Using Driver State Detection in Automated Vehicles

SAFETY RESEARCH USING SIMULATION

UNIVERSITY TRANSPORTATION CENTER

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Table of Contents

List of Figures

List of Tables

Abstract

The next several years will bring a large increase in automated vehicle capabilities. High levels of automation will require bi-directional transfers of control between the driver and vehicle. These control transfer situations pose one of the greatest potential safety shortfalls. One specific issue that arises is that drivers may be unfit or ill-prepared to retake control from the vehicle because of distraction, drowsiness, or intoxication. Driver state monitoring systems based on eye tracking, head tracking, and other measures may be useful in such situations. The goal of this project was to examine how driver state monitoring could be used in the context of an automated vehicle. Using data from a production driver monitoring system, we examined two approaches to using driver state information. One method provided feedback throughout the drive when drivers were classified as distracted (i.e., attentional maintenance). The other method utilized state-contingent takeover messages, which provided earlier warnings when drivers were distracted. These were compared against a baseline drive in which the automation did not use driver state information. The results indicated that providing attentional maintenance alerts throughout the drive increased drivers' situational awareness and enhanced takeover during unexpected automation failures. Although state-contingent takeover requests improved some components of the takeover process, there was limited evidence that they improved takeover performance relative to baseline. This study highlights the potential utility of data from driver monitoring systems in the context of partial vehicle automation.

1 Introduction

1.1 Background

More than 90% of road accidents are caused by human error [1]. By taking some or all vehicle control responsibilities from human drivers, automation has the potential to significantly reduce crash risk and increase safety. SAE defines five different levels of automation based on the allocation of control between the driver and the automated system [2]. These levels range from 0, or no automation, to 5, or complete automation capable of entirely controlling the vehicle in any context. From a human factors perspective, some of the greatest challenges arise at SAE Levels 2 and 3, or what is commonly referred to as partial or conditional automation. Here, automation controls the vehicle within a defined operational context, but the driver is considered the fallback, capable of taking back control quickly should the automation fail or encounter a situation it is not capable of handling.

This expectation then necessitates that the driver remain attentive and engaged in the driving task (i.e., in the control loop). Because failures or other takeover situations may arise at any time, they should never disengage from the dynamic driving task to an extent that they cannot quickly retake control from the automated system. This essentially turns driving into a monitoring task, where the driver monitors both the environment and automation. Decades of research, however, have shown that humans are poor monitors [3]. Within many monitoring tasks, such as tracking air traffic control displays, even short periods of monitoring result in vigilance decrements. Recent research indeed shows that disengagement from driving can slow takeover time and quality [4].

1.2 Driver Monitoring

Recent technological developments make it possible to actively monitor the state of the driver. Such systems rely on a host of data sources, from camera-based systems that monitor the driver’s head and eyes, to steering wheel manipulation and lane position [e.g., 5, 6, 7]. In the context of partially and highly automated vehicles, camera-based methods will be most effective because vehicle control systems are under automated control.

If one is able to understand when the driver is or is not engaged with the driving task, it may be possible to provide feedback and keep the driver in or on the control loop. An example of one such system is GM Super Cruise, which uses a camera-based system to monitor the driver and provide feedback in the form of alerts when the driver’s eyes have been off the road for several seconds.

Driver state information could also be used to modify the takeover process by allowing distracted or otherwise impaired drivers more time to retake control of the vehicle. Out-of-the-loop drivers require more time to reestablish situation awareness (SA) than attentive drivers [8], so providing additional transition time, when possible, might allow distracted drivers sufficient time to reengage SA and decide on and execute responses.

1.3 Objectives and Research Questions

The goal of this project was to examine how driver state monitoring can be used in the context of conditional vehicle automation. The study used a production camera-based driver monitoring system (DMS) and custom state classification algorithm to identify driver distraction. We used this driver state information to drive two human-machine interfaces for driver distraction, one meant to keep drivers attentive to the driving scene and the other designed to provide extra takeover time to distracted drivers.

Two research questions were addressed in this study:

1. Can attentional monitoring alerts be used to maintain drivers' situation awareness and improve performance during automation failures?
2. Can driver monitoring be used to augment takeover for distracted drivers, and does such modification improve takeover success?

2 Method

2.1 Participants

The sample population consisted of 24 participants (12 male and 12 female) who were between 21 and 45 years old, had at least three years of driving experience, and were in good general health.

2.2 Apparatus

Data were collected on the NADS-1 driving simulator at the National Advanced Driving Simulator (NADS) at the University of Iowa (Figure 2.1). The NADS-1 simulator consists of a 24-foot-diameter dome that encloses a full-size sedan. The 13-degree-of-freedom motion system provides accurate acceleration, braking, and steering cues to drivers as if they were actually driving. The NADS-1 uses 16 high-definition (1920x1200) light-emitting diode (LED) projectors to display seamless imagery on the interior walls of the dome with a 360-degree horizontal and 40-degree vertical field of view. The simulator cab is a 2014 Toyota Camry equipped with active feedback on steering, brake, and accelerator pedals, and a fully operational dashboard. Data were sampled at 240 Hz.

