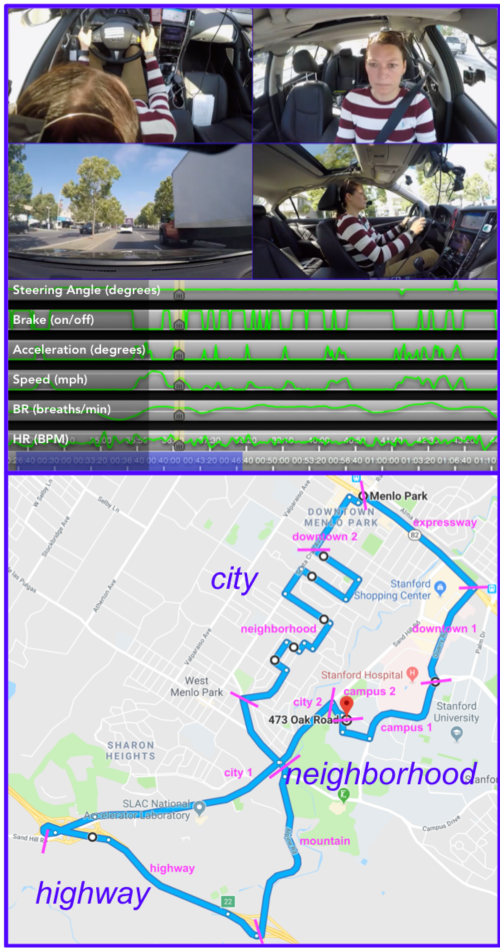

Figure 1: Participant in commute traffic and data streams of multiple sensors that monitor driver, car, and road (top). Driving course through city, highway, and neighborhood roads (bottom).

On-road stress analysis for in-car interventions during the commute

Stephanie Balters
School of Medicine
Stanford University
Stanford, CA, USA
balters@stanford.edu

Madeline Bernstein
School of Engineering
Stanford University
Stanford, CA, USA
mbern@stanford.edu

Pablo E Paredes
School of Medicine
Stanford University
Stanford, CA, USA
pparedes@stanford.edu

ABSTRACT

This paper focuses on the larger question of *when* to administer in-car just-in-time stress management interventions. We look at the influence of driving-related stress to find the right time to provide personalized and contextually-aware interventions. We address this challenge with a data driven approach that takes into consideration driving-induced stress, driver (cognitive) availability, and indicators of risky driving behavior such as lane departures and high steering reversal rates. We ran a study with (N=16) commuters during morning and evening traffic while applying an in-situ experience sampling. During 45 minutes of driving through various scenarios including city, highway, and neighborhood roads we captured physiological measurements, video of participants and surroundings, and CAN bus driving data. Initial review of the data shows that stress levels changed greatly between 2 and 9 (out of a 0-min to 10-max scale). We conclude with a discussion on how to prepare the data to train supervised algorithms to find the right time to intervene stress while driving.

SIGCHI 2019, May 2019, Glasgow, UK

The definitive Version of Record was published in *Proceedings of ACM CHI Conference (SIGCHI 2019)*, https://doi.org/10.1145/nnnnnnn.nnnnnnn.

CCS CONCEPTS

• **Human-centered computing → Haptic devices**; *Ubiquitous and mobile computing systems and tools*; • **Applied computing → Consumer health**; *Psychology*; • **Computer systems organization → Sensors and actuators**.

KEYWORDS

Stress; Driving-induced stress; Stress measurement; On-road; Commute; Stress management; Just in time intervention; Health; Mental health; Health interventions; Safety; Driving behavior.

ACM Reference Format:
Stephanie Balters, Madeline Bernstein, and Pablo E Paredes. 2019. On-road stress analysis for in-car interventions during the commute. In *Proceedings of ACM CHI Conference (SIGCHI 2019).* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

MOTIVATION

The commute has been proposed as a vital time for in-car stress* management interventions [11], because it provides, firstly, a physical platform for stress sensors (e.g., stress level detection via a steering wheel [10]), and interventions (e.g., actuators embedded in the seat [1]); and secondly, an increased user receptiveness during the (so far) idle commute time. The aim is to reduce stress accumulated during the workday and mitigate driving-induced stress that could otherwise exacerbate stress-related symptoms [6]. Various ideas for in-car stress interventions have been proposed such as soothing temperatures and music, bio-feedback interfaces [5], and chatbots [8]; and first proof-of-concepts have been validated, e.g., in-car body movements [9] and breathing interventions [1, 11].

