2017 IEEE Intelligent Vehicles Symposium (IV)
June 11-14, 2017, Redondo Beach, CA, USA

Assessing Driver Cortical Activity under Varying Levels of Automation with Functional Near Infrared Spectroscopy

Srinath Sibi*, Stephanie Balters**, Brian Mok*, Martin Steinert**,Wendy Ju*

Abstract— **Information about drivers' mental states can be vital to the design of interfaces for highly automated vehicles. Functional near infrared spectroscopy (fNIRS) is a neuroimaging tool that is fast becoming popular to study the cortical activity of participants in HCI experiments and driving simulator studies in particular. The analysis methods of the fNIRS data create requirements in the experimental design such as repeated measures. In this paper, we present a study of the event related cortical activity of the drivers of manual, partially autonomous, and fully autonomous cars when performing lane changes using functional near infrared spectroscopic measures. We also present the experimental methodology that was adopted to meet the needs of the fNIRS measurement and the subsequent analysis. The study (*N*=28) was conducted in a driving simulator. Participants drove for approximately 7 minutes and performed 8 lane change maneuvers in each mode of automation. Multiple streams of data including 4 time-synced video recordings, NASA TLX questionnaires and fNIRS data were recorded and analyzed. It was found that the dorsolateral prefrontal cortex activation during lane changes performed in a partially autonomous mode of operation was just as high as that during a manual lane change, showing that drivers of partially automated systems are as cognitively engaged as drivers of manually operated vehicles.**

I. INTRODUCTION

Designers of automotive interfaces have a balancing act to play. They need to provide drivers with enough information to enable trust or skilled performance. At the same time, they must refrain from overloading the driver and causing stress or distraction. Because of this, cognitive activity measures can be important in assessing the suitability of new automotive interaction designs. Cognitive over-loading of drivers leads to an increase in lane keeping variation, reduced longitudinal speed [1] and decreased response time to reduction of longitudinal speed of vehicles ahead [2]. On the other hand, cognitive under-loading during the operation of automated systems could be just as dangerous as cognitive overloading is during the operation of manually operated systems [3]. Drivers in automated vehicles show an increased tendency for drowsy or sleepy behavior when they are cognitively under-stimulated [4][5], which can render drivers unavailable or impaired in emergency situations. Hence, when designing automotive interfaces, it is vital to assess the cognitive activity of drivers in partially and fully autonomous systems. This is done so that the computer can be aware of the availability of the operator, and adjust its behavior accordingly–either working to arouse and focus the driver, or to take more agency over the driving task.

*Stanford University, Stanford, California
**Norwegian University of Science and Technology, Trondheim, Norway

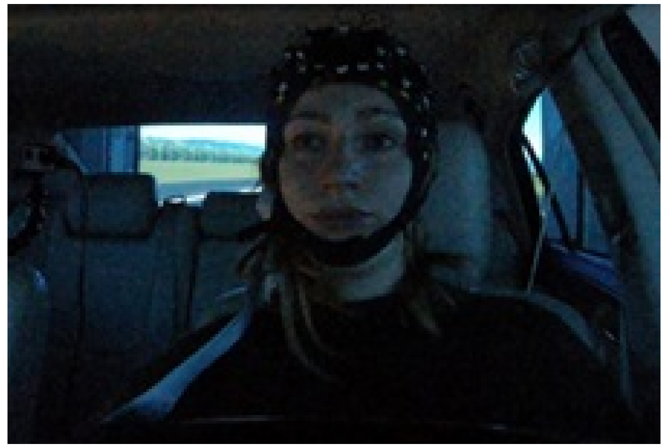

Fig. 1. Study participant wearing the fNIRS cap in the simulator

Recent research suggests that an increase in cognitive load can be linked to a corresponding increase in the frontal cortex activation. An increase in the load placed on the working memory of a user results in an increase in the activation of the frontal cortex of the user. This activation in turn causes an increase in blood flow in the frontal cortex which can be observed using NIRS [6][7].

In this study, fNIRS is used to analyze activation of the frontal cortex which is theorized to be responsible for working memory and attention [8], [9]. Like other physiological measures, fNIRS can be deployed for monitoring continuous, uninterrupted and long-term cortical activity and the corresponding cognitive load [10] [11]. In comparison to self-reporting schemes, such as the NASA TLX [12], fNIRS provides therewith the advantage of non-intrusiveness regarding the experimental task, of not depending on the participants' recollection of the study, and the exclusion of subjectivity in particular. In benchmark with EEG, fNIRS offers less temporal resolution yet higher spatial accuracy within collected data. Moreover, fNIRS measurement devices are characterized by lower presence during the experiment as well as easier removal of motion artifacts [13] compared to EEG. fNIRS technology has been used reliably in the study of cognitive activity in a wide variety of experimental scenarios [14] [15] [13]. fNIRS devices are becoming increasingly portable and can be integrated in a number of scenarios [16] and provides for unique advantages to the evaluation of cognitive activity for in situ simulator and on-the road driving experiments [17].

978-1-5090-4803-8/17/$31.00 ©2017 IEEE

II. Prior Work

A. Cognitive Load in Driving

In the past, cognitive load has been often studied in the context of manual driving. Numerous studies have recorded reduced driving performance and attention to the road. Jamson et al. [18] studied the effect of cognitive load imposed by a secondary task on driving. They used a secondary visual task and audio task on a surrogate in-vehicle information system to increase the load on the driver. It was found that with increased load, drivers showed reduced anticipation of braking and reduced time to collision. Studies by Blanco et al.[19], Nunes et al.[20], Haigney et al.[21] present similar findings. In another study by Lee et al.[22], increased cognitive load due to a secondary task diminished drivers' confidence in their ability to detect changes in the environment.

