A Preliminary Investigation into Learning Behaviors in Complex Environments for Human-in-the-Loop Cyber-Physical Systems

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The field of Cyber-Physical Systems (CPS) is increasingly recognizing the importance of integrating Human Factors for Human-in-the-loop CPS (HiLCPS) developments. This is because psychological, physiological, and behavioral characteristics of humans can be used to predict human-machine interactions. The goal of this pilot study is to collect initial data to determine whether driving and eye tracking metrics can provide evidence of learning for a CPS project. Six participants performed a series of 12 repeated obstacle avoidance tasks in manual driving. Lane deviations and fixation-related eye data were recorded for each trial. Overall, participants displayed either conservation/safe or aggressive/risky in their lateral position with respect to the obstacle during successive trials. Also, eye tracking metrics were not significantly affected by trial number, but observational trends suggest their potential for aiding in understanding adjustments humans make in learning. Results can inform predictive modeling algorithms that can anticipate and mitigate potential problems in real-time.

INTRODUCTION

In recent years, the field of Cyber-Physical Systems (CPS) has witnessed unprecedented research activity, given the rapid development of smart and connected technologies. By definition, CPS is “a new generation of systems with integrated computation and physical capabilities that can interact with humans through many new modalities” (Baheti & Gill, 2011). CPS aims to integrate knowledge from multiple disciplines and theories such as Controls, Human-Computer Interaction (HCI), learning theory, software, and Electrical, Mechanical, and other engineering areas to solve some of CPS’s most difficult design tasks. One particular task is to effectively incorporate Human-in-the-Loop (HiL) into CPS to ensure that humans have a good understanding of the operations of the systems for which they interact. Farooq & Grudin (2016) explain that “the era of human-computer interaction is giving way to the era of human-computer integration—integration in the broad sense of a partnership or symbiotic relationship in which humans and software act with autonomy, giving rise to patterns of behavior that must be considered holistically.”

Munir et al. (2013) highlights challenges to a HiLCPS approach that suggest the complexity of modeling the dynamic nature of the human. They include: (1) “the need for a comprehensive understanding of the complete spectrum of types of human-in-the-loop controls,” (2) “the need for extensions to system identification or other techniques to derive models of human behaviors,” and (3) “determining how to incorporate human behavior models into the formal methodology of feedback control.”

Several initiatives exist to overcome these challenges. For example, in driving, Liu & Salvucci (2001) inferred driver’s intentions through vehicle control actions, e.g., steering and accelerating, and Munir et al. (2013) suggested that this type of data can be used to develop a model to convert this open loop system to a controlled driver assistive feedback closed loop system that allows the vehicle to provide interventions, such as taking over control or sending alerts. Munir et al. (2013) discusses the remaining challenges in CPS that relate to the need to develop more robust predictive modeling and stochastic predictive control modeling to aid in avoiding preemptive problems and creating adaptive control. This activity will require an even greater understanding of the human.

The field of Human Factors plays a critical role in CPS in order to ensure that human psychological, physiological, and/or behavioral characteristics, as they relate to interactions with systems, are well-understood and captured appropriately in models. The recently funded National Science Foundation (NSF) project, “CPS: Frontier: Collaborative Research: Cognitive Autonomy for Human CPS: Turning Novices into Experts,” recognizes this critical need and integrates work from Computer Science, Electrical, Mechanical, and Industrial Engineering, Human Factors, and Psychology in order to develop methods that hasten learning curves for individuals performing new, complex tasks.

Specifically, this project aims to develop CPS that continually adapts to the human to significantly reduce training time, increase the breadth of the human's experiences with systems prior to operation in a safety-critical environment, and improve overall safety and joint human-machine performance. As part of this work, learning models of the human in various complex environments first need to be generated and then a human-centric architecture for "cognitive autonomy" can be developed that couples human psychophysiological and behavioral measures with objective measures of performance.

As an initial step, this project built upon prior work related to complex driving tasks, and specifically focused on observing learning in obstacle avoidance tasks. To inform research activities, seminal papers that used obstacle avoidance tasks in manual driving were identified. For example, Adams et al. (1995) investigated vehicle controls of braking and steering when an obstacle was present. Their study found that drivers’ initial response was to steer when encountering an unexpected obstacle at higher speeds, but brake when given more time. Also, more optimal obstacle avoidance maneuvers included steering around obstacles and coasting, in combination with braking. In contrast, less effective maneuvers included steering straight while decelerating, accelerating ahead, and simply staying on course without taking actions, which all resulted in collision with the obstacle. In a different study, Broen & Chiang (1996) examined braking response times to unexpected obstacles during a driving simulator task. The main finding that informed the current study was that when drivers were traveling at 25mph, it took on average 1.33 seconds to react and step on the brake pedal.

