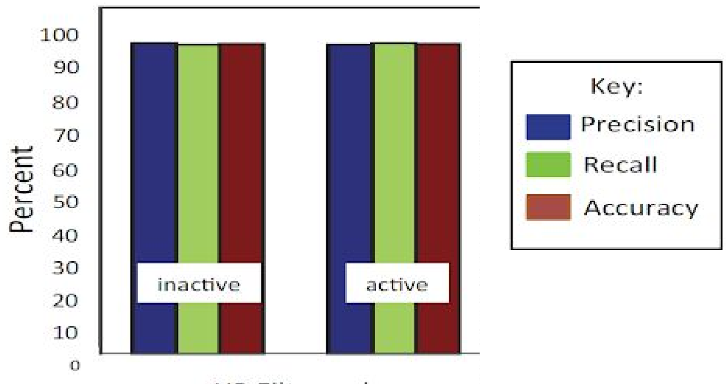

Figure 5 Muscular activity recognition results

Figure 5 shows the results of recognition for the leg muscles. The subject tense of muscle is vs. relaxed in the seat is measured and the results 97% accuracy of the activity recognition. This result can lead to detection of changes in stress level while in the car due to driving situation changes.

5. Outcomes

Publications, conference papers and presentations

Mokaya, F., Lucas, R., Noh, H. Y., & Zhang, P. (2015, September). Myovibe: Vibration based wearable muscle activation detection in high mobility exercises. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 27-38). ACM.

Other Dissemination Activities

1. We gave a seminar on this work at the Department of Mechanical Engineering, Virginia Tech, Blacksburg, VA, Mar. 25, 2015
2. We presented a seminar at Korea Institute of Civil Engineering and Building Technology, Ilsan, South Korea, Jun. 9, 2015
3. We presented our work at Bosch LLC, Pittsburgh, PA, Jul. 27, 2015
4. We presented a seminar at University of Michigan, Ann Arbor, MI, Nov. 12, 2015

6. Conclusions

This project showed the viability of a vibration based sensing seat system that can measure a person's posture and physiological status of breathing and muscle activity. These results shows a possible future of smart car seats that can not only respond to the driver's driving status but can be a health tool as well.

References

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[3] Kim, J., Kim, H., Lakshmanan, K., & Rajkumar, R. R. (2013, April). Parallel scheduling for cyber-physical systems: Analysis and case study on a self-driving car. In Proceedings of the ACM/IEEE 4th International Conference on Cyber-Physical Systems (pp. 31-40). ACM.

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