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Q1 # Fleet analysis of headway distance for autonomous driving

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A R T I C L E I N F O

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Modern automobiles are going through a paradigm shift, where the driver may no longer be needed to drive the vehicle. As the self-driving vehicles are making their way to public roads the automakers have to ensure the naturalistic driving feel to gain drivers' confidence and accelerate adoption rates. By understanding the relation between human driving and their surroundings, the naturalistic driving behavior can be quantified and used to refine the control algorithms developed for automated driving. This paper analyzes a subset of radar data collected from SHRP2 program with focus on characterizing the naturalistic headway distance with respect to the vehicle speed.

1. Introduction

Despite recent discussions and media coverage about transformative aspects of self-driving cars, society still remains rather reluctant on adopting a fully autonomous vehicle. Nearly all responders in Schoettle and Sivak (2016) still would like to have the steering wheel and pedals available as a back-up solution to override the vehicle's self-driving features. On the other hand, a low level vehicle automation such as Advanced Driver Assistance Systems (ADAS) has already been widely adopted and the automated braking system will be a standard feature on nearly all cars sold in US by 2022 (NHTSA, 2016).

The benefits of widely adopting the self-driving vehicles include increase in safety, comfort, and productivity. The key aspect in achieving this goal is to make the self-driving functions transparent and predictable to the driver. Exploring this naturalistic feel is the focus of this paper, more precisely analyzing the headway from a subset of SHRP2 data.

This approach is similar to fleet learning (Frommer, 2016), but uses only signals from on-board radar and vehicle speed to identify the naturalistic headway distance. In Lu et al. (2015) authors identified four (Q6) distinct categories of the driver's behavior in the car-following scenario used to pre-set the Adaptive Cruise Control (ACC) behavior. Categories ranged from normal to aggressive based on the headway gap and its closing velocity. Another previous study (Nakayama et al., 2009) focused (Q7) on traffic jam formation. It also suggested an existence of the natural relationship between vehicles' speed and headway used to categorize driving styles. This paper aims to identify the naturalistic headway gap using the SHRP2 database and quantify its distribution in the recorded subset. The findings can be used to further refine the self-driving features and to close the gap between engineering intuition and human expectations to accelerate the adoption.

The paper starts with describing the method used, radar capabilities, and an initial filtering process to obtain valid observations from noisy radar data. The second section looks closer to the ensemble data to establish a general relation between headway distance and vehicle speed. The next section elaborates on the individual driving style characteristics in order to discern aggressive driving behavior. The paper ends with discussion about possible refinements and summarizing the results.

2. Method

Around 3,800 trips from 39 individual vehicles, were selected from the SHRP2 query builder (SHRP2, 2016). The trip durations ranging from 17 to 24 min and less than 5-minute stop time were purposely selected in order to include highway driving scenarios where the car following situations are more prominent. The radar data from these trips are further filtered and used to analyze the headway distance.

The used radar allows tracking up to eight objects simultaneously, both in longitudinal and lateral positions (Gorman et al., 2015) including (Q8) on-coming vehicles and vehicles in neighboring lanes. An example of the radar output data is shown in Fig. 1. As the radar does not have the ability to sort and track the recognized targets, several data filtering steps are developed to identify a steady object in front of the vehicle pertaining to the car-following situation.

The radar has the capability of tracking objects in the range of about 200 m (650 ft.) longitudinally and about 40 m (130 ft.) laterally, left and

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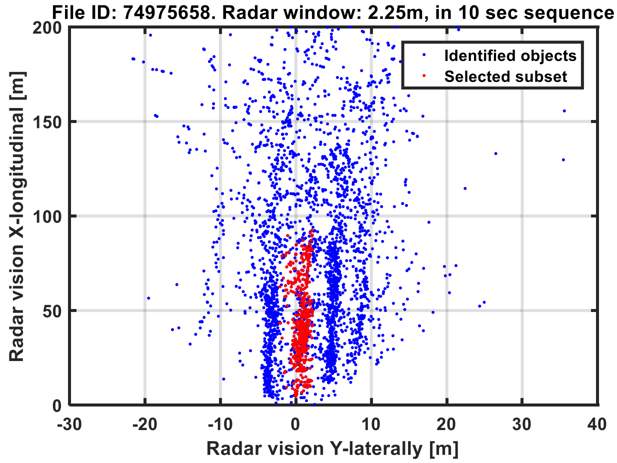

Fig. 1. Radar data example.

right. An interesting point is that if the radar data are aggregated a data cloud (Fig. 1) can be used to approximately cross-check the line width measurement derived by the image recognition algorithm. The overall radar data are analyzed at z rate of 1 Hz.

This study focuses on headway distance therefore raw radar data are further filtered to consider only objects that fulfill the following conditions:

- Are within 2.25 m (7.4 ft.) laterally, which considers some radial misalignment. Assuming that the standard lane width is 3.65 m (12 ft.) (Administration, 2014).
- Consecutive record of the object for at least 10 s to avoid "ghost target" records.
- Headway gap change below 2 m/s is to be considered as a steady state car following scenario of the interest.

