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Non-intrusive Driver Fatigue and Stress Monitoring Using Ambient Vibration Sensing

FINAL RESEARCH REPORT

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#69 Non-intrusive Driver Fatigue and Stress Monitoring Using Ambient Vibration Sensing
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1. Problem

Autonomous vehicles will define the automotive industry in the near future. Autonomous vehicles are expected to improve the space utilization of the road systems by eliminating inefficiencies due to human driving (e.g., large distances between cars to allow for slow human reaction, parking needs after commute, accidents due to driver distraction, etc.), while providing extra free time to the drivers [1-3]. The current state of the art involves the use of externally and internally mounted sensors, such as laser rangefinders, cameras, inertial sensors, infrared sensors, etc., to provide the autonomous car with rich view of the world around it. With these sensors the car can drive autonomously under fairly regular and perfect conditions.
However, the autonomous car would have to give back control to a *capable* driver when it is confronted by unusual road or weather conditions (e.g., snow covered roads with invisible road lane markings, other aggressive road users, unexpected events such as road lane closures, etc.). Such conditions may interfere with, or even blind, the embedded on-board sensors. Whereas human drivers have the ability to compensate and adapt to such conditions, the autonomous vehicle would be limited to only what its sensors can perceive.

Before giving control back to the driver, it is essential for the car to know/estimate the state of the driver and determine whether the driver is capable of taking control or the car needs to take other cautious actions. For example, handing back control to a driver who was sleeping, startled and overly stressed about the situation, or even an absentee driver that was away from the driver's seat, moving around in the cabin of the car, would be dangerous. By monitoring the state of the driver through her/his movements and other physiological variables, we can avoid such situations.

Prior work has explored a number of 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 focus on maintaining the driver’s attention, as oppose to understand the level of inattention, stress and physical fatigue due to the current driver state.

To this end, we develop data analysis methods to 1) extract detailed driver’s physiological states (including movement, cardiovascular functions) and 2) infer higher level states (including stress, physical fatigue, and their physiological indicators such as heart rate and breathing rate), under various driving scenarios. The main challenge resides in high noise level due to the moving vehicle and sensing constraints relying only on contacts. To address these challenges, we utilize signal processing for multi-sourced, high-resolution and high frequency data with hybrid modeling approach to minimize uncertainties and obtain reliable information.

2. Our Approach

We are developed a driver fatigue and stress monitoring system using embedded accelerometers in car seats. These sensors can sense physiological states of the driver that cuses a physical vibration, such as movement, heart rate, and breathing, muscle activation and MMG vibrations. Our algorithm combines analytical human model with data-driven approaches to reduce modeling uncertainties.

The proposed research consists of two main thrusts: 1) Combining signal- and physics-based models to simultaneously estimate driver's movement, heart rate, and heart rhythm from inertial sensor data; and 2) Inferring stress and fatigue level from driver's physiological states. Both thrusts focuses on separating the signal of interest from the large amount of noise. More details for each thrust is provided below, in the Methodology Section.

3. Methodology

We separate our research into two thrusts. 1) obtain the physical indicators of stress (heartbeat and breathing), and 2) fatigue indicators from the muscles. Both of these thrusts focuses on extracting the small signals from large amount of environmental noise.

Movement and heart beat extraction: Heart rate could be used for cardiac monitoring inside the vehicle to measure stress level, particularly, the variation of heart rate [10]. By determining heart beats and model the power spectrum of the heart-rate variability, we can then infer stress. This thrust incorporate physical models of human body to data-driven models to extract driver's movement and heart beat information. Based on the physical model of human movement, we simply model the type of movement (periodic vs. intermittent). We demonstrated detecting the presence and posture of the driver whilst in the driver seat using time-frequency spectrum and spatial distribution of signal energy are good indicator of the user's large physical movements. Using these movements we create a threshold that first determine if a signal would be present and detectable. We then further use the wavelet spectrum to detect changes in the signal due to driver's movement, since the singularity represents large change in signal characteristics. The posture change before and after the movement are inferred from signal energy distribution and the physiology of human body.

Like motion, heartbeat of a person exert a vibration on the car seat. Unlike body motion, this vibration is small and periodic. Thus, we identify frequency domain features from the expected hear rate range from each axis of the accelerometer located near the driver's heart in the seat back. We extract frequency features from each axis to capture vibrations due to the person regardless of the exact location and orientation in the chair which they occur. The heart rhythm are estimated by reconstructing the signal with the harmonics of the detected frequency components.

