Gap Acceptance Behavior at Priority Intersections in Mixed - Human Driven and Automated - Vehicle Traffic

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KEY WORDS

Automated Vehicles; Mixed Traffic; Behavioral Adaptation; Gap Acceptance; Driving simulator; Critical gap

Introduction

In the coming years, Automated Vehicles (AVs) are expected to be deployed on public roads, therefore driving alongside Human Driven Vehicles (HDVs). Such a “mixed” traffic condition could result in different types of interaction. Recent studies, including field test experiments, have shown that human drivers adapt their driving behavior in the presence of AVs, such as by maintaining smaller car-following headways. A crucial behavior for traffic safety and efficiency is gap acceptance at priority T-intersections wherein a vehicle on a minor road (approach) merges onto a major road. In this situation, the minor road vehicle generally comes to a complete stop or slows down (before a Stop sign or a Give-Way sign, respectively) and waits until it finds an appropriate gap in the major road traffic stream. Most existing gap acceptance studies looked at conventional traffic conditions, hence there is very limited insight into the nature of gap acceptance behavior in mixed traffic conditions. With increasing deployment of AVs in traffic, knowledge on such mixed traffic interactions at priority intersections is required, especially crucial aspects of AVs such as their recognizability and driving style. Authorities and decision makers can then take appropriate measures that not only minimize and possibly prevent negative and dangerous effects but also that may drive positive effects.

Methodology

A driving simulator experiment was set up to observe the effects of AVs’ recognizability and their driving style on drivers’ critical gaps. Drivers had to navigate three T-intersections, prior to which they drove in traffic to experience the traffic conditions before approaching the intersection. Each driver drove four scenarios that differed in two aspects: the recognizability and the driving style of AVs. Drivers were assigned to one of three groups, which differed in terms of AV driving styles: Defensive AVs, Aggressive AVs, and Mixed AVs. In the scenario of Mixed AVs, both Defensive and Aggressive AVs were present in the volume ratio of 3:2. Throughout the experiment the penetration level of AVs was fixed at 50%. At the three T-intersections, traffic on the major road was generated with gaps drawn randomly between 3 and 10 seconds from a uniform distribution. The driving behavioral difference between AVs and HDVs was defined by their desired speeds and their following time gaps.

The critical gap estimation was performed using Wu’s method (Wu, 2006). Statistical testing of the estimated critical gaps was performed using the Kolmogorov–Smirnov test. The significance level was kept at 0.05 While presenting the results, a specific nomenclature is used. For instance, *App (AV) DS (AV) Follower App (HDV)* describes the gap acceptance observations for the scenario where AVs were recognizable, driving according to the AV driving style, but the driver accepted gaps at the intersection in front of an HDV. As there are three groups, namely Aggressive, Defensive, and Mixed AVs, this may also be specified in the nomenclature as *DS (Agg AV)*, *DS (Def AV)*, or *DS (Mix AV)* respectively.

Results

95 drivers participated in the experiment of which 71 (74.7%) were male and 24 females. The total number of accepted gap observations in the dataset was 948 observations. Wu’s method was used to estimate the critical gaps for different conditions. The mean and standard deviation of the distributions were also computed. Table 6 presents the calculated mean and standard deviations of the critical gaps for different conditions. As can be noticed, the mean critical gap for the scenario App (AV) DS (Def AV) Follower App (AV) is the lowest, while for App (AV) DS (Agg AV) Follower App (AV) is the highest.