While studies indicate a decline in performance due to the increase in the cognitive load of a driver following the addition of a secondary task, the inverse may be true for operation of cars with automated driving systems. The Yerkes-Dodson law states that both significantly low arousal and significantly high arousal can lead to a decrease in performance. In Verplank's thesis [3], it was hypothesized that cognitive under-loading for operators of automated systems could be just as dangerous as overloading in manually operated systems. Miller et al. [4] also showed that drivers often fell asleep while supervising a simulated automated vehicle due to lack of stimulation. Such behavior could prove to be dangerous especially in critical scenarios where the automated systems driving the car fail and the driver needs to take charge. Catastrophes resulting from operator sleepiness or drowsy behavior when using automated flight control systems have been recorded in the aviation industry [23].

B. fNIRS and Cognitive Load

In a study by Sibi et al. [24], fNIRS was used to calculate the mean block oxygenation in the pre-frontal cortex of drivers of partially automated vehicles, during automated driving. They confirmed the finding from Miller et al. [4] and showed that the cognitive load of drivers who were supervising automated driving was significantly lower than while driving the vehicle themselves. The mean block oxygenation levels and the derived cognitive load of drivers engaged in secondary activities such as reading or watching a movie was higher than that during the monitoring of the vehicle. This highlights the necessity of cognitively stimulating drivers in automated vehicles. Sibi et al. proposed that the lack of cognitive stimulation during the monitoring could place the drivers of autonomous vehicles in the lower arousal regions of the Yerkes-Dodson curve.

fNIRS has also been used in other recent studies to study the cognitive activity of drivers of manual operated vehicles. Yoshino et al. found significant hemodynamic changes in the pre-frontal cortex while drivers accelerated and decelerated in a manually operated vehicle on an expressway [25]. Tsunashima et al. recorded significant hemodynamic differences in the frontal lobe using fNIRS when the subjects drove using adaptive cruise control (ACC) and manually [26]. In another experiment, Shimizu et al. recorded hemodynamic responses in the frontal cortex under different driving conditions in a driving simulator [27]. They found increased activity in the frontal lobe when the driver was presented a difficult driving task or an attention demanding scenario, thereby demonstrating the usefulness of fNIRS in measuring cognitive load. Due to these results and the success of prior research using fNIRS in driving scenarios, we chose fNIRS to analyze the cognitive activity in our experiment.

Past studies have shown the difference between operators of fully autonomous vehicles and active drivers using mean block oxygenation. However, to the best of our knowledge there have been no efforts to understand the differences between the cortical activity of operators of autonomous vehicles across various levels of autonomy. The use of GLM analysis (see section on fNIRS Data Analysis), an established methodology in neuroscience, required repeated measures of cortical activity during the same stimuli. Lane changes are ecologically valid and can be used repeatedly to understand the cortical activity using GLM based fNIRS analysis.

III. Experiment Goals

The goals of this experiment were to:

1. Design an experimental study design for the measurement of cortical activity using fNIRS in a driving simulator.

2. Study the effects of different levels of automation [manual, partially autonomous and fully autonomous modes of operation] on the cortical activity of the participant.

IV. Experimental Setup

A. Experiment Settings

The study was conducted in a fixed-base driving simulator with 270° seamless projection and individual channels for the side view mirrors and the rear view (Figure 2). The driving simulator had an in-vehicle interface and instrument cluster which could be used by the participant to monitor and control the vehicle during the experiment. The driving scenarios and the world in the simulation were entirely designed and programmed by the authors.

The simulator had three modes of control: manual, partially autonomous and fully autonomous. In the manual mode of operation, the driver was in control of all aspects of driving such as longitudinal speed, lane keeping and direction. In partially autonomous mode of control, the vehicle was in charge of longitudinal speed and lane keeping. However, the vehicle needed directional input from the driver whenever a lane change was required. The directional input was provided through the use of the turn indicator lever. Hence, in order to shift to the left on a two lane road, the participant turned on the left indicator and in order to shift to the right lane, the participant turned on the right indicator. This follows the model of automation input used in the Tesla Model S

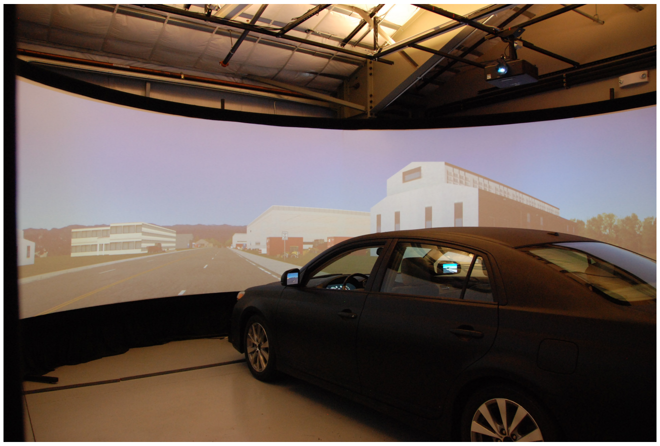

Fig. 2. Driving Simulator showing the 270 ° projection with side mirrors and in-simulator vehicle

autopilot [1]. In fully autonomous mode, the vehicle was in control of all aspects of driving and could determine the need for a lane change maneuver and execute the lane change when needed without any input from the driver. The driver was asked to monitor the car during the period the fully autonomous mode drove the vehicle.

Both partial autonomy and full autonomy modes were engaged by pressing two different buttons on the steering wheel. The partially autonomous and fully autonomous modes of control were programmed to obey all the rules of the road. Partial autonomy and full autonomy, when engaged, were distinguished from each other through a display icon on the instrument cluster. A series of icons were displayed over 5 seconds to indicate the transfer of the mode of operation from manual to either mode of operation. The icons to indicate the transfer of control are shown in sequence in Figure 3. Once the transfer was complete, the last icon stayed on the screen to indicate the mode that was currently engaged. A similar process was used to indicate the transfer of control back to the manual mode of operation.