3. Overall headway distance observations

Fig. 2 shows an example of the proposed filtering method. Fig. 2 shows the relation between the vehicle speed and the headway distance. Blue dots represent recorded data while red dots represent filtered data respectively after the filtration described above is applied. Fig. 2 further shows that when the highway cruising speeds are reached (around 120 km/h — 75 mph) the headway position can change significantly. The reason behind can be that during the high speed cruising the traffic situation in vehicle surrounding is relatively stabilized and the radar can clearly track the headway of the leading car.

In order to estimate the relationship between the headway and the vehicle speed, the mean value of the headway is calculated for each 10 km/h speed intervals up to 140 km/h. This is depicted by a green dot in Fig. 2 for each speed interval for a single trip observation. It can be seen that there is a nearly linear relation between the headway and the vehicle speed, except between 40 and 60 km/h (25 and 35 mph), which is much higher and can be due to this specific trip rather than repeatable behavior for following the lead vehicle.

In order to make the relation between the headway and the vehicle speed more pronounced and eliminate any trip-specific discrepancies, the trips were further filtered to consider only individual trip records where:

- Each trip has at least 600 data points satisfying the selected criteria mentioned in the previous paragraph to maintain consistency.
- Analyze only vehicles with more than 100 recorded trips to facilitate the identification of patterns in individual driving behavior. Out of 39 vehicles initially in the subset, 14 vehicles met these criteria.

The aggregated headway distances from roughly 350,000 data points are shown in Fig. 3 as a box and whiskers chart. It can be seen that the relationship between the vehicle speed and the headway resembles very closely to a linear relationship, where the headway increases with the increasing speed. This confirms the idea of the naturalistic safety distance.

A similar finding can be described in terms of Time to collision (TCC), which is the time needed to traverse the headway distance at current vehicle speed. Depicted in Fig. 4, the TTC is decreasing with increasing vehicle speed and then stabilizes slightly below 2 s. The larger TTC observed during the city-speed driving can be due to a large variety of driving situations, which are harder to anticipate by the driver. The TTC with less than 2 s during high speed driving can be explained by a much slower relative change of the driving situation, which is well in accordance with the previous study in (McGehee et al., 2000). Q9

4. Individual driving styles

Once the patterns between the headway distance and the vehicle speed are validated, the individual driving styles can be discussed. Fig. 5 shows 14 different vehicles and their averaged TTC for the speed interval between 90 and 100 km/h (roughly 55–65 mph) which corresponds to a freeway speed where the steady state car following scenario is the most prominent. Fig. 5 shows significant differences among individual vehicles, when TTC is sorted by the median. From left, the first

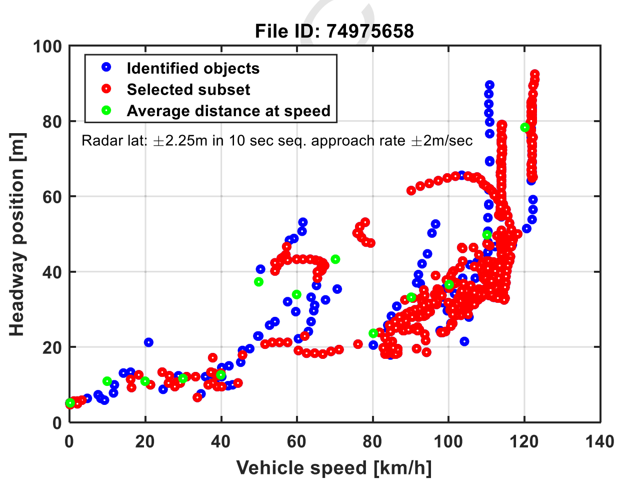

Fig. 2. Vehicle speed vs. Headway distance. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

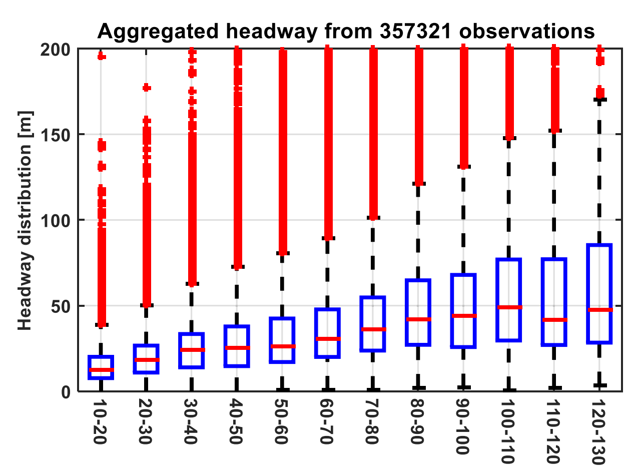

Fig. 3. Aggregated headway.

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