Figure 2.1 - Exterior and interior of the NADS-1 simulato.

The Aisin DMS was integrated into the NADS-1 cab and provided data to be used for driver state classification. The system uses a camera that observes the state of the driver by detecting the face orientation, eye gaze direction, and opening and closing of eyelids.

A simple algorithm was developed to measure drivers' attention on the road in front of them. Only the face orientation was used in the algorithm. It classified face orientation into one of two states: facing the front roadway, and facing away from the road. First, the nominal face orientation while driving manually was estimated up to the point where the driver first transferred control to the automation. This orientation was used as the center of a circle with radius ten degrees (face direction is given in angles). A face orientation signal was defined with respect to this circle as

$$\rho = \sqrt{\frac{(\theta-\theta_0)^2}{100} + \frac{(\phi-\phi_0)^2}{100}}, \qquad \text{Eq. 1}$$

where θ and ϕ are the pitch and yaw of the driver's face. The value of ρ is less than one if the orientation falls within the circle, one if it's on the circle, and greater than one if outside the circle.

An inattention signal was initialized to zero at the beginning of the drive. It was then incremented by the value of the time step if the camera wasn't tracking the face or if $\rho > 1$. On the other hand, if $\rho \leq 1$, then the inattention signal was decremented by 10x the value of the time step. In other words, the inattention signal, while rising, could be interpreted as the time since the face turned away from the road, but after facing front, it fell very quickly. The inattention signal was capped on the low end at zero, and on the upper end at 60. Attention alerts were issued when the inattention signal exceeded 30 and could not repeat at a rate faster than once per 30 seconds.

2.3 Study Drive and Events

2.3.1 Study Drive and Secondary Task

The study drive lasted for approximately forty minutes of interstate driving with light to moderate ambient traffic. The road network consists of four lanes of separated interstate (two in each direction) with a 65 mph speed limit. Drivers were instructed to begin driving and accelerate to 65 mph, then engage automation, dubbed Autodrive, via a specified button on the steering wheel. When Autodrive was engaged, drivers heard an auditory chime and saw an icon on the instrument cluster (see Figure 2.2 below).

The Autodrive system was developed as part of a previous SAFER-SIM research project [9] and designed to mimic SAE Levels 2+, which include automated speed control and lane keeping. The scenario author is able to implement warnings and take-over requests within scenario, thus setting the exact functionality (and therefore level) of the system. Drivers could engage the system when the vehicle was traveling at least 45 mph. When engaged, the system fully controlled both the speed and lateral position of the vehicle.

Figure 2.2 - Autodrive button and instrument cluster icon

To mimic the disengagement from the driving task that might be encountered with Level 3 automation, drivers were incentivized to interact with a trivia game (TriviaPlaza.com) on an external iPad. Participants were instructed that if they completed 100 questions within the study drive, they would receive additional compensation. In reality, all participants received the additional compensation and were debriefed appropriately following the study drive. This task was used to prompt drivers to disengage from the driving task during automated driving during the previous NADS SAFER-SIM AV study [9]. Participants could select from a large number of categories, which was intended to engender similar levels of engagement with the secondary task across participants.

2.3.2 Events

Drivers encountered three different types of events during the study drive. Four freeze probe events were included to measure SA at points throughout the drive. The freeze probe events are based on Endsley's SAGAT technique [10], to provide an index of how aware drivers were of surrounding traffic at seemingly randomly points during the drive. During these events, the simulator screens were suddenly blanked white. The researcher in the simulator cab immediately handed a sheet (Figure 2.3) to the participant, who had previously been instructed to mark the position and color of surrounding vehicles in the moment before the screens were masked. Participants had approximately thirty seconds to indicate the position before the driving scene resumed and they were to hand the scoring sheet back to the researcher.

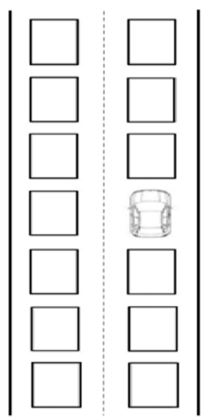

Figure 2.3 - Freeze probe response form

Participants also experienced four total instances of two types of takeover scenarios: two sudden dropouts and two planned takeovers. During sudden dropout events (hereafter referred to as dropouts), steering perturbation was gradually added to the automated vehicle steering algorithm as the vehicle navigated a curve. Once the perturbation reached a certain threshold, the automation deactivated and issued a takeover request to the driver. If no action was taken, the vehicle depart the right side of the lane.