It must be noted here that any impact on the response function shape was removed by ensuring an almost constant vehicle speed throughout the segments of interest. Speed signs were placed along the side of the road and the participants were instructed to obey the speed limit at the start of drive.

During the study, the hemodynamic activity in the pre-frontal cortex was recorded with a NIRSport fNIRS system (made by NIRx Medical Technologies LLC). The NIRSport device has 8 emitters and 8 detectors and allowed a total 20 channels of measurement. The configuration of the emitter and detectors are shown in Figure 5 and the projection of the channel positions onto the surface of the brain are shown in Figure 6. The emitters use optical signals of two wavelengths, 760nm and 850nm, emitted simultaneously by each source. The data were calibrated at the start of the experiment and recorded using the NIRStar acquisition software.

[1]Tesla Autopilot, 2016. Available online at https://www.teslamotors.com/presskit/autopilot

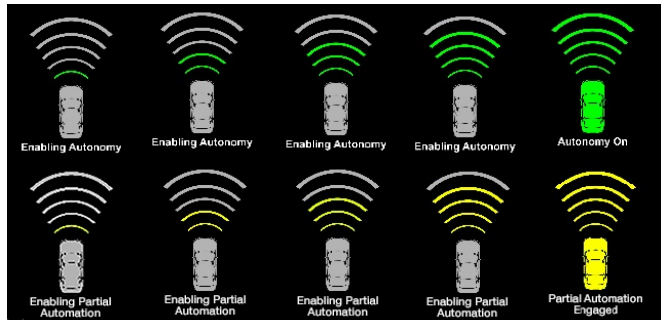

Fig. 3. Series of icons displayed on instrument cluster showing the transfer of control from manual to fully autonomous (*top*) and manual to partially autonomous (*Bottom*)

B. Participants

A total of 28 participants (18 male and 10 female) between the ages of 17 to 71 (Mean = 31.11 and SD = 12.76) participated in the study. Each participant drove in all three modes of operation and the order of occurrence of the modes was counterbalanced in order to avoid ordering effects. Participants were recruited through online postings on public forums.

C. Procedure

The study lasted for 35 - 40 minutes depending on the speed of the driver during the segments of manual driving. The structure of the study is shown in Figure 5. The study contained 4 segments: one practice segment and three main segments, during which the participants drove using manual, partially autonomous or fully autonomous mode of control. The participants were told that during the study, they would encounter vehicles that obstruct their path, creating a need for a lane change maneuver. During the practice section, the participant drove the vehicle in all three modes of control so that they could get acclimated to the transfer of control and modes of lane change. Also during the practice segment, the participant performed 2 lane changes in manual mode and 1 lane change each in the partial and fully autonomous modes.

In each of the main study segments, participants performed a total of 8 single lane changes, where each lane change was required due to a car moving at a much slower speed than the speed limit in the same lane as the participant. Participants were instructed to only perform single lane changes and were asked to obey all rules of the road. At the end of each segment (practice and 3 main segments), participants were asked to pull over to the side of the road and fill out a questionnaire comprising of the NASA TLX questionnaire [12]. At the end of the study, participants were asked to fill a questionnaire comprising of questions that qualified the operation of the vehicle on a Likert scale.

Markers were placed in the fNIRS data in order to synchronize the fNIRS data and the simulator events. Virtual sensors placed in the simulated environment, in conjunction with the trigger module of the NIRSport package, allowed for placing markers in the fNIRS data. The start and end of

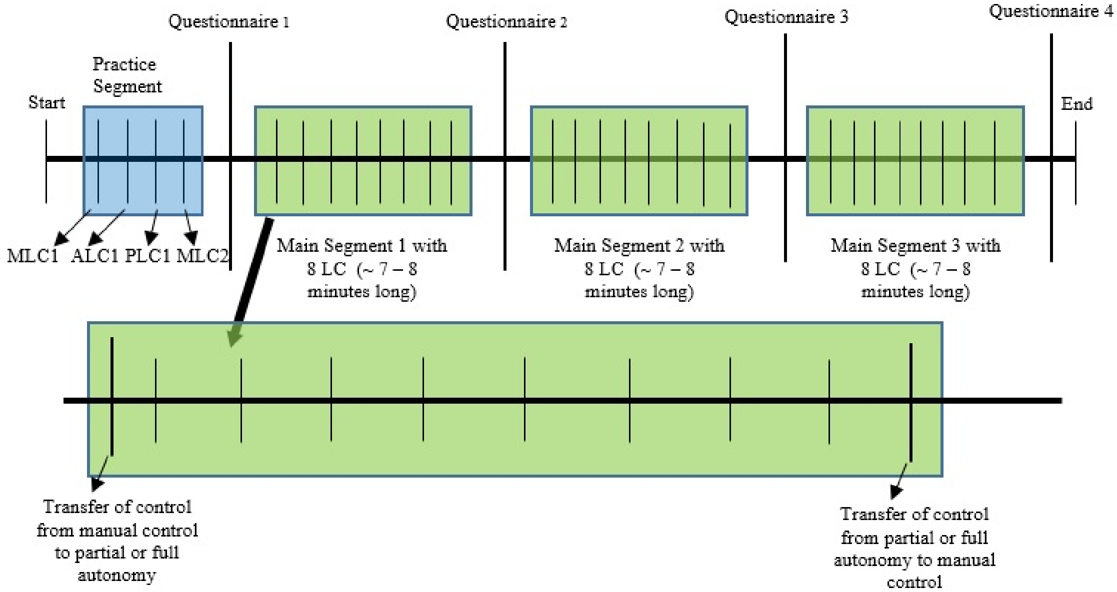

Fig. 4. Time Line of the study showing the single lane changes in each segment.(MLC - Manual Lane Change, PLC - Partially autonomous lane change, ALC - Fully Autonomous Lane Change) (Diagram not to scale)