While these studies are informative regarding the situational strategies that drivers utilize for vehicle handling, as well as the time associated with their decisions, they did not consider other factors that could contribute to the complexity of the task, such as characteristics of the driving environment. They also did not collect psychophysiological data, focused on learning trends, which for today's CPS work is needed to better characterize the human for system adaptations. Research that has studied drivers' gaze behavior primarily focused on driver handling and identifying factors that influence driver performance and safety (e.g., Calvi & Bella, 2014; Grüner & Ansorge, 2017). But, Rosch & Vogel-Walcutt (2013)'s review on eye tracking applications for the purposes of training expresses the need for more research in adaptive environments, including driving.

Thus, in this paper, we report findings from a pilot study that used the obstacle avoidance paradigm to collect preliminary data to evaluate whether evidence of learning could be ascertained. In particular, we designed an experiment with an added level of complexity not required by previous studies, requiring non-dominant hand steering and driving during the nighttime. We also utilized eye tracking to begin gathering psychophysiological data related to human learning in complex tasks. Our goal was to investigate various driving-related and eye tracking metrics that would enable us to describe trends of learning with experimental outcomes. We focus on manual driving, which we expect to provide baseline knowledge regarding how humans complete complex tasks that can inform future studies involving automation.

METHOD

Participants

A total of six participants (3 male, 3 female) with a mean age of 21.33 years (SD = 0.82) volunteered for this pilot study. Participants were recruited from Purdue University (IRB Protocol #1905022220) and were all engineering senior undergraduate students. The average number of years driven across participants was 4.17 years (range: 1 to 7 years). A total of five out of the six participants reported driving less than 10k miles per year, and one participant drove an average of 12k miles per year.

Equipment

This study used a fixed-based medium-fidelity driving simulator developed by the National Advanced Driving Simulator (NADS miniSim). The system is equipped with three 48-inch monitors and one 18.5-inch monitor for displaying the driving environment and the vehicle dashboard display, respectively. There are also two foot-pedals and a steering wheel to capture driver inputs. The system's sampling rate is 60Hz.

Also, a FOVIO FX3 eye tracking system (31cm × 40cm), developed by Seeing Machines Inc. Canberra, Australia was utilized. This system is contact-free and mounted behind the steering wheel located below the main center display. This system also has a sampling rate of 60Hz. Eye tracking data was collected and analyzed using the EyeWorks Suite (EyeTracking, Inc., USA).

Driving Scenario

The driving environment was a two-lane nighttime city environment. The roadway consisted of four S-curve shaped segments and four straightaways that preceded each S-curve segment. One obstacle (an old vehicle tire) was placed at the beginning of each S-curve at the same location (see Figure 1). There were no other vehicles in the scenario, i.e., no oncoming traffic, leading, nor trailing vehicles. Streetlights were present along both sides of the road for the duration of the drive. The obstacles were placed within the curves, so they were not visible to the participant until they rounded the curve.

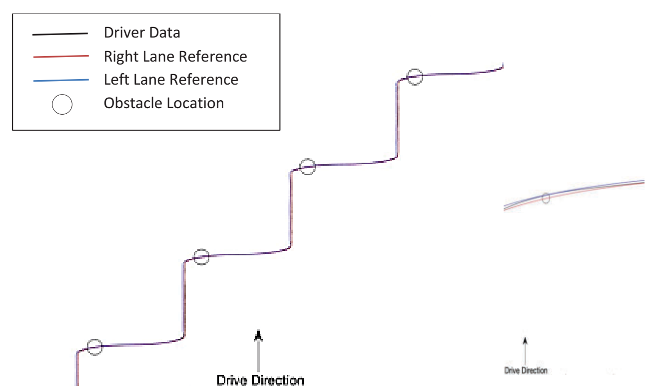


Figure 1. Bird's-eye view of road network of the driving scenario with right and left reference lanes and driver data; zoomed in reference window (right-side image)

