Technologies for Safe & Efficient Transportation

THE NATIONAL USDOT UNIVERSITY TRANSPORTATION CENTER FOR SAFETY

Carnegie Mellon University | UNIVERSITY of PENNSYLVANIA

Non-Intrusive Driver Distraction Monitoring Using Vehicle Vibration Sensing

FINAL RESEARCH REPORT

Hae Young Noh: PI
Pei Zhang: PI

Contract No. DTRT12GUTG11

DISCLAIMER

#47 Non-Intrusive Driver Distraction Monitoring Using Vehicle Vibration Sensing
01/01/2017 - 08/31/2018

1. Problem

Every year about 1.3 million people die, and 50 million people are injured from road traffic crashes [1]. In particular, traffic related death is the leading cause of death among the young world-wide and is projected to continue to increase. Among many causes for road traffic injuries, driver distraction has been identified as an increasing concern for policy makers and researchers, including the usage of mobile phones and other technologies. Recently, the National Safety Council's studies have shown that smartphones are responsible for 26% of these accidents [2, 3].

However, comprehensive monitoring of driver distraction without further interference is a challenging task. Causes of driver distraction is a complicated process and is categorized into four different types: visual, auditory, cognitive, and physical. Combination of more than one type can happen simultaneously, triggered by either internal (in vehicle) or external sources of distraction [1]. Prior work has explored camera, or on-body sensors to monitor and maintain a particular type of distraction of the driver [4-8]. These works often have sensing requirements that require direct contact or line-of-sight with the driver, making them unsuitable for casual drivers and can in cases increase driver distraction. In addition, these system sense a predetermined effects, while other effects are hidden. While the causes of distraction are various, the response of the driver tends to be physical (changing radio stations, leg placements, etc.) or cognitive (stressed, inattention, etc.). Among them, heart rate variability is a key indicator of driver's stress level. By capturing the heart rate variability of the driver, we can combine it with other driver's physiological states, extracted using our prior work with previous support from the University Transportation Center (UTC) in 2015 and 2016, to comprehensively infer both physical and cognitive distraction of the driver.

Building on our prior work on using inertial sensors for driver status monitoring [4, 8] (supported by the University Transportation Center (UTC) in 2015 and 2016), we developed more in-depth analysis methods to extract heart rate variability of a driver using inertial sensors that are embedded into car seats. Specifically, we developed data analysis methods to extract heartbeats of a driver in a running car.

2. Our Approach

We introduced a system of inertial sensors in a car seat to provide ambient monitoring of a driver's heart rate and heart rate variability (specifically, RR intervals). At every beat, the heart is polarized and depolarized to trigger its contraction, electrical activity which is often measured by an ECG. The R interval describes the depolarization of the main mass of the ventricle, causing the largest peak in an ECG. The RR interval is defined as the distance between the peaks of two R waves. The RR-interval, then, describes the duration of one complete cardiac cycle. In this project, we use inertial sensors instead of ECG, so the peaks of the waves we measure correspond to the heart's movement, not its electrical activity. The RR interval can be used to calculate heart rate and heart rate variability. This heart rate variability is a key indicator of stress. We have been focusing on acquiring successive RR intervals of drivers from a car seat in noisy in-car scenarios.

3. Methodology

Our research attempts to use the vibration of heartbeats through the body's forces on the car seat in an automobile to measure RR-intervals. This poses many challenges which our system addresses with a multifold approach. Our main challenges are:

1. the sometimes low signal to noise ratio (heartbeat forces on the seats are small),
2. human motion noise (movement noise can overwhelm the signal),
3. engine noise (periodic engine noise increases the noise floor), and
4. sensor placement (the best location to capture the heart motion varies between persons and over time. We can intuitively understand this because people are different heights and they sit in different ways).

Below we show a diagram of the system overview with 3 modules. 1) The sensing module acquires the signal using a grid of accelerometers to capture the heart motion that can occur at different locations. 2) The target signal extraction module removes high motion parts induced by human motion. Then it performs denoising on the remaining signal to remove periodic noise (e.g. engine noise). Next, it smooths the signal to enhance peaks, followed by a wavelet filter to further enhance the impulse signal in the heart rate frequency range. 3) Finally, the RR-interval estimation module addresses the sensor placement challenge with a sensor selection algorithm, and outputs the final RR-interval estimation.

