Probabilistic Lane-Change Decision-Making and Planning for Autonomous Heavy Vehicles

Wen Hu, Zejian Deng, Dongpu Cao, Member, IEEE, Bangji Zhang, Amir Khajepour, Member, IEEE, Lei Zeng, and Yang Wu

Abstract—To improve the safety and driving stability of the autonomous heavy truck, it is necessary to consider the differences of driving behavior and drivable trajectories between the heavy trucks and passenger cars. This study proposes a probabilistic decision-making and trajectory planning framework for the autonomous heavy trucks. Firstly, the driving decision process is divided into intention generation and feasibility evaluations, which are realized using the utility theory and risk assessment, respectively. Subsequently, the driving decision is made and sent to the trajectory planning module. In order to reflect the greater risks of the truck to other surrounding vehicles, the aggressiveness index (AI) is proposed and quantified to infer the asymmetrical risk level of lane-change maneuver. In the planning stage, the lateral and roll dynamics stability domains are developed as the constraints to exclude the candidate trajectories that would cause vehicle instability. Finally, the simulation results are compared between the proposed model and the artificial potential filed model in the scenarios extracted from the naturalistic driving data. It is shown that the proposed framework can provide the human-like lane-change decisions and truck-friendly trajectories, and performs well in dynamic driving environments.

Index Terms—Autonomous heavy truck, decision-making, driving aggressiveness, risk assessment, trajectory planning.

I. INTRODUCTION

Almost one third of accidents are caused by trucks while they only account for 10% of the road vehicles, and the fatality of accidents caused by trucks is also much higher than that in the passenger cars related crashes [1]. The applications of autonomous trucks could help to reduce the accidents caused by the fatigue and distracted of driver which are common in the long-distance transport. However, their typical features are not stressed well in the decision-making and planning process [2], [3]. Therefore, this study aims at proposing the lane-change decision making and trajectory planning model for the heavy trucks by considering their unique characteristics.

To address the lane-change (LC) of autonomous heavy trucks, the differences between the heavy trucks and the passenger cars should be introduced. Firstly, the motivation and frequency of lane-change are different. The passenger car drivers are likely to change lane to obtain higher driving speed while the truck drivers may not in the same scenario with more weightings on the driving safety [4]. Secondly, the lateral and rollover dynamics stabilities of trucks are inferior to them of the passenger cars because of the higher center of mass and worse braking capability [1], [5]. Thus, the lateral speed and lane change spans differ in a large range, leading to various distributions of lane change trajectories [6]. Moreover, the trucks have greater impact on other traffic participants due to larger size and weight. Their wider perception blind areas also increase the driving risks [7].

Lane-change behavior can be modeled based on integrated or hierarchical frameworks [8]. The decision-making process is weakened with lane keeping and lane changing trajectories not distinguished in the integrated framework [9], [10]. On the contrary, the hierarchical architecture focuses more on understanding the lane-change behavior of real human drivers [8], which can be divided into lane-change decision, trajectory generation and optimization [11], [12]. Toledo modeled the lane-change behavior decision using utility theory and gap acceptance model [13]. However, the acceptable gaps vary greatly for different types of vehicles and drivers. In the existing publications about lane-change decision [14], [15], only a few involved with the driving behavior of heavy trucks at the individual vehicle level. Chen et al. [4] and Aghabayk et al. [6] revealed that the car-following behavior and lane-change decision of trucks are different with cars by analyzing the real driving data. Moridpour et al. developed a lane-changing decision model of trucks for the microscopic traffic simulation based on fuzzy logic [3]. Nevertheless, the characteristics of trucks are not highlighted with mathematic model. Moreover, the above microscopic traffic models ignore the feasibility of lane-change trajectory.

Trajectory generation and optimization is part of the motion planning research [16], where plenty of methods can be applied [17], such as interpolating curve, sampling-based approach, graph search, artificial potential field [9], etc.
nominal curve is an effective method thanks to the generated path satisfying the continuity of the first and second derivatives [10]. However, although extensive researches in the motion planning have been published, they rarely focus on the particularity of heavy trucks in the dynamics feasibility [18]. Concretely, the vehicle dynamics stability is concerned in path tracking and motion control [19], [20], while it is seldom included in path planning study [21]. Obviously, the path following performances and vehicle stabilities of autonomous heavy truck can be improved if the dynamics are considered in the previous path planning.

Risk prediction and assessment plays a key role in the decision-making of autonomous vehicles [22], [23]. The state-of-the-art risk evaluation methods include surrogate safety measures [24], statistics-based metrics [25] and field-based metrics. Li et al. used the conditional random field model to synthesize different safety measures into a collision function [26]. Wang et al. introduced the risk indexes respectively for road boundary, non-crossable and crossable obstacles based on the motion prediction [27]. Nevertheless, a majority of risk metrics generate the same results for the two conflict objectives with different weights or sizes, while it is inapplicable for real traffic, considering the heavy trucks have more potential aggressiveness and destructiveness to other road users.