Procedure

Participants were first asked to complete a practice drive during daytime on an open highway to familiarize themselves with the driving simulator and task. The actual driving scenario was comprised of an obstacle avoidance task. The task was to drive in a nighttime context on a two-lane city highway (see Figure 2) and avoid any roadway obstacles that might be present. Each participant was given the same set of instructions: (1) practice safe driving (i.e., stay within the lane boundaries), (2) drive at a constant speed of 45 mph throughout the session, and (3) if an obstacle was encountered, avoid the obstacle by moving into the opposite lane as quickly as possible; once cleared, move back into the original lane and resume a constant speed of 45mph.

Each participant drove the scenario on three separate trials (four obstacles in each), for a total of 12 obstacle events. Each drive lasted approximately four minutes. As mentioned, to increase the level of difficulty of the task, participants were asked to drive one-handed, with their non-dominant hand, throughout the entire pilot experiment.

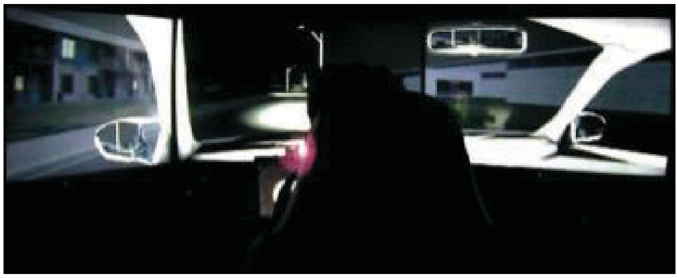


Figure 2. Nighttime driving scene from pilot study

Dependent Measures and Data Analysis

Driving performance was measured using the vehicle's lane deviation (in feet), similar to lateral movement measured in Adams et al. (1995). This represented the distance between the subject vehicle and the obstacle at the time of avoidance. In other words, this measure indicated the maximum distance the subject vehicle was from the obstacle as it entered into the left, opposite lane.

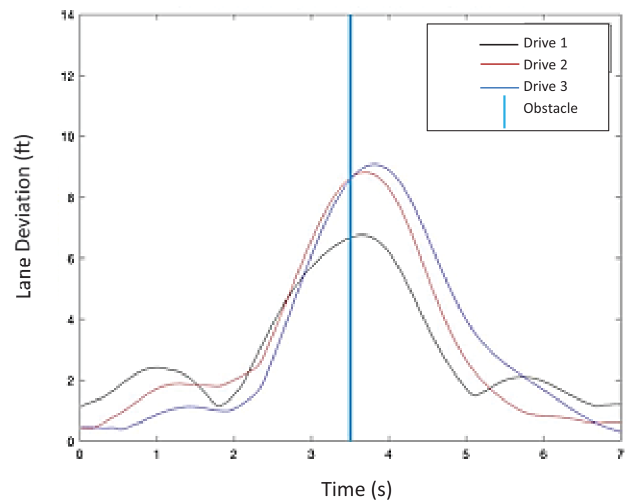
Eye tracking is often used in Human Factors research to assess attention allocation (e.g., Rosch & Vogel-Walcutt, 2013; Zhang et al., 2020). For the eye tracking analysis, the driving scenario was divided into three segments: (1) 7 seconds on the straightaway before the first curve with an obstacle, (2) 3 seconds during obstacle avoidance period, and (3) 7 seconds on the straightaway at the end of the S-curve (and obstacle). An area of interest (AOI) was drawn in the subject vehicle's lane during the straightaway sections, and also around the obstacle in the 3-second section. Eye tracking metrics included: (1) number of fixations in each AOI (i.e., all fixations within the defined area and period), (2) average fixation duration in AOIs (i.e., total duration of all fixations in defined area), (3) gaze percent observed in each AOI (i.e., percentage of gazes within the defined area), and (4) mean fixation pupil size dilation (in millimeters) in AOIs (i.e., average pupil dilation within the defined area and period). These metrics represent the number of times, the location, and the length of time drivers fixate in the AOIs in the divided segments (Moacdieh & Sarter, 2015). The fixation threshold was set to 100 milliseconds.

Observational analysis was performed on the behavioral measure. Also, Friedman tests were conducted on the eye tracking data using IBM SPSS Statistics 26. Results were considered significant at $p < 0.05$.

