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Fast & Furious: Detecting Stress with a Car Steering Wheel

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[1]This is a conditionally accepted version. The final version can be found at https://chi2018.acm.org/

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RESUMEN

La siguiente investigación explora la detección de estrés mental por medio del movimiento del volante del carro. Se realiza un experimento controlado con 25 participantes a los cuales se les induce estrés por medio de ejercicios matemáticos y posteriormente se los hace conducir un simulador. Se prueba que la tensión muscular producida por el estrés mental es detectable analizando el movimiento del volante y modelando este movimiento como un sistema de resorte masa y amortiguación. El coeficiente de rigidez del resorte modelado durante el manejo bajo estrés prueba ser significativamente superior al coeficiente de rigidez del resorte modelado durante un manejo sin estrés.

ABSTRACT

Stress affects the lives of millions of people every day. In-situ sensing could enable just-in-time stress management interventions. We present the first work to detect stress using the movements of a car's existing steering wheel. We extend prior work on PC peripherals and demonstrate that stress, expressed through muscle tension in the limbs, can be measured through the way we drive a car. We collected data in a driving simulator under controlled circumstances to vary the levels of induced stress, within subjects. We analyze angular displacement data to estimate coefficients related to muscle tension using an inverse filtering technique. We prove that the damped frequency of a mass spring damper model representing the arm is significantly higher during stress. Stress can be detected with only a few turns during driving. We validate these measures against a known stressor and calibrate our sensor against known stress measurements.

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INTRODUCTION

Stress response is an evolutionary mechanism that mobilizes body resources to help cope with daily challenges and life-threatening situations. While acute stress is the short-term response to a particular challenge (i.e., a stressor) [22], chronic stress is the longer-term response that may appear when experiencing extreme life experiences [34]. Both chronic stress and repetitive daily acute stress have been associated with a variety of patho-physiological risks such as cardiovascular disease and immune deficiencies, which can dramatically impair quality of life and shorten life expectancy [9].

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Figure 1. Experimental setup: (left) Participant driving in the simulator; (upper right) street view; (lower right) steering wheel rotation angular signal: right turn (>0°), left turn (<0°).

This research explores the opportunistic sensing of daily stressors by detecting mental stress from the way we drive a car. We do not propose the use of traditional stress sensors, such as Electrocardiogram (ECG) or Electro-Dermal Activity (EDA), but we rather propose the development of a new opportunistic infrastructure-mediated sensor [30]. We design this in-situ sensor by re-purposing existing infrastructure embedded in modern cars. We extend the work by Sun et al. [39] to focus on signals that may already capture the changes in muscle tension in the limbs. We propose that the fight or flight response to stress, which affects the trapezius and other muscles activated with the motion of the upper limbs, can be extracted from the pattern of changes to the steering wheel angle.

Stress affects driving performance in two ways. On the one hand, it is a source of traffic accidents and road rage [11]. On the other hand, it can increase performance [25]. Having an in-situ sensor of stress in a car can support the design of on-the-road interventions for stress regulation. Monitoring stress continuously, without the need for the driver to wear any additional sensors can lead to more fine-grained models of stress, driving performance, and their interacting effects on each other, without introducing any user burden. Importantly, understanding on-the-road stress patterns can also be used to improve the quality of the commute itself, by informing the design of commute interventions [7] (e.g., to promote work-life balance, relaxation coping, and general psychological wellness) and, in turn, potentially even increasing perceived quality of life [27].

Certainly, there are other tools to measure stress, which could be use in conjunction with our technique. Nevertheless, the most commonly used tool to measure stress continues to be self-reports, with a recent increase in the use of wearables [10, 2, 5]. Only highly motivated individuals answer survey questions about stress, or remember to wear a stress device after a few weeks. Furthermore, self-reporting in the car context is a less desirable approach, considering how the distracting nature of the reporting activity could both produce an unreliable measurement (given one's attention is not fully attending to it) and be a safety risk (taking focus off driving). An in-car stress sensor can guarantee, at a minimum, a couple of readings per day.

This paper extends the work from Sun, et al. [39] to demonstrate that the damped frequency of a second order mass spring damper (MSD) model can be effectively linked to muscle stiffness derived from mental stress. We performed a within-subjects study (N=25) counterbalancing calm and stress conditions. We carefully selected a driving circuit and stressors to avoid any alteration in driving that may not be due to mental stress only. Subjective measurements, ECG, and EDA information was obtained to validate the efficacy of the stressors. We used the data from the already existing angular sensors from the steering wheel of the driving simulator (Figure 1). Our results confirm a significantly higher damped frequency, i.e. an increase in muscle stiffness, for the stress condition. We also prove that the results hold even for a decimated signal, indicating the feasibility of our approach in real-world setups, where it would be viable to leverage the low resolution sensors found in most modern vehicles.

BACKGROUND AND PRIOR WORK

In this section we introduce fundamental work that explains the effects of stress on muscle tension, the ways one can measure these effects, and traditional stress measurements required to calibrate our new sensor.

Stress Measurement

Stress can be measured in two ways, via self reports or through physiological signals. Stress self-report (SSR) is usually measured through some variation of the widely used Perceived Stress Scale (PSS) [6, 35]. Usually, a simplified version with a single 10-item scale of stress is used in repeated measure studies.

The most accepted and traditional way to measure stress is by capturing a signal correlated with arousal, i.e., an activation of the Autonomic Nervous System (ANS). The most common metrics are heart rate variability (HRV) and electrodermal activity (EDA). HRV is a second-order metric derived from the reading of an electrocardiogram (ECG) wave and is a proxy for the variability of HR due to the respiratory sinus arrhythmia (RSA). RSA stimulates the valgus nerve, which is the main driver of the Autonomous Nervous System (ANS). The ANS has two main branches: the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). While SNS activation is associated with the "fight or flight" stress response, where many organs are activated to overcome a particular challenge or threat, the PNS works antagonistically to maintain a stable functioning condition.

In general, higher HRV indicates a prevalence of the PNS over the SNS (i.e., a balanced/calmer state). HRV is commonly evaluated in the time-domain with the Root Mean Square of Subsequent Samples (RMSSD) or in the frequency-domain with the Low Frequency (LF) and High Frequency (HF) components. RMSSD represents short term variability and is inversely correlated with arousal. EDA, previously known as Galvanic Skin Response (GSR), is a measurement of skin conductance due to the activation of the eccrine sweat glands, which are purely innervated by the SNS. High average levels and increased number of EDA peaks have been associated with stress [3].

Detecting Stress through its Musculoskeletal and Movement-Based Expressions

Mental stress has a direct effect in musculoskeletal activity. Muscle tension increases due to mental stress even at rest [4, 8]. Tension in the forehead, the neck, and arms increases with stress and anxiety [38, 18]. Traditional lab stressors, such as mental arithmetic, have shown clear effects on the shoulder's trapezius muscle [23], as well as the biceps and triceps [41]. Driving experiments with on-road stressors have also revealed an increased level of muscle tension in the trapezius muscle captured by burdensome instruments infeasible for eveyday use[13, 25].