In this work, a novel decision-making and trajectory planning framework of lane change behavior is proposed to improve the performances of the autonomous heavy truck, as shown in Fig. 1. In the decision stage, the utility theory is firstly employed to determine the desired lane based on the motion prediction. Then, the risk levels of the target lane at present and in future are evaluated based on the Bayesian inference. The lane-change decision will be determined if the safety probability of the target adjacent lane is dominant. After the lane-change decision is made, a set of candidate trajectories will be generated by sampling the driving speed and lane change duration. Then the optimal trajectory is selected by minimizing the defined cost function. The motion and dynamics characteristics of heavy trucks are introduced to design the constraints and cost function. To better validate the proposed framework, several straight lane scenarios are considered, the curved roads with coordinate transformation will be studied in the future work.

The main contributions of this study are summarized as follow: 1) Aiming at enhancing the safety and stability of the autonomous heavy trucks, we propose a hierarchical probabilistic decision-making and trajectory planning frame-work. The utility theory and risk assessment are utilized to respectively model the intention and feasibility for the lane-change behavior. 2) To reduce the impacts of the autonomous heavy truck’s lane-change maneuver on other vehicles, the aggressiveness index (AI) is proposed to quantify the asymmetrical risks to the surrounding traffic participants with the vehicle size and mass considered. 3) The lateral and roll dynamics stabilities are considered in the trajectory planning module to plan the dynamically feasible and more truck-friendly lane-change trajectory.

The rest of this paper is structured as follows. In Section II, the driving behavior is modelled based on utility theory and risk assessment. The optimal lane-change trajectory is planned with dynamic constraints and various costs considered in Section III. Simulation results are presented in Section IV, followed by conclusion and future works in Section V.

### II. Driving Behavior Modeling

For the lane change task of the autonomous vehicles, it is firstly required to select the desired lane based on the driving environment. Afterwards, the safety of the desired lane should be evaluated. The lane-change or lane-keep decision will be made if the risk is below the pre-set threshold. Therefore, the LC decision process is mainly divided into two steps in this section, i.e., target lane selection and risk assessment, which respectively correspond to the intention and availability.

#### A. Target Lane Selections

There are some factors affecting the lane-change decision. Firstly, the gaps between the lane change vehicle and other vehicles are apparently important. Secondly, the passenger
cars may frequently change lanes to drive faster, while the speed desire of the heavy trucks is not as strong as that of the passenger cars. Thirdly, the desired driving lane is directly affected by the traffic law applied in the highway, the trucks are normally required to drive in the slow lane. Moreover, the surrounding vehicles type can also affect the truck drivers’ evaluations with the future expectations being different.

Considering the factors mentioned above, the utility theory is used to model the lane selection process and comprehensively show the relationship between the factors and final decisions.

Fig. 2 presents a general driving environment where the red truck is the ego vehicle (EV) following a preceding vehicle (PV) on the three-lane highway. The leading and lag vehicles are represented as LEV and LAV respectively. There are up to three alternative driving decisions for EV: staying in the current lane (CL), changing to right (RL) or left (LL). The utilities of each lane can be represented using the existing framework in [13] but with varieties by considering the features of heavy trucks:

\[
\begin{align*}
U_j(t) &= U_j^0 + \theta_j X_j(t) + \varepsilon_j(t), \\
V_j(t) &= U_j^0 + \theta'_j X_j(t),
\end{align*}
\]

where \(U_j^0\) are the initial utilities of three lanes, which are designed to avoid frequent target lane switches and are assigned as \(-1.5, -1, 0\) corresponding to left, right and current lane respectively. The CL has the initial maximum utility to make the vehicle keep the lane until the right or left lane has larger utility. The \(\varepsilon_j\) are random terms that represent the location and velocity uncertainties caused by sensor noise, and the \(V_j(t)\) are the utilities of lanes without random terms. \(X_j\) are the explanatory variables which consist of the influence factors of driving behavior. \(\theta_j\) are the weighting vectors.

\[
\begin{align*}
X_{CL}^L(t) &= \begin{bmatrix} \Delta v_{pv}(t) & \Delta d_{PV}(t) & \delta_{CL}(t) & L_{a}(t) \end{bmatrix}^T, \\
X_{AL}^L(t) &= \begin{bmatrix} \Delta v_{lev}(t) & \Delta v_{lav}(t) & \delta_{CL}(t) & L_{a}(t) \end{bmatrix}^T
\end{align*}
\]

where the superscripts \(CL\) and \(AL\) represent the current lane and adjacent lane (RL/LL); The subscripts \(pv\), \(lev\), \(lav\) and \(f_v\) denote the specified vehicles; \(\Delta v_{pv}(t)\), \(\Delta v_{lev}(t)\) and \(\Delta v_{lav}(t)\) are speed differences between \(EV\) and \(PV\), \(LEV\) and \(LAV\) respectively; \(\Delta v_{max}(t)\) is the gap between current speed and the maximum speed limit; \(\Delta d_{PV}(t)\) and \(\Delta d_{lev-lav}(t)\) are the distance from \(EV\) to \(PV\), and the space between \(LEV\) and \(LAV\); \(\delta\) and \(L_a\) are the vehicle type and lane properties respectively, and they are given by

\[
\delta(t) = \begin{cases} 0 & \text{car} \\
1 & \text{otherwise} \\
-1 & \text{fast lane} \\
0 & \text{middle lane} \\
1 & \text{slow lane}.
\end{cases}
\]

