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Enhance SIL Simulation Through Driver Behaviour Modeling at Unprotected Left-Turn Scenario for Autonomous Driving SOTIF Analysis

Shiming Liu [a], Qunli Zhang [a,1], Peng Wang [a], Bin Feng [a], Chengqiang Huang [a], Yulin Zhang [b], Lanyue Tang [b], Lishengsa Yue [b], Jian Sun [b]
[a] *RAMS Lab, Huawei Technologies Co., Ltd., China*
[b] *Department of Transportation Engineering, Tongji University, China*

Abstract. As the rapid advancement of artificial intelligence (AI), information and communication technologies, autonomous driving system (ADS) has increased permeation into the traditional automotive industry in recent years. To reduce the Safety of the Intended Functionality (SOTIF) risk of autonomous driving system hence improving its dependability, SIL simulations are extensively exploited as virtual mileage test in compensation of the prohibitively expensive and inefficient road test. In SIL simulation, unprotect left-turn is an intricate traffic scenario to be reproduced due to the intensive interaction between vehicles at the intersection. However, most state-of-the-art commercial simulation software omit the interaction modeling. Thus, in this paper, we proposed a driver behavior modeling approach at unprotected left-turn scenarios to enhance the authenticity of SIL simulation. The left-turn scenario was modelled through three stages, including interaction selection, interaction decision and driver behavior modeling, of which a logit model and intelligent driver model (IDM) were used for the latter two stages. After model calibration, it proves this approach can generate highly authentic traffic flow with unbiased feature distribution towards the real-world, indicating its potential in SIL simulation performance improvement.

Keywords. SOTIF, ADS dependability, SIL, Driver Behavior Model, Unprotected Left-turn

1. Introduction

The development of autonomous driving technologies has witnessed a rapid progress in decades. As a safety-critical AI system, it is extremely important to guarantee the dependability of the running vehicle deployed with ADS. Due to its superior effectiveness, software-in-loop simulation becomes one of the essential SOTIF procedures to discover potential hazardous scenarios and examine the inability of the system before released to public. It is reported more than 40% of collisions and 20% of fatalities occur at intersections while unprotected left-turn scenarios account for a high

[1] Qunli Zhang, RAMS Lab, Huawei Technologies Co. Ltd., Shenzhen, China; E-mail: zhangqunli1@huawei.com.

portion [1][2][3]. Therefore, it is urgent to establish a highly authentic interactive behavior model at this scenario to improve validity of SIL analysis [4].

This challenge has motivated extensive research activity on the investigation of driver behaviors at unprotected left-turn intersections. Based on the literature review, it is found that there are 4 types of major simulation modeling schemes: data-driven learning method, optimization algorithms, multi-agent systems and traffic flow theoretical method [5][6]. Data-driven learning model is trained and implemented to simulate more human-like driving behaviors by feeding great amount of naturalistic driving data. It can be further categorized into machine learning [7], end-to-end deep learning [8], recurrent neural network [9] and deep reinforcement learning [10][11]. This type of method relies on the quantity, quality and diversity of training dataset, which would lead to performance deterioration in the presence of uncertainties. Multi-agent system takes account of complicated interactions between individual traffic participants and the surrounding environment [12]. Cellular automata is usually employed to model key parameters of the agent, formalized interactive rules including traffic rules, and predict the state transition during turning process [13][14]. Although multi-agent framework has been continuously developed over years, the calibration of large number of parameters and the lack of interpretability limits its implementation. Optimization algorithms define the cost function and constraints to determine the behaviors of each interactive participant [15]. The heuristic framework normally includes object model, kinematic and dynamic models, and proper optimization policies [16]. These independent models along with the specific constrains are utilized to simulate the passing situation at intersections practically. However, the obtained constrains would increase the complexity of solving the optimal as the non-convex quadratic programming (QP) problem leads to high computation cost and hence inefficient application [17]. Traffic flow theoretical method is widely adopted owing to its advantages of well-abstracted scenario representation, high adaptively to complex interactive behaviors, good simplicity and interpretability of the model, and low computational cost [18][19][20].

This study proposes an innovative framework to model driver behaviors at unprotected left-turn intersections with high accuracy and low computational cost. The interactive process consists of three stages as interaction object selection, interaction decision and driver behavior modeling, which is modelled by a logit model and an intelligent driver model (IDM) respectively. Logistic regression model predicts the potential conflict points between the interactive vehicles and the corresponding optimal yield/take right-of-way (ROW) possibilities. Based on the decided interactive behavior, the IDM model provides the constant-velocity or decelerated driving trajectories.

