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# Monitoring Driver Cognitive Load using Functional Near Infrared Spectroscopy in Partially Autonomous Cars

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*Abstract*—**In partially automated cars, it is vital to understand the driver state, especially the driver's cognitive load. This might indicate whether the driver is alert or distracted, and if the car can safely transfer control of driving. In order to better understand the relationship between cognitive load and the driver performance in a partially autonomous vehicle, functional near infrared spectroscopy (fNIRS) measures were employed to study the activation of the prefrontal cortex of drivers in a simulated environment. We studied a total of 14 participants while they drove a partially autonomous car and performed common secondary tasks. We observed that when participants were asked to monitor the driving of an autonomous car they had low cognitive load compared to when the same participants were asked to perform a secondary reading or video watching task on a brought in device. This observation was in line with the increased drowsy behavior observed during intervals of autonomous system monitoring in previous studies. Results demonstrate that fNIRS signals from prefrontal cortex indicate additional cognitive load during manual driving compared to autonomous. Such brain function metrics could be used with minimally intrusive and low cost sensors to enable real-time assessment of driver state in future autonomous vehicles to improve safety and efficacy of transfer of control.**

## I. INTRODUCTION

What secondary activity should drivers of partially autonomous cars perform while the automated system drives the car?

In NHTSA Level 3 automation, drivers can engage in secondary activities while the vehicle drives. Traditionally, research around brought-in devices usage during driving has been the provenance of distracted driving research. However, secondary activities require significant cognitive processing resources which may affect the driver’s ability to retake control if necessary. Thus it is important to identify ways to monitor drivers’ cognitive load while performing secondary activities while the car drives. Accurate assessment of mental workload could prevent operator error and allow facilitate intervention by predicting performance decline that can arise from either work overload or under-stimulation [5, 6, 7, and 8]. This assessment also helps the designers of partially automated driving systems better understand the mental processes of the driver.

Physiological measures are used with increasing reliability to assess driver state indicators such as stress, alertness and cognitive load [9]. They offer the possibility of passively monitoring driver states over an extended period of time without disrupting subject immersion in the experiment. Physiological measures such as heart rate, heart rate variability and respiration rate have been shown to be sensitive to operator workload [10]. Other physiological measures such as eye tracking and blink detection are popular research tools that have been adopted by human computer interaction researchers [11]. Pupil dilation, gaze directions and blink rate [12,13] provide vital information into operator workload and have been used with high levels of success in detecting difficulty levels of in vehicle and driving tasks.

Functional near infrared spectroscopy (fNIRS) is an emerging portable brain imaging approach that utilizes near infrared light and provide cortical oxygenation changes to assess localized brain activity. Traditional Neuro-ergonomic approaches based on measures of human brain hemodynamic or electromagnetic activity can provide for sensitive and reliable assessment of human mental workload in complex driving environments [14]. Neurological measures such as Electroencephalograph (EEG) have been used to study the cognitive load and attentional demand of experimental subjects [15, 16]. However, the artifacts in an EEG output due to muscle activity during motion, movement of electrodes and loss of contact during an experiment make the experiment and the subsequent analysis cumbersome. fNIRS systems provide some advantages over traditional neuro-ergonomic research in human computer interaction [14]. fNIRS systems are able to measure the oxygenated and deoxygenated hemoglobin content in the surface of the prefrontal cortex. They are reliably used to study the cognitive workload of subjects using derived oxygenation values in the prefrontal cortex [17, 18, 19, 20]. The fNIRS systems can be miniaturized, built as battery operated and wearable sensors. Furthermore, fNIRS provides balance of spatial and temporal resolutions compared to traditional neuroimaging systems. These qualities pose fNIRS as an ideal candidate for Neuro-ergonomic investigations of the brain in real world settings. In recent years, the use of fNIRS grew exponentially as the systems matured and has proven particularly beneficial for measuring workload during complex cognitive tasks [21, 22,

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23, 24, 25, 26]. These measurements can provide a "ground truth" to benchmark and provide correlate measurements for less invasive and lower cost sensors that might be deployed for commercial installation in cars.

