Enabling Adaptive Autonomy: Brain & Body Sensing for Adaptive Vehicles

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Introduction

The promise of advanced autonomous capabilities in vehicles has potentially game-changing implications for drivers and passengers on the road. As the role of the driver in the system moves from direct control of the vehicle to a more supervisory role, the possibilities for in-vehicle experiences open, as do the safety implications. To enable appropriate adaptive behavior of the in-vehicle technology and autonomy mechanisms, we aim to understand the changing cognitive state of the driver through detection of natural physiological and brain signals occurring during driving. Through simulator and on-road studies of drivers performing secondary tasks during driving, we have developed models to identify user cognitive state based on physiology, brain signals and driver metrics. Here, we focus on the integration of functional near-infrared spectroscopy brain sensing into our sensing platform and the steps so far to identify patterns related to cognitive workload.

Background

Previous research has considered measures of peripheral physiological signals such as heart rate, respiration and skin conductance [6] as a proxy for workload in the vehicle. Recently, functional near-infrared spectroscopy (fNIRS) [2,13] has been used in human-computer interaction research to assess signals from the central

nervous system, in real-time, during tasks on a computer [1,3,8,9,10] and in the vehicle [4,7,12]. Functional near-infrared spectroscopy (fNIRS) provides a measure of changes in oxygenated and deoxygenated blood in the cortex. Light of near-infrared wavelengths is sent into the brain where it scatters. The main absorber of this light is the oxygenated and deoxygenated hemoglobin in that area of the brain. A sensitive light detector can determine the intensity of the light that returns back to the surface of the head. This raw light intensity value can be used to calculate oxygenation in the blood, which reflects brain activity in that area.

Because fNIRS measures cognitive activity more directly than peripheral physiology such as heart rate, it may offer complementary information to the other sensors. In addition, it may be more appropriate than other brain-sensing technologies because it is resilient to movement and noise artifacts [8]. Here, we integrated fNIRS measurement from the pre-frontal cortex, with other physiological and contextual sensors. By combining and contrasting these measures, we can assess whether fNIRS has promise as a method for driver monitoring and interaction during in-vehicle tasks. Specifically, we have investigated the sensitivity of fNIRS to working memory demands, using the n-back task.

Figure 1. Driving simulation environment (top). The participants sit in the car and are instrumented with fNIRS (bottom) and other physiological sensors (EKG, skin conductance). The screen in the front presents the simulated driving environment.

Experiment

The goal of our study was to explore working memory demands that come from secondary tasks during driving. While there is a wide range of secondary tasks that a driver may perform, we used a variant of the n-back task, which has established capacity for eliciting scaled levels of working memory demand [5,11]. This task serves as a proxy for various secondary tasks that a driver may perform. Our experiments were conducted in a driving simulator equipped with fNIRS.

Simulator Environment. The driving simulator consists of a fixed-base, full-cab Volkswagen New Beetle in front of an 8 × 8ft projection screen. Participants have an approximately 40-degree view of a virtual environment at a resolution of 1024 × 768 pixels. Graphical updates to the virtual world are computed by using Systems Technology Inc. STISIM Drive and STISIM Open Module based upon a driver's interaction with the wheel, brake, and accelerator. Additional feedback to the driver is provided through the wheel's force feedback system and auditory cues. Custom data acquisition software supports time-based triggering of visual and auditory stimuli and is used to present prerecorded instructions for the cognitive task.

Figure 2. SCL sensor (top) and ECG sensors (middle, bottom) were applied before participants entered the vehicle.

Brain and Body Sensing Setup. The fNIRS device was a multichannel frequency domain Imagent from ISS Inc. Two probes were placed on the forehead over the Fp1 and Fp2 locations on the 10-20 International System for EEG placement. The source-detector distance was 3 cm. Each source emits two near-infrared wavelengths (690 nm and 830 nm) to detect and differentiate between oxygenated and deoxygenated hemoglobin. Physiological data was obtained from a MEDAC System/3 instrumentation unit (NeuroDyne Medical Corporation). A modified lead II configuration was employed for electrocardiograph (ECG) recording in which the negative lead was placed just under the right clavicle (collar bone), ground just under the left clavicle, and the positive lead on the left side over the lower rib. Skin conductance was measured utilizing a constant current configuration and non-polarizing, low impedance gold plated electrodes that allowed electrodermal recording without the use of conductive gel. Sensors were placed on the underside of the outer flange of the middle fingers of the non-dominant hand.

