Analysis of Driver Behavior in Mixed Autonomous and Non-autonomous Traffic Flows

Jundi Liu[1] and Linda Ng Boyle[1,2]
[1] Industrial and Systems Engineering, University of Washington, Seattle, WA
[2] Civil and Environmental Engineering, University of Washington, Seattle, WA

Autonomous vehicles are expected to improve road safety and efficiency in future transportation systems. A driving simulator study was designed to identify driving styles and the cooperation between human drivers and other AVs. The study captured driver's following behavior in a fully autonomous driving environment at unsignalized intersections. Participants were asked to make a series of maneuvers (straight through intersection, left turn, and right turn) in two different speed conditions (30, 40 mph) and two different traffic density conditions (with or without other traffic). Analysis of Variance showed that drivers had a significantly larger deviation (defined as the area between two trajectories) during left turn maneuvers when they were traveling at higher speeds. Moreover, the first turning operation had smaller deviation than the second turning operation. The findings have implications for the design of driver-assistance guidance systems in future mixed autonomous and non-autonomous traffic flows.

INTRODUCTION

Studies show that advanced autonomous vehicles (AVs) can improve road efficiency and safety by significantly reducing car crashes (Hamid et al., 2017). However, before the transportation system can reach fully autonomous driving, there will be a long transition as market penetration gradually increases. Hence, the interaction of autonomous and non-autonomous vehicles on the road will exist for some time.

One advantage of AVs is that they can communicate their space-time planned routes and vehicle control information through vehicle-to-vehicle (V2V) communication technologies. Additionally, they are good at following the planned trajectories with minimum deviations and errors. As a result, the AVs can achieve increased road efficiency and minimize injuries and fatalities due to crashes (McGehee et al., 2016). However, the existence of human drivers can negate these advantages given variations and ability to follow such planned trajectories. This variation can impact the effectiveness of driver-assistance systems.

Many tools have been explored to assist human drivers in cooperating with AVs. An augmented reality (AR)-based slot reservation system can be designed to help the drivers visualize the guidance information while driving through an unsignalized intersection for connected vehicles. Wang et al. (2020) showed how guidance can be displayed using colored lanes on the windshield. Other information that can be presented in AR can include navigation arrows and bounding boxes for the scene objects (Liu et al., 2021; Akash et al., 2020). For route guidance, one can also superimpose a lead vehicle to help guide the human driver on their route. Rahmati et al. (2019) showed statistically significant differences in human driver's behavior when they follow another human driver when compared to following an AV. The human drivers tend to feel more comfortable following the AV. Moreover, the simulation results showed the importance of capturing human behavior in mixed driving environments to improve road efficiency.

The objective of this work is to provide insights on driver behaviors following a specific trajectory in mixed autonomous and non-autonomous driving environment and implications on the design of guidance information to minimize crash risks. This objective was examined using a driving simulator study designed to collect driving trajectories while following a predefined route in a suburban environment with mixed flows. The findings of this study reveal significant factors that affect driver performance in the car-following task and indicate the necessity of dynamically adapting the driver assistance systems to the changes in driver behaviors during the interactions.

METHOD

A driving simulator study was conducted with drivers from the Seattle, Washington area. The simulator study was designed to capture driver behaviors while following a virtual lead vehicle through unsignalized intersections with autonomous and non-autonomous vehicles.

Participants

There were 32 participants (21 males and 11 females) between the ages of 19 and 69 years (mean: 32 years old) who completed the study; 2 additional participant withdrew due to simulator sickness. The participants were recruited and screened using an online questionnaire. The screening tool was used to ensure that participants had a valid driver's license for more than two years, drove at least once per week, and had not participated in any driving simulator study in the past six months. The compensation was $40 and each participant provided their written consent. The study was approved by the Institutional Review Board (IRB) at the University of Washington.

Driving Simulator Study Design

A fixed-base National Advanced Driving Simulator (NADS) miniSim was used for the driving study. The simulator was equipped with three 48" main view monitors in a Quarter Cab.

The driving simulator was designed to be a suburban environment, with two lanes in each direction and a dedicated left-turn lane for the intersection. The environment contained simulated commercial buildings, sidewalks, and restaurants and was always presented as daytime with clear weather. A lead vehicle was also included to guide the participant through various unsignalized intersections.

Figure 1: Sample view from the driving simulator. The driver is driving through a busy intersection following the lead vehicle marked with the red box.

Four video recording units were used to capture the driver's behavior in real time. During the study, the participants were instructed to follow a virtual lead vehicle through five consecutive intersections (three going straight intersections, one left turn intersection, and one right turn intersection) while also maintaining a safe distance between 50 to 200 feet. An example of the driver's view is shown in Figure 1. The driver was instructed to follow the virtual lead vehicle without stopping for any intersections during the entire drive. To avoid any risk of collision during the experiment, all other traffic were AVs equipped with collision avoidance systems to ensure the safety of the participant's vehicle. Three within-subject factors were considered for the study: traffic density, speed of the lead vehicle, and operation orders of the left turn and right turn. In summary, we had a 2 by 3 within subject design with eight different scenarios. The order of the eight scenarios was randomized for each participant to minimize any ordering effect.

