Analysis of Unprotected Intersection Left-Turn Conflicts based on Naturalistic Driving Data

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Abstract—Analyzing and reconstructing driving scenarios is crucial for testing and evaluating automated vehicles. This research analyzed left turn / straight-driving conflicts at unprotected intersections by extracting actual vehicle motion data from a naturalistic driving database collected by the University of Michigan. Nearly 7,000 Left turn across path opposite direction (LTAP/OD) events involving heavy trucks and light vehicles were extracted and used to build a stochastic model of such LTAP/OD scenarios. Statistical analysis showed that vehicle type is a significant factor, whereas the change of season seems to have limited influence on the statistical nature of the conflict. The results can be used to build HAV testing environments to simulate the LTAP/OD crash cases in a stochastic manner, which is among the top priority light-vehicle pre-crash scenarios.

I. INTRODUCTION

Before Highly Automated Vehicles (HAVs) can be released to the general public, a well-defined process for testing and evaluating them must be established. The Google self-driving car project experienced its first shared-responsibility crash in February 2016 [1]. Moreover, Tesla Autopilot failed to detect a semi-truck and is at least partially responsible for its first fatal crash happened in May 2016, and was criticized for using the consumers as beta testers [2]. Fig. 1 briefly demonstrates how the crash occurred, with the red sedan representing the Tesla. The NHTSA is now considering the possibility putting a pre-market approval process into place [3], in addition to a rigorous self-certification process still anticipated from the vehicle manufacturers.

A key factor in HAV testing is the test scenarios and behaviors of other road users, particularly those of other vehicles. The test conditions need to be not only realistic but also feasible for repeated safety tests. Test scenario models can be divided into two types. The first type has fixed scenarios, such as the EURO NCAP tests of Lane Support Systems (LSS) [4] and Autonomous Emergency Braking (AEB) [5]. A major advantage of this type is that it is repeatable. However, it is hard to use this type of models to represent the stochastic nature of the human driving environment. Moreover, HAVs could be adjusted to pass certain fixed scenarios while their performance under broad conditions might not be well assessed. To overcome these drawbacks, we proposed a second type of models. In our previous works [6], [7], [8], we proposed a stochastic test method and built a test environment for car-following and lane-change scenarios. In this paper, we will focus on the intersection scenario.

The intersection has been one of the most challenging scenarios for HAVs, due to the variety of road users, complexity of traffic flow and the unpredictability of vehicles and pedestrians. According to [9], crashes at intersections took up a major portion, about 44\%, of all the traffic crashes in the US. Among all kinds of scenarios with potential risks at an intersection, unprotected left turn across path - opposite direction (LTAP/OD) is a typical one. This scenario is ranked 2\textsuperscript{nd} among 10 priority V2V light-vehicle pre-crash scenarios [10]. In an LTAP/OD scenario, two vehicles are considered: the turning vehicle (TV) and the straight-driving vehicle (SDV).

Although a lot of research, such as [11], [12], has been conducted on traffic conflict analysis of LTAP/OD scenarios, the factor of vehicle type has not been widely investigated. Now that the crash of the Tesla with Autopilot system has been attributed to its failure to detect the truck turning ahead [13], it is crucial that more attention should be paid to scenarios involving heavy trucks. Moreover, there has been insufficient research on the influence of season change on driving behaviors at intersections. As extreme weather such as storm and fog have a strong impact on the driving behaviors of human drivers, we propose that they are possibly influential to also HAVs.

This research focused on two major tasks: first, it built a stochastic model of traffic conflicts in the LTAP/OD scenario based on naturalistic driving data. Events involving both light vehicles (LVs) and heavy trucks (HTs) as the SDV were extracted from the database, reconstructed into realistic...
The database provides adequate information for this research. For event extraction, data from the on-board GPS sensor is used to locate the instrumented vehicle; the data from the front long-range radar is used to reconstruct the trajectory of target vehicles; the video recordings from vision cameras around the vehicles are used as a supplemental tool for event screening. In addition, as the IVBSS test lasted approximately one year, driving data under a variety of weather conditions throughout the year were covered, enabling us to uncover the influence of season factors.