## II. Prior Work

There are many reasons to believe that drivers will use brought-in devices, such as cellular phones or table computers, in partially autonomous cars. Already, the usage of brought-in devices is increasing in vehicles: NHSTA reports that most drivers make use of cellular phones while driving [2]; there is a growing trend towards use of smart phones and other brought in devices [3]; a third of drivers 18-24 years of age believe they can take their eyes off the road for 3 to 10 seconds without increasing risk of accident [4]. The advent of automation makes such behaviors less risky, but a sudden transfer of control due to failure of automation or occurrence of a critical event on the road ahead at a moment when the driver is distracted could result in an accident after the transfer.

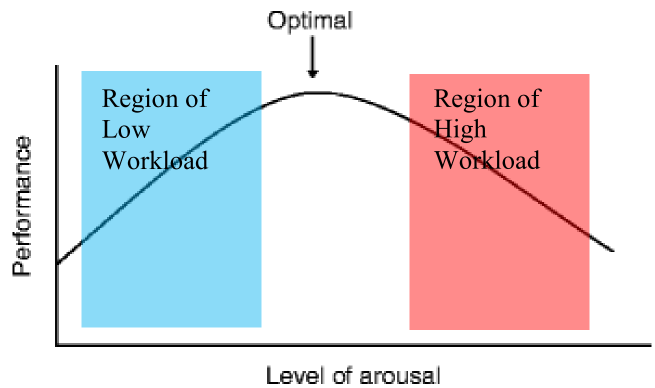
Studies of traditional manual driving indicate that increases in driver cognitive load from secondary tasks lead to a decrease in driving performance. In a study by Blanco et al [27], it was found that there were significant decreases in performance for both automobile and truck drivers when they were asked to perform cognitively demanding secondary tasks on an in-vehicle information system. In another study conducted by Engstrom et al [28] in a driving simulator, cognitive load was manipulated using a secondary task on an in vehicle display where subjects had to identify the presence of an upward facing arrow (target arrow) in a matrix of arrows. It was found that increasing the difficulty of the secondary (arrow identification) task decreases the longitudinal speed of drivers and increases the standard deviation of their lateral position on the road.

Conversely, in studies of partially automated systems, operator underload or under stimulation of operators also causes a reduction in performance. In a recent study conducted by Miller et al [29], drivers exhibited higher incidences of drowsy behavior when monitoring the autonomous car's driving than when they performed a secondary activity on a brought in device. Drowsiness was measured by number of incidences of prolonged eye closure and yawns. While this finding is novel for partially autonomous vehicles, it echoes findings present in earlier research works. The Yerkes-Dodson law, for example, states that the performance follows an inverted U-function with respect to arousal. In other words, performance for easier tasks is improved by increasing the arousal and for tougher tasks can be improved by reducing arousal to an optimal level [31,32]. Verplank proposed in his studies with tele-robotic operators that little or absence of any cognitive workload ("cognitive underload") would be just as dangerous as high cognitive workload ("cognitive overload") in operators of partially automated systems [30].

## III. Experiment Goals

Prior works indicate while that a secondary task is detrimental to driver performance when manually driving, the lack of secondary task in automated driving causes drowsiness and sleepy behavior. We hypothesize that the addition of a secondary task causes the operator workload during manual operation to shift to the higher arousal region of the Yerkes-Dodson U function, while the absence of a secondary task when automation is engaged causes the operator workload to shift to the lower arousal regions. Hence both cases result in a decrease in driver performance.

Figure 1. Inverted U function of performance and arousal, Yerkes-Dodson law




In order to analyze the effect of secondary tasks on operator workload during automated driving further, we replicate the study design created by Miller, et al, but with neuro-ergonomic measures that allow us to better monitor arousal and cognitive load during the course of the experiment. As in Miller's study design, drivers were assigned different secondary tasks in different portions of the simulated drive when the car's automation systems were engaged. The three secondary tasks were reading (R), watching a video (V) and monitoring the car's driving (M). The reading and video activity (performed on a brought in device) were chosen in order to visually and cognitively stimulate the driver. The monitoring activity in combination with a low stimulating simulation environment was expected to cause a decrease in driver workload.

The goals for the experiment were:

1. To measure the cognitive load for three separate secondary tasks and while using the autonomous driving control of a partially autonomous vehicle and the cognitive load during manual driving.
2. To understand the effect of cognitive load imposed by the secondary task on driving performance immediately after the transfer of control.