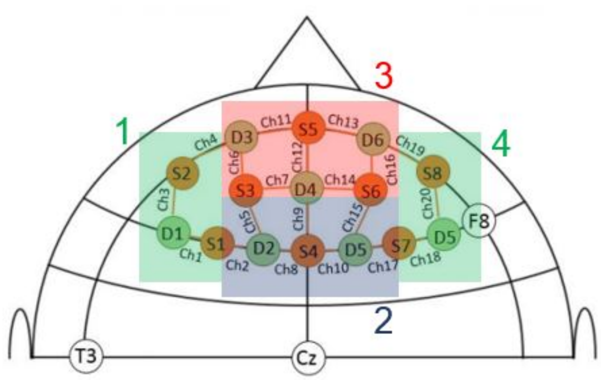

Fig. 5. Source Detector Configuration of the optical probes placed on the frontal cortex region of the participant. The map of the optode on the right shows a total of 20 channels.(S_i: Source, D_i: Detector), Ch_i: Channel. The Regions of Interest (ROI) have been shown as in red (region 3: Ventral), green (regions 1 and 4: Lateral) and blue (region 2: Dorsal) and the channels included in the estimation of activation for the ROIs are included in the region

each driving segment and the occurrence of the lane change tasks were marked using 4 different markers. The start of the lane change event is marked by the appearance of a car in the same lane as the driver. This moment is registered in the fNIRS data stream using markers specific to each mode of automation. In this way, the driving data from the simulation is synchronized with the fNIRS data. Additionally the screen recording of the fNIRS recording computer was synchronized using a quad multi-viewer with the simulation video output in order to contextualize the observed frontal cortex activity with the events and participant behavior. The time-line of all the markers placed is shown in Figure 4.

In order to avoid any frontal cortex activity that does not

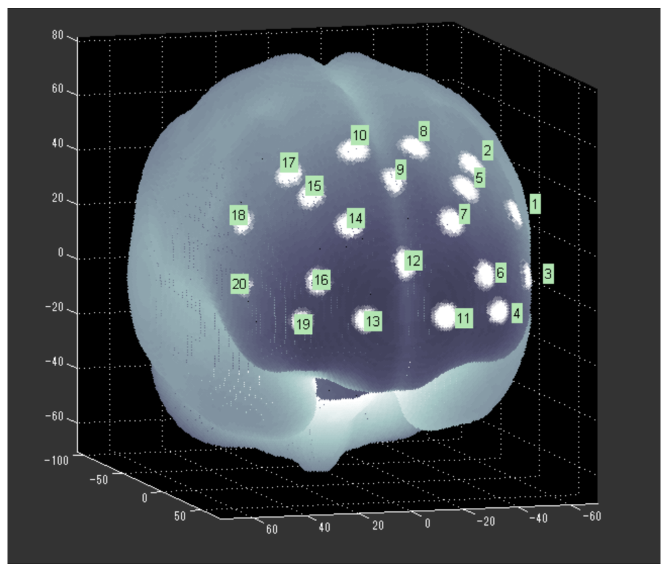

Fig. 6. Projection of the fNIRS device channel positions on the surface of the brain in the Montreal Neurological Institute(MNI) Coordinate Space

correspond to the operation of the vehicle, the experimenters designed the system to be as minimally stimulating as possible. The simulation did not have any ambient traffic. Only signs to indicate the speed limit were placed on the side of the road. In each main study segment, the 8 single lane changes were divided into 4 right lane changes and 4 left lane changes to balance any lateralization effects arising due to the right or left handedness of the activity in the fNIRS data.

V. RESULTS

The fNIRS data were analyzed using the open source HOMER2 scripts implemented in MATLAB [28] and the SPM

MATLAB package (open source neuro-imaging data analysis tools made available at http://www.fil.ion.ucl.ac.uk/spm/). The time-synced video streams were analyzed to identify anomalous participant behavior. Based on the video analysis, two participants' data were excluded from analysis due to incorrect task performance, participant adjusting the NIRS cap due to discomfort and excess unwarranted movements by the participant. One other participants data were excluded due to failures of the NIRS recording device during the experiment. fNIRS data from a total of 25 participants and questionnaire data from 28 participants were analyzed.

A. fNIRS Data Analysis

The fNIRS data were analyzed using the HOMER2 MATLAB scripts. To begin, the raw data were converted into the change in optical density using the hmrIntensity2OD function. Said function uses the normalized changes of light incident on a detector from a source. The function employs a logarithmic relation described in [28]. Once, the change in optical density was estimated, the channels of data that had a signal to noise ratio less than 2 or had values that were higher 10^7 or lower than 0 were removed using the enPruneChannels function. A band-pass filter, hmrBandPassFilt, was used with cut off frequencies of 0.01 Hz and 0.5 Hz to eliminate background physiological signals (such as blood pressure variations and cardiac pulsations) and machine noise. The data were then passed through the homer function motion artifact correction algorithm hmrMotionCorrectWavelet using a inter-quartile range of 1.5. Prior works [29] have shown that the performance of the wavelet correction is the most effective among contemporary motion correction algorithms. Motion artifacts were then identified by any sudden increases in the optical density greater than 20 times the standard deviation and an amplitude increase greater than 0.3 using the hmrMotionArtifact function and eliminated using the enStimRejection function. The corrected optical density data were then converted to HbO, HbR and HbT concentrations using the hmrOD2conc function using partial pathlength factors of 6 for both wavelengths (760nm and 850nm). The markers placed during the study were then used to calculate the onset times of the events and the rest periods. The duration of the lane change events (from the appearance of a vehicle in the subject's lane to overtaking the vehicle) was 18 seconds and the rest periods (duration of vehicle operation with no incidents in the simulation) were 10 seconds. For the purpose of the GLM analysis, only Oxygenated Hemoglobin (HbO) data were chosen. The GLM analysis was performed to calculate the response signal strength of the HbO data (designated as β henceforth).