Study Procedure

Upon arrival to the lab, the participants were screened again for eligibility to participate in the study. After the final screening, consent forms that explained the basic information and potential risks of the study were given to the participants. Once written consent was obtained, a driving history questionnaire and a demographic questionnaire were completed. The main driving part started with a tutorial session to let the participants become familiar with the operations of the driving simulator. After familiarization, the main study started. There were eight drives, each lasting approximately five minutes, for a total of 45 minutes in the simulator. Once the simulator was complete, the participants were asked to complete a wellness questionnaire to make sure no potential physical and mental harm had occurred during the study. In total, the entire study took approximately one hour to complete.

Independent Variables

Traffic density (within subject). The participants encountered high (with traffic) and low traffic (without traffic) density at each intersection. This independent variable promoted understanding of the effect of other AVs on the participant's behavior. The with-traffic scenario is designed to have competing traffic within the intersections. The trajectories of AVs and the participant's vehicle have overlap but no potential crash risk. That said, as long as the driver is following the given trajectories according to the instructions, there was no risk of collision. The without-traffic scenario included only the lead vehicle and the participant's vehicle. We expect the existence of the other AVs will affect driver behaviors while following given trajectories, especially in dense traffic conditions.

Speed of the lead vehicle (within subject). The speed of the lead vehicle included two levels: 30 and 40 mph. The two levels were chosen based on the standard speed limit for a two-lane suburban environment. The speed of the lead vehicle helped in understanding the variations in driver behavior for following different speeds.

Operation orders (within subject). We used different orders of turning operations to reduce the ordering effects of left turns and right turns. The two levels included:

- Order 1: straight, left-turn, straight, right-turn, straight

- Order 2: straight, right-turn, straight, left-turn, straight

The two orders of the operations were randomized in each participant's study scenarios.

Dependent Variables

Trajectory deviation. Two dependent variables are considered separately: trajectory deviations of left turns and right turns. The trajectory deviation of the human driver was computed as the area between the lead vehicle trajectory and the participant trajectory. To estimate the area between two curves, the trapezoidal rule was used to approximate the definite integral of the area of deviation.

Data Analysis

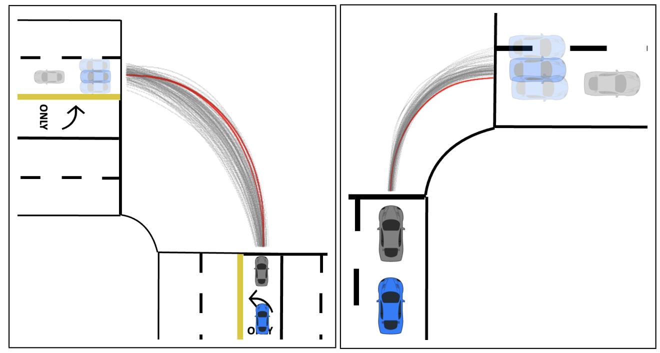
Data visualization was used to examine potential behaviors during the car following task. We then conducted two models, both were 2 (traffic density) x 2 (speed limit) x 2 (operation order) fixed effects analysis of variance (ANOVA). The outcome of interests were the trajectory deviation for left turn and right turn respectively. A Box-Cox transformation of trajectory deviation was applied in order to satisfy the assumptions of normality. The coefficients for each independent variable were then estimated using fitted linear regression models. Significance was assessed at $\alpha = 0.05$.

All data processing, visualization and analysis is performed on a macOS Monterey version 12.1 using python 3.7 with statsmodels v0.13.1.

RESULTS

Data Visualization

The data visualization shows that participants performed well when following the lead vehicle while going straight. There is no significant deviation of the participant trajectories from the lead vehicle trajectories. However, a significant deviation was observed when making left-turn and right-turns at intersections. Figure 2 shows the visualization of the turning trajectories of both lead vehicles and participants. Figure 2a shows that drivers tend to make narrower left turns than the lead vehicles. However, for right turns, the drivers tend to make wider turns than the trajectories given by the lead vehicles from Figure 2b.



(a) Left turns. (b) Right turns.

Figure 2: Trajectories of the lead (red curve) and participants' vehicles (gray) for all tested conditions.

Since the significant deviations occur in right-turn and left-turn intersections, the dependent variables, trajectory deviations, are only calculated for the right-turn and left-turn scenarios. The following analysis is performed to understand the driver behaviors in turning operations in the intersections.

Analysis of Variance (ANOVA)

We performed two ANOVAs on the Box-Cox transformation of trajectory deviation of left turns and right turns, respectively. For the left-turn scenario, the ANOVA result confirms that the trajectory deviation was significantly different across the different order of the turning operations ($F(1,163)=32.48$, $p < 0.001$). Also, the trajectory deviation of left turns was significantly different across different speeds of the lead vehicle ($F(1,163)=5.59$, $p < 0.01$). However, the effect of traffic density on trajectory deviation of the left turns was not significant ($F(1,163)=1.66$, $p = 0.19$).

