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

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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 sixteen 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

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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.

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.

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]. In this paper we use the term "stress" as a proxy for autonomic arousal. 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].

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:

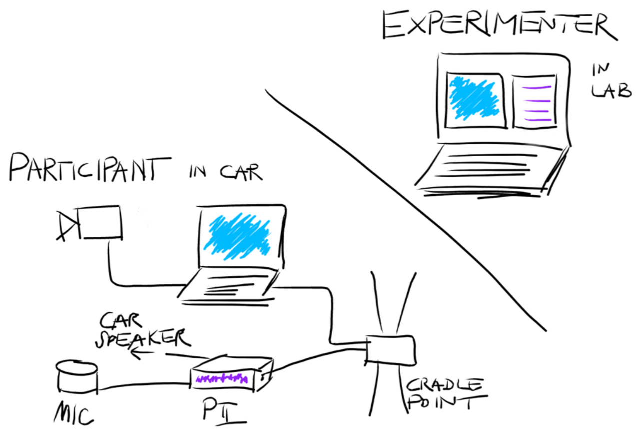

Figure 2: EMS in-situ feedback system.

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

(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, with min = 20 and max = 59 years). 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. We recruited participants via advertisement on the department's homepage.

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, connected via wireless internet and plugged to the car speaker. The experimenter could operate the device via a secure remote access (RealVNCh - https://www.realvnc.com) from a computer inside the research facility. Text could be transferred from the laboratory to the car and converted into voice. Video streams of the participant and driving environment (Figure 1) were merged and shared with the experimenter, allowing live monitoring of the participants on the road.

Procedure. The experimenter 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. The experimenter 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 post-experimental questionnaire asked participants about their driving experience and perceived driving-induced stressors. All procedures were approved by the Institutional Review Board (IRB).

In-situ Experience Sampling. To assess stress levels, we measured subjective stress responses via a simplified version of the Perceived Stress Scale (PSS) [13]: *"How stressed do you feel right now?"*. We complemented stress questions with three additional ancillary 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?"*. The experimenter instructed the participants to answer all questions on a 11-point scale from 0 = "low" to 10 = "high". To obtain relevant labels, we extended conventional Experience Sampling Method (EMS) [3] by adding questions triggered by relevant driving events. The system automatically sent out batches of question-quartets (stress, arousal, valence, concentration) in randomized order throughout the length of the drive. The delay between each batch as well as between each question was between 45 and 90 seconds, e.g., approximately 8 batches in 45 minutes. To capture high stress and low stress moments, the experimenter sent out four additional stress questions (2 for each condition). High arousal situations included (among others) traffic congestion, narrow roads, hazards and indications of hazards, passing trucks and cyclists, and vehicle malfunctions [2]; and low arousal situations, that apply during the absence of the above.

Measurements. Beyond the *subjective stress measures* described above, we captured the following *physiological stress measures*: breathing rate (brpm, 1 Hz), heart rate (HR) (1 Hz), and ECG data (250 Hz) using the Zephyr BioModule (https://www.zephyranywhere.com) worn around the torso, and electro-dermal activity (EDA) (4 Hz) with the Empathica E4 bracelet (https://www.empatica.com) attached around the participants' non-dominant arm wrist. We plan to use ECG data to estimate heart rate variability (HRV). We recorded video streams that could be post-processed with vision-based algorithms for cognitive load estimation while driving [4]. Finally, we recorded Controller Area Network bus *CAN bus* data, specifically: 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]. We can also use steering angle data to estimate stress based on muscle tension [10].

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 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 the 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

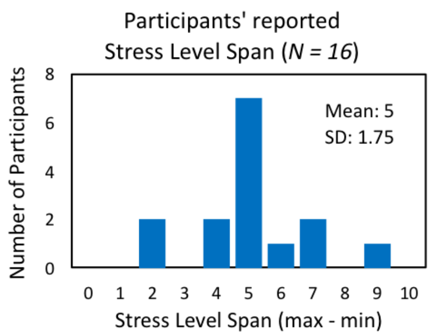

Figure 4: Reported stress level span throughout the drive across participants.

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. We further captured GPS data to create contextual labels to be used in more advanced models.

NEXT STEPS

Moving forward, we will explore data models to understand intuitive, desirable, and effective times to intervene. First, we will use 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. Subsequently, we want to train algorithms to automatically recommend (personalized) appropriate times for interventions. The driver state estimation system 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). Another relevant question is to assess the overall stress level of the ride and its tendency, based on the first few minutes of the ride.

To generate a valid training data set, we will process the various data streams (including e.g. artifact correction), and 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). Finally, we plan to label driver-dependent 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.

CONCLUSION

In this paper we describe a method to create a multi-modal dataset with carefully chosen labels to identify stress patterns derived from the act of driving itself. We plan to use this data to answer the question of *when* to suggest interventions to reduce stress while driving. The dataset was created with a focus on the daily commute, which is a special case where drivers could benefit from stress interventions for either road or daily life stressors.

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