To eliminate the effects of unit and scale differences between the explanatory variables, the factors in (2) are normalized in terms of the relative speed \(\tilde{v}_j = \Delta v_j / \max(\Delta v_{max}, \Delta v_{max})\), \(i=\{pv, lev, lav\}\) and distance for the adjacent lane \(\tilde{d}_{lev-lav} = \Delta d_{lev-lav} / \max(\Delta d_{max}, \Delta d_{lev-lav})\), where \(\Delta v_{max}\) and \(\Delta d_{max}\) are the maximum speed limit and perception distance respectively. The utility of CL will be reduced and the truck will generate lane-change intention if the \(EV-PV\) distance is less than the minimum safety distance \(d_{min}\). Thus, the distance \(\tilde{d}_{pv}(t)\) is normalized as following:

\[
\tilde{d}_{pv}(t) = \begin{cases} \frac{(\Delta d_{pv} - d_{min})}{d_{min}}, & \Delta d_{pv} < d_{min} \\
\min\left((\Delta d_{pv} - d_{min})/(d_{max} - d_{min}), 1\right), & \Delta d_{pv} \geq d_{min}.
\end{cases}
\]

It is noted that the utilities have upper and lower boundaries after normalizing. It is assumed that the random terms \(\varepsilon_j\) are independent and satisfy the Gumbel distribution [13]. Then the choice probabilities of lanes conditioning on the random term are obtained by a standard multinomial logit model formulation.

\[
P_j(t) = \frac{\exp[V_j(t)]}{\sum_{k \neq j} \exp[V_k(t)]}.
\]

The same calculation process is applied for multiple time step within a prediction horizon \(t \in [t, t + T_P]\) to determine the future lane utility \(U_j(t)\) and the probability of being selected as target lane \(P(t)\). Therefore, the target lane (TL) is selected by considering the present and future traffic states.

\[
TL = \arg \max_j \left(\int_t^{t+T_P} P_j(\tau) d\tau\right).
\]

### B. Risk Assessment Metric

After the lane change intention is generated, it is important to estimate the feasibility of lane-change. Differently from the gap acceptance model of [13], the risk assessment module with considering vehicle heterogeneity is designed to determine the lane change execution time. The asymmetric risks are firstly estimated for \(LAV\) and \(LEV\) by considering the independent potential collisions as well as the aggressiveness. Then the synthetic evaluation index is proposed.

#### 1) Risk Measures for Ego Vehicle

Time to collision (TTC) is a frequently used metric to describe the predicted collision time. However, the drastic variations can happen with the small change of the denominator when it is close to zero. The inverse of TTC (TT Ci) is therefore introduced.
where \( x_f \) and \( x_m \), \( v_f \) and \( v_m \) are the longitudinal positions and velocities of leading and following vehicles, respectively.

In the real traffic, the abrupt motion variation of traffic participants could happen. Keeping enough distance from the leading vehicle helps improve safety. Considering the heterogeneity risks caused by different braking and accelerating capabilities of passenger cars and heavy trucks, the safety distance index (SDI) is proposed as following:

\[
SDI = \frac{d_{\text{min}}}{x_f - x_m}
\]

where the minimum safety distance \( d_{\text{min}} \) is calculated by the responsibility-sensitive-safety (RSS) model in [28].

\[
d_{\text{min}} = v_f \tau + \frac{a_f \tau^2}{2} + \frac{(v_f + a_f \tau)^2}{2b_f} - \frac{v_m^2}{2b_f}
\]

where \( a_f \) and \( b_f \) denote the maximum acceleration and deceleration of following vehicle, respectively; \( b_f \) is the maximum deceleration of leading vehicle; \( \tau \) is the response time.

2) Aggressiveness to Surrounding Vehicles

Collisions with the heavy trucks can result in higher fatality rate. On the other hand, the collision probabilities are not distributed equally. As a comprehensive index, the aggressiveness should consider both collision probability and subsequent collision severity.

The analysis of the collision probability in the lane-change scenario is shown in Fig. 3, where the EV executes lane-change from the lane center with constant speed, and the LAV and LEV maintain the motion states. The potential collision is related to the time interval \( \Delta t \) between the moment when the EV invades the driving area (the green shadow) of the LAV/LEV and the moment when the LAV/LEV reaches the same position (the red star). The shorter the time interval is, the higher the probability of collision will be. Then the two intervals are defined as

\[
\Delta t_{\text{lav}} = t_{\text{lav}} - t_e, \quad \Delta t_{\text{lev}} = t_e - t_{\text{lev}}
\]

where \( t_e, t_{\text{lav}}, \) and \( t_{\text{lev}} \) are the moments when EV, LAV and LEV reach the conflict point, respectively.

\[
t_e = \Delta y / v_y, \quad t_s = \left( -v_s \pm \sqrt{v_s^2 + 2a_s s_1} \right) / a_i, \quad i = \text{LEV, LAV}
\]

where \( s_{\text{lav}} \) and \( s_{\text{lev}} \) are the distances of the LAV and LEV to the conflict point respectively; \( a_{\text{lav}} \) and \( a_{\text{lev}} \) represent accelerations of LAV and LEV respectively; \( \Delta y \) refers to the lateral distance of the side edges between EV and LAV or LEV.