III. Extraction of Left Turn Scenario

In order to extract eligible left-turn events from the database for both the LV and the HT platform, three major tasks were performed. First, we processed data from radar for further use. Second, we searched in the database for all left-turn events that meet our criteria. Each event is defined solely by vehicle number, trip number, start time and end time. Finally, data points in each event were interpreted into trajectories of the TV and the SdV.

A. Target Association of Truck Data

For radar data from the HT platform, we need to associate and mark data points together that belong to the same target in order to screen out unfit targets and create a trajectory for every eligible TV. To cluster points of interests, we apply the following criteria to processing HT data:

- Only objects (TVs) that move in the opposite direction
- Only points with small azimuth angle (|α| < 5.5°) are considered, as the effective detecting range of the radar is 11°.
- Only points within a small time slot (\([t(i), t(i) + 0.85 \text{s}]\)) are considered.
- Only neighbor points that satisfy the following rules are considered:

1) Strong correspondence between range, range rate and time difference:

\[
|1 - \frac{\delta t_{pred}}{t(j) - t(i)}| < 0.3
\]

where

\[
\delta t_{pred} = |2 \cdot \frac{r(j) - r(i)}{rr(j) + rr(i)}|, \quad \text{Here, } r(i) \text{ is the range of point } i, \text{ and } rr(i) \text{ it the range rate of point } i
\]

2) Reasonable difference in transversal.

\[
\frac{tr(j) - tr(i)}{t(j) - t(i)} < 20 \text{m/s}
\]

Here, \(tr(i)\) is the transversal of data point \(i\), and \(t(i)\) is the time.

Fig. 3 shows an example of data points that are associated and divided into different groups. The smooth curves formed by points with the same color show trajectories of targets, while red dots do not belong to any group and are seen...
as noise. In such a typical LTAP/OD scenario, a vehicle is turning in front of the instrumented truck. Fig. 3(a) shows how the range of target points change over time. As target vehicles cross the intersection when the instrumented vehicle is moving forward at a steady speed, the ranges to different targets are decreasing linearly. Moreover, Fig. 3(b) shows that the transversal of multiple targets is increasing from negative to positive, indicating that they cross from left to right in the view of the instrumented vehicle. Once data points from each target are clustered, the HT platform can be used for further event extraction for eligible LTAP/OD scenarios.

B. Event Screening

An LTAP/OD scenario can be recorded by either the SdV or the TV. In this paper, we use only the scenarios recorded by the SdVs. Fig. 4 demonstrates the configuration of the instrumented vehicle, i.e., the SdV and the target vehicle, i.e., the TV for event extraction in LTAP/OD scenarios. For both the LV and HT platforms, eligible left-turn events are queried based on the following criteria:

- The intersection has a stop sign or a set of signal light.
- The instrumented vehicle is moving straight (speed less than 3 m/s & change of heading angle smaller than 10°).
- The target vehicle is moving towards the instrumented vehicle (the longitudinal projection of speed smaller than -0.5 m/s) and moving from left to right (transversal goes from positive to negative for LVs, and from negative to positive for HTs).
- Time duration of the event is adequate (more than 1.5 s).
- Max time difference between two consecutive points (defined as \( \delta t \)) in an event should be small enough to be seen as points of the same target (max\{\( \delta t \)\} < 1 s).

Event extraction follows a similar procedure for LV and HT. For the LV platform, we first select all straight-driving occurrence at intersections; we then extract those with left-turn objects from the opposite direction. These tasks are completed in the SQL Server Management Studio (SSMS). Afterwards, the extracted events are exported to MATLAB for the last round of screening, which guarantees reasonable speed, targets, and time duration. For the HT platform, the only difference is that after retrieving all the occurrences of straight-driving at intersections, we export data from the database server directly into MATLAB for target association and the following extraction tasks.

C. Trajectory Reconstruction

Once all eligible events have been selected, the trajectories of both TV and SdV in each event are then reconstructed. The exact position of SdV comes from the on-board GPS sensor; the data from the front long-range radar are used to extract the relative position of TV in the coordinate of SdV. Each target vehicle is regarded a point of mass. After synchronization on GPS and radar data, the trajectories of TV and SdV are generated. Fig. 7 shows the reconstructed trajectory for SdV and TV in one event. Here, dots with the same color represent the position of TV and SdV at the same moment. The TV crossed intersection before the SdV in this example.
IV. CONFLICT ANALYSIS AND COMPARISON