## IV. Experiment Setup

### A. Experiment Settings

The experiment used a driving simulator with a fixed base vehicle, a seamless 270-degree cylindrical projection screen (Fig 2), separate channels for the side and rear view mirrors and an in-vehicle instrument cluster interface (Fig 3). The simulated world for the driving simulator was designed and

Figure 2. Driving Simulator used in experiment, showing the 270 degree cylindrical screen and in-simulator vehicle

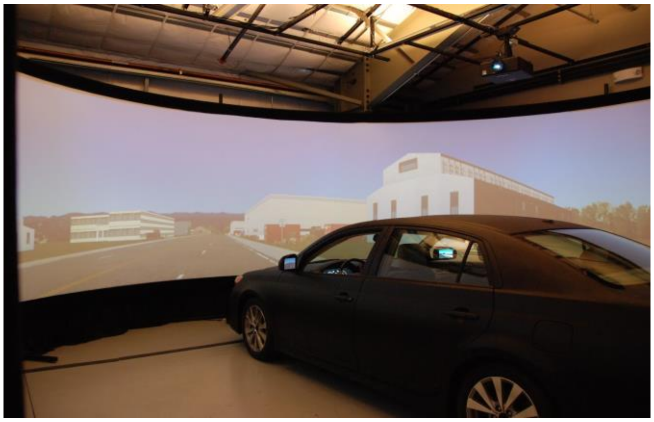


Figure 3. Steering wheel and Instrument Cluster inside the simulator vehicle.

constructed by the experimenters of this study.

The simulator has an autonomous control feature which, when engaged, controls the longitudinal speed, steering and lane keeping functions of the car in the simulator. The autonomous system avoids collisions and stops at traffic signals and stop intersections as required by rules of the road. All drive data from the experiment is recorded as a log file in the form of time series of data at 60Hz. Drive data such as accelerator pedal position, brake pedal position, steering angle position, longitudinal speed etc. are recorded and are used to study driver performance.

### B. *Participants*

A total of 14 subjects, 11 males and 3 females, between the ages of 18 to 30 (M = 24.08, SD = 3.55) participated in the study. Participant performed all three secondary activities and the order of the secondary tasks was counterbalanced. Participants were recruited using on-line postings on public forums.

### C. *Procedure*

The duration of the study ranged from 35 to 40 minutes, depending on the participant's driving speed. During the drive, participants were provided audio and visual alerts indicating an impending transfer of control from the automated system. Once the transfer of control was initiated, the drivers had 5 seconds to take over control of the car from the automated driving system or cede control of the car to the automated driving system. If the driver did not take or cede control, the control was automatically transferred at the end of the 5 second interval.

The overall study structure is shown in Figure 4. After a short (~5 min) practice segment, the study contained three 8 minute 30 second intervals of autonomous driving. During these intervals, participants were asked to pursue the secondary activities: reading, video watching or monitoring the car's driving. Each interval of autonomous driving was followed by a critical event to test driver performance immediately after the transfer of control.

Two types of critical events were used in the study. The Car Cut-off event and the Pedestrian event. In the Car Cut-off event, another car in the environment approached the driver's car in the adjacent lane and moved quickly and laterally in front of the subject. In the Pedestrian event, an "actor" in the simulation crossed the road in front of the driver. These events are shown in the Figure 5.

Throughout the experiment, the anterior prefrontal cortices of participants were monitored using a continuous wave fNIR Device model 1100 fNIR system that was designed at Drexel University and manufactured by fNIR Devices LLC (Photomac MD; www.fnirdevices.com). During the study, the data from the fNIRS device were recorded on a separate system using COBI Studio software [33]. To prevent ambient

Figure 4. Study design showing the duration of drive and the occurrence of transfer of controls. All number indications are duration of segments in minutes.

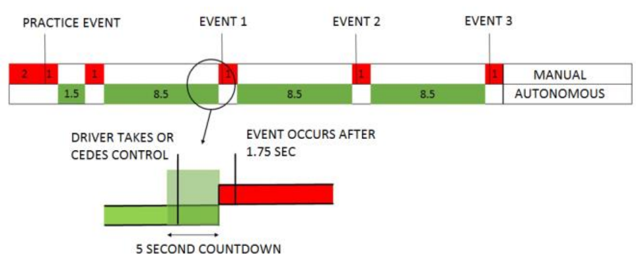



Figure 5. Illustration of Car Cut-off event (top left to right) and Pedestrian Event (bottom left to right)

Figure 6. Participant wearing the fNIRS device with covering headband to prevent ambient light (top). Brain measurement locations, optodes, on prefrontal cortex brain surface image (bottom)


light leakage, participants wore a black covering cloth band over the fNIRS sensor pad. Data for durations of automated and manual driving were extracted identified using markers.