****Stress** is defined as a proxy for auto nomic arousal.*

The implementation of those concepts is not trivial due to the complex nature of the underlying driving task. Studies show, for example, that an engagement into a secondary task (e.g., dialing on the phone) can lead to poorer driving performance and increased accident risk due to distracted focus [12]. A safe engagement requires therefore sufficient driver resources, e.g., cognitive load. Moreover, stress management is complex: while low to moderate (acute) stress is a much-needed reaction to acquire physiological resources for executing the driving activity; too much stress can lead to poorer driving performance due to impaired cognitive abilities, situational awareness, and increased response time [6].

We envision a context-aware, personalized system that can sense a driver's state and driving conditions in order to adaptively apply health enhancing interventions if deemed beneficial, comfortable, and safe. The task is to develop robust driver state estimation algorithms that successfully operate in on-road (noisy) driving environments. This requires a rich data set. Our contributions are therefore:

(1) Methodological advancements by combining experience sampling method with observation and in-situ sampling.
(2) Creation of a real world driving data set of commuters in commute traffic, including psycho-physiological measurements, video, and CAN bus driving data. Data set will be made publicly available.
(3) Discussion on how to prepare the data to train supervised algorithms to find the right time to intervene stress while driving.

SYSTEM DESIGN

As the great majority of Americans commute by car alone [7], and driver behavior might change with passengers on board [16], we sent participants as single passengers into morning (7.00 to 10.00 am) or evening (3.30 to 8.00 pm) commute traffic.

Participants. We recruited (so far) a total of sixteen participants (N = 16, 7 females). Average age was M = 38.3 years (SD = 11.4). To ensure a driving habituated cohort, we invited only frequent commuters. Five participants reported to commute every day, whereas eleven commuted only a few times per week.

Driving Course. We chose a 12.3 mile long driving course to include a variety of different driving environments and contexts, namely campus, neighborhood, city, highway, and mountainous roads (Figure 1). The course comprised nineteen left and fifteen right turns, twenty-three stops signs, and twenty-four traffic lights. Participants needed in average M = 50 minutes (SD = 9) to finish the route.

Apparatus. As experimental vehicle we used an Infinity Q50. We equipped the car with seven cameras (Figure 1): four cameras were placed to record the participant from front, top, and side views; one camera recorded the street in front; and two cameras were placed on each frontal fender to record the distance between tire and lane marking. We placed a voice-reactive microphone on the middle console within participants visibility (Figure 3). The microphone was connected to a raspberry pi, which in turn was linked to a cradle point for wireless access. The experimenter (E1) could operate the pi via a secure remote access (RealVNCh - https://www.realvnc.com) from a computer inside the research facility. Via a text to speech program, any text entry could be transferred from the laboratory to the car. We used Mac OS system voice “Samantha”. The Pi was connected to the car’s speaker system. Video streams of the participant and driving environment (Figure 1) were merged via a quad multiviewer and displayed on a laptop inside the car’s trunk. Via a second screen sharing tunnel, the quad view video stream was accessible for E1, allowing live monitoring of the participants on the road.

Procedure. E1 introduced the commuters to the conversational agent “Carla” (Figure 3), and further explained that the study’s aim would be to produce a data set that would allow Carla to learn about driver states. E1 instructed the participants to follow a provided GPS navigation route, and to answer Carla’s questions throughout the drive (see section below). After the drive, a

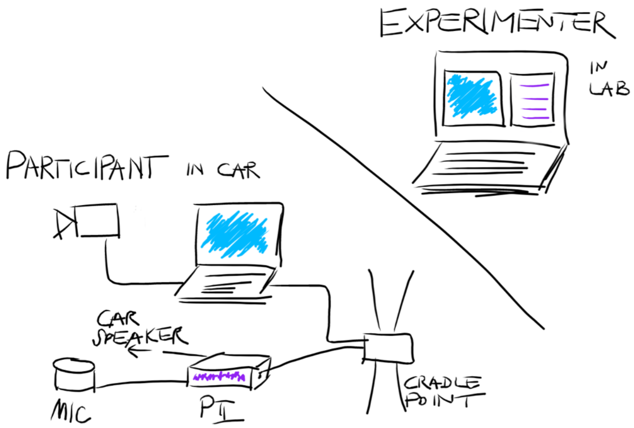

Figure 2: EMS in-situ feedback system.

Figure 3: Voice-reactive microphone while in speech detection mode.

post-experimental questionnaire asked participants about their driving experience and perceived driving-induced stressors. The Institutional Review Board (IRB) approved all procedures. Participants signed consents, and were insured against accidents upon approval of a valid driver's license.