Table 6. Critical gap mean and standard deviation for different conditions

Condition no.	Description	Critical gap (s)	
		Mean	**SD**
1	App (HDV) DS (HDV)	6.43	1.43
2	App (HDV) DS (AV)	6.44	1.36
3	App (AV) DS (AV)	6.59	1.42
4	App (AV) DS (HDV)	6.33	1.52
5	Def	6.43	1.42
6	Agg	6.41	1.42
7	Mix	6.51	1.46
8	App (AV) DS (Def AV) Follower App (AV)	**6.15**	1.38
9	App (AV) DS (Agg AV) Follower App (AV)	**6.86**	1.22
10	App (AV) DS (Mix AV) Follower App (AV)	6.32	1.64
11	App (AV) DS (Def AV) Follower App (HDV)	6.66	1.37
12	App (AV) DS (Agg AV) Follower App (HDV)	6.69	1.69
13	App (AV) DS (Mix AV) Follower App (HDV)	6.76	1.34
14	App (HDV) DS (Def AV) Follower App (HDV)	6.53	1.30
15	App (HDV) DS (Agg AV) Follower App (HDV)	6.31	1.30
16	App (HDV) DS (Mix AV) Follower App (HDV)	6.48	1.43

The 2-sample K-S test was used to check significant differences. Table 7 presents the results with the largest difference (D-statistic) and the critical D values for the conducted tests.

Table 7.
Critical gap mean and standard deviation for different conditions.

Condition 1	Condition 2	D-stat	Critical D	Inference on distributions
Def	Agg	0.041	0.070	Similar
Def	Mix	0.046	0.070	Similar
Agg	Mix	0.056	0.067	Similar
App (AV) DS (Def AV) Follower App (AV)	**App (AV) DS (Agg AV) Follower App (AV)**	**0.300**	**0.169**	**Different**
App (AV) DS (Def AV) Follower App (AV)	App (AV) DS (Mix AV) Follower App (AV)	0.144	0.176	Similar
App (AV) DS (Agg AV) Follower App (AV)	**App (AV) DS (Mix AV) Follower App (AV)**	**0.205**	**0.158**	**Different**
App (AV) DS (Def AV) Follower App (HDV)	App (AV) DS (Agg AV) Follower App (HDV)	0.128	0.181	Similar
App (AV) DS (Def AV) Follower App (HDV)	App (AV) DS (Mix AV) Follower App (HDV)	0.113	0.166	Similar
App (AV) DS (Agg AV) Follower App (HDV)	App (AV) DS (Mix AV) Follower App (HDV)	0.131	0.176	Similar
App (HDV) DS (Def AV) Follower App (HDV)	**App (HDV) DS (Agg AV) Follower App (HDV)**	**0.131**	**0.130**	**Different**
App (HDV) DS (Def AV) Follower App (HDV)	App (HDV) DS (Mix AV) Follower App (HDV)	0.065	0.129	Similar
App (HDV) DS (Agg AV) Follower App (HDV)	App (HDV) DS (Mix AV) Follower App (HDV)	0.118	0.123	Similar

Conclusions

Firstly, the critical gaps were **not significantly different** at an aggregate level over all scenarios between the Defensive, Aggressive, and Mixed AV groups. Secondly, critical gaps of drivers in Aggressive and recognizable AV traffic were **significantly larger** than those in Defensive and Mixed recognizable AV traffic, when merging in front of a recognizable AV. Thirdly, when traffic had recognizable AVs, critical gaps of drivers when merging in front of an HDV were **not significantly different** between Defensive, Aggressive, and Mixed AV traffic. For this condition, it may be noted that the standard deviation of the critical gaps in the Aggressive group stood out (1.69) compared to the Defensive (1.37) and Mixed group (1.34). A key finding was that aggressive AVs induce more defensive driving among human drivers when they are recognizable and induce more aggressive driving when they are not recognizable. Future work could study gap acceptance behavior with traffic present on the approach road, both leading and following the driver. Gap acceptance behavior at left turns wherein drivers need to accepted two gaps could also be an interesting direction to explore. Another research direction could be the effect of different penetration levels of AVs in traffic.

Acknowledgements

This work was supported by Applied and Technical Sciences (TTW), a subdomain of the Dutch Institute for Scientific Research (NWO) through the Project Safe and Efficient Operation of Automated and Human-Driven Vehicles in Mixed Traffic (SAMEN) under Contract 17187. The authors also acknowledge the contribution of Dr. Wouter Schakel who implemented the scenarios in the simulation software.