## V. Results and Analysis

### A. Brain Activation Results

For each participant, raw light intensity fNIRS data (16 optodes×2 wavelengths) were low-pass filtered with a finite impulse response, linear phase filter with order 20 and cut-off frequency of 0.1 Hz to attenuate the high frequency noise, respiration and cardiac cycle effects. All participant data were checked for any potential saturation (when light intensity at the detector was higher than the analog-to-digital converter limit) and motion artifact contamination by means of a coefficient of variation based assessment [34]. The fNIRS data for each task block were extracted using time synchronization markers of task onset and end marked during the experiment and hemodynamic changes for each of 16 optodes during each trial block were calculated separately using the Modified Beer Lambert Law (MBLL). The final output of each optode is a measure of mean block oxygenation that is the difference in oxygenated hemoglobin and deoxygenated hemoglobin concentration changes.

First, we compared the manual and autonomous only driving conditions. As expected, autonomous driving required less mental effort which was reflected in lower activation. Results indicated that a significant difference was present for optode 5 ($F_{1,17}$ = 13.6 $p<0.002$), optode 7 ($F_{1,17}$ = 7.51 $p<0.02$), optode 9 ($F_{1,13}$ = 13.56 $p<0.003$), optode 11 ($F_{1,17}$ = 7.98 $p<0.02$), optode 13 ($F_{1,21}$ = 5.93 $p<0.03$), optode 14 ($F_{1,15}$ = 7.08 $p<0.02$) and optode 15 ($F_{1,19}$ = 16.6 $p<0.001$) using nonparametric Friedman's test with false discovery rate (FDR) correction. These results are shown in Figure 7.

Figure 7. Comparison of manual and autonomous driving mental effort as indicated by oxygenation changes in left and right hemisphere. Error bars are the standard error of the mean (SEM).

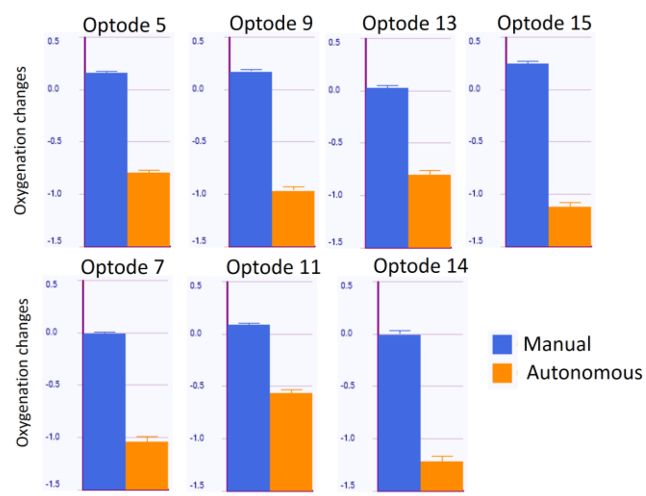



Figure 8. Projection of F-statistics map on brain surface image indicates right hemisphere dominance. Based on [x], BSpline interpolation was used to generate surface representation from F values of comparisons of manual vs. autonomous conditions along with thresholding determined by FDR.