A. Definition and Metrics of Conflicts

In this section, conflict is used to describe risky events in traffic. According to [18], conflict is defined as an observational situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged. Many conflict metrics have been used for measuring the level of safety for an LTAP/OD event, including post-encroachment time (PET), leading buffer (LB) and trailing buffer (TB) used by [19], and gap time (GT) used by [20]. For this paper, as the goal is to construct a stochastic model, we choose only the most representative time slice in each event to model LTAP/OD conflicts. The heading angle of the SdV is taken as constant during each event, with any small deviation being ignored. Thus, a conflict point is naturally defined as the location of the TV when its transversal in SdV’s radar crosses zero, and this exact moment is regarded as the representative moment of this conflict, defined as $T_x$. Consequently, four variables at $T_x$ are chosen to model conflict, including two modified conflict metrics: time to conflict point ($T_{cp}$) and Distance to conflict point ($D_{cp}$):

- $D_{cp}$: Distance to the conflict point for the SdV at $T_x$
  \[ D_{cp} = \text{dist}(P_{SdV}(T_x), P_{TV}(T_x)) \]  

Here $P_{SdV}$ and $P_{TV}$ are the positions of SdV and TV

- $T_{cp}$: Time to the conflict point for the SdV at $T_x$
  \[ T_{cp} = D_{cp}/v_{SdV} \]  

• $v_{SdV}$: Speed of the SdV at $T_x$
• $v_{TV}$: Speed of the TV at $T_x$

First, we demonstrate an example of conflict analysis on a single LTAP/OD event. Here we use the aforementioned occurrence, where the TV crossed the intersection before the SdV did. Fig. 8 uses $T_{cp}$ to demonstrate how the SdV and the TV interacted in one real LTAP/OD event. The vertical axis indicates predicted time to the point of conflict of the SdV, whereas the horizontal axis shows the real elapsed time relative to the moment when the TV crosses the intersection, that is, $T_x$. In this scenario, time to conflict point decreased linearly over time, indicating the margin between the TV and the SdV was large enough for the SdV to maintain a nearly constant speed when the TV was crossing. When the TV reached the conflict point, there was a 2.3-second margin for SdV, that is, $T_{cp}$, which is demonstrated by the red dot. Here, $T_{cp}$ described the essence of this interaction between the SdV and the TV.

Then, the following modeling and analysis will ignore the detailed interaction of the TV and the SdV, paying attention only to the four aforementioned variables in each event. We use all events we retrieved in the previous section from both the HT and LV platforms as the source for modeling.

B. Comparison between Truck and Sedan

In this section, the effect of vehicle type on traffic conflict in LTAP/OD scenarios is discussed. Distributions of variables for LVs and HTs are compared.

![Fig. 8. Time to the conflict point of the SdV in a left-turn scenario](image)

Fig. 9 shows that events with an HT as SdV have larger

![Fig. 9. Distribution of (a) distance to the conflict point($D_{cp}$) and (b) time to the conflict point($T_{cp}$); distribution of (c) the reciprocal of $D_{cp}$ and (d) the reciprocal of $T_{cp}$ (fitted with GEV distribution)](image)

| Type of the SdV | LV       | HT       |
|----------------|----------|----------|
| $D_{cp}^{-1}$  | $-6.68 \times 10^4$ | $-4.37 \times 10^4$ |
| $T_{cp}^{-1}$  | $-1.12 \times 10^4$ | $-1.32 \times 10^4$ |
function (pdf) of GEV when $\xi > 0$ describes data. We found that the distribution of $D_{cp}$ and $T_{cp}$ to put these risky but rare events in the tail for a better fitting result. Here, when $D_{cp}^{-1}$ or $T_{cp}^{-1}$ increases, there are fewer points of data, giving rise to a shape with a long tail. A standard MATLAB package [21] is used to search for a proper distribution to fit both $D_{cp}^{-1}$ and $T_{cp}^{-1}$. It examines 17 different types of distributions and evaluates the fitting results by using Bayesian Information Criterion (BIC) [22]. The smaller BIC value is, the better is the model for describing data. We found that the distribution of $D_{cp}^{-1}$ and $T_{cp}^{-1}$ can all be fitted with General Extreme Value(GEV) distribution with an impressive BIC. The probability density function (pdf) of GEV when $\xi > 0$ is:

$$f(x; \mu, \sigma, \xi) = \frac{1}{\sigma} \left[1 + \xi \left(\frac{x - \mu}{\sigma}\right)\right]^{(-1/\xi)-1} \exp\left\{-\left[1 + \xi \left(\frac{x - \mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

(5)

Here $\mu$ indicates the location of distribution, $\sigma > 0$ indicates the scale and $\xi$ is a parameter for the shape. When $\xi$ increases, the distribution has a longer tail.