To our understanding, there is no prior work on using the signal from the steering wheel to detect stress. Our work, however, extends prior work on stress detection and emotion through the use of computer peripherals. Sun, et al. were the first to show a direct effect of stress on the way a PC mouse is handled [39]. Their approach uses an inverse filtering technique, which directly correlates features from a second order oscillatory system back to the muscle tension. Other approaches have shown signals of stress in the way people hold a mouse and their typing pressure [16] or the way people swipe on touch devices [12]. As explained earlier, due to the lack of understanding of the effects of induced stress in drivers, this is the first study focused on obtaining lab data from a driving simulator. We captured data from a gaming steering wheel connected to a driving simulator running a commercial driving school training software – see the Apparatus section for additional details.

MODELING THE HUMAN ARM WHILE DRIVING

In this work, we extend prior work on human arm modeling from PC peripherals to car driving tasks. We focus on modeling the human arm as it operates a simulator steering wheel.

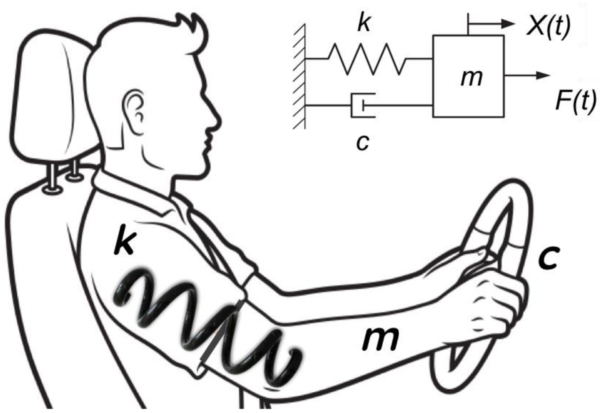

Figure 2. MSD model of the human arm while driving

Neuromuscular Dynamics

Prior work has successfully shown the use of a Mass Spring Damper (MSD) system to model a human arm while handling a steering wheel. Systems with a single degree of freedom [32] or two degrees of freedom [31] have been tested. The MSD is regularly used in modeling arm motion [17] in diverse tasks ranging from handwriting [19] to robotics [26] to assistive technology [36]. More recently Sun, et al. successfully modeled the arm as a single degree of freedom applied to interactions with computer peripherals [39]. In this work, they describe a MSD system applied to each direction of movement of a PC mouse.

In the single order MSD system, the mass component represents an aggregate sum of the arm, hand, and wheel. The spring components represent the muscle tension in the arm, while the damper represent also muscular interaction in the arm and the damping effect of force feedback of the simulator steering wheel (see Figure 2). The input force F(t) of the arm produces an output movement X(t) in the steering wheel, measured in radians. An MSD responds with a oscillation frequency driven by the spring component (k) and a characteristic decay function determined by the friction of the damper component (c). This damped oscillatory behavior can be fully characterized by the damped frequency (ω) and the damped ratio (ζ). For a system with constant mass, the spring coefficient is directly proportional to the damped frequency: $\omega \approx \sqrt{k}$ and the damping ratio is indirectly proportional to the square-root of k while being directly proportional to c: $\zeta \approx \frac{c}{\sqrt{k}}$. These relationships show a direct relationship between muscle tension, caused by stress, and the MSD model.

Inverse Filtering

Since the steering wheel angle is the output signal of the MSD system, we have to apply an inverse filtering technique to infer the system's fundamental parameters. A successful technique used to model a single degree of freedom model is linear predictive coding (LPC). It is well-documented that an ideal second order system, such as the MSD, can be inferred via LPC using only two samples from the past [28]. Conversely, if we model a second order LPC we should be able to recover the characteristic MSD parameters.

MSD Computation

We use a logger that samples the steering wheel with a sampling period of about (M = 1.1, SD = 0.34) seconds. The wheel has a resolution of 0.0056° and a maximum range of 450° on each direction. Positive angle rotations are recorded when the wheel turns clockwise, i.e., when the car turns right, and negative angle rotations are recorded when the wheel turn counterclockwise, i.e., when the car turns left. The signal are interpolated with a shape preserving function, and resampled to obtain a uniformly sampled signal. The LPC model is calculated using an interpolation order of (p=4) to obtain a sequence of coefficients that can effectively model the underdamped MSD system. The complex roots (r) of this polynomial characterize the MSD's damping behavior. The absolute value of the imaginary part represents the damping frequency ($\omega = |\Im(r)|$), while the ratio of the real part to its absolute value represents the damping ratio ($\zeta = \frac{|\Re(r)|}{||r||}$).

METHOD

In this section, we outline our hypothesis, describe the experimental design, and detail our data collection methods.

Hypothesis

Based on the preliminary discussion we propose a single hypothesis:

(H): The damped frequency ω should be higher due to higher stress compared to a calm baseline.

In contrast to prior reports by Sun et al., we do not see merit in formulating a hypothesis around the damping ratio ζ, as we have no way to directly measure the damping effects of the steering wheel. Furthermore, a careful examination of their paper does not reveal a reduction in the damping ratio. This could be due to the effect of the damping coefficient of the arm muscles. We also do not evaluate turn completion time as a variable correlated with stress for two reasons: first, it is hard to truly evaluate the complete duration of a turn, and second, mental stress usually affects task completion, which in this case would be measured by lap completion, which is affected by changes in acceleration or speed, as opposed to the speed of turning.

Participants

We recruited 25 participants, 13 females and 12 males, with ages ranging from 18 to 67 (M = 34.43, SD = 15.05). Prior to participating in the experiment, we asked their preferred genre of music. We used their selection to find a playlist from Spotify[1]. No participant reported liking heavy metal music, which we used in the stressor portion of our study.

Experiment Design

In this section, we describe the procedure, the driving task and the stressors for our experiment.

[1]http://spotify.com

Figure 3. Experiment Procedure. Counterbalanced conditions: a) Calm –> Stress; b) Stress –> Calm

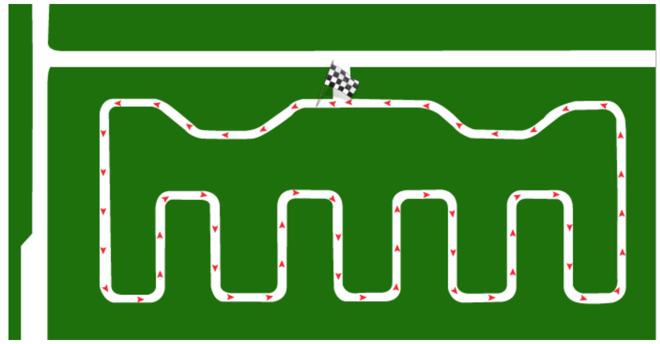

Figure 4. Driving circuit with 28 (16 left and 12 right) turns per lap. The circuit was traversed counterclockwise. The bright green dot indicates the starting point.