The statistical analysis was performed with IBM SPSS Statistics 23 software. All β values had to be multiplied by factor 10^6 to overcome the software's limitations on analyzing numeric values as low as micro to picco range. Following the methodological approach from prior works [10], [30], 4 regions of interest (ROI) were defined, left and right lateral, ventral and dorsal regions of the prefrontal cortex (Figure 5) [31]. Paired-samples t-test were performed in order to investigate whether there was a statistically significant difference between β values of lane change maneuvers (designated as LCP, LCM LCA for lane changes in partially autonomous, manual and fully autonomous modes of operation) and rest driving (Partial (P) vs Manual (M) vs Autonomous(A)) for each condition and region (Figure 7, top). Further, one-way repeated measures ANOVAs were used to test whether there was a difference in basal driving between conditions and whether there were differences between the contrasts (differences in β values between lane change tasks and corresponding rest condition, ΔLCPP, ΔLCMM, ΔLCAA) between modes of automation. Data are mean $\pm$ standard deviation, unless otherwise stated, and the two-tailed significance level ($p \leq .05$) is used (Figure 7, bottom). Outliers were detected with 1.5 box-lengths from edge of the box in a boxplot and the assumption of normality was assessed by Shapiro-Wilk's test ($p \geq .05$). In case ANOVA tests of within-subject effects revealed statistically significant differences, the post hoc analysis with Bonferroni adjustment for multi comparison was applied to test all possible pairwise combinations of mean values of measures within a region. Further Mauchly's test of sphericity was used to test whether the assumption of sphericity had been violated. All regions and conditions that indicate any significant differences in the β values have been highlighted in Figure 7.

The most interesting result observed in the results is that increase in activation in the lateral prefrontal cortex (shown by the response signal strength β) across all the modes of operation. It is also observed that highest increase in activation is in the partial automation lane change.

Statistically significant increase in frontal cortex activations were also observed across the dorsolateral regions (regions 1, 3 and 4) when the participant executed autonomous lane change tasks. A comparison of the contrasts observed during the lane changes across conditions in regions 2 and 3(shown in lower half of Figure 7) showed the contrasts for autonomous lane changes were highest, followed by partial and manual modes of operation. No significant differences were observed between the activations of the rest conditions between the three mode of automation in any region.

B. Questionnaire Data Analysis

The data from the three in-experiment and one post-experiment questionnaire were analyzed. To determine if there were any differences between the three driving systems in terms of the participants' post drive questionnaire response, we performed a one-way ANOVA on the levels of automation. For this test, we removed outlier responses that were two standard deviations from the mean. We saw a significant difference between the groups on measures of whether the system of the car was Easy to Drive ($F(2,76)=4.94$, $p=0.01$), Fun to Drive ($F(2,78)=4.19$, $p=0.019$), and Safe ($F(2,78)=5.22$. $p=0.007$).

We also see a moderately significant difference for whether the system of the car was Trustworthy ($F(2,77)=3.09$, $p=0.05$). A Tukey post-hoc analysis revealed that there was a significant difference between the Manual Mode and Full Autonomous

	LCP vs P paired-samples t-test	LCM vs M paired-samples t-test	LCA vs A paired-samples t-test
Region 1	Δ = 0.0148 ± .214 t(74) = .598, p = .552	Δ = 0.0043 ± .211 t(74) = .178, p = .859	Δ = 0.0581 ± .191 t(74) = 2.626, p = .010**
Region 2	Δ = 0.0095 ± .176 t(174) = .717, p = .475	Δ = -0.0456 ± .213 t(174) = - 2. 835, p = .005**	Δ = 0.0504 ± .190 t(174) = 3.530 p = .001 ***
Region 3	Δ = -0.0728 ± .228 t(174) = - 4. 221, p < .0005***	Δ = -0.1021 ± .215 t(174) = - 6.288, p < .0005***	Δ = 0.0280 ± .188 t(174) = 1.963 p = .051
Region 4	Δ = 0.0477 ± .170 t(74) = 2.427, p = .018*	Δ = 0.0362 ± .140 t(74) = 2.242, p = .028*	Δ = 0.0455 ± .125 t(74) = 3.150 p = .002**

	P vs M vs A repeated measures ANOVA	ΔLCPP ΔLCMM ΔLCAA repeated measures ANOVA
Region 1	F(2,148) = .648, p = .525 ΔPM = .004 ± .018, p = 1.000 ΔPA = -.018 ± .021, p = 1.000 ΔMA = -.021 ± .021, p = .910	F(2,148) = 1.751, p = .177 Δ(ΔLCPP ΔLCMM) = .010 ± .028, p = 1.000 Δ(ΔLCPP ΔLCAA) = -.043 ± .031, p = .519 Δ(ΔLCMM ΔLCAA) = -.054 ± .031, p = .270
Region 2	F(2,348) = 1.188, p = .306 ΔPM = -.019 ± .013, p = .405 ΔPA = -.005 ± .013, p = 1.000 ΔMA = .014 ± .014, p = .880	F(2,348) = 11.304, p < .0005*** Δ(ΔLCPP ΔLCMM) = .055 ± .021, p = .031* Δ(ΔLCPP ΔLCAA) = -.041 ± .020, p = .119 Δ(ΔLCMM ΔLCAA) = -.096 ± .020, p < .0005***
Region 3	F(2,348) = 2.213, p = .111 ΔPM = -.005 ± .012, p = 1.000 ΔPA = .019 ± .012, p = 0.400 ΔMA = .024 ± .012, p = .129	F(2,348) = 22.157, p < .0005*** Δ(ΔLCPP ΔLCMM) = .029 ± .020, p = .449 Δ(ΔLCPP ΔLCAA) = -.101 ± .020, p < .0005*** Δ(ΔLCMM ΔLCAA) = -.130 ± .021, p < .0005***
Region 4	F(2,148) = 2.562, p = .081 ΔPM = -.004 ± .017, p = 1.000 ΔPA = -.033 ± .017, p = .156 ΔMA = -.029 ± .013, p = .097	F(2,148) = 0.132, p = .876 Δ(ΔLCPP ΔLCMM) = .011 ± .027, p = 1.000 Δ(ΔLCPP ΔLCAA) = .002 ± .024, p = 1.000 Δ(ΔLCMM ΔLCAA) = -.009 ± .020, p = 1.000