The paper is organized as follows. The overall modeling process of unprotected left-turn scenario is described in Section 2. Section 3 demonstrates driver modeling method and model details. Subsequently, Section 4 introduces the model calibration method and the calibration results. Section 5 demonstrates the efficacy of utilizing the developed model to perform SIL simulation to analyses SOTIF issues for autonomous driving vehicles. Finally, Section 6 summarizes the study and discuss the future work.

2. Overall modeling process of unprotected left-turn scenario

To simulate the unprotected left-turn scenario, an overall modeling process was devised, which was composed of three stages: interaction object selection, interaction decision and driver behavior modeling.

2.1. Interaction object selection

In the process of selecting interaction targets, we first identified all vehicles that may potentially conflict with ego vehicle based on the road network topology. This process started from determining conflicts among internal connectors within the intersection based on the overlapped region between trajectories. For instance, as shown in Figure 1, Connector X and Connector Y were considered to have potential conflict. For the ego vehicle, we traversed potential conflict points and searched for opposing lanes that might lead to potential conflicts. Subsequently, the conflicting vehicles within these lanes were identified.

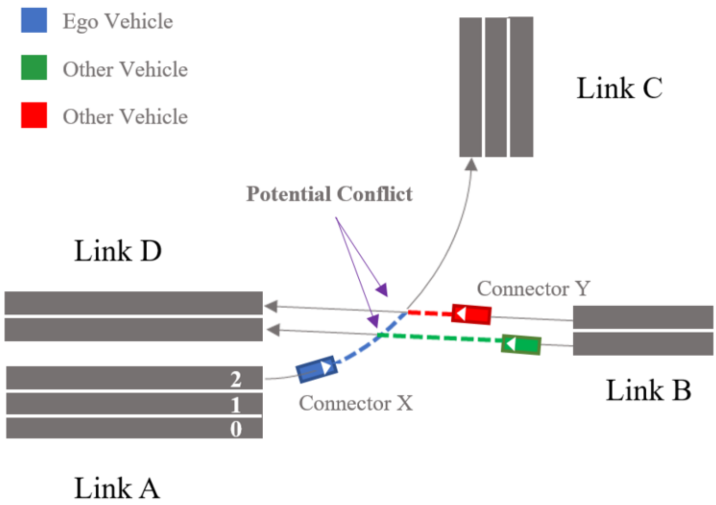

Figure 1. Potential conflicts between vehicles.

By constantly collecting real-time locations and heading angels of ego vehicle and potential conflict vehicles, the distance and angle between the pair of interactive vehicles were calculated. Two criteria were devised for interaction object selection, as shown in Figure 2:

- Whether the object vehicle was in the view field of the ego vehicle, i.e. within the range of [-60°, 60°] in the front.
- Whether the distance between the object and ego vehicles was less than 25 m.

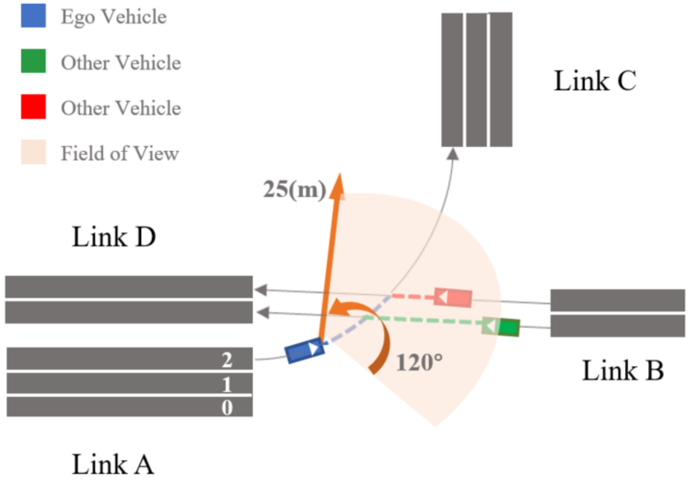

Figure 2. Field of view of the ego vehicle: sector-shaped view with an angle of 120° and a radius of 25 m.

The design of this field of view conformed to the real-world interaction process at the intersection, which not only enhanced the anthropomorphism of the modeling approach but also improved simulation efficiency by reducing redundant computations.

2.2. Interaction decision

At the 2nd stage, we utilized a logit model [21], a statistical model widely used for classification and predictive analytics, to determine the interaction mode: whether the vehicle take or yield the ROW of its interacting vehicles. The model estimated the probability of ego vehicle taking the ROW, based on key parameters including the speed, acceleration of ego vehicle and its distance to the conflict point, etc.