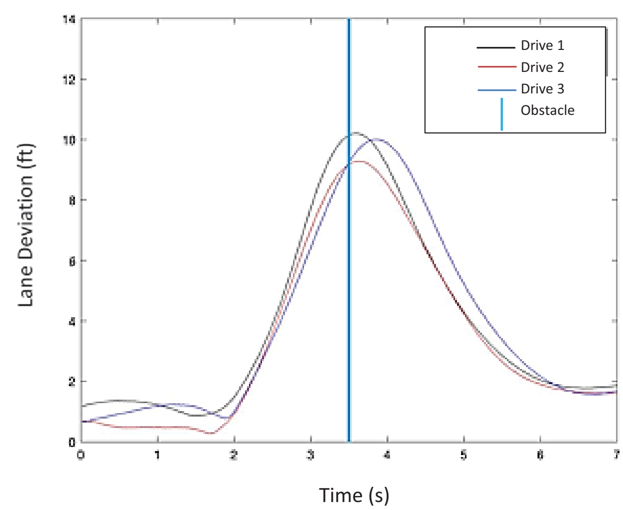
RESULTS

Lane Deviation

As mentioned, there was a total of three trials, or drives, completed by each of the six participants. The average lane deviation over four obstacle avoidances was calculated, and the results were combined into a single plot that depicted each drive. Two distinctive patterns emerged from the participants' behavior in terms of how they navigated the curves. The first was that four out of the six participants displayed more conservative driving behavior in that they tended to drive farther away from the obstacle in successive trials compared to their first drive (see Figure 3a). The second trend was that two out of the six participants showed more aggressive behavior, meaning that they tended to drive closer to the obstacle in subsequent drives compared to their first drive (see Figure 3b). Currently, these categorizations are being used to label driver behavior for prediction modeling within the larger CPS team. In Figures 3a and 3b, the solid vertical line at time = 3.5 seconds denotes the location of the obstacle.



(a) Conservative



(b) Aggressive

Figure 3. Representation of lane deviation (obstacle avoidance) output for (a) one conservative/safe driver and (b) one aggressive/risky driver over their three trials/drives

Eye Tracking

Using the trends noted in the lane deviation data, eye tracking data were stratified based on conservative vs. aggressive classifications. However, since there were only two participants in the aggressive group, we only analyzed eye data for the conservative group. Also, at this stage of the project, only two metrics appeared to have observational trends, i.e., average fixation duration in AOIs and average fixation pupil size in AOIs. In addition, only in the 7-second straightaway segment before the first curve with the obstacle generated any further observational trends for these metrics (see Figures 4 and 5, respectively).

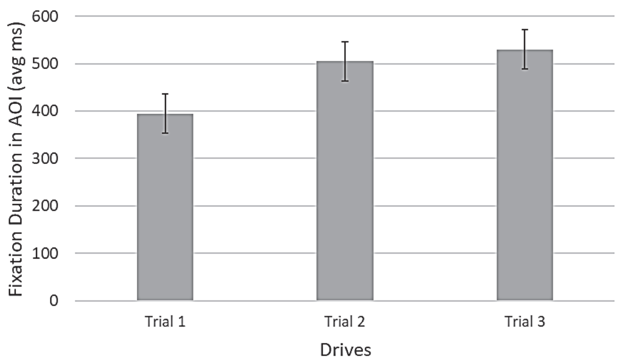


Figure 4. Average fixation duration in AOI (milliseconds) for all four conservative drivers for each trial
Note. Error bars: ±SE

A Friedman test was used to determine whether the distributions for Trial 1, Trial 2, and Trial 3 were the same for the average fixation duration in AOI for the 7 seconds before the first curve. Average fixation duration did not significantly increase between the trials, $\chi^2(2) = 1.500$, $p = .472$ (i.e., Trial 1 *Median (Mdn)* = 427.50 secs; Trial 2 *Mdn* = 481.50 secs; Trial 3 *Mdn* = 452.00 secs).