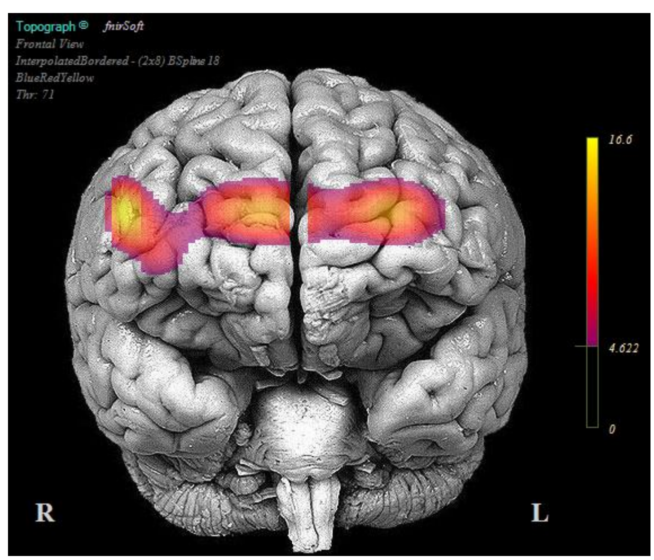
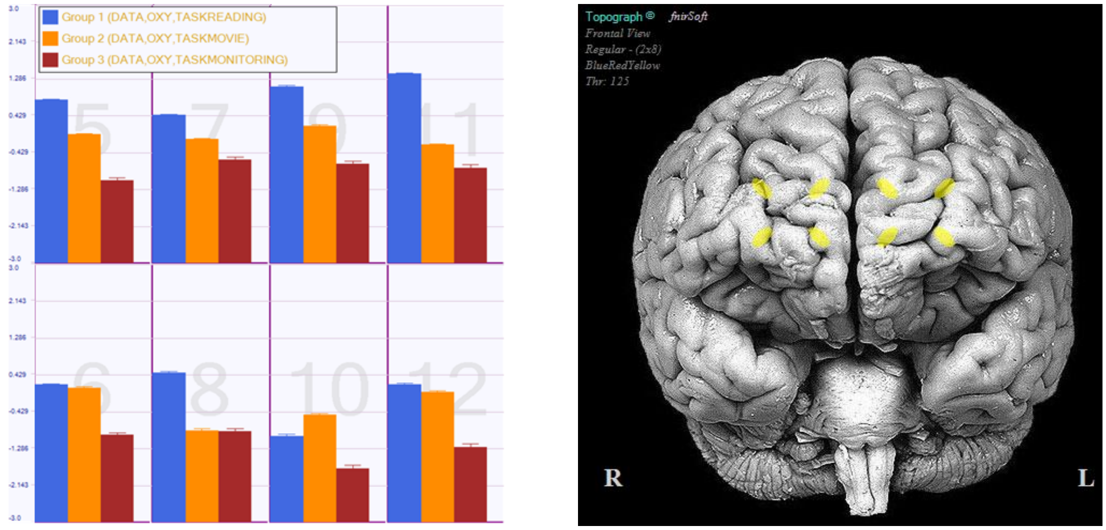


Figure 9. Comparison of Reading, Video Watching and Monitoring Activity mental effort as indicated by oxygenation changes in prefrontal cortex(left) (Error bars are standard error of the mean). Optodes where the oxygenation changes were measured (bottom).

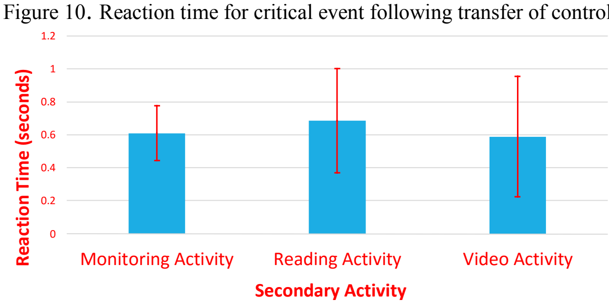



For each participant, the oxygenation changes during the three activities (reading, video watching and monitoring tasks) were also analyzed. The activities were all performed while the automated systems in the car controlled the car's driving. The oxygenation levels for each activity were measured and averaged over intervals between markers placed during the experiment and are indicative of the relative cognitive load of the driver while performing the secondary tasks. The oxygenation levels in the frontopolar region are shown in Figure 9 below.

### *B. Driver Performance Analysis*

Data from the simulator were extracted and analyzed using MATLAB®. Driver performance was measured using the reaction time of driver to critical events. The start of Car Cut-off event is marked by the instant the cut-off car begins its lateral transition into the subject's lane. The start of the pedestrian critical event is marked by the instant the pedestrian begins walking into the subject's driving lane. Reaction time was measured from the start of the event (marked by an event marker in the simulator log) to the first instance of response by the driver in the simulator. Upon analysis of results, it was found that there was no significant difference in reaction times across all three conditions. The results are analyzed and displayed below in Figure 10.