The planned takeover events involved the driver approaching a work zone with a lane reduction that required traffic to merge into the left-most lane. Drivers received a takeover request seven seconds in advance of the work zone. If no action was taken, the automation was programmed to simply pull to the side of the road before the work zone and stop.

Table 1 - Event order

Order	Event
1	Freeze Probe 1
2	Dropout 1
3	Freeze Probe 2
4	Takeover 1
5	Freeze Probe 3
6	Takeover 2
7	Dropout 2
8	Freeze Probe 4

2.4 Takeover Requests and Experimental Design

The study was designed with automated vehicle human-machine interface (HMI) as a between-subjects variable with three levels. The HMI consisted of two key pieces, how the HMI behaved during nominal (i.e., non-event) driving and how the HMI handled dropouts and takeover situations. A between-subjects analysis was set up with three groups of eight subjects, with each subject randomly placed in a group. There were four males and four females in each group.These HMI groups are described below.

2.4.1 Baseline Group

The baseline group was meant to mimic an automated vehicle system that does not utilize driver state information. During periods of nominal riding with automation, participants saw the

Autodrive icon on the instrument cluster. During dropout events, participants received a takeover request, shown below (Figure 2.4), at the point of the dropout. During takeover events, participants received the takeover request seven seconds in advance of reaching the work zone. In each instance, the takeover request was paired with a loud beeping.

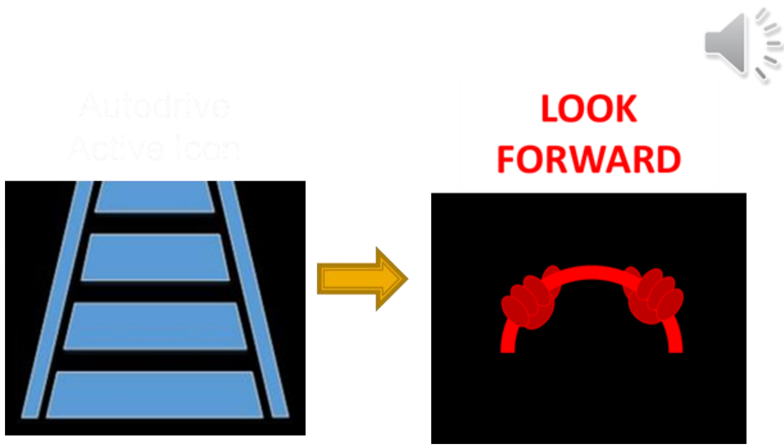

Figure 2.4 - Sequence of takeover icons for the baseline group

2.4.2 Attentional Maintenance Group

The attentional maintenance (AM) group was intended to mimic an automated vehicle HMI that used driver state feedback to keep drivers aware of the driving situation and prevent them from falling out of the loop. Using output from the continuously running state classification system, the automated system provided attentional reminders (the same “Look Forward” messages used for the state-contingent takeover (SCT) group; Figure 2.5) when drivers had been looking away from the road for at least thirty seconds. The system continued issuing alerts until drivers looked back at the road for several seconds. The HMI messages during the dropout and takeover events were identical to those in the baseline condition.

Figure 2.5 - Attention reminders in the AM group, appearing on instrument cluster

2.4.3 State-Contingent Takeover Group

For the SCT group, driver state information was used to modify takeover requests when drivers were distracted. During periods of nominal driving, the automated system and HMI functioned identically to the baseline condition. In both the dropout and takeover events, however, participants in the SCT group received an additional, earlier message on the instrument cluster if the state classification algorithm defined them as distracted. This message, consisting of a white flashing rectangle surrounding the Autodrive icon paired with text that said “Look Forward” and a repeated dinging, occurred three seconds before the takeover request icon (Figure 2.6). That is, in the dropout events, drivers in the SCT group got the look forward message three seconds before the event. In the takeover events, SCT drivers got the look forward message three seconds before the takeover request, or ten seconds before the vehicle reached the construction zone.

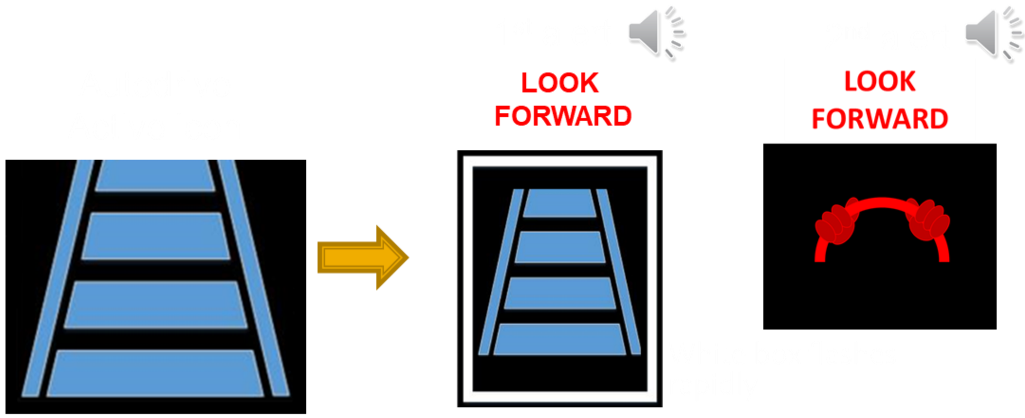

Figure 2.6 - Sequence of takeover icons in for the SCT group, starting with normal Autodrive