In-situ Experience Sampling. To interrogate participants stress levels, we extended conventional Experience Sampling Method (EMS) [3] by interleaved questions triggered by in situ events. We measured subjective stress responses via a simplified version of the Perceived Stress Scale (PSS) [13]: *"How stressed do you feel right now?"*. To camouflage that the intent of the study was to derive stress-levels and avoid potential biasing of the participants, we added three additional questions: the Affect Grid dimensions [14] *"How energized do you feel right now?"* and *"How pleasant do you feel right now?"*, as well as level of concentration: *"How concentrated do you feel right now?"*. E1 instructed the participants to answer all questions on a 11-point scale from 0 = "low" to 10 = "high". The system automatically sent out batches of question-quartets in randomized order throughout the length of the drive. We chose the duration between the questions within a batch as well as between batches to be random between 45 and 90 seconds, e.g., 8 batches in 45 minutes. To ensure that data included points of peaks and troughs in stress response time series, E1 sent out four additional stress questions (2 for each condition) following procedure: based on automotive literature [2], we defined high arousal situations, including (among others) traffic congestion, narrow roads, hazards and indications of hazards, passing trucks and cyclists, and vehicle malfunctions; and low arousal situations, that apply during the absence of the above. E1 monitored participants and driving contexts and sent out the additional stress questions when she detected low and high arousal situations.

Measurements. As foundation for driver state estimation algorithms, we collected a series of data streams previously used in the community. Beyond the *subjective stress measures* described above, we captured *physiological stress measures*. Specifically, we recorded breathing rate (brpm, 1 Hz) and ECG data (250 Hz) for heart rate (bpm) and heart rate variability (RMSSD in ms) analysis using the Zephyr BioModule (https://www.zephyranywhere.com) worn around the torso. We further collected electro-dermal activity (EDA) (4 Hz) with the Empathica E4 bracelet (https://www.empatica.com) attached around the participants' non-dominant arm wrist. To calculate *driver cognitive load*, we will apply a vision-based algorithm previously validated for the "in the wild" driving context [4] using driver video streams. From *CAN bus data*, we stored steering angle (100 Hz, degrees), speed (50 Hz, mph), acceleration pedal position (50 Hz, degrees), and brake pedal position (25 Hz, degrees) to further calculate stress-induced changes in driving behavior, e.g., changes in speed, acceleration, braking, lane keeping, and steering reversal rates [15].

EARLY INSIGHTS

We derived participants' subjective stress measures and labeled corresponding driving scenario and environment of the data point, i.e. type of road, traffic density, and driving task. Results show that

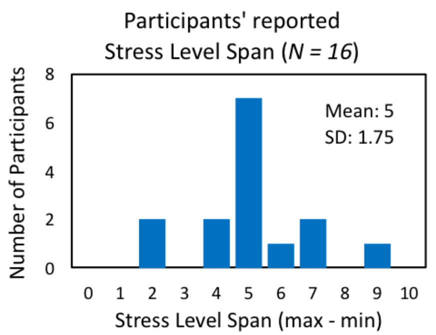

Figure 4: Reported stress level span throughout the drive across participants.

participants' reported stress level span (max - min value) ranged between 2 and 9 with a mean value of M = 5 points (SD = 1.75) (Figure 4). Overall, one-third of participants reported increasing stress while one-forth reported decreasing stress throughout the drive. Further, we noted fewer high stress peaks on highways, expressways, and mountain roads compared to city, campus, and neighbourhood driving environments. Stress peaks were often concurrent with road obstructions or making wrong turns. The considerable variance in driving-induced stress responses emphasizes the need for context-aware and adaptive intervention systems.

NEXT STEPS

Further, we will deepen inferences to understand intuitive, desirable, and effective times to intervene. Firstly, we will focus on additional time series analysis of driving-induced (subjective and physiological) stress to validate early findings. Preliminary results showed two groups of participants that had either continuous increases or continuous decreases throughout the commute route. This might suggest that interventions are specifically effective and required at either the beginning or end period of an individual's commute.