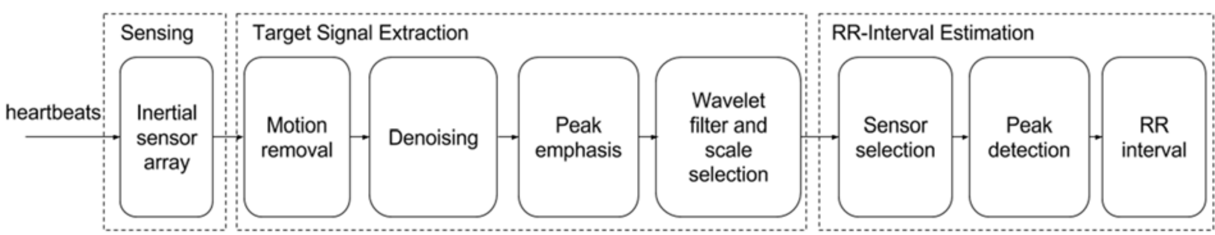

Figure 1: System Overview

In the **sensing module**, we use a set of inertial sensors to pick up movement caused by the subject's beating heart as the subject sits in the car seat. The heartbeat causes their chest and stomach to vibrate, which in turn causes the seat to vibrate. Because we detect the vibration of heartbeats from the vibration of the seat, the location of the sensor relative to the body greatly impacts the signal magnitude. Intuitively, the closer the sensor is to the heart, the stronger the signal. This raises two challenges: 1) People are different heights, so when they sit in the car their hearts are in different locations. And 2) people sometimes shift position and do not always sit leaning back. To address the first challenge, we use a network of sensors that lie against the backrest of the car seat and can pick up signals from a larger area. To address the second challenge, we use a sensor in the seat belt to pick up the stomach vibration caused by the heartbeat. We choose a sparse sensor array instead of many sensors for a lower-cost and low-computational-power design. We use piezoelectric accelerometers, which are excellent for vibration monitoring due to their wide frequency response, linear frequency response curve, and high sensitivity. We use the W354C03_010G10 piezoelectric accelerometer, sampled at 2 kHz [9].

The **target signal extraction module** handles both human motion and engine noise. It first extracts windows of data where there is less human motion noise. It then applies denoising and a wavelet filter to remove engine noise.

Our first step is recognizing and discarding portions of the signal that are excessively noisy due to person movement. We found that most large spikes of noise in the data were due to person movement, either talking, coughing, laughing, gesturing, or shifting positions. To identify this type of signal, we use a sliding window on the vibration signal and extract the maximum value of the window. If this value is above a threshold, we skip one second of data (i.e., label it as motion noise) and try again with a new window, moving forward by one second each time until we have a window that doesn't exceed our threshold. We skip one second at a time because we observe experimentally that noise in the data tends to last from between half a second to several seconds and takes about half a second to subside. We set our threshold by fitting a probability distribution to the first minute of data for each person using kernel density estimation and then using the inverse cumulative distribution function (ICDF) to compute a threshold to detect high motion noise. The threshold is determined empirically, considering the tradeoff between data preservation and accuracy (i.e., high threshold leads to more data but lower accuracy, while low threshold increases accuracy but wastes lots of data).

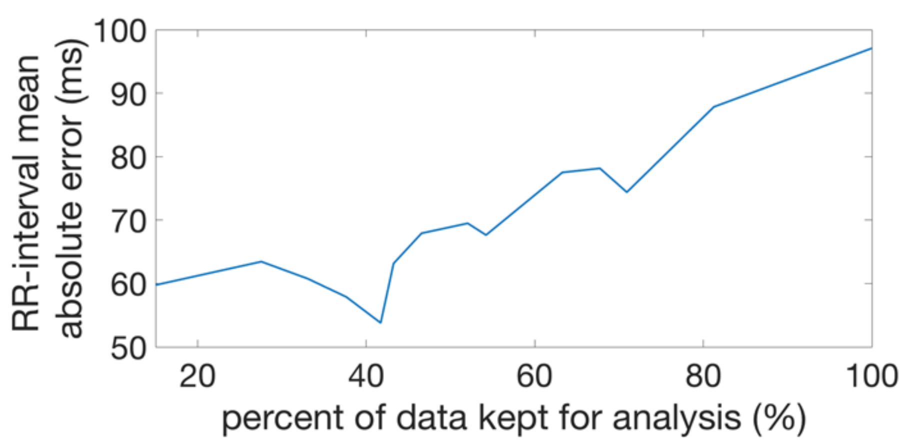

Figure 2: As we lower our noise threshold and keep less data, our error lowers due to increased sensitivity to including heartbeats and then increases due to erroneous detections.