2.5 <u>Procedure</u>

Upon arrival, participants received a study description and provided written informed consent. Participants then completed a survey on trust of technology and a general demographics survey. This was followed by a presentation on the automated vehicle and general simulator procedures. As part of the study description, participants were told they would be driving an automated vehicle and that they may engage in other activities while it is in operation. The incentive scheme associated with the trivia task was described, as were the potential automation interfaces and their meanings.

Participants were then escorted to the simulator, where they were provided with a brief overview of the cab layout and allowed to adjust the seat, steering wheel, and mirrors. Participants were encouraged to engage in the secondary task and reminded that they can do whatever feels safe while under automated control. Participants then completed a ten-minute practice drive, where they practiced engaging and driving with automation, practiced performing the secondary task and freeze probe, and saw examples of the look forward and takeover messages (above). Participants then completed a wellness survey to assess symptoms of simulator sickness, followed by the 40-minute study drive and a post-drive wellness survey.

After exiting the simulator, participants completed a post-drive survey to evaluate trust, acceptance, and mental models of the automation and a realism survey about the simulator. Participants were then debriefed on the actual incentive scheme and its purpose.

3 Results and Discussion

3.1 Can attention monitoring alerts be used to maintain drivers' situation awareness and improve performance during automation failures?

The first set of analyses focused on whether attentional alerts improved SA and takeover performance. Situation awareness was measured with a combination of performance on the freeze probe events and gaze metrics measured during periods of nominal driving. For this analysis, we compared the attentional monitoring (AM) group to the group of baseline drivers.

3.1.1 Freeze Probe Accuracy

For each position on the freeze probe form, a response was correct if it matched the actual value of that position in the driving scene (i.e., whether there was or was not actually a vehicle in that position). Percent correct scores were computed for each of the four trials and reflected the proportion of locations participants correctly identified; the scores were then aggregated across the three HMI conditions. Freeze probe accuracy was higher in the AM condition than the baseline condition ($t(15) = 2.07$, $p = 0.057$), as shown in Figure 3.1. Participants in the AM group correctly identified 80% of vehicle locations, whereas participants in the baseline group identified 73% accurately. This demonstrates that providing attentional feedback using a DMS increased awareness of surrounding traffic conditions.

3.1.2 Situation Awareness Gaze Metrics

We also computed gaze metrics that indicate how attentive drivers were to the forward roadway. While gaze measures do not necessarily provide insight into the cognitive state of the driver, as the mind wandering and cognitive distraction literatures show [11], significant eyes-off-road time is one of the greatest risk factors for distraction-related crashes and fatal crashes [12]. These measures were calculated during periods of nominal (i.e., non-event) driving in automation. It was assumed that drivers who spent more time looking forward were generally more aware of traffic conditions.