Testing Procedure

The experiment consisted of five stages: (1) Arrival, (2) Baseline: Soothing Video + Training Drive, (3) Stimulus 1, (4) Drive Task 1, (5) Stimulus 2, and (5) Drive Task 2. The first three stages lasted on average 3 minutes each, while the driving stages lasted were expected to last 10 minutes on average. The Arrival stage was used to gather pre-test information. During the Stimulus stages, participants either received an acute stressor or a soothing intervention, as described in the Stimulus section. During the Driving task users received a relaxing stimulus to maintain a low level of stress or an exacerbating stressor to maintain the level of stress during the whole duration of the experiment. Calming and Stress stimulus + driving tasks were counterbalanced across participants (see Figure 3). We called each of the four different stages: stress, calm, wheel_stress, and wheel_calm.

Driving Task

The selection of the driving task is of crucial importance to isolate the effects of mental stress. Neither the task, nor the stressor, should alter the cognitive, attentive or performance responses. For this reason, the driving circuit had no traffic, pedestrian distractions, traffic symbols, or bumps. We chose a driving training circuit with 28 turns, 12 turns to the right and 16 to the left (see Figure 4). To record a minimum of turns, participants were asked to complete four laps around the circuit, for a total of 108 turns, and a minimum of at least 48 turns in each direction. Due to procedural errors, one participant completed only three laps while five participants completed five laps each. Participants were requested to drive as the would normally drive a vehicle in the city. Turns were mostly 90° turns with a radius of about 12 feet. There were no interruptions between turns. All drivers circulated around the lap in a counterclockwise direction. It is important to note that most participants made an effort to drive as they would normally drive a vehicle during the first half of the laps. However, some participants, perhaps due to boredom, adopted more playful behavior towards the end, making more mistakes and being less precise in taking the turns.

Apparatus

The experiment was performed in a laboratory setting, using a half-car (buck) Skyline simulator setup [1] with a Logitech G29 gaming steering wheel and pedals[2]) (see Figure 1). The car seat was positioned to a comfortable position, and sound effects were held constant. For the driving simulation environment, we used a commonly used driving school simulator, City Car Driving[3]). The data from the steering wheel was sampled at 916HZ with an angular resolution of 0.056°. This raw data was captured with a lossless computer logger that recorded the information directly from Logitech's steering wheel drivers.

Stimulus

The calming and stress conditions were each composed of two parts: An acute pre-driving stressor or soothing intervention coupled with arousing or soothing music while driving (see Figure 3).

a. Pre-driving Stimulus. For the calming pre-driving stimulus, we had participants view a soothing video; this is recommended by other researchers as opposed to doing nothing to engender calm[33]. For the pre-driving acute stressor, we implemented a math stressor from the Trier Social Stress Test (TSST) [20]. The task involved participants performing a series of subtractions out loud (13 from 2017, 13 from 2014 and so forth). If the participant made a mistake, the researcher asked the participant to start again. To add more stress, we created penalties associated with long response times – if users took more than four seconds to respond, they had to start over. We refer to this stressor as Math.

b. Sustaining Stimulus. To capture enough data from driving, we had to ensure that the effect of the acute stressor would last during the four driving laps. During the driving tasks, participants heard either their self-selected music genre or heavy metal music. The latter is associated with increased levels of arousal. [21] We used a medley of songs from the album "At the Heart of Winter" by Immortal[4].

Stress Data Acquisition & Processing

During the experiment, stress was measured through self-reports and physiological measurements. Self-report stress (SRS) measurements were obtained after using a simplified version of the Perceived Stress Scale (PSS) [35], a 10-point

[2] http://gaming.logitech.com/en-us/product/g29-driving-force
[3] http://citycardriving.com
[4] https://www.youtube.com/watch?v=VeOlPQqJR-o

scale question: "What is your current level of stress?" with end points "Low" and "High" immediately after completion of each stage (see Figure 3). SRS was normalized and corrected against its baseline per participant to minimize potential individual differences. As ancillary self-reported metrics we asked the level of Tension from 0-"Low" to 10-"High", the level of Concentration, also with the same range, and the dual affective components: Arousal and Valence, based on Russel's affect circumplex [37]. As will be explained later in the stress evaluation section, these metrics, together with task performance analysis, were used to verify that our stressor did not induce changes that could not be attributed solely to mental stress.

An Electrocardiogram (ECG) signal (250Hz) was measured with the Zephyr BioModule Device 3.0[5]. The strap was wrapped around the participant's torso just under the chest area, so that the sensor unit was aligned with their left lateral side. HRV is a second-order metric derived from the ECG signal. HRV is evaluated by detecting the maximum peaks (R peaks) of the ECG signal. In the time-domain, HRV is commonly measured using the Root Mean Square of Subsequent Samples (RMSSD), which represents short term variability and is inversely correlated with arousal. R-peak detection of the ECG signal was manually examined following the recommendations of the HRV task force [40] using the Kubios software[6]. RMSSD was normalized and baseline-corrected per individual.

EDA, previously known as Galvanic Skin Response (GSR), is a measurement of skin conductance due to the activation of the eccrine sweat glands which are purely innervated by the SNS. High average levels and increased number of EDA peaks have been associated with stress [3]. EDA (4Hz) was measured with the Empatica E4 sensor [7]. The Empatica E4 band was wrapped around the participant's non-dominant arm wrist. The device was mounted to allow proper skin contact without restricting blood flow. The Event Marking feature of the Empatica device was used to record time stamps for both devices. Several processing steps were applied. First, exponential smoothing ($\alpha = 0.08$) was applied to reduce high-frequency artifacts due to motion. Second, each of the sessions was normalized between 0 and 1 [24] to amplify EDA changes and minimize daily differences due to sensor placement. Third, phasic EDA components were automatically extracted with the Ledalab library [8]. Finally, we extracted the average number of phasic peaks for each part of the experiment (see the Results section). The peaks were extracted with the FINDPEAKS function of MATLAB and were normalized for each session to be between 0 and 1 to further minimize session differences.

Steering Wheel Data Acquisition & Processing
Data acquisition and preprocessing were performed to create a signal viable for analysis with a linear predictive coding technique.

[5]https://www.zephyranywhere.com/
[6]http://www.kubios.com/
[7]https://www.empatica.com/
[8]http://www.ledalab.de/

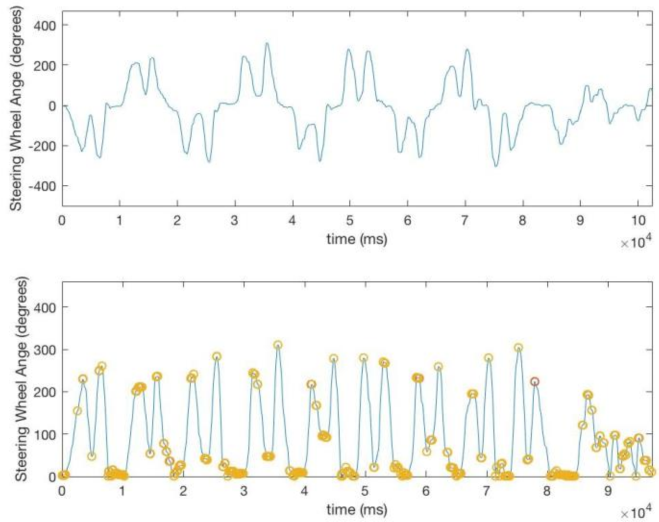

Figure 5. Turns. a) Excerpt of the original signal; b) Absolute value of the signal with peaks and valleys.

