Interactions Between Human-Driven and Autonomous Vehicles on Public Roads

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Interactions between human-driven and autonomous vehicles on public roads.

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Abstract

To achieve the level of safety and efficiencies promised by autonomous vehicles (AVs), understanding of interactions between human driven vehicles and AVs is crucial. The limited access to publicly available AV data in the field has been the main source of challenge to explore these questions. Using recently released annotated AV data released by Waymo, we investigate interactions between AVs with Human-driven manual vehicles (MVs) in a public road environment. A scalable methodology is presented to study interactions between AVs and MVs. This research reports two main findings (a) AVs tend to be more conservative than MVs at higher speeds on arterials and at lower speeds on freeways (b) No statistical differences in the mean reaction times between MVs and AVs, however, MVs following MVs were found to have statistically significantly lower variance in reaction times. These findings demonstrate the broader impacts of AVs on traffic flow and capacity.

1 Introduction

There is a growing sense of anticipation that Autonomous Vehicles (AVs) will replace human drivers and help eliminate human errors and delays¹. With the advent of a new class of drivers, i.e., AVs, human drivers will have to interact with AVs and vice-versa. Human controlled manual vehicles (MVs) are expected to be a significant part of the vehicle fleet and traffic mix for many years while market penetration of fully autonomous technology ramps up². Consequently, it is imperative to understand the emerging human-machine interaction (interaction of AVs with MVs) in a traffic stream.

AVs are expected to have significantly lower reaction time³ to be able to react quickly to potential risks; however, this could result in the following vehicle unable to stop in time, resulting in secondary crash risks. These potential cases make it essential to understand current trends in human-machine interactions (AVs and MVs) in traffic streams. Previous studies introduced techniques for enhancing the safety behaviour of AV^{4,5} but interaction with neighbouring MVs remains an area for research. In this study, we attempted to use space headway and speed to investigate the different interactions between AV and MV in diverse driving environments (arterial, freeway, and streets). Furthermore, this study investigates reaction times of drivers (AV or MV) in AV-MV, MV-AV and MV-MV interactions.

Adaptive Cruise Control (ACC), which is considered a partially automated functionality, has been quite widely studied from a traffic safety and traffic flow perspective. One particular field study³ found that ACC enabled vehicles had reaction time close to MVs, which were bound to impact traffic flow and safety. These conclusions have been corroborated by simulation studies^{6,7,8} have found larger time gaps enhance safety and reduce traffic capacity, while smaller time gaps increase the likelihood of traffic disturbances and crashes.

A comprehensive study⁹ that studied reaction times using data reported by AV OEMs (Original Equipment Manufacturers) (e.g. Mercedes-Benz and Google) to the California Department of Motor Vehicles (CA DMV) found that the mean reaction time to take over an AV during a system failure

was approximately 0.83 seconds. A controlled laboratory study¹⁰ evaluating human performance to take over control from an AV during a system failure found that reaction time increases as the time disengaged from the driving task increases. A similar study¹¹ evaluating reaction time under different non-driving tasks found no statistically significant differences in average reaction times across the different driving tasks, impact of incentives and failure probabilities. Though these studies have used field data or lab data to study the reaction time of humans in critical events such as system failures in AVs, there is however no study evaluating reaction times of AVs interacting with MVs and vice-versa in normal traffic flow situations not involving critical events. Reaction times in normal traffic flow can be inferred as the time taken by the following vehicle to accelerate or decelerate to follow the lead vehicle can be used to infer *reaction times*. Understanding reaction times is critical for safer and more efficient infrastructure design. This study addresses this gap in knowledge.

Although there has been significant work undertaken to develop real-world simulation environments for testing AVs¹², field testing on public roads provides real-world insights that could also help inform the development of simulation environments. This study leverages the Waymo open dataset, providing access to a significant range of autonomous miles driven^{9,13} across different environments and interactions. Furthermore, the credibility of the datasets was assured as the annotations were undertaken and reviewed by trained labellers using production-level labelling tools¹⁴. Annotated data was used to infer the objects and interactions. The data is further discussed in detail in the Methods section of this paper. The authors are unaware of any studies that have used such comprehensive field data to investigate the traffic dynamics flow characteristics and dynamic responses of AV. The methods proposed in this study can be generalised to infer reaction times of AVs from other datasets^{15–18} to better understand human-machine interaction in traffic streams.

2 Results

2.1 Car Following Interactions Between Autonomous and Manual Vehicles

There are two main interactions associated with AVs in a traffic stream, namely (a) MV-AV (MV is the leader and AV is the follower) and AV-MV (AV is the leader and MV is the follower).