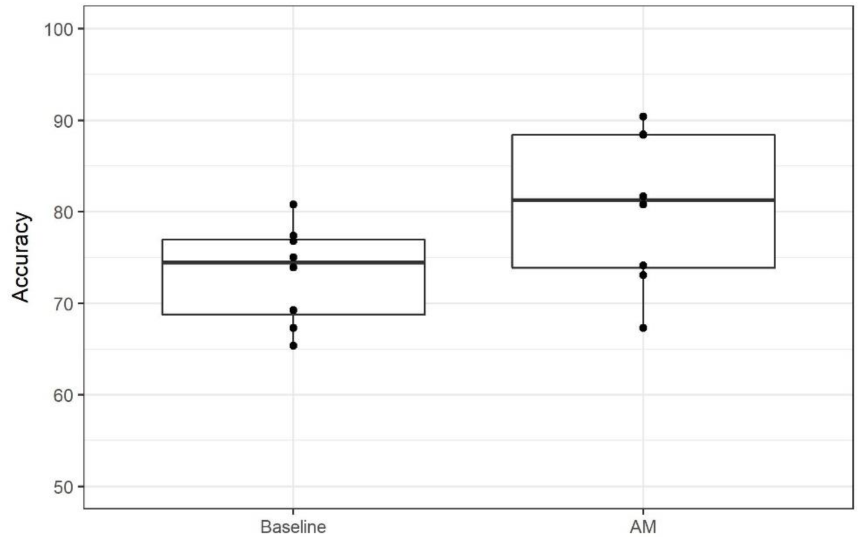

Figure 3.1 - Freeze probe accuracy; each point represents a participant mean

Percent road center gaze (PRCG) was calculated using head angle from the DMS. PRCG is the number of glance data points that fall within the road center area during a specified time period, in this case seventeen seconds [13]. This provides a measure of how much drivers were looking forward when automation was engaged and in control of the vehicle. Figure 3.2 shows PRCG across the two groups of drivers. Drivers in the attentional monitoring group had a higher PRCG (35%) than drivers in the baseline group without the AM alerts (15%; $t(15) = 2.83$, $p = 0.02$).

We also compared the average inattention value (see description of the algorithm in the methods above). Higher values indicate greater inattention, with a maximum value of 60 (see Figure 3.3). Drivers in the AM group had significantly lower ratings, on average, than baseline drivers ($t(15) = 2.53$, $p = 0.03$), indicating that the algorithm classified them as more attentive.