For the collision severity, the vehicle mass and speed differences before and after crash are selected as the measures. It is assumed that the crash between the heavy truck and other vehicles is inelastic. Then the severity can be obtained based on the law of conservation of momentum.

\[
\begin{align*}
\Delta v_{\text{fol}} &= v_{\text{fol}} - \check{v} = m_{\text{fol}} (v_{\text{fol}} - v_{\text{lead}}) / (m_{\text{fol}} + m_{\text{lead}}) \\
\Delta v_{\text{lead}} &= v_{\text{lead}} - \check{v} = m_{\text{fol}} (v_{\text{lead}} - v_{\text{fol}}) / (m_{\text{fol}} + m_{\text{lead}})
\end{align*}
\]

The exponential function is introduced to address the situation that the velocity difference is negative. Sequentially, the aggressiveness of truck imposes on surrounding road user during lane-change is defined as following:

\[
AI = \frac{1}{\Delta t} \frac{m_e}{m_s, m_e}, i = \text{LAV, LEV}
\]

where \( m_s \) and \( m_e \) are masses of surrounding vehicle and EV respectively. If the accelerations are considered, the \( \Delta y \) in (13) will be modified as \( \Delta y_{\text{lav}} = v_{\text{lav}} + a_{\text{lav}} t - v_e - a_e t_e \) and \( \Delta y_{\text{lev}} = v_e + a_e t_e - v_{\text{lev}} - a_{\text{lev}} t_{\text{lev}} \) for LAV and LEV respectively, in which \( a_e \) is the acceleration of EV. Consequently, the \( AI \) value increases with the speed of the following vehicle. In addition, the heavy truck performing lane-change has a less aggressiveness on another truck, which is consistent with the conclusion that the type of surrounding vehicle has an effect on the lane-change decision of the heavy trucks.

Above three metrics are finally selected to evaluate the risk level, and the traffic conditions of target lane are described as \( X \in \Phi = \{TTCi, SDI, AI\} \).

C. Risk Level of Target Lane

The purpose of the risk assessment is to determine the discrete decisions for lane change or lane keeping. Therefore, three discrete risk levels are defined as a random variable \( \Xi \in \varepsilon = \{D, A, S\} \) with respect to the values of the aforementioned metrics vectors, which include Dangerous, Alert and Safe.

There are three risk levels, then two critical values are required to map the observed traffic conditions to the corresponding risk levels through a likelihood function. It is supposed to be the following S-shaped membership function:

\[
P(X = x_m | \Xi = \xi_i) = \begin{cases} 
(2 - 4\beta)/(1 + \exp(-\alpha_s (x_m - \xi_{i})}}}) + (3\beta - 1), & \text{if } x_m > \xi_{i} \\
(4\beta - 2)/(1 + \exp(-\alpha_s (x_m - \xi_{i})}}}) + (1 - \beta), & \text{if } x_m \leq \xi_{i} \\
\beta, & \text{otherwise}
\end{cases}
\]

where \( x_m \) is the measured value of an element in the threat metrics vector \( \Phi \); \( \xi_i \) \((i = D, A, S)\) is the inferred risk level; \( \alpha_s \) is the shape parameter, representing the uncertainty of the observed threat metrics; \( \beta \) is the regularization factor and assigned 0.9 in this work; \( \xi_{i}^\gamma \) and \( \xi_{i}^\alpha \) are upper and bottom thresholds respectively.
The posterior probability can be determined and normalized with weightings of multiple threat metrics [25], and then the probability of a certain risk level with all threat metrics measured can be obtained.

\[
P(\Xi = \xi_j | X_j = x_j^m) = \frac{\sum_{j=1}^{N_j} \omega_j P(\Xi = \xi_j | X = x_m)}{\sum_{j=1}^{N_j} \omega_j}, \quad j = 1, 2, 3.
\]  

(15)

For a specific lane change, the risks are from the \(LAV\) and \(LEV\) in the target lane. Therefore, the lane change risks probabilities should be a combination of each risk level with a new function [25].

\[
\begin{align*}
P(\Xi = D) &= 1 - \prod_{k=LAV,LEV} P(\Xi_k = \xi_k) \\
P(\Xi = S) &= \prod_{k=LAV,LEV} P(\Xi_k = \xi_k) \\
P(\Xi = A) &= 1 - P(\Xi = D) - P(\Xi = S)
\end{align*}
\]  

(16)

where \(X_j^{LAV}\) and \(X_j^{LEV}\) are the random variables that represent the threat metrics of \(LAV\) and \(LEV\) respectively; \(x_j^{LAV}\) and \(x_j^{LEV}\) denote their measured values.

The future risks in prediction horizon are also determined using the above procedure. Thus, the inferred risk level of lanes can then be determined by synthesizing the current risk \(P(\Xi = \xi)\) and future risk \(P(\Xi = \xi)\), \(\tau \in [t, t + T_p]\). Through evaluating the lane change risks, the driving conditions around the ego vehicle are quantified, which offers the quantitative threat information for the later decision-making.

D. Driving Behavior Decision

After obtaining the probability of choosing each lane as the target lane and the risk levels of each lane, a decision logic is proposed to determine whether to change lane or not. As shown in Fig. 4, the proposed decision-making model will generate lane-keep decision when the utility of the current lane is the maximum value. Otherwise, if one adjacent lane has the maximum total utility over the prediction horizon, it is selected as the potential target lane. Then the current and future risk levels are evaluated based on the predicted \(TTC\) \((\tau), SDR(\tau),\) and \(AL(\tau)\). Lane change decisions will be made only if the safety requirements are always satisfied over the prediction horizon \(\tau \in [t, t + T_p]\) to avoid frequent decision switches. In this work, the linear prediction is adopted in the two sub-modules.