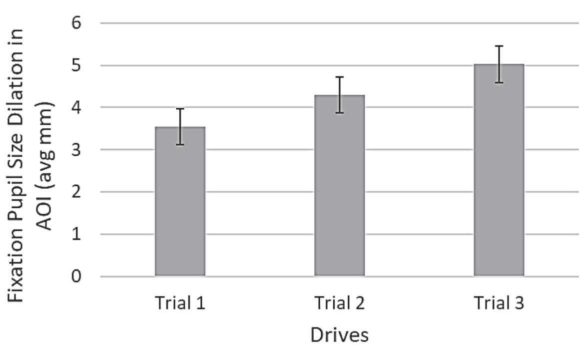


Figure 5. Average fixation pupil size dilation (millimeters) for all four conservative drivers for each trial
Note. Error bars: ±SE

Similarly, average pupil size did not significantly increase between the trials, $\chi^2(2) = 0.500$, $p = .779$ (i.e., Trial 1 *Mdn* = 3.57 mm; Trial 2 *Mdn* = 5.09 mm; Trial 3 *Mdn* = 5.05 mm).

Overall, although preliminary visual inspection suggests increasing trends in the eye tracking measures, at this stage in the pilot study, no statistical differences were found among the drives.

DISCUSSION

The goal of this pilot study was to investigate driving-related and eye tracking metrics that could enable us to observe learning from the experimental data. To this end, participants completed a series of drives, where they needed to avoid 12 roadway obstacles. Two notable obstacle avoidance trends emerged from the data: some drivers displayed conservative/safe driving behavior, while others showed more aggressive/risky navigation around obstacles. Also, though not significantly different between the driving trials with the current dataset, preliminary eye tracking data highlight potential for aiding in understanding adjustments humans make during the learning process. This work represents an important first step in evaluating, modeling, and predicting human behavior, which is considered an essential aspect to Human-in-the-Loop cyber-physical systems (HiLCPS) (Jirgl et al., 2018).

It is not too surprising that a dichotomous pattern was observed in the behavior of our participants, given individual differences and the variety of ways that people can respond to aspects in life. In fact, the conservative and aggressive categorizations have been exploited in previous research. For example, Das & Ahmed (2019) utilized conservative and aggressive driving behavior designations for naturalistic manual driving but, in contrast, monitored lane-changing under weather conditions. Their designations were related to drivers' risk perception, and they found that aggressive drivers drove at higher speeds and initiated more lane changes than conservative drivers, regardless of traffic or weather conditions. For our research, these categorizations are useful in delineating different approaches to skill development over time. In contrast to Adams et al. (1995), who measured lateral movement to investigate whether drivers collided with or avoided obstacles, we first used this direct (lateral) measure to implicate the process of learning. However, given the nature of our driving task, several other complementary driving-related metrics could be informative regarding one's learning behavior. For example, braking response time, maximum braking force, and average pedal acceleration position can be used to identify various input strategies employed by drivers for a given task, as well as how they change over time. For example, it may be implied that a driver is adopting a coasting strategy if pedal acceleration position decreases, while braking force remains at zero. We plan to analyze and report the findings from these measurements as our CPS study continues.

For the eye tracking data, visual inspection of the pilot data suggests that both average fixation duration in AOI and average pupil size could become sensitive to repeated trials with a larger sample size (as the study continues). If this is the case, in terms of learning, one can speculate that as the average fixation duration increases with successive trials, participants may be spending more time visually preparing for the future imminent obstacles. This could also explain why pupil size may potentially increase. Pupil dilation has been found to reflect changes in cognitive workload (Charles & Nixon, 2019), and drivers may devote more time and attention to (thus experience higher workload in) subsequent trials, in hopes to improve handling behavior. It is also feasible to posit that as a person practices this particular task overtime, gaze duration in the AOI will likely decrease due to familiarity and skill development gained through repetition – both of which may lessen the level of vigilance needed on successive trial. Alternatively, as the study progresses, if no differences in eye behavior among trials are observed, then the design of the driving task may not induce significantly changes to drivers' cognitive workload.

In summary, to assess human behavior for interactions with future adaptive and highly autonomous systems, it is important to employ methods that enable obtaining data about human interactions through devices/sensors (Spurgin, 2009). Given that this is a pilot study working towards this goal, we are continuing our data collection efforts. In addition, our CPS project is creating algorithms for predictive modeling and verification, e.g., via stochastic reachability, that can anticipate and mitigate potential problems in real-time. Findings from this pilot study will be used to inform the design of future experiments that will consider the use of additional psychophysiological sensing techniques, such as electroencephalography (EEG) and Galvanic Skin Response (GSR), new experimental designs/platforms, and additional data analysis.

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