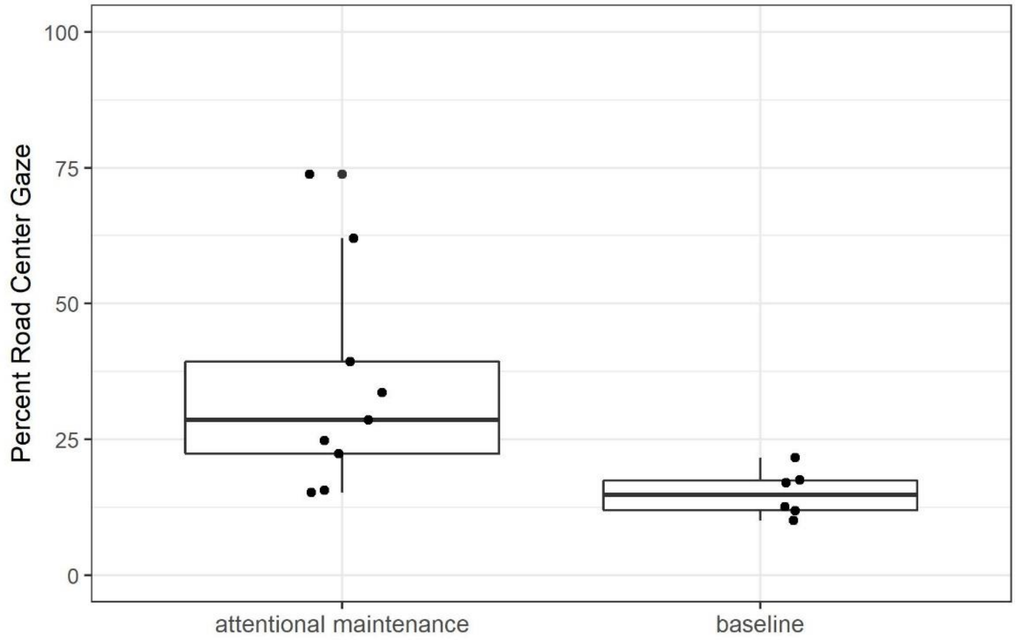

Figure 3.2 - Percent road center gaze; points represent subject means

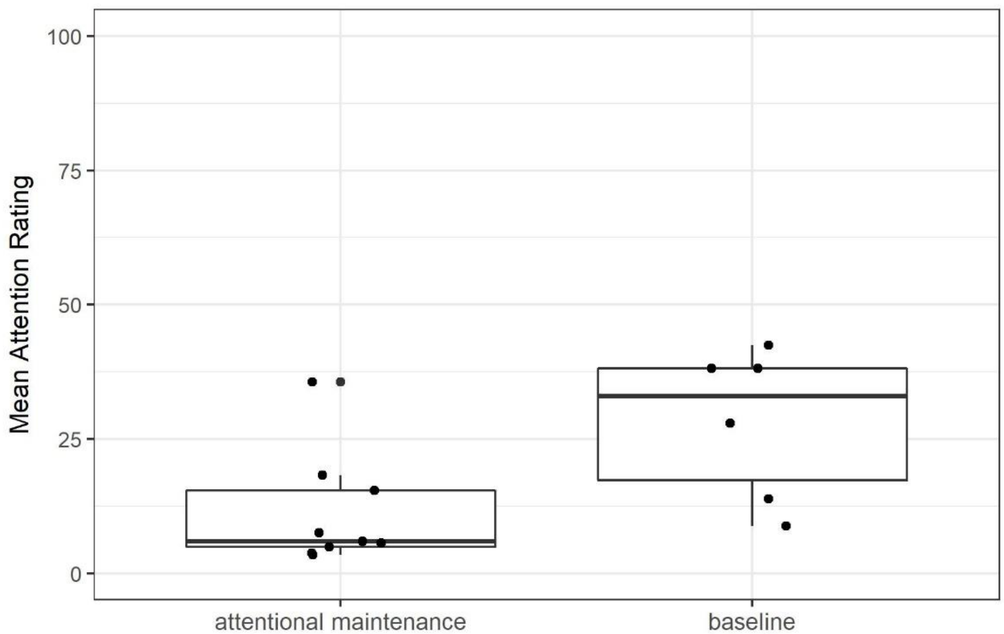

Figure 3.3 - Mean attention rating from the algorithm; points represent subject means

3.1.3 Takeover Performance

In addition to examining whether attentional alerts changed how drivers attended to the environment in conditional automation, we also investigated whether drivers with this system showed enhanced responses when the automation failed unexpectedly. As discussed in the introduction, the expectation for Level 3 automation is that drivers remain capable of quickly taking back control of the automation in a failure situation.

To understand whether attentional alerts impacted response, we looked at behavior in the dropout events. These events were designed to mimic a sensor failure, where the driver had little or no warning that the automation was about to fail. Takeover from automation is a staged process. Drivers must reestablish SA, grab the wheel and move feet to the pedals, and select and execute a response. We selected three time points to examine this process of takeover. Each of these points was drawn from the point of the takeover warning.

1. *Hands on wheel time*, measured as the first instance of drivers placing their hands on the steering wheel, identified through video coding.
2. *Steering response time*, measured by the first instance of a steering wheel movement greater than three degrees in magnitude.
3. *Maximum lateral exceedance,* measured as the maximum distance from the center of the lane. This measure provides an index of the severity of the event, with greater values representing larger deviations.

Hands on wheel time is shown in Figure 3.4. Drivers in the AM group were quicker to move their hands back to the wheel than drivers in the baseline group ($t(15) = 2.06$, $p = 0.05$). A similar pattern of results was seen for steering response time. Drivers with attentional monitoring were quicker to initiate steering responses than baseline drivers ($t(15) = 1.92$, $p = 0.07$). These faster responses led drivers with the AM alerts to drift less from the center of the lane. Figure 3.4 shows maximum lateral lane deviation. Drivers in the AM groups had shorter maximum lane deviations than baseline drivers ($t(15) = 2.36$, $p = 0.03$), indicating that baseline drivers drifted farther out of the lane, on average, during the dropout events.

In sum, these data provide strong support for the efficacy of attentional monitoring and alerts in enhancing the SA of drivers in conditional vehicle automation. Drivers with attentional monitoring spent more time looking at the road than drivers without, and performed more accurately on the SA freeze probe task. Importantly, these changes in attentional allocation and SA translated to improved performance during a sudden unexpected automation dropout. Drivers in the attentional monitoring group responded faster and had smaller lane deviation than drivers who did not receive AM messages.