III. INTEGRATION WITH THE TRAJECTORY PLANNING

After the lane-change decision is made, a feasible trajectory is required for the heavy truck to execute the lane-change, in which the multiple objectives should be considered, including safety, driving stability, aggressiveness on other vehicles, etc.

A. Candidate Trajectories Generation

Two polynomial curves are respectively applied to lateral and longitudinal axes in order to generate a set of smooth trajectories.

\[
\begin{align*}
x(t) &= a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 \\
y(t) &= b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5
\end{align*}
\]  

(17)

\[
\begin{align*}
\frac{d}{dt}x(t) &= a_1 + 2 a_2 t + 3 a_3 t^2 + 4 a_4 t^3 \\
\frac{d}{dt}y(t) &= b_1 + 2 b_2 t + 3 b_3 t^2 + 4 b_4 t^3 + 5 b_5 t^4
\end{align*}
\]  

(18)

where \(\{a_0, \ldots, a_4\}\) and \(\{b_0, \ldots, b_5\}\) are coefficients of polynomial functions that are estimated through the following boundary conditions:

\[
\begin{align*}
x(0) &= x_0, \quad \dot{x}(0) = v_{x0}, \quad \ddot{x}(0) = a_{x0}, \\
y(0) &= y_0, \quad \dot{y}(0) = v_{y0}, \quad \ddot{y}(0) = a_{y0}, \quad (y_T, y_T, \dot{y}_T, \ddot{y}_T) = (y_0, y_0, \dot{y}_0, \ddot{y}_0) = (0, 0, 0, 0)
\end{align*}
\]  

(19)

The terminal longitudinal acceleration, lateral velocity and acceleration are assumed zero when a lane-change is completed. Therefore, the sample spaces are simplified to cover all possible motions.

\[
\begin{align*}
\{T \in [T_{min}, T_{max}] \}
\quad \{v_{xT} \in [max(v_{xT} - \Delta v, 0), max(v_{xT} + \Delta v, v_{xmax})]\}
\end{align*}
\]  

(20)

The following multi-objective optimization problem is built to obtain an optimal trajectory from the candidates:

\[
\begin{align*}
\xi_T, j^* &= \arg \min_{\xi_j} \{ f(\xi_j | S, \omega) \} \\
\text{s.t. } x_{\xi_j} &= g(x_{\xi_j}, \xi_j) \\
y_{\xi_j} &\in [y_{min}, y_{max}], f_{\text{collision}}(\xi_j) = 0, \\
x_{\xi_j} &\in \Omega
\end{align*}
\]  

(21)

where \(f\) is the cost function with weighting parameters \(\omega\) when driving in environment \(S\); \(y_{min}\) and \(y_{max}\) are the lane boundary; \(\Omega\) denotes the dynamics stability constraints that involve the lateral and roll motions when the truck tracks the trajectory \(\xi_j\).

B. Trucks Dynamics Model

It is important to ensure the vehicle stability apart from the collision free requirement for the heavy trucks’ lane-change. It is worth mentioning that the polynomial trajectories are generated by assuming the vehicle is a particle. However, some candidates may not be trackable for the long-haul trucks, such as...
as tractor semi-trailer based on this assumption. Furthermore, roll dynamics should be taken into account due to higher center of mass and larger weight of the heavy trucks. Therefore, a dynamical feasibility evaluation method is proposed for trajectory candidates based on the dynamics model simulation. The tractor semi-trailer is applied to illustrate the optimization process of the trajectory candidates.

The bicycle model with a semi-trailer part is shown in Fig. 5. The lateral, yaw and roll dynamics equations of tractor and trailer are given by

\[
\begin{align*}
\dot{v}_t^y + v_t^y \cdot r_t &= F_{t_y}^f + F_{t_y}^r - F_{t_y}^h \\
m_t \left( \dot{v}_t^r + v_t^r \cdot r_t \right) &= F_{t_x}^f + F_{t_x}^r \\
I_t^y \ddot{r}_t &= a F_{t_y}^f - b F_{t_y}^r + c F_{t_y}^h \\
I_t^y \ddot{r}_t &= e F_{t_y}^f - f F_{t_y}^h \\
I_t^y \ddot{r}_t &= K_s \phi_t \phi_t + C_s \phi_t |\phi_t| + F_{t_y}^f \left( \dot{v}_t^y + v_t^y \cdot r_t \right) \\
I_t^y \ddot{r}_t &= K_s \phi_t \phi_t + C_s \phi_t |\phi_t| + F_{t_y}^f \left( \dot{v}_t^y + v_t^y \cdot r_t \right)
\end{align*}
\]

(21)

where the subscript \(h\) denotes the hitch point. The equilibrium and constraints of hitch point approximately satisfy

\[
\begin{align*}
\dot{v}_h^y &= v_h^y, \quad \dot{v}_h^r = v_h^r - v_t^y \cdot c - v_t^y \cdot r_t \\
\dot{r}_h &= \gamma + r_t, \quad F_{t_y}^h = F_{t_y}^s
\end{align*}
\]