Figure 10. Reaction time for critical event following transfer of control.




## VI. Discussion

The frontal cortex oxygenation changes indicate a significantly lesser cognitive load of the drivers during the autonomous mode than during manual driving mode. This supports the hypothesis that drivers are cognitively under-loaded when the automation is engaged and the use of automated driving systems shifts operator workload to the lower arousal regions of the Yerkes-Dodson inverted U-function.

Cognitive load as measured by prefrontal cortex activation for the secondary tasks performed showed that the drivers experienced relatively lower cognitive load when asked to monitor the driving of the automated system and relatively high cognitive load while reading. Extended periods of lower cognitive load correlates with drowsy and sleepy behavior and is consistent with observations made by Miller et al [29].

While the observations in cognitive load show clear trends, there is no significant difference in the reaction time of the driver during the critical events following the transfer of control. This highlights in the additional information gained from brain activity measures. We believe that the structured nature and lengthy time duration of the transfer of control are the reasons for this observation.

## VII. Limitations

While the use of functional near infrared spectroscopy is effective in providing fine-grain measurement of cognitive workload, it may not be suited for everyday use in cars yet. However, this type of measure can provide deeper explanations for behaviors witnessed in cars--sleepiness due to lack of cognitive load, for example. These measures can be used in conjunction with other physiological measures-- gaze detection, heart rate, respiration measurements, etc.--to indicate key driver states before the onset of resulting behaviors arise. Such physiological sensing devices and methods are becoming decreasingly intrusive [35] and have been shown by researchers in the past to be effective for continuous cognitive load measurement [9].

## VIII. CONCLUSION

This study demonstrates the usefulness of fNIRS technology in understanding driver states during automated and manual driving. The contribution of this paper is to understand the mechanism behind previously observed behaviors in autonomous vehicle operators (e.g. vigilance) and analyze the correspondence with cerebral activity changes.

## IX. ACKNOWLEDGMENTS

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## REFERENCES


[1] N. H. T. S. Administration, "Preliminary statement of policy concerning automated vehicles," Washington, DC, 2013..

[2] J. Tison, N. Chaudhary, and L. Cosgrove, "National phone survey on distracted driving attitudes and behaviors," 2011.

[3] M. A. Harrison, "College students' prevalence and perceptions of text messaging while driving," Accident Analysis & Prevention, vol. 43, pp. 1516-1520, 2011.

[4] S. G. Klauer, F. Guo, B. G. Simons-Morton, M. C. Ouimet, S. E. Lee, and T. A. Dingus, "Distracted driving and risk of road crashes among novice and experienced drivers," New England journal of medicine, vol. 370, pp. 54-59, 2014.

[5] H. Ayaz, M. P. Çakır, K. İzzetoğlu, A. Curtin, P. Shewokis, S. C. Bunce, et al., "Monitoring expertise development during simulated UAV piloting tasks using optical brain imaging," in Aerospace Conference, 2012 IEEE, 2012, pp. 1-11.

[6] H. Ayaz, B. Willems, B. Bunce, P. A. Shewokis, K. Izzetoglu, S. Hah, et al., "Cognitive workload assessment of air traffic controllers using optical brain imaging sensors," Advances in understanding human performance: Neuroergonomics, human factors design, and special populations, pp. 21-31, 2010.

[7] P. Hancock and R. Parasuraman, "Human factors and safety in the design of intelligent vehicle-highway systems (IVHS)," Journal of Safety Research, vol. 23, pp. 181-198, 1993.

[8] N. Meshkati, P. A. Hancock, M. Rahimi, and S. M. Dawes, "Techniques in mental workload assessment," 1995.

[9] 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, 2014, pp. 4057-4066..

[10] B. Mehler, B. Reimer, and J. F. Coughlin, "Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task an on-road study across three age groups," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 54, pp. 396-412, 2012.

[11] O. Palinko, A. L. Kun, A. Shyrokov, and P. Heeman, "Estimating cognitive load using remote eye tracking in a driving simulator," in Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications, 2010, pp. 141-144.

[12] T. W. Victor, J. L. Harbluk, and J. A. Engström, "Sensitivity of eye-movement measures to in-vehicle task difficulty," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 8, pp. 167-190, 2005.