Often, however, the noise of the car and body motion will overwhelm the heartbeat signal. Therefore, the system must be able to model the motion noise as well as the heartbeat. A second observation is that the sensed signal from other noise (e.g., car, body motion, etc.) results in higher amplitude "outlier" sensor values, compared to the sensed signal during no significant noise. By modeling the distribution of the "outliers" and eventually selectively eliminating a majority of these higher/extreme segments that experience high motion noise, the system reduces the effect of high noise level in the accelerometer signal. We modeled the "outlier" as extreme value distribution [9] and perform an outlier detection to remove these noise.

Stress and fatigue inference:

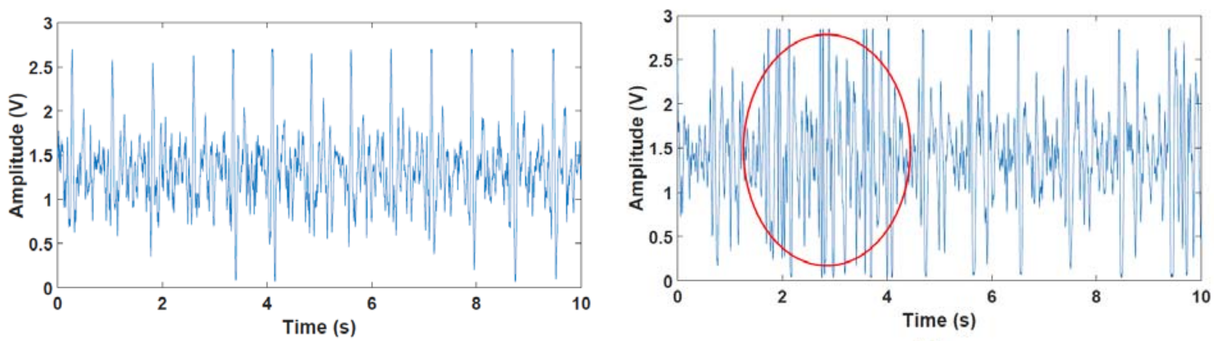
Physical fatigue plays a large role in determining driver attention. By utilizing sensors placed near the leg, we infer the fatigue level of the driver especially when the muscles are tensed. Furthermore, the system can infer response time and position of legs for driving style analytics.

As mentioned earlier, accelerometer sensor measures both large motion and the minute muscle vibrations. Our system first monitors the motion to determine if large motion is present. Only when the large motion is not present and the user is present a measurement is made of the fatigue.

After a suitable region is located, we calculate the mean power frequency (MPF) feature. This feature captures the current overall center of the muscle activation frequency. We observe through experimentation that this frequency shifts to lower values when the muscle is fatigued. Thus, the system finally uses this value to determine the current fatigue, and utilize the slop to estimate future fatigue.

4. Findings

The results from the research shows that the key stress indicators of heartrate measurements and physical muscle fatigue can be sensed with embedded accelerometers. Here we present our findings.



(a) (b)

Figure 1: shows the time domain signal of the vibration received by a sensor close to the heart in contact with the back. a) shows the heart beat in a quiet environment and b) shows the result when a noise is added (red circle)

Figure 1 shows the raw time-domain heart rate signal. Figure 1a shows the signal without noise and the user sitting still. The sensor is on the back of the user. The periodic high vibration peak of heartbeat signals can clearly be seen. Figure 1b shows the same setting but with environmental noise circled in red. The signal is no longer visible.

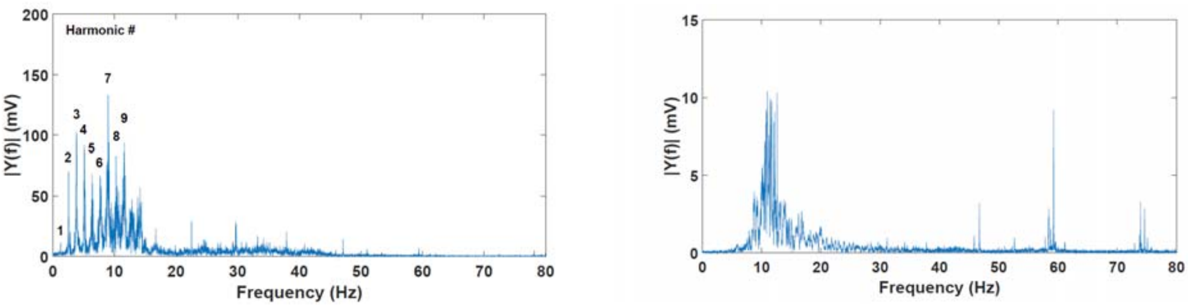


Figure 2: (left) Frequency domain of the heart beat signal without noise (right) signal of wide-spectrum noise similar to a car.