(22)

where the superscripts and \(s\) denote the tractor and trailer, respectively; the indexes \(f\) and \(r\) represent the front and rear axles; \(v_t\) and \(v_r\) are longitudinal speeds; \(r, \gamma, \phi\) are yaw rate, roll angle and hitch angle. \(F_y\) is the lateral force of tire; \(m_t\) and \(m_r\), \(m_h\) are the CG distances between tractor and trailer, \(c\) and \(f\) are the distances from CG of trailer to hitch point and rear axle, respectively; \(h_h\) is the CG height of sprung mass from the rear axle; \(F_{t_y}^f, F_{t_y}^r, F_{t_y}^h\) are the front, rear and hitch forces, respectively; \(K_s\) and \(C_s\) are roll stiffness and damping respectively. The tire model [29] is adopted to calculate the lateral force of tire.

\[
F_y = \begin{cases} 
\frac{C \tan(\alpha)}{3 \eta m F_z} \tan(\alpha) + \frac{C^3 \tan(\alpha)^3}{27 \eta^2 \mu^2 F_z^2}, & |\alpha| < \alpha_{sat} \\
\eta m F_z \text{sign}(\alpha), & \text{otherwise}
\end{cases}
\]

(23)

where \(\eta\) is the model parameter; \(C\) is cornering stiffness; \(F_z\) is normal load; \(\alpha\) is tire slip angle and it can be obtained by

\[
\alpha_{f} = -\frac{v_t^r + a r_t}{v_t^y}, \quad \alpha_{r} = -\frac{v_t^r - b r_t}{v_t^y}, \quad \alpha_{s} = -\frac{v_t^r - f r_t}{v_t^y}
\]

(24)

where \(a\) is the front steering angle \(\delta\) can be obtained through the pure pursuit tracking method [2].

C. Dynamics Stability Envelope Constrains

In terms of the tractor semi-trailer, it has been demonstrated that the lateral vehicle stability depends on the tractor state variables [30], which means the tractor would lose stability first due to the hysteresis of the trailer. On the contrary, the trailer could become unstable first in the roll motion because of the greater load and higher center of gravity [1], [31]. Thus, the lateral stability domain of the tractor and the roll stability domain of trailer are separately built to ensure the driving stability of the planned trajectory.

The maximum steady-state yaw rate \(\bar{r}\) is deduced using the lateral motion equation of (21) at steady state and given \(\dot{v}_t^y = 0, \dot{r}_t = 0, \gamma = 0, \bar{r}\) [29].

\[
\begin{align*}
\bar{r}_1 &= \frac{(a + b)(e + f) F_{t_y}^f}{v_t^y (m_t f (b - c) + m_r b (e + f))} \\
\bar{r}_2 &= \frac{(a + b)(e + f) F_{t_y}^r}{v_t^y (m_t f (a + c) + m_r a (e + f))}
\end{align*}
\]

(25)

where \(F_{t_y}^f, F_{t_y}^r\) are the saturated lateral forces provided by front and rear axles of tractor. The yaw rate boundary is chosen from the minimum of the two steady values \(\bar{r} = \min(\bar{r}_1, \bar{r}_2)\). Subsequently, the steady-state boundary of lateral velocity of tractor can be reached.

\[
\bar{v}_t^y = b \bar{r}^2 - v_t^y \bar{r}^2.
\]

(26)

Rollover is the main type of heavy trucks related accidents in highway. Therefore, it is necessary to limit the roll motion to prevent rollover. The lateral load transfer ratio of trailer is applied in this study [32], which is a commonly used rollover index (RI) calculated through roll moment balance.

\[
RI = \frac{|F_{zR} - F_{zL}|}{F_{zR} + F_{zL}} = \frac{2 \left( m_h \left( \dot{v}_r^y + v_r^y \cdot r_t \right) + K_s \phi_t \phi_t + C_s \phi_t |\phi_t| \right)}{m \cdot g \cdot L}
\]

(27)

where \(L\) is the wheel track of trailer, and \(h_h\) is the height of roll axle. The RI has a safety range of \([0, 1)\) and \(RI \geq 1\) indicates the one-side wheels lift off the road.

Equations (25)–(27) define the dynamics stability envelope, in which the coupling effects of lateral and roll dynamics are ignored. Thus, a scale factor \(\kappa\) is applied on the stability region to guarantee the safety of the planned trajectories.

The lateral and rollover stability performances are analyzed in Fig. 6 when the autonomous heavy truck tracks the possible trajectory candidates. The driving speed, lane-change duration and vehicle load are considered as the key parameters to affect the vehicle stabilities. The lateral stability envelope is shown in Fig. 6(a), it consists of the boundaries of the yaw rate and lateral velocity, with the shape of parallelogram. \(\xi_1 \sim \xi_4\) are four trajectories with lane-change durations of 2 s, 3 s, 4 s, 5 s, respectively. It is implied from the comparisons that the higher speed would narrow down the stability region, while the heavier vehicle load could slightly increase it. This is because the maximum lateral force is magnified by the increasing of vertical load.