Preprocessing
Several steps were followed to process the steering wheel signal. First, the signal was filtered to eliminate high frequency components. We used a 20 pole Butterworth low-pass filter with a cutoff frequency of $\omega = 0.2 * \pi$ rad/sample. After this, we eliminated repeated timestamps, which accounted for about 9.69% of the samples. We then interpolated the signal to correct the original sampling period τ = (M = 1.0918, SD = 0.5179)ms to have a uniformly sampled signal τ = (M = 1, SD = 0)ms.

Segmentation
To extract valuable data segments, several assumptions were made based on exploratory analysis of the signal. First, the data was transformed from a +/- 450° signal into its absolute value (0 to 450°). This way, all positive "peaks" represented either right or left turns. (see Figure 5).

We decided to use only monotonically increasing segments, since they represent direct activation of the muscles. Although the monotonically decreasing segments could carry some signal from the muscle, it can also carry some of the effect of the steering wheel's force-feedback mechanism. Furthermore, in real-life settings the steering wheel return path is also many times strongly guided by the force of the wheels returning to their initial position. To discover these segments we used the FINDPEAKS function from Matlab to find the signal's peaks and valleys. We extracted all segments between a valley and a peak (in that order).

To capture the activation of the arm and shoulder, rather than small movements from the forearm only, we decided to eliminate segments that are smaller than 40°. As observed in Figure 5, most of the turns are larger than this value. On the other end of the range, most turns were at most 280 to 320°. We did not include turns larger than that, as they could have been done in a hurry, perhaps trying to take a rapid turn to correct for

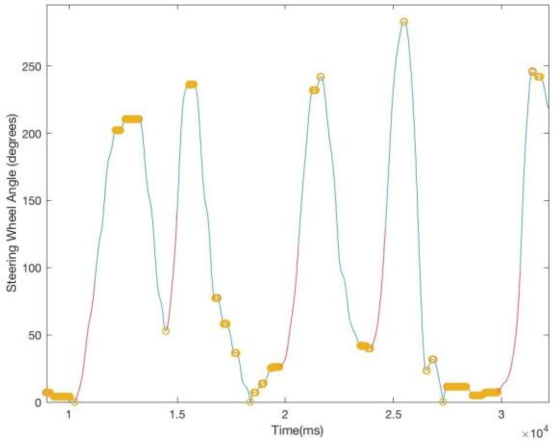

Figure 6. Detail of a couple of steering wheel turns. Extracted segments marked in red.

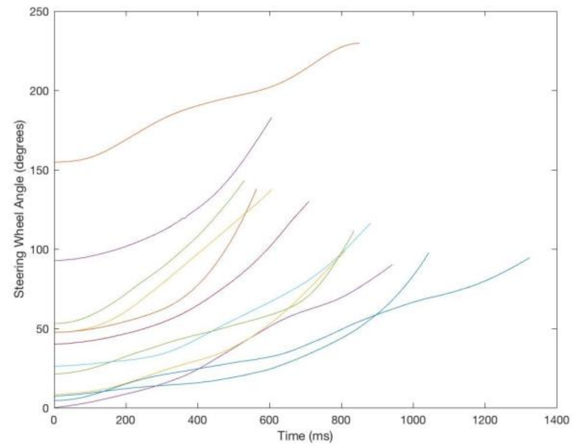

Figure 7. Some sample segments from participant P2's calm driving condition.

some mistake. One final observation of the data showed that for larger turns, around 90° there seemed to be a secondary "impulse." We decided to truncate these turns to keep only the "first" muscle impulse, to avoid readings that may be confounded by the existing inertia of the turn. In summary, we decided to pick turns that were larger than 40°, but smaller than 320°, and we truncated turns larger than 90 degrees (see Figure 6).

We acknowledge that these meta parameters could be further validated with a more detailed study of the activation of the arm muscles with either EMG sensors or motion capture cameras. We did a quick observational run with a male and a female drivers to see if our parameters were minimally acceptable. We asked the drivers to drive around the city and report when they felt that the whole arm was activated. They reported that the arm was active when taking turns that were about 45 to 70 degrees. Smaller turns seemed to be performed by using the arm's weight or just wrist or forearm activation only. The users reported feeling that their arm was fully engaged for up to 90 to 180 degrees, which was close to our observation of a secondary "impulse" happening around 90 to 120 degrees.

We felt that our meta parameters were conservative and realistic enough to capture the desired movement activation. During wheel_calm, we obtained (M = 22.92, SD = 10.12) segments per participant per lap with a duration of (M = 748.75 SD = 152.98)ms and for wheel_stress we obtained (M = 23.48, SD = 7.12) segments with a duration of (M = 658.70, SD = 163.30)ms for the wheel_stress condition. On average, we obtained 23.2 turns, which represent roughly 83% of the 28 actual turns of our driving circuit. Figure 7 shows a few turn segment samples from the calm condition for participant P2. Most of the samples show an exponentially accelerating curve, characteristic of an under-damped oscillatory system.

Pole Selection

Finally, the selected segments were processed with a fourth order linear predictor coding (LPC) algorithm. This configuration generates a representation of a second order MSD system. We focused on extracting only the under-damped poles, i.e. those with an imaginary part larger than 0. By picking the under-damped poles we retained 88.34% of the total segments per user in the wheel_calm condition and 89.94% of the total segments per user in the wheel_stress condition. As explained in the modeling section, under-damped poles have a direct relationship with the k coefficient of a MSD system representing the human arm.

RESULTS

In this section, we present the validation of both the stressor with self-reported and physiological measurements, and the model, which is derived from steering wheel measurements.

Stress Evaluation

First, we validate that our stressor only elicits mental stress by discarding the effect of concentration or task performance artifacts. Then, we present self-reported and physiological measurements that prove the efficacy of our stressor.