(a) MV-AV interaction on Arterials

(b) AV-MV interaction on Arterials

(c) MV-AV interaction on Freeways

(d) AV-MV interaction on Freeways

Figure 1: Relationship between Headway and Follower' Speed

Interactions in the traffic stream can be characterised by how vehicles tradeoff between how close they are driving (i.e., space headway) and their speed. For instance, a vehicle closely following another vehicle tends to maintain lower speeds to be able to stop in a timely manner. Similarly, vehicles tend to maintain higher following speeds when the space headways are larger. This tradeoff manifests itself as a relationship between speed and space headway, which is also equivalent to the macroscopic speed-density relationship of traffic flow.

Figure 1 presents the relationship between space headway and speed for MV-AV and AV-MV interactions across different road types (arterials and freeway), as road environments are known to affect the driving behaviour^{19,20}. It is observed that on arterials, AVs (Figure 1a) are conservative and maintain larger headway as compared to MVs (Figure 1b) at higher speeds. However, on Freeways, AVs (Figure 1c) were found to maintain larger headways at lower speeds than MVs (Figure 1d). This indicates a more conservative kinematic profile of AVs at low speeds on freeways.

These findings are further corroborated by comparisons shown in Figure 2. On Arterials, at speeds less than 5m/s and speeds greater than 20m/s, AVs following the MV maintain larger headways than MVs following AV.

Figure 2: Difference of headway for different speed bins.

2.2 Reaction time

As discussed earlier, reaction times are inferred as the time taken by the following vehicle to accelerate or decelerate to follow the lead vehicle. The trajectory datasets were found to have leader-follower behaviour that was used to infer the reaction times. The non-parametric distributions of reaction times for AV-MV, MV-AV and MV-MV interactions are shown in Figure 3.

No statistically significant differences were found in the mean reaction times across the different interactions, however, the reaction times of MVs following MVs were found to have statistically significantly lower variance (F-test with p-values < 0.05) than reaction times for MVs following AVs

or vice-versa. This could reflect the underlying uncertainties in the interactions of AVs and MVs, that manifest in a more diffused distribution for reaction times.

Figure 3: Non-parametric distribution of reaction times

3 Discussion

Based on an extensive literature review, this is one of the first studies in the public domain to systematically characterise interactions between autonomous and human-driven vehicles using field data. More such results need to be published in peer-reviewed journals to help agencies and the public understand and build trust in autonomous vehicles.

This study is able to identify three main characteristics of AV-MV and MV-AV interactions. Namely,

- (1) On Arterials, autonomous vehicles were found to maintain larger headways at higher speeds compared to human vehicles.
- (2) On Freeways, autonomous vehicles were found to act conservatively and maintain larger headways at lower speeds than human-driven vehicles.
- (3) Finally, though no significant differences were observed in the mean reaction times between autonomous and human-driven vehicles. The variance of reaction times when a human-driven

vehicle is following another human driven vehicle is statistically smaller than other interactions.

The fact that we find AVs being conservative at lower speeds on freeways and higher speeds on Arterials, perhaps is an indication of the predictability and uncertainties in the traffic conditions in these two regimes. Similar findings were reported in partially automated vehicles with ACC³. Given these specific differences in behaviours it is critical to develop traffic management strategies to improve expectations among all drivers to mitigate any safety issues.

Though previous studies have analysed reaction times during critical events during disengagements^{9,13}. There have been no studies in the public domain that have characterised reaction times during normal car-following operations using field data. Though no statistically significant differences were observed in the mean reaction times across the different interactions, there was, however, a statistically significant lower variance in reaction times in the MV-MV interactions. As identified in earlier studies that larger variances in reaction times help stabilise vehicular traffic flow²¹. This suggests that the mere presence of an autonomous vehicle could help reduce sudden braking and improve overall stability in the traffic flow due to higher variance in reaction times.

The methodology proposed in this research to evaluate and study interactions between various road entities is novel and scalable to large and diverse datasets^{14,22–24}. This is particularly critical as several technologies and OEM providers are developing autonomous vehicle technologies; the proposed method allows to evaluate and characterise AV behaviour from a traffic engineering and safety perspective.

4 Methods

4.1 Data

For this study, we used the Waymo open dataset that included data from Phoenix, Mountain View and San Francisco (Figure 4) at varying time of the day (day, night and dawn) in both urban and suburban areas. This data included 1,150 snippets each spanning 20 seconds. The data contained synchronised and calibrated high-quality LiDAR and camera data. The LiDAR data consisted of high quality

manually annotated 3D ground truth bounding boxes that tracked and identified objects within a 75m radius, which was used in this study.