[13] J. Veltman and A. Gaillard, "Physiological workload reactions to increasing levels of task difficulty," Ergonomics, vol. 41, pp. 656-669, 1998.

[14] R. Parasuraman and G. F. Wilson, "Putting the brain to work: Neuroergonomics past, present, and future," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 50, pp. 468-474, 2008.

[15] 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, pp. 60-69, 1997.

[16] W. Klimesch, H. Schimke, and G. Pfurtscheller, "Alpha frequency, cognitive load and memory performance," Brain topography, vol. 5, pp. 241-251, 1993.

[17] 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, 2012.

[18] D. Afergan, E. M. Peck, E. T. Solovey, A. Jenkins, S. W. Hincks, E. T. Brown, et al., "Dynamic difficulty using brain metrics of workload," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2014, pp. 3797-3806.

[19] H. Ayaz, P. A. Shewokis, S. Bunce, K. Izzetoglu, B. Willems, and B. Onaral, "Optical brain monitoring for operator training and mental workload assessment," Neuroimage, vol. 59, pp. 36-47, 2012.

[20] S. C. Bunce, K. Izzetoglu, H. Ayaz, P. Shewokis, M. Izzetoglu, K. Pourrezaei, et al., "Implementation of fNIRS for monitoring levels of expertise and mental workload," in Foundations of augmented cognition. Directing the future of adaptive systems, ed: Springer, 2011, pp. 13-22.

[21] H. Ayaz, B. Willems, S. Bunce, P. A. Shewokis, K. Izzetoglu, S. Hah, et al., "Estimation of cognitive workload during simulated air traffic control using optical brain imaging sensors," in Foundations of Augmented Cognition. Directing the Future of Adaptive Systems, ed: Springer, 2011, pp. 549-558.

[22] B. Abibullaev and J. An, "Classification of frontal cortex haemodynamic responses during cognitive tasks using wavelet transforms and machine learning algorithms," Medical engineering & physics, vol. 34, pp. 1394-1410, 2012.

[23] N. Naseer and K.-S. Hong, "Classification of functional near-infrared spectroscopy signals corresponding to the right-and left-wrist motor imagery for development of a brain–computer interface," Neuroscience letters, vol. 553, pp. 84-89, 2013.

[24] C. Bogler, J. Mehnert, J. Steinbrink, and J.-D. Haynes, "Decoding vigilance with NIRS," 2014.

[25] G. Derosière, S. Dalhoumi, S. Perrey, G. Dray, T. Ward, and Y. Hoshi, "Towards a near infrared spectroscopy-based estimation of operator attentional state," PloS one, vol. 9, p. e92045, 2014.

[26] C. Herff, D. Heger, O. Fortmann, J. Hennrich, F. Putze, and T. Schultz, "Mental workload during n-back task—quantified in the prefrontal cortex using fNIRS," Frontiers in human neuroscience, vol. 7, 2013.

[27] 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, pp. 895-906, 2006.

[28] 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, pp. 97-120, 2005.

[29] D. Miller, A. Sun, M. Johns, H. Ive, D. Sirkin, S. Aich, et al., "Distraction Becomes Engagement in Automated Driving," in Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 2015, pp. 1676-1680.

[30] W. L. Verplank, "Is there an optimum workload in manual control? p. 72, 1976.

[31] K. J. Anderson, "Impulsitivity, caffeine, and task difficulty: A within-subjects test of the Yerkes-Dodson law," Personality and Individual Differences, vol. 16, pp. 813-829, 1994.

[32] H. Cai, Y. Lin, and R. R. Mourant, "Study on driver emotion in driver-vehicle-environment systems using multiple networked driving simulators," in Proceedings of the Driving Simulation Conference North America (DSC'07), 2007.

[33] H. Ayaz, P. A. Shewokis, A. Curtin, M. Izzetoglu, K. Izzetoglu, and B. Onaral, "Using MazeSuite and functional near infrared spectroscopy to study learning in spatial navigation," Journal of visualized experiments: JoVE, 2011.

[34] L. C. Schudlo and T. Chau, "Dynamic topographical pattern classification of multichannel prefrontal NIRS signals: II. Online differentiation of mental arithmetic and rest," Journal of neural engineering, vol. 11, p. 016003, 2014.

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