Fig. 7. Results from paired-samples t-test and one-way repeated measures ANOVAs. Results were significant at the 0.05 level (2-tailed) with p < .001 (***), p < .01 (**), and p < 0.5 (*). Data are mean $\pm$ standard deviation. Region 1 = [Channel 1, Channel 3, Channel 4]; Region 2 = [Channel 2, Channel 5, Channel 8, Channel 9, Channel 10, Channel 15, Channel 17], Region 3 = [Channel 6, Channel 7, Channel 11, Channel 12, Channel 13, Channel 14, Channel 16], Region 4 = [Channel 18, Channel 19, Channel 20]. All beta values were multiplied by fraction 10^6.

Question	Partially autonomous mode of operation	Manual mode of operation	Fully autonomous mode of operation
Easy to drive	M = 5.96, SD = 0.65	M = 5.69*, SD= 0.84	M = 6.31*, SD = 0.62
Fun to drive	M = 4.19, SD = 1.17	M = 4.50*, SD = 1.55	M = 3.44*, SD = 1.40
Trustworthy	M = 5.59, SD = 0.89	M = 5.11¹, SD = 1.01	M = 5.77¹, SD = 1.11
Safe	M = 5.22, SD = 1.09	M = 4.86*, SD= 1.09	M = 5.81*, SD = 1.10

Fig. 8. ANOVA results of questionnaire data. (* p < 0.05 for the measures that had significant differences, M^1 - moderately significant difference p = 0.0526. Questions were presented on a 7 point Likert scale.)

Mode for the questions of Easy to Drive (p=0.007) Fun to Drive (p=0.016) and Safe (p=0.005). There were no statistically significant differences between the Partially Autonomous Mode and the other modes. Based on the questionnaire results (see figure 8), participants found that Fully Autonomous Mode to be easier and safer to use, but not as fun to drive compared to the Manual Mode. The questionnaire presented to the participants to understand the driver perception that yielded the above results were presented on a 7 point Likert scale that ranged from Strongly agree to Strongly Disagree.

VI. DISCUSSION

A. *Cognitive Activity as a function of Vehicle Automation*

The role of the dorsolateral prefrontal cortex in working memory and attention is well established [8], [32] and an increase in the demand for working memory is expected to cause an increase in the activation in this region. An increase in the dorsolateral frontal cortex activity (measured by the response signal strength values) during the partial lane changes shows that participants dedicate as much, if not more cognitive resources to the operation of the vehicle than they do during the manual mode of operation. The increased frontal cortex activity observed in the partial automation mode could be explained by the need for the driver to remain in the loop. Though the car's driving systems reduce the driver's involvement in driving, the driver needs to maintain engagement to give input to the automated system at the appropriate moments. Changes in dorsolateral prefrontal cortex activity in manual driving was lower than that in partial automation though the driver is responsible for all aspects of driving control. This is because the manual mode of operation is commonplace and familiar.

In the fully autonomous mode of operation, it was found that the increase in the cortical activity after the onset of the stimulus was significant in variance to the hypothesis in [24], [4]. This variance could be due to several of the participants experiencing the autonomous feature of the car for the first time. The increase in the activation could be explained by the experience and use of a novel feature in driving. This result could also be due to a learning effect that occurs over the duration of operation of the vehicle in the autonomous mode. The questionnaire data shows that the participants trust the vehicle and feel that it is safe to drive. However, it is important to note that participants develop trust in the system over the duration of the test segment. This longitudinal impact on the cortical activity of the participant was not studied in the work presented here. Participants were also asked at the start of the experiment to monitor the driving of the vehicle at all times and to not pursue other activities. In a fully autonomous vehicle, this might not be the case and drivers would almost certainly pursue other activities.

In lower levels of automation (NHTSA levels 1 and 2), the driver is constantly engaged in the supervision of the automated system and is in the control of the vehicle through inputs. Since the mental load during partial automation operation is shown to be the same during manual driving, it is possible that the addition of secondary tasks to operation of vehicles with partial automation could be damaging to driver performance. Past studies [19], [1] have demonstrated the decrease in driver performance with added operator load which correlates with our finding as well. On the other hand, the increased cognitive load is preferable to the potentially cognitively under-loading conditions associated with higher level partial automation (NHTSA Level 3) as stated in prior works [4], [24]. The fact that the Fully Autonomous mode was not rated as very fun to drive is an indication that people prefer more cognitive engagement than what is offered by full automation.

B. Limitations and Future Work

In order to apply GLM analysis, repeated measures for each driving mode were required. The repeated exposure to the same stimulus might lead to order effects and related decrease of mental efforts over time. Repeated trials often result in a learning effect and the mental effort needed for task execution would be lowered. This study does not account for these effects in the design of the order of activities but provides a firm base upon which future studies may be built. Further studies could implement a randomized design in the order of the driving tasks to eliminate driver learning and adaptation. Specifically, an investigation into the variation of the trust and the frontal cortex activity over a prolonged period of usage might provide vital information in the design and engineering of an automated driving feature.