We note that as we lower our noise threshold, there are sometimes small peaks that buck the general trend. This is because our thresholding method occasionally cuts out some data that gives good results, causing a small rise in our error. We observe that at about 41% of data from the optimal sensor kept across all subjects, the error starts to rise. Setting the threshold to the ICDF function for 89% minimizes this error.

We then do denoising to further reduce the noise in the signal. We place one sensor near the bottom of the backrest, away from the heart, to characterize noise. We observed that the level of noise recorded by each sensor is different, so it works best to partially subtract one sensor's signal from the other. We multiply the noise sensor signal by a fraction (we obtained 20% heuristically) and subtract it from the rest of the sensors.

In order to enhance the weak peaks of the heartbeat signal, we do root-mean- square averaging, which preserves the peaks in the data and smooths the high-frequency noise.

To further reduce the noise, we isolate the periodic nature of the heartbeat using a continuous wavelet transform (CWT). The CWT compares the signal to compressed and stretched versions of a wavelet, the CWT 's analyzing function. The Mexican hat wavelet has been widely used for characterizing impulse signals, which fits our target signal profiling. It is described by

$$\psi(t) = \frac{2}{\sqrt{3}\pi^{\frac{1}{4}}}(1 - t^2)e^{\frac{-t^2}{2}}$$

The stretching and compressing of the wavelet performed by the CWT is known as "scaling": the CWT is a function of scale (*a*) and position (*b*):

$$C(a, b; f(t), \psi(t)) = \int_{-\infty}^{\infty} f(t)\frac{1}{a}\psi(\frac{t-b}{a})dt$$

Where f(t) is the signal, t is time, and ψ(t) is the wavelet function. By varying the values of the scale parameter, *a*, and the position parameter, *b*, we obtain the CWT coefficients *C(a,b).* We chose the scale that best represents our data and varied the position coefficients to obtain a one-dimensional filtered signal.

Once the signal is enhanced and filtered, the **RR-interval estimation module** calculates RR-interval with the sensor with the highest signal amplitude.

To adapt to a wide range of heart positions with sparse sensors, we displace the sensors with minimum overlapping sensing range and choose the sensor closest to the heart. In each window, we calculate the mean of the wavelet coefficients for each sensor, and select the one with highest mean, indicating highest Signal-to-Noise Ratio. This algorithm depends on our having removed noisy parts in the signal and reduced the noise in the remaining signal, as high amounts of noise could also cause a higher mean, and cause the incorrect selection of a sensor as "optimal".

For the first step in our peak detection algorithm, we do root-mean-square averaging of the wavelet coefficients, which smooths the data, limiting small false peaks and emphasizing larger peaks. We find local maxima by calculating the derivative of our signal in two points in time and comparing them to see if the difference lies above a given threshold. Then we pick points near the local maxima and apply Least Squares Curve Fitting over them to refine the peak location

We occasionally detect extra peaks or drifted peaks from noise in the signal, which we remove to get accurate RR-intervals. Since heartbeats occur at periodic intervals, we discard the lowest magnitude peak of any pair of peaks that are closer than 220 beats per minute, which we take as our maximum heart rate (well above the normal resting heart rate of 60-100 beats per minute). This will not affect HRV monitoring in healthy subjects, because while heart rate does oscillate over time, it is not so irregular that it would have beats this close together and maintain a normal heart rate. Then we find the distance in time between the first two peaks in our sliding window and consider that our RR-interval. Now that we have our RR-interval, we take our next window of data starting at a location just past the 1st peak, ensuring that we don’t miss any heartbeats as we move the window forward.

4. Findings

We found that our research can accurately use the vibration of heartbeats through the body’s forces on the car seat in an automobile to measure RR-intervals. The outcomes include our hardware system integrated with algorithm software that removes noise from car and driver movements and extracts RR-interval. Filtering, wavelet signal decomposition and extreme value analysis techniques are used for effective separation of heart rate information from other noise. The system has been tested on real cars and drivers when the car is on and off.