2.3. Driver behavior modeling

Once the interaction decision of ego vehicle had been determined, an intelligent driver model (IDM) [22] was used to model the driver behavior at vehicle control level. IDM describes the position and velocity dynamics of a single vehicle, which is widely used as a car-following model. For this reason, a virtual lead vehicle was introduced for vehicle behavior modeling, which was performed based on the interaction decision:

- Yield ROW: a stationary virtual lead vehicle was placed at the conflict point, the yield behavior to interaction vehicles was thus modeled by yielding the lead vehicle.
- Take ROW: the lead vehicle passed the intersection freely, and the take-way behavior was modelled by following the lead vehicle.

3. Driver modeling

3.1. Logit model

As introduced in Section 2.2, a logit model was established to predict whether the ego vehicle yields or takes the ROW during interacting, which was defined as follow:

$$log\left(\frac{P_r}{1-P_r}\right) = \beta_0 + \beta_1 V_e + \beta_2 a_e + \beta_3 d_e + \beta_4 V_o + \beta_5 a_o + \beta_6 d_o \tag{1}$$

Where P_r represents the probability of the vehicle taking ROW, and the key variables include following factors: the speed of ego vehicle V_e, ego acceleration a_e, distance from ego vehicle to the conflict point d_e, speed of interacting object V_o, acceleration of interacting object a_o, and distance from of interacting object to the conflict point d_o. β_0 is a constant term, and $\beta_i (i = 1,2,\ldots,6)$ are parameters to be estimated from experience.

3.2. IDM

As introduced in Section 2.3, IDM was used to model the driver behavior at the intersection. Thus, the acceleration of the vehicle was calculated as Eqs. (2) and (3).

$$\dot{v} = a * \left[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right] \tag{2}$$

$$s^*(v,\Delta v) = s_0 + \max\left(0, s_1\sqrt{\frac{v}{v_0}} + T * v + \frac{v*\Delta v}{2\sqrt{ab}}\right) \tag{3}$$

where $\dot{v}$ is the acceleration of ego vehicle, v_0 is the desired speed, Δv is the speed difference between ego and lead vehicle, s is the distance to lead vehicle (rear-end gap), s^* is the desired distance to lead vehicle, T is the reaction time, a is the initial acceleration, b is the comfortable deceleration, δ is the acceleration index, s_0 is the safe distance to stop and s_1 is a speed-dependent safe distance selection parameter.

4. Model calibration

4.1. Logit model calibration results

The logit model was calibrated using naturalistic driving data collected at the Jianhe Road - Xianxia Road intersection in Shanghai. The long term driving data were first preprocessed to segments which were useful for model calibration, including the key driving factors of ego and interacting vehicles as shown in Eq. (1). Subsequently, the preprocessed date were used to calibrate the model parameters (β_0-β_6) through logistic regression.

The calibration results of the parameters are shown in Table 1, which achieved a fairly high McFadden R square of 0.959.

Table 1. Logit model calibration results (McFadden R square: 0.959)

Parameters	Regression Results					
	Coefficient	***Standard Deviation***	***z***	***Wald χ2***	***p-value***	***OR-value***
V_e	4.16	0.65	6.39	40.55	0.000	64.16
a_e	5.09	0.95	5.37	28.82	0.000	161.97
d_e	-1.31	0.21	-6.13	37.63	0.000	0.27
V_o	-3.00	0.40	-7.55	56.96	0.000	0.06
a_o	-8.54	1.30	-6.58	43.22	0.000	0.00
d_o	0.83	0.13	6.39	40.81	0.000	2.29
β_0	4.33	1.30	3.35	11.25	0.001	76.26

Table 2 shows the 95% confidence interval of each parameter of the logit model during calibration. In order to enrich the effect of the decision model, the logit model parameters were randomly sampled from the 95% confidence interval during the long-term traffic flow simulation.

Table 2. 95% CI OR-value of logit model parameters

Parameters	***OR-value 95% CI***	***Parameters***	***OR-value 95% CI***
V_e	17.823 ~ 230.970	V_o	0.023 ~ 0.109
a_e	25.283 ~ 1037.832	a_o	0.000 ~ 0.003
d_e	0.177 ~ 0.410	d_o	1.776 ~ 2.953
β_0	6.055 ~ 960.414		

4.2. IDM calibration and results

The parameter calibration of microscopic traffic flow simulation is essentially a combinatorial optimization problem with a specified objective function, and the key to this problem is to determine the appropriate objective function. In this study, we exploited genetic algorithm (GA) for IDM parameter calibration [23], with the objective to minimize the deviation between the simulated and real-world vehicle distance at each simulation step. The objective function was defined as Eq. (4), with which GA gradually converged towards the optimal parameters combination.