From Fig. 9(c) and Fig. 9(d), we can conclude that the mean values and variance of the reciprocals of $D_{cp}$ and $T_{cp}$ are smaller for HTs than for LVs.

Fig. 10 shows the distributions of $v_{SdV}$ and $v_{TV}$. The distribution of $v_{SdV}$ for HT and LV platform both have a triangular shape. Most $v_{SdV}$ ranges from 12 to 20 m/s, whereas most $v_{TV}$ is less than 10 m/s at the conflict point. Though there is no obvious difference with the distribution of $v_{SdV}$ between events with LV and HT as the SdV, the $v_{TV}$ tends to be significantly higher when the SdV is an LV than an HT. Combined with the previous results of $D_{cp}$ and $T_{cp}$, we can conclude that for left-turn conflicts where HTs are SdVs, conflict metrics have significantly higher value, and TVs tend to turn with less aggressive speed. This means that when the TV chooses the time of turning and commences turning action, it behaves more conservatively when confronted by an HT coming from the opposite direction than an LV. The difference in vehicle type does influence the driving behavior of the TV and the severity of the conflict.

C. Analysis of Season Factor

In this section, we uncover the influence of season factor on behaviors of SdVs and TVs in LTAP/OD scenarios. During the test, 7% of driving for HTs [16] and 15% [17] for LVs took place in freezing temperature. The months with events that took place in freezing temperatures are defined as winter, which includes December through March of the following year. This period also coincides with the time when the average snowfall in Ann Arbor is over 8 inches. On the other hand, summer is defined as being from June to August. $T_{cp}^{-1}$, $D_{cp}^{-1}$, $v_{SdV}$ and $v_{TV}$ are compared for summer and winter driving. Mann-Whitney-Wilcoxon (MWW) test [23] is a non-parametric hypothesis test of the null hypothesis that two populations are the same against an alternative hypothesis. Here, we used it to determine whether the conflict metrics differ between summer and winter.

Fig. 11 shows the result of the comparison. It can be concluded that for both LV and HT platforms, the mean values for summer and winter all four variables that describe conflict at LTAP/ODs for both SdVs and TVs are very close. As the p-value from the MWW test is large (p-value > 0.6) for all the eight distributions, we were not able to distinguish between the left-turn pattern in summer and in winter in terms of $D_{cp}^{-1}$, $T_{cp}^{-1}$, $v_{TV}$ and $v_{SdV}$. This result indicates that despite a large difference in climate, there is no significant difference between the way people drive in winter and in summer at LTAP/OD scenarios in the Great Lakes area. This conclusion has its significance for the designing of HAVs, as it means that a system designed and built for good conditions and weather can probably also work well with LTAP/OD scenarios in Michigan winters, in which snow and freezing weather prevail.

V. CONCLUSION

In this research, traffic conflicts of TV and SdV in LTAP/OD scenarios are modeled and analyzed based on nearly 7,000 left-turn events extracted and reconstructed from the naturalistic database. The two modified conflict metrics, $T_{cp}$ and $D_{cp}$ are used to model turning behavior of the TV. This stochastic model can be further used for developing simulation tools for evaluating HAVs.

The significance of vehicle type and season are also addressed in the research. In general, when the straight vehicle is an HT, the driver of the TV tends to turn in a more conservative fashion, with a wider margin. Surprisingly, despite a huge difference in climate between summer and
winter in Michigan, driving behavior in LTAP/OD scenarios for both TV and SdV during the N-FOT test did not differ significantly. These two conclusions can be useful for the design of automated driving algorithms and for establishing regulations and policies for HAVs.

In the following research, we will improve the accuracy of trajectory reconstruction by conducting sensor fusion to the GPS and yaw rate sensor, and by re-synchronizing data from different channels. We will also facilitate the model to build a stochastic simulation environment for the testing and evaluation of HAVs.

**DISCLAIMERS**

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