Figure 2 (left) shows the FFT results of a 30-second signal when a subject, with an average heartbeat rate of 76.86 bmp, lay still on the bed. In the figure, we mark the heartbeat signal's fundamental frequency (with the number 1) and a few harmonic signals (2 means the second harmonic frequency). In order to clearly show the harmonic frequencies in this result, we adjusted the amplification circuit such

that the resulting heartbeat amplitude is close to 3V. (right) shows the raw FFT of only the noise. In this case, our amplifier circuit output for heartbeats is kept at 200mV. Although the signals are of similar strength, the harmonics of the heartbeat is high and much lower frequency than the noise. Thus, our work focuses on the extraction of the heart harmonics and not the fundamental frequencies.

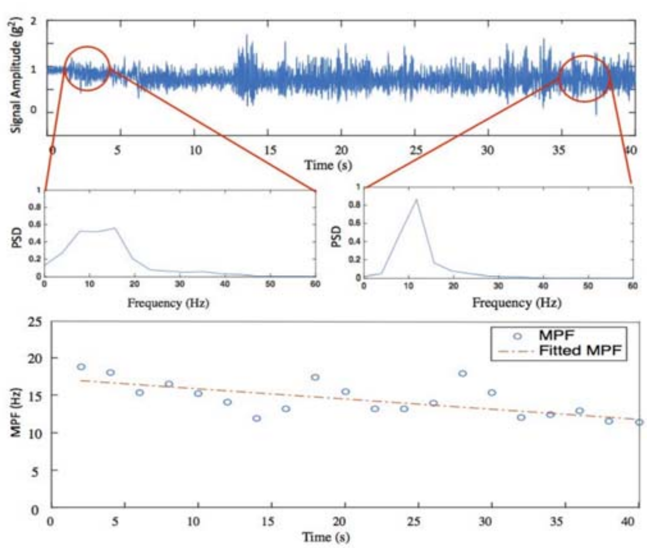


Figure 3: (Top) time domain signal of a vibration extracted from muscle under stress. (Middle) The start and end FFT of the signal showing the frequency shift. (bottom) the MPF feature that shows the downward shift showing the progress of fatigue.

Figure 3 (top) shows sample MMG data from a fatiguing isometric exercise. The signal amplitude is the summation of square of the individual accelerometer axes data. (Middle) graph shows the normalized power spectral density (PSD) calculated from a 2 second window of data (red circles) at the beginning (left) and then towards the end of the exercise(right). There seems to be a shift of signal power to lower frequencies evidenced by the change in shape of the PSD graph. There is also an increase in signal power as the muscle fatigues. (Bottom) graph shows a scatter plot of the MPF points and a fitted MPF line, extracted from consecutive 2 second windows throughout the 40 second exercise. The gradient of the fit decreases further into the fatiguing exercise. This suggests a decreasing MPF trend with increasing muscle fatigue.

5. Outcomes

Publications, conference papers and presentations

1. Mokaya, F., Lucas, R., Noh, H., & Zhang, P. (2016). Burnout: A Wearable System for Unobtrusive Skeletal Muscle Fatigue Estimation. The 15th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN '16).

2. Jia, Z., Alaziz, M., Chi, X., Howard, R. E., Zhang, Y., Zhang, P., ... & An, N. (2016, April). HB-phone: a bed-mounted geophone-based heartbeat monitoring system. In *Proceedings of the 15th International Conference on Information Processing in Sensor Networks* (p. 22). IEEE Press.

3. We presented this work at The International Conference on Mobile Systems, Applications, and Services (MobiSys), Women's Workshop, Singapore, Jun. 26, 2016.

Other Dissemination Activities

1. We presented our work at Intel, February 2016.
2. We gave a seminar on this project at Lehigh University, Bethlehem, PA, April 2016.
3. We presented our work at Microsoft Research, May 2016.
4. We presented at EPFL Singapore, Singapore, Jun. 30, 2016 and at the Department of Computer Science, National University of Singapore, Singapore, Jul. 1, 2016.
5. We presented this work at LG, Pyungtaek, South Korea, Jul. 28, 2016.
6. We gave a seminar on this work at the Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea, Aug. 17, 2016.

6. Conclusions

We presented a vibration-based system that can be imbedded into a car seat to measure key indicator of stress (heart rate and fatigue). The system leverages the fact that heart rate and muscle fatigue create minute vibrations that changes over time to increase the accuracy of our inference. In addition, our algorithm presents several methods to extract small signals of interests from the large noise that is present in the automotive environment.

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