Driving Task and Secondary task. The experiment followed a protocol similar to that described in [5,11], but instead of on-road driving, the participants sat in a stationary car and drove in a simulated environment. While driving, they received auditory prompts to perform "n-back" tasks of varying difficulty levels. A series of single-digit numbers (0-9) were presented aurally in random order. The participant responded to each new number presentation by saying out loud the number n-positions back in the sequence. Difficulty of the task increases as n increases. Each block also included a reference period in which participants were asked to

'just drive'. Participants completed three blocks separated by a 90-second cool down.

Preliminary Results

Our analysis includes 19 participants (8 female) with an average age of 24.7 (SD=3.63). Participants achieved an average 100% accuracy on the 0-back, 97.3% on the 1-back, and 95.8% on 2-back. To look at the effect of *difficulty* and *block* for the heart rate, SCL, fNIRS and driving metrics, we conducted a factorial repeated-measure ANOVA. When Mauchly's indicated violations of sphericity, the Greenhouse-Geisser correction was used. There was a significant main effect of *difficulty* on average HbR, $F(2.453, 44.155)=3.919$, $p=.020$. Contrasts revealed that average HbR for blank-back $F(1,18)=6.170$, $p=.023$, 0-back $F(1,18)=11.249$, $p=.004$, 1-back $F(1,18)= 6.893$, $p=.017$, and 2-back $F(1,18)=7.898$, $p=.012$ all were significantly lower than the average HbR during single-task driving (Fig 4). There was no significant effects of block, nor was there a significant interaction effect of difficulty*block. Similar results were found looking at the min HbR values over the task period. There were no significant effects on avg HbO, avg HbT, max HbO, max HbT. There were significant main effects of both difficulty ($p<.001$) and block on heart rate ($p=.002$) as well as a significant interaction effect of difficulty * block ($p<.001$) (Fig 3). For the SCL measures, there was a significant main effect of difficulty ($p=.029$), but not block nor interaction effect of difficulty * block. Steering wheel reversals showed a significant main effect from difficulty, but not block or any interaction effect. There was no significant effect on velocity.
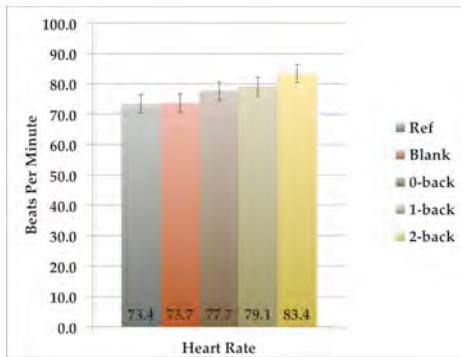
Figure 3. Average Heart Rate and Standard Error per Condition.
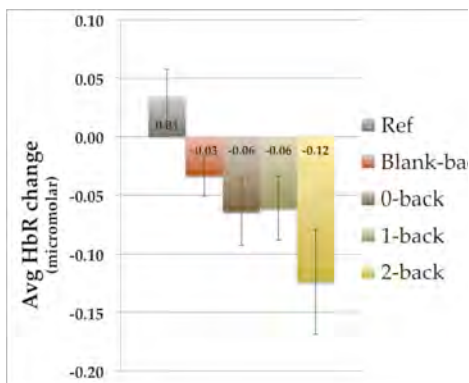
Figure 4. Average Change in Deoxyhemoglobin and standard error.

Discussion and Conclusions

This study explores the feasibility of measuring fNIRS signals during driving tasks. We verified that fNIRS signals could be collected in a vehicle with simultaneous ECG and SCL measurements. We began looking at differences in the physiological signals, brain signals, and driving metrics to understand how they change with increased working memory demands. Our initial results show similar changes in peripheral physiology and brain signals as demand increases. We continue to analyze this dataset to build robust models that take advantage of the complementary information coming from the brain, body, and driver activity. This builds on our prior work [11] building machine learning models to classify working memory demand from secondary tasks. By integrating brain data, we hope to uncover features in the signal to make our classifiers more robust.

This research was motivated by the need to examine the working memory demands of new interfaces being introduced to vehicles and could be used during design stages of such interfaces. In addition, as vehicles become increasingly intelligent and autonomous, it will be valuable to understand the real-time cognitive state of the driver so that the vehicle can adapt to be more responsive to the individual's changing state. Future studies will expand this to more realistic tasks, and to real-time assessment, as well as on-road assessment.

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