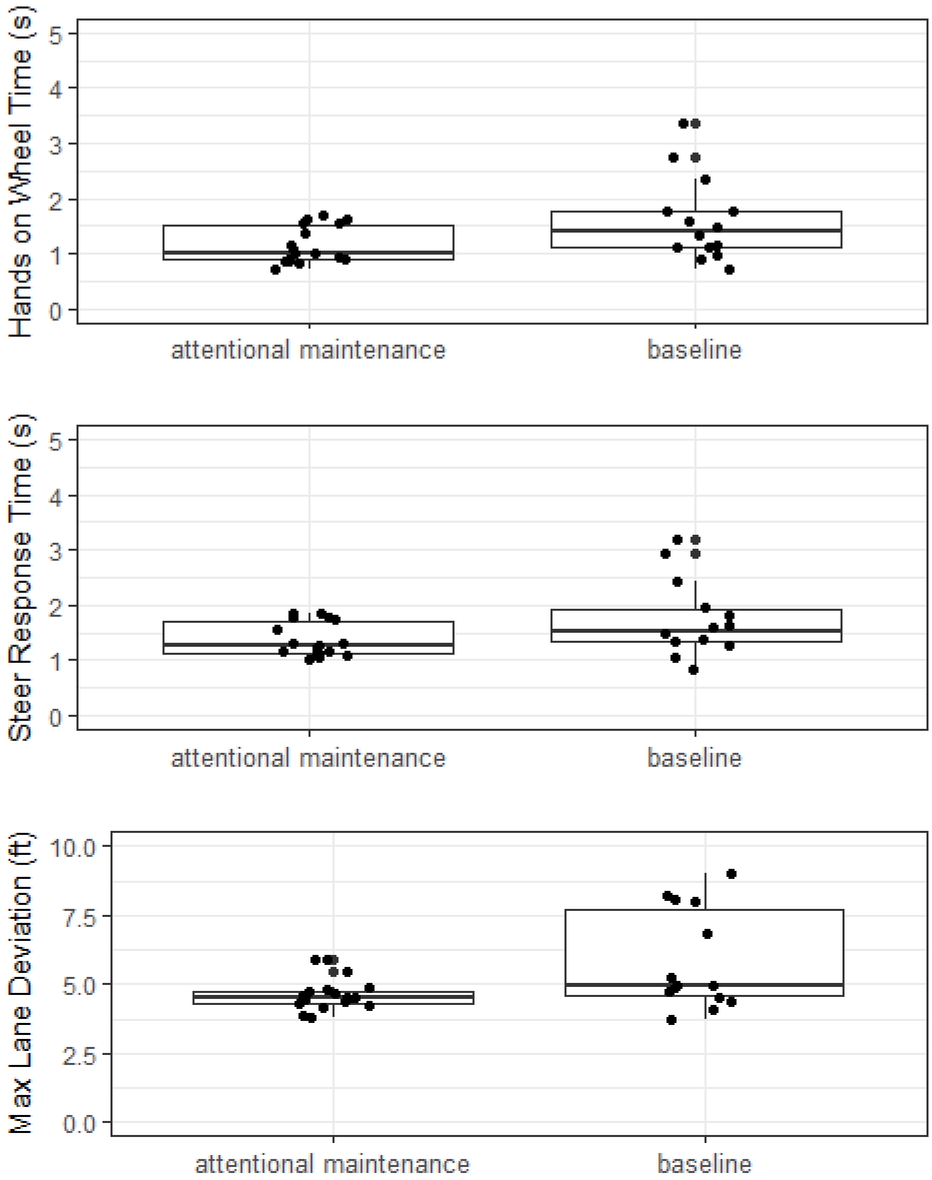

Figure 3.4 - Response measures in the dropout event; points represent individual participants

3.2 Can driver monitoring be used to augment takeover for distracted drivers, and does such modification improve takeover success?

To examine whether state-contingent attention alerts improved behavior during takeover events, we compared the takeover performance of the SCT group in both the takeover (i.e., work zone) and dropout events. Takeover behavior was considered as both the time for drivers to return their hands to the steering wheel and the time to initiate a steering response. If SCT messages prompted drivers to reengage with the dynamic driving task earlier, we predicted that both the hands on wheel and steering response times would be faster in the SCT condition than in the baseline condition.

Figure 3.5 shows hands on wheel and steering response times for takeover events. Though drivers in the SCT group tended to respond earlier than baseline drivers, the difference was not significant ($t(15) = 1.41$, $p = 0.18$). There also was not a significant difference in steering response time between the SCT and baseline groups ($t(15) = 0.11$, $p = 0.92$).

For the dropout events, shown in Figure 3.6, there was a marginally significant difference between the SCT and baseline groups ($t(15) = 1.85$, $p = 0.09$), with drivers in the SCT group returning their hands to the wheel faster, on average, than drivers in the baseline group. The difference in steering response time, however, was not significant ($t(15) = 1.49$, $p = 0.16$). This suggests that although drivers in the SCT group tended to return their hands to the steering wheel earlier, this did not translate into faster steering responses.