$$J_{GA} = \frac{1}{N}\sqrt{\frac{\sum_{i=1}^{N}\left(gap_i^{real} - gap_i^{sim}\right)^2}{\sum_{i=1}^{N}\left(gap_i^{real}\right)^2}} \tag{4}$$

As introduced in Section 2.3, the driver behavior was modelled in accordance with the interaction decision. Thus, the IDM was respectively calibrated in both scenarios. Since a virtual lead vehicle was introduced during calibration, a 6th parameter, d_0 (initial distance between the ego and lead vehicle), was also determined during calibration. Similar to the calibration process of the logit model introduced in Section 4.1, the calibration data were acquired through preprocessing the naturalistic driving data collected at the Jianhe-Xianxia Road, with which the model parameters (s_0, T, a, b, v_0, d_0) were calibrated. Table 3 presents the IDM parameters calibration results.

Table 3. IDM parameters calibration results (d_0: Initial distance)

Yield or take ROW	Calibration Results					
	$S_0(m)$	$T(s)$	$a(m/s^2)$	$b(m/s^2)$	$v_0(m/s)$	$d_0(m)$
Yield	8.74	5.00	4.76	1.67	9.58	-
Take	6.93	1.51	3.00	2.96	8.49	10

5. SIL simulation analysis – highly authentic traffic flow

To evaluate the human behavior modeling results at the unprotected left-turn, we deployed the well-calibrated driver behavior models to a long-term simulation. The simulation was generated, using in-house codes, at a virtual Jianhe Road-Xianxia Road intersection which was reproduced based on the real-world road dimension. We extracted the maximum acceleration of the left-turn vehicle before any vehicle passed the conflict region, which was defined as the overlapped region of the trajectories from the left-turn and go-straight vehicles. As presented in Figure 3, the distribution of the maximum acceleration from simulation was compared with that extracted from real-world data. It can be seen that both distributions had a fairly good match, fulfilling a Gaussian distribution with mean equal to 0.59 m/s^2. Thus, the driver behavior modeling approach calibrated with real-world data can produce highly authentic traffic flow in the unprotected left-turn scenario with unbiased traffic feature distribution to the real-world.

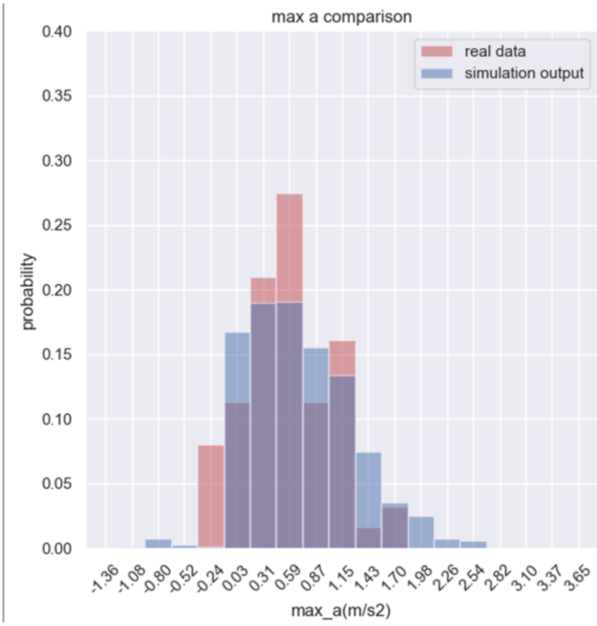

Figure 3. Comparison between the simulated and real-world traffic flow at Jianhe-Xianxia Road intersection

6. Conclusions

In this paper, we proposed a driver behavior modeling approach at unprotected left-turn scenarios to enhance the SIL simulation for autonomous driving SOTIF risk reduction and ADS dependability analysis. The modeling process consisted of three stages: interaction object selection, interaction decision and driver behavior modeling. The driver behavior models were calibrated using real-world traffic data, which were deployed to generate traffic flow at a virtual intersection reproduced based on real-world dimension. From the modeling results, the following conclusions can be drawn:

- The driver behavior modeling approach can produce highly authentic traffic flow with unbiased feature distribution to the real-world, it can be utilized to improve the SIL simulation authenticity and thus facilitating the reduction of autonomous driving SOTIF risk through virtual mileage test.

Future work can seek further improvement in SIL simulation authenticity for SOTIF risk reduction, such as extending the driver behavior modeling approach to more traffic scenarios and developing more advanced driver behavior models. Potential research challenge could reside in improving the model generalization in different traffic scenarios.

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