We tested our system on four subjects, who laughed, talked, shifted positions, gestured, and coughed at various times. We noted the time when these activities happened, and found that laughing and coughing caused the most obvious noise in the data. We found that the system was able to effectively recognize and ignore these noisy parts of the data by fitting a distribution to the data and introducing a threshold, as described in the methodology section. The following figure shows the results of these experiments by subject. When we look at the data by subject, we can see that there is some variation in the data. This can partly be explained by the way the subjects behaved. The extent to which the different subjects talked, laughed, coughed and shifted positions is reflected in the error rate and percent of data under the noise threshold for each subject.

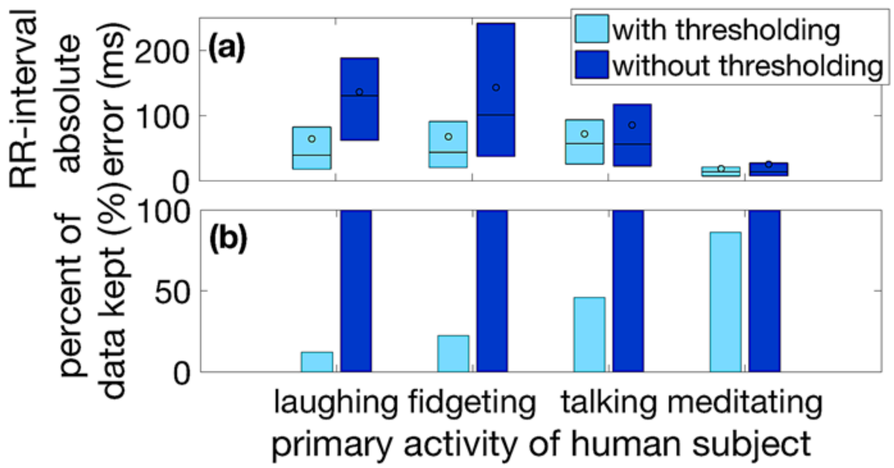

Figure 3: Graph (a) shows the 25% and 75% confidence intervals of the RR-interval absolute error for each human subject. The circles mark the mean error and the horizontal lines mark the median error. (b) shows how much data for each human subject was kept before and after the thresholding algorithm. One can see that there is variation per person in the amount of data under the noise threshold and the error.

Subject 1 watched funny videos while sitting in the car, and his frequent laughter caused significant noise in the data. However, data with laughing noise was effectively ignored by our algorithm, which greatly reduced both the amount of his data that we used and the error associated with it.

Subject 2 talked frequently and fidgeted. The thresholding algorithm also discarded a lot of her data, but it didn't reduce the error by as much. This could be because some of her periodic fidgeting was confused with heart motion. Subjects 1, 3 and 4 were all between 177 and 180 cm, while subject 2 was 167 cm, significantly shorter than the other subjects. Additionally, the sensor selected for Subject 2 was the one across the lap, while for the other subjects it was a sensor in the backrest. This suggests that either Subject 2 spent a lot of time leaning forward, or the sensors in the backrest were in a bad location to pick up heart rate for shorter subjects. In the future, more subjects with varying heights will help us determine this.

Subject 3 also talked during most of the data collection, with occasional coughing or laughing. This behavior occurred less than subject 1, so less of his data was discarded.

Subject 4 preferred to sit quietly and meditate, so his data had much less motion noise and the lowest error. Subject 4's results suggest that keeping as much data as possible to acquire RR-intervals is a crucial component of obtaining accurate HRV measurements.

Overall the mean absolute error for RR-intervals was 54 ms across all subjects. 84% of our data under threshold was accurately categorized to within the 100 ms error defined in medical literature. [10]

5. Outcomes

Publications, conference papers and presentations

1. Bonde, A., Pan, S., Jia, Z., Zhang, Y., Noh, H., & Zhang, P. (2018). VVRRM: Vehicular Vibration-based Heart RR-Interval Monitoring System. *The 19th ACM International Workshop on Mobile Computing Systems and Applications (HotMobile 2018).*

2. Bonde, A., Mirshekari, M., Fagert, J., Pan, S., Noh, H., & Zhang, P. Seat Vibration for Heart Monitoring in a Moving Automobile. *The First International Workshop on Data: Acquisition To Analysis (DATA '18) in SenSys 2018,* Shenzhen, China.