Mental stress validation

To validate that our mental stressor does not elicit task-related performance or concentration effects, we analyze two metrics: perceived concentration and lap duration. First we averaged concentration levels before and after the driving conditions. No difference was found between wheel_calm (M = -0.344, SD = 0.324) and wheel_stress (M = -0.323.519, SD = 0.371) ($t(48) = 0.223$, $p = 0.824$). Lap duration, defined as the time to complete a complete lap around the driving circuit, which could be affected by an intrinsic or extrinsic motivation, also did not show a difference between wheel_calm (M = 2.33, SD = 0.45) and wheel_stress (M = 2.34, SD = 0.33) states ($t(48) = -0.0466$, $p = 0.963$). Furthermore, no differences were observed in pairwise lap duration comparisons (see Figure 8). Finally, we tested the difference in time duration across the turn segments. Again, we found no significant difference between wheel_stress and wheel_calm states. These results ensure us that our math+heavy metal music stressor produced mainly changes in mental stress rather than in task-related

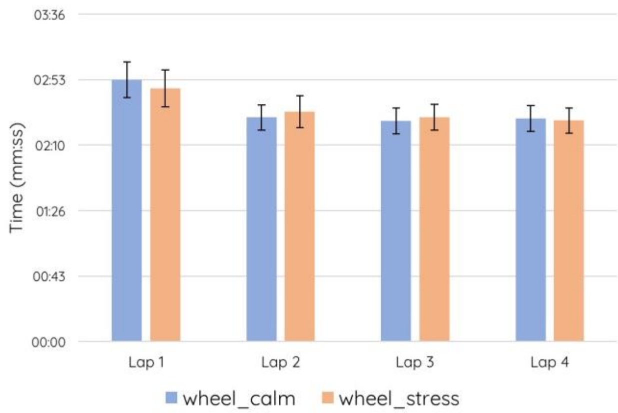

Figure 8. Lap duration in mm:ss. Error bars represent standard errors.

concentration or performance, which in turn should affect muscle tension in the upper limbs.

Self-reported Stress (SRS)

We normalized and baseline-corrected SRS per user. We then averaged the readings before and after the driving tasks. We found a significant difference between wheel_calm ($M = -0.192$, $SD = 0.397$) and wheel_stress ($M = 0.172$, $SD = 0.396$) ($t = 2.123$, $p < 0.01$). As expected, SRS was higher in the presence of stress (see Figure 9 - Self-Report). It is also important to note a significant difference between the relative scores reported before ($M = 0.188$, $SD = 0.276$) and after ($M = 0.380$, $SD = 0.369$) wheel_calm ($t(48) = -2.094$, $p < 0.05$). This difference is potentially relevant, as it may indicate that stress builds due to simply driving. This suggests a need to have a more detailed analysis of stress differences per lap. It is important to state that these temporal effects are not due to ordering effects, as the stress conditions were counterbalanced.

In addition to SRS we found that (normalized/baseline-corrected) Tension was significantly higher for wheel_stress ($M=-0.323$, $SD=0.433$) than for wheel_calm ($M=0.129$, $SD=0.437$) ($t(48)=3.744$, $p < 0.001$) and highly correlated with SRS ($r = 0.59$, $p < 0.001$). This indicates that people perceived the stressor also as affecting their muscle tension. We did not find a significant difference for Arousal/Energy, however, (normalized/baseline-corrected) Valence/Feelings was significantly lower for wheel_stress ($M=-0.045$, $SD=0.435$) than for wheel_calm ($M=-0.346$, $SD=0.415$) ($t(48)=-2.554$, $p < 0.05$). The latter result indicates that people perceived our stressor as "distressing" rather than simply arousing. These ancillary metrics support the notion that we were successful in inducing stress (distress) during our experiment.

Physiological Stress

As stated in the stress measurement background subsection, we focused our attention on the Root Mean Squared of Successive Differences (RMSSD) metric. This is a time-domain measurement of heart rate variability (HRV), known to be inversely correlated with acute stressors. We normalized and baseline-corrected RMSSD and observed a significant difference between wheel_calm ($M = 0.517$, $SD = 0.194$) ms and wheel_stress ($M = 0.368$, $SD = 0.292$) ms ($t = 2.123$, $p < 0.05$).

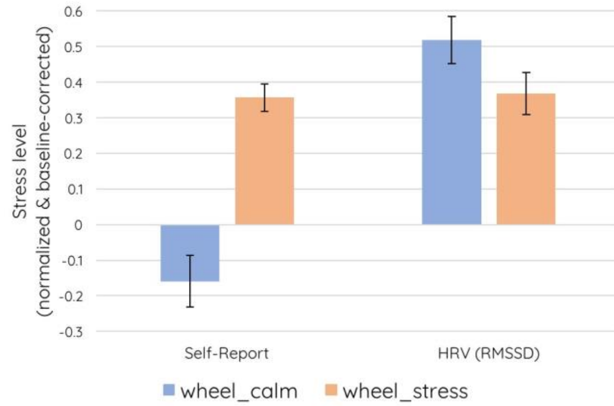

Figure 9. Stress levels (normalized and baseline-corrected) for Self-Reported Stress (SRS) and Root Mean Squared of Successive Differences (RMSS) heart rate variability (HRV). Error bars represent standard errors.

As expected, RMSSD was lower in the presence of stress (see Figure 9 - right). We did not find significant differences in any of the Electro-dermal Activity (EDA) metrics. This could be due to motion artifacts of the wrist-worn EDA sensor during driving [42]. We found however a difference in EDA peaks between the first ($M = 0.1312$, $SD = 0.198$) and second ($M = 0.037$, $SD = 0.067$) laps ($t = 2.244$, $p < 0.05$). As in SRS, this again indicates a potential increase in arousal due to driving.

Stress Steering Wheel Sensor Test

As previously described, we want to verify if the angular movement of a steering wheel can be used to model an approximation of a mass-spring damper model (MSD) of the human arm. We expect that the spring coefficient k representing muscle stiffness increases with stress. We use an inverse coding technique, linear predictive coding (LPC) to estimate the damped frequency of the MSD, which is proportional to the spring constant $\omega \approx \sqrt{k}$.

We define ωc and ωs as the damped frequency for all users' turn segments in the wheel_calm and wheel_stress conditions respectively. ω values will always be measured in rad/s. We tested the entire dataset: 4 laps, ($M=10:07$, $SD=3.05$) minutes which includes ($M = 96.12$, $SD = 27.12$) turn segments per participant. ωs ($M = 0.1$, $SD = 0.012$) was found to be significantly higher than ωc ($M = 0.093$, $SD = 0.01$) ($t = (48) = 2.047$, $p = <0.05$) (see Figure 10). This result rejects the null hypothesis for H and implies that ω was able to represent effectively the muscle stiffness of the arm. We have successfully shown, for the first time, that it is possible to use the angular displacement of the steering wheel as an effective instrument to detect mental stress.

Sensitivity evaluation

With encouraging results, we proceeded to do explore the sensitivity of our sensor. We explored the sensitivity of the sensor with less data to determine the minimum amount of data for it to still effectively sense mental stress. First, we reduced the number sample size and then we decimated the sampling rate to ensure these techniques would work in existing vehicles.