Secondly, the aim is to leverage our data set to train algorithms to automatically recommend appropriate times for interventions. The goal for the driver state estimation system is three-fold; it ought to be: (1) robust to variable on-road conditions, (2) preferably unobtrusive, and (3) capable of generating an accurate classification of driver stress state given only limited time of measurement data (e.g., 30 sec). To generate a valid training data set, we will process the various data streams (including e.g. artefact correction). Further, we will generate post-hoc labels of all road events include destination-related events [2] (e.g., arriving, leaving, parking), traffic-related events (e.g. tailgating, passing construction), call related events (e.g. call attempt and speaking on the phone), blind turns; passing behaviors (e.g. vehicles, cyclists and pedestrians); and driving-related events (e.g. changing lanes), and interactions with other vehicles (e.g. aggressive comment by other vehicle, tailgating); and in-vehicle stressor events (e.g., elicited by interaction with GPS, and/or by system alarms). By means of supervised learning, we aim at distilling: (1) those events that are stress inducing, and/or cognitively demanding, and/or prone to risky driving. We grade those periods as critical to apply stress management interventions. After starting to test algorithms, we will evaluate the need for running additional participants.

REFERENCES

[1] Stephanie Balters, Elizabeth Murnane, James A. Landay, and Pablo E. Paredes. 2018. Breath Booster! Exploring In-car, Fast-paced Breathing Interventions to Enhance Driver Arousal State. *Proceedings of the PervasiveHealth Conference* (2018).

[2] Sonia Baltodano, Jesus Garcia-Mancilla, and Wendy Ju. 2018. Eliciting Driver Stress Using Naturalistic Driving Scenarios on Real Roads. In *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular*

Applications. ACM, 298–309.

[3] Mihaly Csikszentmihalyi and Reed Larson. 2014. Validity and reliability of the experience-sampling method. In *Flow and the foundations of positive psychology*. Springer, 35–54.

[4] Lex Fridman, Bryan Reimer, Bruce Mehler, and William T. Freeman. 2018. Cognitive Load Estimation in the Wild. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 652.

[5] Javier Hernandez, Daniel McDuff, Xavier Benavides, Judith Amores, Pattie Maes, and Rosalind Picard. 2014. AutoEmotive: bringing empathy to the driving experience to manage stress. In *Proceedings of the 2014 companion publication on Designing interactive systems*. ACM, 53–56.

[6] Robert R. McCrae. 1984. Situational determinants of coping responses: Loss, threat, and challenge. *Journal of personality and social psychology* 46, 4 (1984), 919.

[7] Brian McKenzie. 2015. Who drives to work? Commuting by automobile in the United States: 2013. *American Community Survey Reports* (2015).

[8] Pablo E. Paredes, Ran Gilad-Bachrach, Mary Czerwinski, Asta Roseway, Kael Rowan, and Javier Hernandez. 2014. PopTherapy: coping with stress through pop-culture. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare*. ICST (Institute for Computer Sciences, Social-Informatics and âĂę, 109–117.

[9] Pablo E. Paredes, Nur Hamdan, Dav Clark, Carrie Cai, Wendy Ju, and James A. Landay. 2017. Evaluating in-car movements in the design of mindful commute interventions: exploratory study. *Journal of medical Internet research* 19, 12 (2017).

[10] Pablo E. Paredes, Francisco Ordonez, Wendy Ju, and James A. Landay. 2018. Fast & Furious: Detecting Stress with a Car Steering Wheel. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 665.

[11] Pablo E. Paredes, Yijun Zhou, Nur Al-Huda Hamdan, Stephanie Balters, Elizabeth Murnane, Wendy Ju, and James A. Landay. 2018. Just Breathe: In-Car Interventions for Guided Slow Breathing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 28.

[12] Matthew P. Reed and Paul A. Green. 1999. Comparison of driving performance on-road and in a low-cost simulator using a concurrent telephone dialling task. *Ergonomics* 42, 8 (1999), 1015–1037.

[13] Jonathan W. Roberti, Lisa N. Harrington, and Eric A. Storch. 2006. Further psychometric support for the 10-item version of the perceived stress scale. *Journal of College Counseling* 9, 2 (2006), 135–147.

[14] James A. Russell, Anna Weiss, and Gerald A. Mendelsohn. 1989. Affect grid: a single-item scale of pleasure and arousal. *Journal of personality and social psychology* 57, 3 (1989), 493.

[15] SAE ISO Standards. 2015. *Operational Definitions of Driving Performance Measures and Statistics*. Society of Automotive Engineers. https://doi.org/10.4271/J2944_201506

[16] Mark Vollrath, Tobias Meilinger, and Hans-Peter Krüger. 2002. How the presence of passengers influences the risk of a collision with another vehicle. *Accident Analysis & Prevention* 34, 5 (2002), 649–654.

ACKNOWLEDGMENTS

We thank the Stanford Precision Health and Integrated Diagnostics (PHIND) Center and the Center for Automotive Research at Stanford (CARS) for supporting this work.