3. Mokaya, F., Noh, H., Lucas, R., & Zhang, P. (2018). MyoVibe: Enabling Inertial Sensor-Based Muscle Activation Detection In High Mobility Exercise Environments. *ACM Transactions on Sensor Network*, 14(1), 6:1-26.

4. Bonde, A., Pan, S., Noh, H., & Zhang, P. (2017). Demo Abstract: Heart and Sole: Shoe-based heart rate monitoring. *Proceedings of the 15th International Conference on Information Processing in Sensor Networks (IPSN '17)*. Pittsburgh, PA.

Other Dissemination Activities

1. We presented our work at University of Houston, Houston, TX, Mar. 23, 2018.
2. We presented our work at University of Duisburg-Essen, Essen, Germany, Nov. 10, 2017.
3. We gave a seminar on this project at Princeton University, Princeton, NJ, Sep. 28, 2017.
4. We gave a seminar at Tianfeng Securities Co Ltd., Shanghai, China, Jul. 18, 2017.
5. We presented at Chulalongkorn University, Bangkok, Thailand, Jul. 4, 2017.
6. We presented at University of California San Diego, San Diego, CA, Jun. 7, 2017.
7. We presented at Seoul National University, Seoul, South Korea, May 12, 2017.
8. We presented at Georgia Institute of Technology (GeorgiaTech), Atlanta, GA, Apr. 22, 2017.
9. We presented at Stanford University, Stanford, CA, Mar. 14, 2017.
10. We presented at California Institute of Technology (Caltech), Pasadena, CA, Feb. 2, 2017.
11. The technology was demoed at the 2017 Cyber Physical Systems Week held in Pittsburgh
12. We also utilized our system as a data collection platform in the graduate level project courses that the PIs teach – Sensing and Data Mining in Smart Structures and Systems and Mobile and Pervasive Computing. These project courses promote the students' interest in project related to safe transportation systems.

Two PhD students (both female) have been supported by this funding.

Open-source dataset: Our data collection with associated description has been accepted by the Data: Acquisition To Analysis (DATA 2018) workshop, which aims to foster data sharing and collaboration and will provide a central repository to archive the data we've collected for at least five years. More information can be found at https://workshopdata.github.io/DATA2018/. We also plan to make our data open source to allow other researchers to work with it and collaborate.

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 heart rate variability). The system leverages the fact that heartbeats create minute vibrations that change over time. In addition, our algorithm presents several methods to extract small signals of interests from the large motion noise and car noise that is present in the automotive environment.

References

[1] World Health Organization. (2011). Mobile phone use: a growing problem of driver distraction.

[2] Hedlund, J. (2011). Distracted Driving: What Research Shows and What States Can Do.

[3] National Safety Council. (2014). Injury Facts.

[4] Mokaya, F., Kuo, C., Jacobson, Q., Nguyen, B., Rowe, A., & Zhang, P. (2013). "MARS: A Muscle Activity Recognition System Enabling Self-configuring Musculoskeletal Sensor Networks", 12th ACM/IEEE Conference on Information Processing in Sensor Networks (IPSN'13).

[5] Brandt, T., Stemmer, R., & Rakotonirainy, A. (2004, October). Affordable visual driver monitoring system for fatigue and monotony. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on* (Vol. 7, pp. 6451-6456). IEEE.

[6] Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011). Driver inattention monitoring system for intelligent vehicles: A review. *Intelligent Transportation Systems, IEEE Transactions on*, *12*(2), 596-614.

[7] Wang, Q., Yang, J., Ren, M., & Zheng, Y. (2006, June). Driver fatigue detection: a survey. In *Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on* (Vol. 2, pp. 8587-8591). IEEE.

[8] 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.

[9] PCB Piezotronics. [n. d.]. W354C03_010G10 datasheet. ([n. d.]). http://www.pcb.com/Products.aspx?m=W354C03_010G10.

[10] Keri J Heilman, Mika Handelman, Gregory Lewis, and Stephen W Porges. 2008. Accuracy of the StressEraser® in the detection of cardiac rhythms. *Applied psychophysiology and biofeedback* 33, 2 (2008), 83–89.