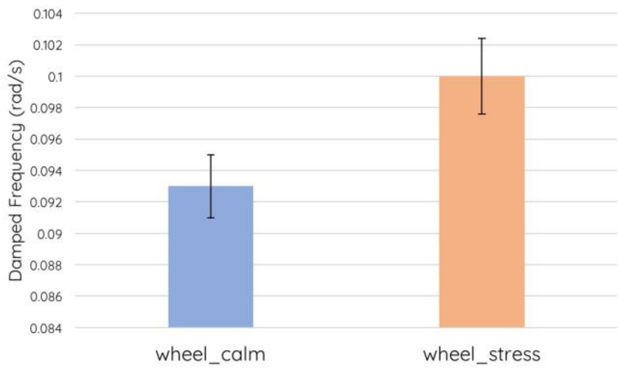

Figure 10. Damped natural frequency (rad/s) for wheel_calm ωc and wheel_stress ωs. Error bars represent standard errors.

Lap analysis

First we looked at the first half of the data, two laps (M = 5:20, SD = 1.45) minutes, accounting for 52.15% of the data and (M = 47.2, SD = 14.9) turn segments per participant. We found ωs (M = 0.099, SD = 0.013) to be significantly higher than ωc (M = 0.091, SD = 0.01) ($t(48) = 2.265$, $p < 0.05$). This difference, apparently higher than the difference with 100% of the data could be due to a higher effect of the math stressor during the earlier part of the drive. With just a single lap (M = 2:50, SD = 0:59) minutes, representing 28% of the data and only (M = 23.2, SD = 8.66) turn segments per participant, ωs (M = 0.097, SD = 0.013) was still significantly higher than ωc (M = 0.084, SD = 0.012) ($t(48) = 2.378$, $p < 0.05$). Finally, to our surprise, with only 10% or of the signal (1 minute on average) and just (M = 7.54, SD = 3.52) turn segments per participant, ωs (M = 0.096, SD = 0.015) remained significantly higher than ωc (M = 0.087, SD = 0.014) ($t(48) = 2.048$, $p < 0.05$) (see Figure 11). We did not find a viable signal with only 5% of the signal. Our exploratory sensitivity analysis reveals an encouraging possibility to potentially detect mental stress with just a few maneuvers of a steering wheel during an urban drive (see Table 1). As it can be observed in Figure 11, the effect of stress is more noticeably changing in wheel_calm than in wheel_stress. This means that, as discussed earlier, there was a sheer effect of stress on driving, which makes is less probable to detect a difference in ω as time passes by and the effect of the initial stressor diminishes. Despite producing a significant differene, the lower sensitivity observed in the 1-minute condition reflects an optimal data-size closer to 1-lap (i.e., 23 samples). Additional data and more extensive testing would be needed to further characterize the lower limits of our sensor.

	Sample Size		Difference Stress-Calm
# of laps	time(mm:ss)	# of turn segments	Mean, SD (rad/s)
2 laps	5:20	47	0.007, 0.008*
1 lap	2:50	23	0.009, 0.013*
<1 lap	1:01	8	0.008, 0.018*

Table 1. Effect of the reduction on the number of laps on the difference ωs - ωc. *p<0.05

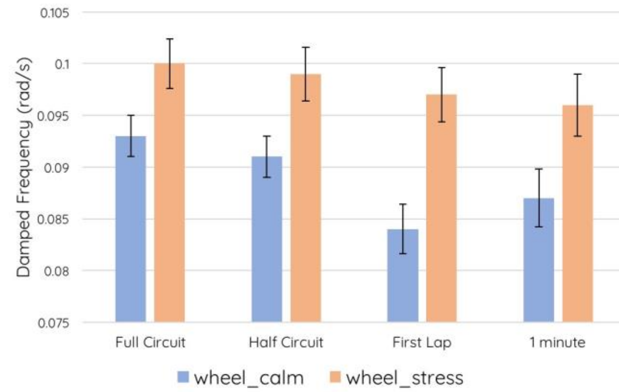

Figure 11. Reduction in sample size. Error bars represent standard errors.

Sample Size	Decimation Factor		
1 lap/2:50 min/19 segments	10	20	50
ω Mean,SD (rad/s)	0.015, 0.028*	0.016, 0.03*	0.016, 0.025*

Table 2. Effect of decimation on the difference on ω between wheel_stress and wheel_calm. *p<0.05, **p<0.01

Decimation

To see if our findings could still work with a smaller sampling frequency (fs) and lower angular resolution (ar), similar to those found in consumer electronics On-Board-Diagnostics (OBD) devices[9], we lowered our sampling frequency. We performed this analysis using the single lap results, which showed a higher difference between ωs and ωc (see Table 2). With a decimation factor of 10 (fs = 100Hz and ar = 0.56°), we observe that ωs (M = 0.186, SD = 0.024) is significantly higher than ωc (M = 0.171, SD = 0.024) ($t(48) = 2.152$, $p < 0.05$). With a decimation factor of 20 (fs = 50Hz and ar = 1.12°), ωs (M = 0.217, SD = 0.025) was still significantly higher than ωc (M = 0.202, SD = 0.025) ($t(48) = 2.323$, $p < 0.05$). Surprisingly, with a decimation factor of 50, (fs = 20Hz and ar = 2.8°), we still found that ωs (M = 0.24, SD = 0.021) was significantly higher than ωc (M = 0.223, SD = 0.02) ($t(48) = 3.01$, $p < 0.01$). A decimation factor of 100 did not render significant results. These results indicate that it is still possible to detect stress with a lower sampling frequency and lower resolution. This is quite relevant, as it open the possibility to use commercial devices commonly used to extract information such as the angular variation of the steering wheel at low frequency rates.

Overall these encouraging lower sensitivity findings suggest that our sensor could potentially be used to monitor acute stress fluctuations during almost any common driving task within a city. A fine grained analysis with larger amounts of data and different driving scenarios should be performed to further evolve the understanding of the steering wheel stress sensor.

DISCUSSION

This work represents the first successful use of a steering wheel as a stress sensor. We were able to successfully induce

[9] https://en.wikipedia.org/wiki/On-board_diagnostics

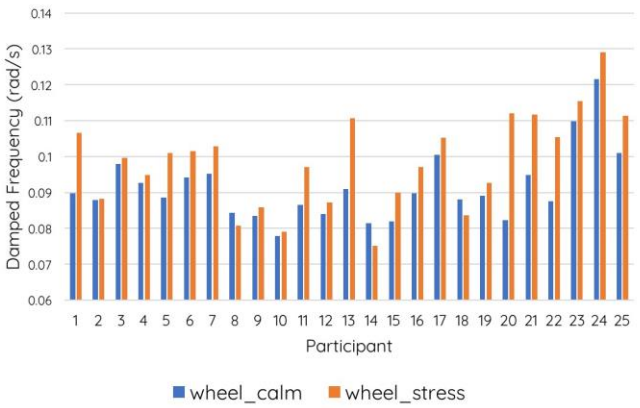

Figure 12. Individual differences for damped natural frequency (rad/s) observed after 2 laps (5:20 minutes).

stress during a driving task using math and without altering performance or driving mechanics. Furthermore, we were able to sustain the effects of stress and calmness with music, despite a natural tendency by drivers to get stressed while driving [14, 25]. We were successful at detecting the difference of our mental stressor through the muscle tension in the arm only using the angular displacement of the steering wheel. Furthermore we showed significant results with as low as eight segments and with a decimated sampling frequency equivalent to 20Hz.