Figure 4: Parallelogram cover of all level 13 S2 cells touched by all ego poses in San Francisco, Mountain View, and Phoenix¹⁴

4.2 Methodology

4.2.1 Car Following

For discerning the different interacting entities, labels were extracted from the original data. Further analysis of the camera data was used to categorise road segments into different driving environments and interactions. Car-Following cases with leaders and followers were identified by manual inspection, ensuring that the vehicles were in the same lane. It was observed that this corresponded to having lateral distances of the vehicle should be within ± 1.17 meters of the lane centerline, and the lateral velocity of the vehicle to be within ± 0.1 m/sec. The information on the coordinate system is provided in Extended Data Fig. 1.

The time-stamped data of the location, space headways, speed and acceleration¹ were extracted for each car-following pair (AV-MV and MV-AV). To understand differences in driving interactions between AV-MV and MV-AV, headway distributions were compared in five speed bins in increments of 5 m/s, namely, 0-5, 5-10, 10-15, 15-20, 20-25 m/s. A T-test was used to evaluate any statistical difference. The results are presented in Figure 2.

¹ Details of analysis of acceleration are available in supplementary data under “Car-Following”.

4.2.2 Reaction Times

Reaction time is defined as the time lag for the following vehicle to adapt to fluctuations in speeds of the lead vehicle. Fluctuations and adaptations to speed in space-time trajectories within vehicle platoons are demonstrated in Figure 5. There are broadly two types of fluctuations, one of which involves accelerating to a higher speed; for example, as shown in Figure 5, vehicle **V1** starts accelerating at the time t_1 , which is followed by vehicle **V2** accelerating at the time t_2 . The second type of interaction involves a deceleration to a lower speed; for example, in Figure 5, at time t_3 vehicle **V1** starts decelerating, which is followed by vehicle **V2** decelerates at the time t_4 . The time instances at which fluctuations in deceleration and acceleration occur can be identified by evaluating spikes in the curvature of the space-time trajectory.

Figure 5: Space-time trajectories of vehicles in the platoon

The curvature (K) for a space-time trajectory defined as $s = f(t)$ is presented in Equation 1. The time instance corresponding to the maximum curvature indicates the time at which acceleration or deceleration occurs. This was achieved by evaluating the curvature using a moving average (within ten frame windows) method.

$$K = \frac{|y''(x)|}{1 + [y'(x)]^2}^{3/2} \quad \text{Equation 1}$$

The curvature plot for the space-time trajectories shown in Figure 5 is presented in Figure 6. Times t_1 and t_2 corresponding to accelerations of vehicles V_1 and V_2 as well as, times t_3 and t_4 corresponding

to deceleration of vehicles V_1 and V_2 are shown in Figure 6. For example, the reaction time can be inferred as a time difference between when the vehicle V_1 accelerates (or decelerates), and when the vehicle V_2 accelerates (or decelerates), i.e $t_2 - t_1 = 8.3 - 7.7 = 0.9 \text{ sec}$ (or $t_4 - t_3$).²

The extracted reaction times were categorised into three types: AV-MV, MV-AV and MV-MV interactions. An AV-MV, MV-AV, and MV-MV interactions represent the reaction time for an MV following an AV, an AV following the MV and an MV following MV, respectively.

Figure 6: Moving average curvature of displacement time.

4.3 Data Availability

Processed data that support the findings of this study are available from the corresponding authors upon request. The original data can be requested from Waymo Open Dataset:

<https://waymo.com/open/>.

² The space-time trajectories, curvature and moving average curvature plots of all the selected segments are available in the repository for the supplementary data under “Reaction Time”

4.4 Code Availability

Scripts for extraction of data and processing can be found in this GitHub Repo

https://github.com/AhmedARadwan/waymo_analysis.

4.5 Acknowledgement

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4.6 Authors Contribution

AS: Conceptualisation, Methodology, Data curation, management and validation, Writing- Original draft preparation, Visualisation, Investigation, Software, Writing- Reviewing and Editing

AR: Data curation, management and validation, Visualisation, Software

VD: Supervision, Conceptualisation, Investigation, Writing- Original draft preparation, Writing- Reviewing and Editing

All authors have read and agreed to this version of the manuscript.

4.7 Competing interests

The authors declare no competing interests.

4.8 Additional information

Supplementary information can be found in the repository

<https://data.mendeley.com/datasets/p3f3k82tz8/draft?a=5b79a44d-3197-4bf5-858e-52d381948c4a>.

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6 Extended Data

Extended Data Fig1: Coordinate system convention used in this study.

Coordinate System

Positive longitudinal distance is the ego vehicle's direction of driving. Distance along the road is referred as longitudinal (X axis) and distance perpendicular to the road is referred as lateral (Y axis) as presented in Extended Data Fig1. Origin (0,0) is the front center of the ego vehicle.