While fNIRS gives an accurate measure of cortical activity, the use of fNIRS in everyday driving is not possible for ergonomic reasons. Past studies [33] have shown the effect of varying cognitive load on the operator's behavioral outcome. Physiological measures such as heart rate, respiration, blink rate, etc. can be used employed in future studies alongside fNIRS so that they might be used as indirect measures in day-to-day driving or cognitive activity. These measures are becoming increasingly commonplace in the automotive cabin space[2].

VII. CONCLUSION

This study analyzes the cortical activity of drivers in manual, partially autonomous and fully autonomous vehicles and addresses the technical difficulties in the building of an experiment with fNIRS as an neurological measure in driving studies. It was found that the dorsolateral prefrontal cortex activation during lane changes performed in a partially autonomous mode of operation was just as high as that during a manual lane change, showing that drivers of partially automated systems are as cognitively engaged as drivers of manually operated vehicles.fNIRS is useful in automation studies because it is a measure that does not rely on self-report that can be used across levels of automation. This means that, unlike most behavioral or performance measures, we can use fNIRS to stage comparisons between different automation contexts. One of the challenges of using fNIRS as a measure is that the hemodynamic signals measured can be obscured by motion artifact noise, so repeated measures study designs, like the lane change tasks used in this study, are required.

The need for these slightly contrived circumstances and relative bare simulation landscapes means that a fNIRS study has limited ecological validity; to design studies that are both ecologically valid and have repeated measures is, thus, cumbersome. These limitations can be overcome by profiling fNIRS measurements against measures of driver load, performance or stress which are less direct but possibly more contextually robust. In any case, this type of study provides vital insight into the cognitive activity of a mode of automation that is expected to become popular in the near future.

[2]http://www.techinsider.io/faurecia-creates-first-passenger-seat-for-driverless-cars-2015-11

VIII. ACKNOWLEDGEMENTS

This study was conducted under IRB Protocol 30016. We would like to thank Lene Harbott, Aaron Piccirilli, Joseph Baker, Andrew Gundran, Dave Miller, Mishel Johns, Ella Gamze Strack and our fellow researchers at the Center for Design Research, Stanford for their advice in the development of the study.

REFERENCES

[1] J. Engström, E. Johansson, and J. Östlund, "Effects of visual and cognitive load in real and simulated motorway driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 8, no. 2, pp. 97 – 120, 2005.

[2] D. Lamble, T. Kauranen, M. Laakso, and H. Summala, "Cognitive load and detection thresholds in car following situations: safety implications for using mobile (cellular) telephones while driving," *Accident Analysis & Prevention*, vol. 31, no. 6, pp. 617 – 623, 1999.

[3] W. L. Verplank, "Is there an optimal work-load in manual control?" Ph.D. dissertation, Massachusetts Institute of Technology, 1978.

[4] D. Miller, A. Sun, M. Johns, H. Ive, D. Sirkin, S. Aich, and W. Ju, "Distraction becomes engagement in automated driving," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, no. 1. SAGE Publications, 2015, pp. 1676–1680.

[5] M. S. Young and N. A. Stanton, "Attention and automation: new perspectives on mental underload and performance," *Theoretical Issues in Ergonomics Science*, vol. 3, no. 2, pp. 178–194, 2002.

[6] H. Ayaz, M. Izzetoglu, S. Bunce, T. Heiman-Patterson, and B. Onaral, "Detecting cognitive activity related hemodynamic signal for brain computer interface using functional near infrared spectroscopy," in *Neural Engineering, 2007. CNE'07. 3rd International IEEE/EMBS Conference on*. IEEE, 2007, pp. 342–345.

[7] K. Utsugi, A. Obata, H. Sato, T. Katsura, K. Sagara, A. Maki, and H. Koizumi, "Development of an optical brain-machine interface," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*. IEEE, 2007, pp. 5338–5341.

[8] A. M. Owen, A. C. Evans, *et al.*, "Evidence for a two-stage model of spatial working memory processing within the lateral frontal cortex: a positron emission tomography study," *Cerebral Cortex*, vol. 6, no. 1, pp. 31–38, 1996.

[9] N. Ramnani and A. M. Owen, "Anterior prefrontal cortex: Insights into function from anatomy and neuroimaging," *Nature Reviews Neuroscience*, vol. 5, no. 3, pp. 184–194, 2004.

[10] F. A. Fishburn, M. E. Norr, A. V. Medvedev, and C. J. Vaidya, "Sensitivity of fnirs to cognitive state and load," *Frontiers in human neuroscience*, vol. 8, 2014.

[11] K. Izzetoglu, S. Bunce, B. Onaral, K. Pourrezaei, and B. Chance, "Functional optical brain imaging using near-infrared during cognitive tasks," *International Journal of Human-Computer Interaction*, vol. 17, no. 2, pp. 211–227, 2004.

[12] S. G. Hart and L. E. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research," *Advances in psychology*, vol. 52, pp. 139–183, 1988.

[13] E. T. Solovey, A. Girouard, K. Chauncey, L. M. Hirshfield, A. Sassaroli, F. Zheng, S. Fantini, and R. J. Jacob, "Using fnirs brain sensing in realistic hci settings: experiments and guidelines," in *Proceedings of the 22nd annual ACM symposium on User interface software and technology*. ACM, 2009, pp. 157–166.

[14] T.-P. Jung, S. Makeig, M. Stensmo, and T. J. Sejnowski, "Estimating alertness from the eeg power spectrum," *Biomedical Engineering, IEEE Transactions on*, vol. 44, no. 1, pp. 60–69, 1997.

[15] E. T. Solovey, B. Mehler, and B. Reimer, "Brain sensing with fnirs in the car," in *Adjunct Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. Presented at the AutomotiveUI*, vol. 12, 2012.