Applications

Because the sensor we have developed requires no new investment of hardware, only signal processing of existing steering wheel angle signals already collected by the vehicle, we believe it would be easy to integrate our sensor into commercial passenger vehicles, converting modern cars into effective sensors for chronic and acute stress episodes.

This work can also be used directly in car simulators, both for educational and gaming purposes. For example, the exact setup of our experiment, a Logitech G29 steering wheel coupled with the City Car Driving application, is a common driving simulation setup for people learning to drive. Gamers at different levels of proficiency could benefit from a steering wheel that reads stress or simply arousal levels. As a matter of fact, a range of games, from simple fun games such as Mario Kart, all the way to complex racing games such as Forza or Grand Theft Auto, could benefit from controls or challenges associated to the stress level of the user.

Looking at individual differences (see Figure 12), we observe that the majority of the participants showed an increase in damped frequency with stress, while only 3 of 25 experienced a decrease. Longitudinal evaluations of commuters or other drivers using cars on a daily basis would enable a deeper understanding of these individual differences.

Next steps

The stressor applied in this experiment, designed to elicit only mental stress as opposed to other cognitive alterations, was effective. However, it was also useful to learn that, despite increased stress levels, people did not have serious incidents while driving in the simulator. Therefore, we believe it is safe to advance this research to testing stress with real vehicles. We propose first controlled studies in closed circuits without actual traffic; in essence, a real-life version of our experiment. Real-driving scenarios should provide additional information of the effects of road-vibration and wheel mass inertia on the steering wheel stress sensor.

We are confident our technology could be adapted in commercial vehicles and further integrated with other stress sensors such as cameras or capacitive sensors in car seats. However, a key question remains: what to do when stress is detected? The fact that stress can be sampled at a relatively high rate means that this sensor could be used as input to interventions for commuters, who may be stressed out from work, to help people manage road rage, or to simply make driving more enjoyable. If the goal is for these unobtrusive sensors to provide effective feedback about stress, complementary work on just-in-time interventions should be developed. Recently, Paredes et. al [29] have suggested that when stress occurs during a drive, some plausible options could be to stretch or conduct breathing exercises. Others have suggested the use of wearables such as Moodwings [25], or light or sound displays such as Autoemotive [15] as ambient and peripheral feedback interventions.

CONCLUSION

In this paper, we have introduced a simple yet effective way to measure mental stress using only the steering wheel of an automobile. We have shown the efficacy of using a simple mass spring damper (MSD) model to detect the stress affecting the muscles of the arm. We calibrated our sensing algorithm against well known stress measurements such as self-reports, heart rate variability (RMSSD), and electrodermal activity (EDA). To validate our model, we have contrasted the damping frequency of the MSD system with well known math and music stressors. Using this model, we have found that it is possible to detect viable signals of stress with only a few turns. This is the first work of this type, opening up new opportunities to use devices already embedded in a car as in-situ non-obtrusive stress sensors.

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REFERENCES

1. Ignacio Alvarez, Laura Rumbel, and Robert Adams. 2015. Skyline: a rapid prototyping driving simulator for user experience. In Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. ACM, 101–108.

2. Urs Anliker, Jamie A Ward, Paul Lukowicz, Gerhard Troster, Francois Dolveck, Michel Baer, Fatou Keita, Eran B Schenker, Fabrizio Catarsi, Luca Coluccini, and others. 2004. AMON: a wearable multiparameter medical

monitoring and alert system. IEEE Transactions on information technology in Biomedicine 8, 4 (2004), 415–427.

3. Wolfram Boucsein. 1992. Electrodermal activity. Electrodermal Activity 3 (1992), 3–67. DOI: http://dx.doi.org/10.1007/978-1-4614-1126-0
4. John T Cacioppo and Louis G Tassinary. 1990. Inferring psychological significance from physiological signals. American Psychologist 45, 1 (1990), 16–28. DOI: http://dx.doi.org/10.1037/0003-066X.45.1.16
5. Jongyoon Choi, Beena Ahmed, and Ricardo Gutierrez-Osuna. 2012. Development and evaluation of an ambulatory stress monitor based on wearable sensors. IEEE transactions on information technology in biomedicine 16, 2 (2012), 279–286.
6. Sheldon Cohen, Tom Kamarck, and Robin Mermelstein. 1983. A Global Measure of Perceived Stress. Journal of Health and Social Behavior 24, 4 (1983), 385. DOI: http://dx.doi.org/10.2307/2136404
7. Anna L Cox, Jon Bird, Natasha Mauthner, Susan Dray, Anicia Peters, and Emily Collins. 2014. Socio-technical practices and work-home boundaries. In Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services. ACM, 581–584.
8. Martha Davis, Elizabeth Robbins Eshelman, and Matthew McKay. 1988. The Relaxation and Stress Reduction Workbook. (1988). DOI: http://dx.doi.org/10.1038/331312b0
9. Elissa S. Epel, Elizabeth H. Blackburn, Jue Lin, Firdaus S. Dhabhar, Nancy E. Adler, Jason D. Morrow, and Richard M. Cawthon. 2004. Accelerated telomere shortening in response to life stress. Proceedings of the National Academy of Sciences of the United States of America 101, 49 (2004), 17312–5. DOI: http://dx.doi.org/10.1073/pnas.0407162101
10. Emre Ertin, Nathan Stohs, Santosh Kumar, Andrew Raij, Mustafa al'Absi, and Siddharth Shah. 2011. AutoSense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field. In Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems. ACM, 274–287.
11. Tara E Galovski and Edward B Blanchard. 2004. Road rage: a domain for psychological intervention? Aggression and Violent Behavior 9, 2 (2004), 105–127.
12. Yuan Gao, Nadia Bianchi-Berthouze, and Hongying Meng. 2012. What Does Touch Tell Us about Emotions in Touchscreen-Based Gameplay? ACM Transactions on Computer-Human Interaction 19, 4 (2012), 1–30. DOI: http://dx.doi.org/10.1145/2395131.2395138
13. Jennifer Healey, Justin Seger, and Rosalind Picard. 1999. Quantifying driver stress: Developing a system for collecting and processing bio-metric signals in natural situations. In Biomedical Sciences Instrumentation, Vol. 35. 193–198.
14. Jennifer A. Healey. 2008. Sensing Affective Experience. In Probing Experience. 91–100. DOI: http://dx.doi.org/10.1007/978-1-4020-6593-4{_}8
15. Javier Hernandez, Daniel McDuff, Xavier Benavides, Judith Amores, Pattie Maes, and Rosalind Picard. 2014a. AutoEmotive: Bringing Empathy to the Driving Experience to Manage Stress. Proceedings of the 2014 companion publication on Designing interactive systems - DIS Companion '14 (2014), 53–56. DOI: http://dx.doi.org/10.1145/2598784.2602780
16. Javier Hernandez, Pablo Paredes, Asta Roseway, and Mary Czerwinski. 2014b. Under pressure: Sensing stress of computer users. In Conference on Human Factors in Computing Systems - Proceedings. 51–60. DOI: http://dx.doi.org/10.1145/2556288.2557165
17. A. V. Hill. 1938. The Heat of Shortening and the Dynamic Constants of Muscle. Proceedings of the Royal Society B: Biological Sciences 126, 843 (1938), 136–195. DOI: http://dx.doi.org/10.1098/rspb.1938.0050
18. Rudolf Hoehn-Saric and Daniel R McLeod. 1993. Somatic manifestations of normal and pathological anxiety. In Biology of anxiety disorders. 177–222. http://ezproxy.net.ucf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=1993-97167-005&site=ehost-live
19. John M. Hollerbach. 1981. An oscillation theory of handwriting. Biological Cybernetics 39, 2 (1981), 139–156. DOI: http://dx.doi.org/10.1007/BF00336740
20. Clemens Kirschbaum, K-M Pirke, and Dirk H. Hellhammer. 1993. The 'Trier Social Stress Test'–a tool for investigating psychobiological stress responses in a laboratory setting. Neuropsychobiology 28, 1-2 (1993), 76–81. DOI: http://dx.doi.org/119004
21. Elise Labbé, Nicholas Schmidt, Jonathan Babin, and Martha Pharr. 2007. Coping with Stress: The Effectiveness of Different Types of Music. Applied Psychophysiology and Biofeedback 32, 3-4 (2007), 163–168. DOI: http://dx.doi.org/10.1007/s10484-007-9043-9
22. Richard S. Lazarus. 1966. Psychological stress and the coping process (print book ed.). New York: McGrawHill series in psychology. xiii, 466 p. pages.
23. Ulf Lundberg, Roland Kadefors, Bo Melin, Gunnar Palmerud, Peter Hassm6n, Uif Lundberg, Peter Hassm˜n, and Margareta Engstr˜m. 1994. Psychophysiological Stress and EMG Activity of the Trapezius Muscle. International Journal of Behavioral Medicine (1994), 354–370. DOI: http://dx.doi.org/10.1207/s15327558ijbm0104{_}5
24. David T. Lykken and Peter H. Venables. 1971. Direct measurement of skin conductance: A proposal for standardization. Psychophysiology 8, 5 (1971), 656–672. DOI: http://dx.doi.org/10.1111/j.1469-8986.1971.tb00501.x