![Fig. 5. Tractor semi-trailer vehicle model.](image-url)
It can be observed that the truck will lose lateral stability when the lane change duration is less than 2 s, while the rollover instability occurs if the duration is up to 3 s or 4 s. It shows that the roll motion is more likely to be unstable in the heavy trucks under the same driving conditions. Furthermore, the increasing of vehicle load will elevate the center of gravity. Thus, the $R_{I}$ of the heavy truck at 30 m/s with vehicle load of 18 t approaches the maximum value of 0.85, although the lane change duration is 5 s.

It is shown that the heavy trucks need longer lane-change duration to ensure the driving stability, and the required time increases with heavier vehicle load. The results may be different for another heavy truck with different parameters, such as the position of the hitch point and the length of tractor and trailer, which deserves further research.

Therefore, it is demonstrated that the dynamics stability constraint is necessary to be considered at the planning stage, and the trajectory can be eliminated in advance that may cause dynamics destabilization.

D. Cost Function

In this section, the optimization objectives are presented in detail, which consist of safety, vehicle stability, the aggressiveness on $LAV$ and driving efficiency.

1) Safety: The candidate trajectories that satisfy the constraints are collision-free, while all candidates have different risk levels. We define an exponential function of time headway to select a trajectory with lower risk in terms of the preceding vehicle in the current lane, $LAV$ and $LEV$ in the target lane.

$$f_s(\xi_j) = \int_0^T \left( e^{-THW_{pl}(\tau)} + e^{-THW_{av}(\tau)} + e^{-THW_{av}(\tau)} \right) d\tau.$$  (28)

2) Vehicle Stability: The lateral velocity and yaw rate of tractor and the $R_I$ of trailer are applied to evaluate the vehicle stability for all of the trajectory candidates.

$$f_a(\xi_j) = \frac{1}{T_j} \int_0^T \left( |v'_l(\tau)| + |v'(\tau)| + |R'_l(\tau)| \right) d\tau.$$  (29)

3) Aggressiveness: Generally, the instant following vehicle in target lane is the most vulnerable when heavy trucks change lanes. Thus, the aggressiveness cost is defined by introducing the $AI$ for the lag vehicle.

$$f_a(\xi_j) = \frac{1}{T_j} \int_0^T AI_{lag}(\tau) d\tau.$$  (30)

4) Driving Efficiency: Human drivers are inclined to complete a lane-change maneuver as fast as possible, which is reflected in higher speed and lower lane-change duration.

$$f_e(\xi_j) = \frac{1}{T_j} \int_0^T |v'_l(\tau)| d\tau + \lambda T_j.$$  (31)

Combining the above cost, the cost function is proposed to evaluate the trajectory candidates.

$$f(\xi_j|\mathbf{S},\omega) = \sum \omega_s f_s(\xi_j) + \omega_d f_d(\xi_j) + \omega_a f_a(\xi_j) + \omega_e f_e(\xi_j)$$  (32)

where $\omega_s$, $\omega_d$, $\omega_a$, and $\omega_e$ are coefficients of the four objectives.

IV. RESULTS AND DISCUSSIONS

In this section, four test scenarios are extracted from the naturalistic driving dataset to verify the performance of the proposed model and its robustness in highly interactive traffic environment. The proposed Decision-making and Planning model is respectively applied to the Autonomous Heavy Trucks (DP-AHT) and Passenger Cars (DP-APC). Then, the integrated planner based on artificial potential field (APF) [9] is adopted as a benchmark. APF is an effective and widely used method in local path planning, in which the vehicle is assumed to move under the virtual forces [33]. Furthermore, the DP-AHT is simulated and analyzed in the robustness validation.

A. Simulation Scenarios Setup

The driving scenarios in this work are extracted from highD dataset [34], which collects the naturalistic vehicle trajectories on the highway with plenty of both trucks and passenger cars data. In the simulations, the ego vehicles are replaced by the proposed model with surrounding vehicles maintaining their states. In this way, two types of comparisons can be made. The first one is the comparison between the model outputs and real drivers’ trajectories extracted from the data. The second comparison is made in terms of the dynamics variables and the aggressiveness when the autonomous heavy truck tracks the trajectories generated from DP-AHT, DP-APC and APF in the same traffic environment.

The particularities of heavy truck are not included when designing the planning model of DP-APC. The lane properties and vehicles type are not included in the explanatory variables when selecting the target lane for DP-APC, and only safe distance $SDI$ and $TTCi$ are considered in the risk assessment module. Besides, the aggressiveness and vehicle dynam-
ies stability are not involved when planning the path for the DP-APC. The maximum speed limits are 27 m/s and 35 m/s for the DP-AHT and DP-APC, respectively, and the perception distance limits are both 200 m. With regarding to the candidate trajectories generation, the lane change duration $T$ is sampled from $[1, 10]$ with an interval of 1 s, and the velocity difference range is $[-5, 5]$ m/s with an interval of 0.5 m/s. In APF, the surrounding vehicles within 30 m of the $EV$ and the lane boundary are both assumed to produce repulsive forces, while the center of lane produces attractive force. Besides, a constant longitudinal attractive force is designed to make the $EV$ drive forward. For the heavy truck in the simulation, a three-axis tractor with two-axis van trailer is chosen from TruckSim, and its dynamics parameters are presented in Table I.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>PARAMETERS OF TRUCK DYNAMIC MODEL</th>
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<tbody>
<tr>
<td></td>
<td>value</td>
</tr>
<tr>
<td>$m_l/m_s$</td>
<td>6810/15 925 kg</td>
</tr>
<tr>
<td>$m_l'/m_s'$</td>
<td>4810/10 925 kg</td>
</tr>
<tr>
<td>$h_l'/h_s'$</td>
<td>0.6/1.5 m</td>
</tr>
<tr>
<td>$K_v'/K_v$</td>
<td>3.5e5/5.1e5 N/m</td>
</tr>
<tr>
<td>$C_f'/C_f$</td>
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</tr>
<tr>
<td>$I_l'/I_s'$</td>
<td>3.34e4/1.51e5 kg/m$^2$</td>
</tr>
<tr>
<td>$I_l'/I_s'$</td>
<td>6879/15 997 kg/m$^2$</td>
</tr>
</tbody>
</table>