In the right-turn scenario, the ANOVA showed that the trajectory deviation was significantly different across the different order of the turning operations ($F(1, 163)=149.00$, $p < 0.001$). However, the effect of traffic density and the speed of the virtual lead vehicle on trajectory deviation of the left turns was not significant ($F(1, 163)=0.37$, $p = 0.54$ and $F(1,163)=0.06$, $p=0.81$, respectively).

The coefficients for each independent variable were then estimated using the linear regression model. The left turn model (Table 1) confirmed that the lead vehicle speed was significantly affected by the trajectory deviation ($p = 0.012$), with higher speeds resulting in larger deviations in trajectory. Interestingly, if participants performed the left turn before the right turn (order effect), a decrease in the trajectory deviation for the left turns ($p < 0.001$) was observed.

Table 1: Linear regression model for left turn deviation as the dependent variable.

	coefficient	t	$P > \|t\|$
Intercept	0.32	11.967	<0.001
Traffic density (High)	0.03	1.29	0.198
Lead vehicle speed (40mph)	0.07	2.54	0.012
Operation orders (Left first)	-0.03	-6.95	<0.001

For the right-turn scenario (Table 2), only the order of the operations significantly affected the trajectory deviations ($p < 0.001$). If the driver performs the left turn before the right turn, it will increase the deviation in right turns. All other independent variables were statistically insignificant in predicting the deviations of the right-turn trajectories.

Table 2: Linear regression model for right turn deviation as the dependent variable.

	coefficient	t	$P > \|t\|$
Intercept	0.07	2.75	0.007
Traffic density (High)	-0.01	-0.32	0.746
Lead vehicle speed (40mph)	0.02	0.64	0.521
Operation orders (Left first)	0.30	12.87	<0.001

DISCUSSION

This study used a driving simulator to examine driver behaviors in mixed autonomous and non-autonomous flows under various traffic conditions in unsignalized intersections. We focused on turning operations because previous studies have shown that significant variations are observed for these operations at intersections (Dias et al., 2020; Alhajyaseen et al., 2013). Therefore, successfully modeling the turning trajectories and trajectory variations in the intersections are crucial for AVs to react the maneuvers of human-driven vehicles and plan their trajectories to minimize the risk of collision accordingly.

There are various factors that can impact a human drivers likelihood to deviate from a planned route. In this study, we examined the impact of traffic density and speed of lead vehicle. The results of the ANOVA and the linear regression model showed that only the speed of the lead vehicle had a significant effect on the trajectory deviation of left turns. The participants tend to deviate more from the given trajectories in left turns when the lead vehicles were traveling at higher speeds. However, right turn behaviors are not significantly affected by the speeds of the virtual lead vehicles. The drivers tend to slow down more during right turn operations, which required a sharper turning radius. On the other hand, the drivers can perform the left turns at a higher speed and wider trajectories. This result indicates the guidance system should account for the larger deviations from the given left-turn trajectories if driving in high-speed conditions.

The order of the turning operations also affected deviations in the turning operations. The first turning operation leads to a smaller deviation from the given trajectory, and the second turning operation was associated with a significantly larger deviation. Therefore, the coordination system should adapt to the changes in driver behaviors when planning the routes for all traffic to avoid a potential collision.

It was surprising to observe that traffic density did not have a significant effect on the trajectory deviations for both left and right turns. Studies have shown that traffic density can impact the ability to control vehicle speed and situational awareness in manual driving context (Heenan et al., 2014), and affect the take-over times and quality in highly automated driving context (Gold et al., 2016).

That said, the drivers were able to maintain high performance in the car-following task even in dense traffic with many AVs. The existence of other AVs will not significantly affect the trajectory deviation in the turning operations.

The findings of this study provide insights and implications on designing guidance systems to assist human drivers in communicating and collaborating with other AVs in mixed traffic flows. The study focused on unsignalized intersections, which are considered a critical task for the safe driving of the AVs (Zyner et al., 2018). For that reason, the vehicle's operation at these intersections are of great interest as the number of AVs and vehicles with automated systems increases on the road. Autonomous and automated vehicles can provide higher throughput and lower wait time in the intersections. However, systematically analyzing the unsignalized intersections with mixed flows is a challenging topic since it involves analyzing and predicting drivers behavior and intentions in such intersections (G. Li et al., 2019), control and optimization of connected vehicles (Bian et al., 2019), and vehicle interactions using game theory (N. Li et al., 2018).

There are some study limitations, which may impact the generalizability of our findings. This study was conducted during the peak of the pandemic, which impacted subject recruitment. For that reason, the number of males and females in our study was not balanced.

The study does provide some insights on trajectory behavior at unsignalized intersection and for mixed flow traffic. This has implications for future systems that seek to provide guidance for the human operator. Future studies could also consider the possibility of augmenting information on guidance from a virtual lead vehicle displayed on the windshield. This could be beneficial in situations where the driver's visibility of the road is impaired. There would need to be further research to understand whether these augmented displays can safely guide the human operator as well as the likelihood that the human operator will adhere to the recommended guidance.

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