25. Diana MacLean, Asta Roseway, and Mary Czerwinski. 2013. MoodWings - A Wearable Biofeedback Device for Real-Time Stress Intervention. Proceedings of the 6th International Conference on Pervasive Technologies Related to Assistive Environments - PETRA '13 (2013), 1–8. DOI:http://dx.doi.org/10.1145/2504335.2504406

26. Thomas H Massie and J K Salisbury. 1994. The PHANTOM Haptic Interface : A Device for Probing Virtual Objects. ASME Winter Annual Meeting, Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems 55 (1994), 1–6. DOI: http://dx.doi.org/10.1145/1029632.1029682

27. Lars E Olsson, Tommy Gärling, Dick Ettema, Margareta Friman, and Satoshi Fujii. 2013. Happiness and satisfaction with work commute. Social indicators research 111, 1 (2013), 255–263.

28. D. O'Shaughnessy. 1988. Linear predictive coding. IEEE Potentials 7, 1 (1988), 29–32. DOI: http://dx.doi.org/10.1109/45.1890

29. Pablo Paredes, Nur Hamdan, Carrie Cai, Clark David, Ju Wendy, and James a. Landay. 2017. Commover: Exploring in Car Mindful Movement for Commuters - To Appear. Journal of Medical Internet Research (2017).

30. Shwetak Patel. 2008. Infrastructure Mediated Sensing. August (2008), 274. http://hdl.handle.net/1853/24829

31. Andrew Pick and David Cole. 2003. Vehicle Steering Task Neuromuscular Dynamics and the Vehicle Steering Task. Measurement October (2003), 1–10. DOI: http://dx.doi.org/10.1080/00423110600882704

32. Andrew Pick and David Cole. 2007. Dynamic properties of a driver's arms holding a steering wheel. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 221, 12 (2007), 1475–1486. DOI: http://dx.doi.org/10.1243/09544070JAUTO460

33. Rachel L. Piferi, Keith A. Kline, Jarred Younger, and Kathleen A. Lawler. 2000. An alternative approach for achieving cardiovascular baseline: Viewing an aquatic video. International Journal of Psychophysiology 37, 2 (2000), 207–217. DOI: http://dx.doi.org/10.1016/S0167-8760(00)00102-1

34. Judith G. Rabkin and Elmer. L. Struening. 1976. Life events, stress, and illness. Science 194 (1976),

1013–1020. DOI: http://dx.doi.org/10.1126/science.790570

35. 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 (2006), 135–147. DOI: http://dx.doi.org/10.1002/j.2161-1882.2006.tb00100.x

36. Jacob Rosen, Joel C. Perry, Nathan Manning, Stephen Burns, and Blake Hannaford. 2005. The human arm kinematics and dynamics during daily activities - Toward a 7 DOF upper limb powered exoskeleton. In 2005 International Conference on Advanced Robotics, ICAR '05, Proceedings, Vol. 2005. 532–539. DOI: http://dx.doi.org/10.1109/ICAR.2005.1507460

37. James a Russell. 1980. A circumplex model of affect. (1980). DOI: http://dx.doi.org/10.1037/h0077714

38. Peter Sainsbury and J. G. Gibson. 1954. Symptoms of Anxiety and Tension and the Accompanying Physiological Changes in the Muscular System. Journal of Neurology, Neurosurgery & Psychiatry 17, 3 (1954), 216–224. DOI: http://dx.doi.org/10.1136/jnnp.17.3.216

39. David Sun, Pablo Paredes, and John Canny. 2014. MouStress: Detecting Stress from Mouse Motion. CHI '14- Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (2014), 61–70. DOI: http://dx.doi.org/10.1145/2556288.2557243

40. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. 1996. Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. European Heart Journal 17 (1996), 354–381. DOI: http://dx.doi.org/0195-668X/96/030354+28{\protect\T1\ textdollar}18.00/0

41. E M van Loon, R S Masters, C Ring, and D B McIntyre. 2001. Changes in limb stiffness under conditions of mental stress. Journal of Motor Behavior 33, 2 (2001), 153–164. DOI: http://dx.doi.org/10.1080/00222890109603147

42. Yuning Zhang, Maysam Haghdan, and Kevin S. Xu. 2017. Unsupervised Motion Artifact Detection in Wrist-Measured Electrodermal Activity Data. (2017), 54–57. http://arxiv.org/abs/1707.08287