[16] R. Mckendrick, R. Parasuraman, R. Murtza, A. Formwalt, W. Baccus, M. Paczynski, and H. Ayaz, "Into the wild: Neuroergonomic differentiation of hand-held and augmented reality wearable displays during outdoor navigation with functional near infrared spectroscopy," *Frontiers in Human Neuroscience*, vol. 10, p. 216, 2016.

[17] S. Balters and M. Steinert, "Capturing emotion reactivity through physiology measurement as a foundation for affective engineering in engineering design science and engineering practices," *Journal of Intelligent Manufacturing*, pp. 1–23, 2015.

[18] A. H. Jamson and N. Merat, "Surrogate in-vehicle information systems and driver behaviour: Effects of visual and cognitive load in simulated rural driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 8, no. 2, pp. 79–96, 2005.

[19] M. Blanco, W. J. Biever, J. P. Gallagher, and T. A. Dingus, "The impact of secondary task cognitive processing demand on driving performance," *Accident Analysis & Prevention*, vol. 38, no. 5, pp. 895–906, 2006.

[20] L. Nunes and M. A. Recarte, "Cognitive demands of hands-free-phone conversation while driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 5, no. 2, pp. 133–144, 2002.

[21] D. Haigney, R. Taylor, and S. Westerman, "Concurrent mobile (cellular) phone use and driving performance: task demand characteristics and compensatory processes," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 3, no. 3, pp. 113–121, 2000.

[22] Y.-C. Lee, J. D. Lee, and L. N. Boyle, "Visual attention in driving: the effects of cognitive load and visual disruption," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 49, no. 4, pp. 721–733, 2007.

[23] G. Singh and M. Manivannan, "Drowsiness detection system for pilots," in *ICoRD'13*. Springer, 2013, pp. 991–1003.

[24] S. Sibi, H. Ayaz, D. Kuhns, D. Sirkin, and W. Ju, "Monitoring driver cognitive load using near infrared spectroscopy in partially autonomous cars," *Accepted to the 2016 IEEE Intelligent Vehicles Symposium, Gothenburg, Sweden*, 2016.

[25] K. Yoshino, N. Oka, K. Yamamoto, H. Takahashi, and T. Kato, "Functional brain imaging using near-infrared spectroscopy during actual driving on an expressway," *Frontiers in human neuroscience*, vol. 7, p. 882, 2013.

[26] H. Tsunashima and K. Yanagisawa, "Measurement of brain function of car driver using functional near-infrared spectroscopy (fnirs)," *Computational intelligence and neuroscience*, vol. 2009, 2009.

[27] T. Shimizu, S. Hirose, H. Obara, K. Yanagisawa, H. Tsunashima, Y. Marumo, T. Haji, and M. Taira, "Measurement of frontal cortex brain activity attributable to the driving workload and increased attention," *SAE International Journal of Passenger Cars-Mechanical Systems*, vol. 2, no. 1, pp. 736–744, 2009.

[28] T. J. Huppert, S. G. Diamond, M. A. Franceschini, and D. A. Boas, "Homer: a review of time-series analysis methods for near-infrared spectroscopy of the brain," *Appl. Opt.*, vol. 48, no. 10, pp. D280–D298, Apr 2009. [Online]. Available: http://ao.osa.org/abstract.cfm?URI=ao-48-10-D280

[29] S. Brigadoi, L. Ceccherini, S. Cutini, F. Scarpa, P. Scatturin, J. Selb, L. Gagnon, D. A. Boas, and R. J. Cooper, "Motion artifacts in functional near-infrared spectroscopy: a comparison of motion correction techniques applied to real cognitive data," *Neuroimage*, vol. 85, pp. 181–191, 2014.

[30] J. M. Baker, N. Liu, X. Cui, P. Vrticka, M. Saggar, S. H. Hosseini, and A. L. Reiss, "Sex differences in neural and behavioral signatures of cooperation revealed by fnirs hyperscanning," *Scientific reports*, vol. 6, 2016.

[31] T. Grossmann and M. H. Johnson, "Selective prefrontal cortex responses to joint attention in early infancy," *Biology Letters*, vol. 6, no. 4, pp. 540–543, 2010.

[32] S. Tsujimoto, T. Yamamoto, H. Kawaguchi, H. Koizumi, and T. Sawaguchi, "Prefrontal cortical activation associated with working memory in adults and preschool children: an event-related optical topography study," *Cerebral cortex*, vol. 14, no. 7, pp. 703–712, 2004.

[33] E. T. Solovey, M. Zec, E. A. Garcia Perez, B. Reimer, and B. Mehler, "Classifying driver workload using physiological and driving performance data: two field studies," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2014, pp. 4057–4066.

[34] H. Harada, H. Nashihara, K. Morozumi, H. Ota, and E. Hatakeyama, "A comparison of cerebral activity in the prefrontal region between young adults and the elderly while driving," *Journal of physiological anthropology*, vol. 26, no. 3, pp. 409–414, 2007.

[35] Z. Li, M. Zhang, X. Zhang, S. Dai, X. Yu, and Y. Wang, "Assessment of cerebral oxygenation during prolonged simulated driving using near infrared spectroscopy: its implications for fatigue development," *European Journal of Applied Physiology*, vol. 107, no. 3, pp. 281–287, 2009.

[36] G. Bonmassar, P. L. Purdon, I. P. Jääskeläinen, K. Chiappa, V. Solo, E. N. Brown, and J. W. Belliveau, "Motion and ballistocardiogram artifact removal for interleaved recording of eeg and eps during mri," *Neuroimage*, vol. 16, no. 4, pp. 1127–1141, 2002.

[37] N. A. Badcock, P. Mousikou, Y. Mahajan, P. de Lissa, J. Thie, and G. McArthur, "Validation of the emotiv epoc® eeg gaming system for measuring research quality auditory erps," *PeerJ*, vol. 1, p. e38, 2013.