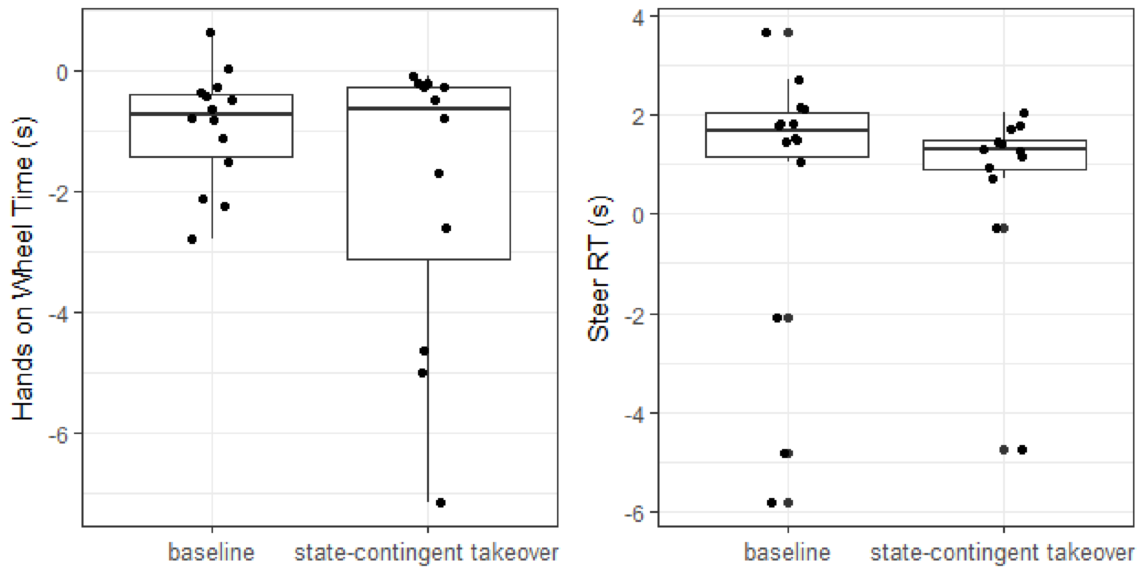

Figure 3.5 - Hands on wheel and steering response times in the takeover events

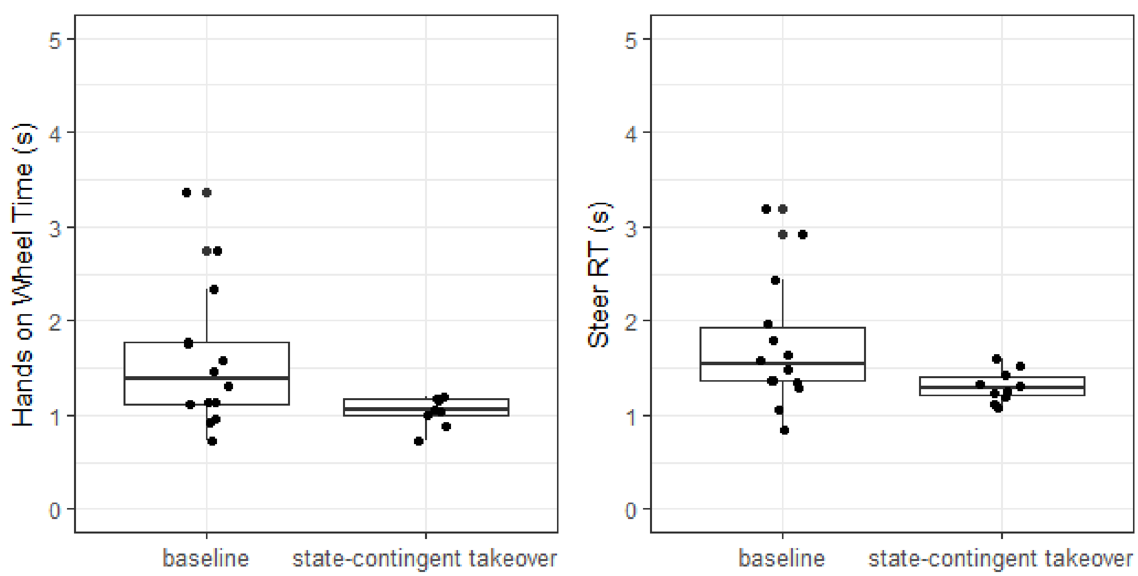

Figure 3.6 - Hands on wheel and steering response times in the dropout events; points represent individual participants

These data suggest that while there may have been slight advantages to STC messages, there were not clear improvements over the baseline condition. It is interesting to note that drivers often responded before the takeover request in the work zone takeover events. This was particularly true of drivers in the SCT group, who received an additional earlier eyes-on-road message. Interestingly, however, this did not translate to faster steering responses. There may have been a ceiling effect, whereby there was no additional advantage to having eyes on road earlier than a certain point, which could have limited the benefits of the SCT condition. It is worth noting that no drivers collided with the work zone, indicating that the takeover warning provided sufficient time for drivers to reengage with the driving task, even when distracted.

4 Conclusions

These results provide support for the role of driver monitoring in partially automated vehicles. The expectation that drivers remain aware of the driving task and the behavior of the automation necessitates that they remain engaged in active monitoring. This is particularly true of so-called “silent failure” scenarios, where the automation does not realize that it has failed

Our data indicate that continuous monitoring using a production driver-monitoring system can be used to estimate the state of the driver. Importantly, we created an attention algorithm that was used to drive an HMI that provided alerts to drivers when they had been looking away for 30 seconds or more. This level of feedback was effective at enhancing SA and, importantly, drivers who had the attention monitoring system responded faster during sudden automation failures than drivers without attention monitoring.

Several limitations are worth mentioning here. First, the sample size for this study was small and drivers had a range of experience with advanced vehicle technology. Additional research is needed to understand the impact of driver monitoring and state feedback systems as a function of individual differences, previous technology exposure, and overall approach to technology. The study was also limited in that we only examined a single HMI to provide attention feedback. Future research is needed to explore the most effective alert for situations of driver disengagement during partially automated driving, including different display locations and modalities.

In sum, this project shows the potential of driver monitoring to mitigate the out-of-the-loop problem likely to arise as vehicles become increasingly automated.

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