B. Effectiveness Analysis

1) Scenario 1: In a typical highway with three lanes, the $EV$ drives on the middle lane with 24 m/s and approaches to the $PV$. At the initialization of record, the vehicles in leftmost lane have greater velocity (about 28 m/s) but smaller driving gap, and the vehicles in rightmost lane have inverse conditions. Fig. 7 shows the results in Scenario 1.

The distance and velocity difference between the $EV$ and $PV$ do not satisfy the expectations, and the $EV$ may produce lane-change intentions. Because of the preferential lane and larger available gap with the right $LEV$ in (2), the probability of selecting the rightmost lane is the highest for DP-AHT. The risks of the rightmost lane are then evaluated using (7)–(16) and the probability of “dangerous” is predominant before 2.6 s as the $EV$ has overlap with the right $LAV$ and the $SDI$ of (8) is much larger during this period. Thus, the behavior decision of lane-keep is produced until the distance between the $EV$ and right $LAV$ increase and satisfies the safety requirement of lane-change. Subsequently, the lane-change maneuver is executed from 2.8 s to 10.4 s because the right lane always has a greater selection probability and the risk level is “safe”. After completing the lane-change, the rightmost lane is still selected with highest probability, and the DP-AHT keeps lanes.

Differently from the DP-AHT, the target lane of the DP-APC switches from the middle to the left one although the right lane has a larger preceding space. This result shows that the DP-APC without lane priority considered focuses more on the speed efficiency instead of driving space according to the model. The DP-APC makes the lane-change decision at 0.4 s even though it already had the intention from the beginning due to the “Alert” risk level of the left lane. It is also observed from the Figs. 7(a) and 7(b) that the DP-APC generates the lane-change intention once again at 9.4 s and carries out the maneuver at 13 s with the decreasing of the distance to the current $PV$ (original left $LAV$).

In terms of the APF planner, as shown in Fig. 7(e), the $EV$ starts a sharp lane-change at 0 s as it is within the influence range of the $PV$. The $EV$ will continue changing lane at 1.5 s under the attraction force of left lane center. After completing the lane-change, the $EV$ is out of the influence range of current $PV$ and $FV$, and it keeps lanes with a constant velocity.

The proposed DP-AHT successfully mimics the preferences of the real human-driven heavy trucks. Both planned path and velocity are close to them generated by the real human drivers with the maximum lateral deviation 0.76 m and longitudinal deviation 1.4 m, which implies nearly no delay considering the high driving speed. In terms of the speed profiles shown in the Fig. 7(c), the DP-AHT has an approximately constant velocity during lane change execution, while the DP-APC has a dramatic acceleration from 24.0 m/s to 30.5 m/s to achieve the similar velocity with the right lag vehicle and keep a safe distance to the left $LAV$. The lane change durations also differ with the DP-AHT, DP-APC and APF taking 7.6 s, 5.6 s and 4.2 s to complete lane change.

Besides the driving efficiency and space, the aggressiveness of (13) is also an important factor that results in the distinct decisions under the same surrounding driving conditions. The trajectories generated from the three planners are tracked by an autonomous heavy truck, and the results are shown in Table II and Fig. 6(d). The paths of both DP-APC and APF have larger $AI$ than that of DP-AHT, and the $AI$ for $LEV$ is larger than that of DP-AHT, and the $AI$ for $LEV$ has overlap with the right $LAV$. The behaviors of the $EV$ shown in Fig. 6(d) reflects the aggressiveness of the left lane driver, which shows that the DP-APC and APF do not focus on the aggressiveness as much as DP-AHT does.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>AGGRESSIVENESS AT THE BEGINNING OF LANE-CHANGE IN TWO SCENARIOS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lev_LL</td>
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<tr>
<td>DP-AHT</td>
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<tr>
<td>Scenario 1</td>
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<td>DP-APC</td>
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<tr>
<td>APF</td>
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<tr>
<td>Scenario 2</td>
<td></td>
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<td>DP-AHT</td>
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<tr>
<td>DP-APC</td>
<td>0.93</td>
</tr>
<tr>
<td>APF</td>
<td>1.12</td>
</tr>
</tbody>
</table>

2) Scenario 2: In a highway with two lanes, the $EV$ follows a slower $PV$ in the rightmost lane, and the $LAV$ and $LEV$ in the left lane have a larger driving speed. Fig. 8 presents the
behavior decisions and planned trajectories.

The DP-AHT decides to change lanes at 1.2 s when the left lane is selected as the target lane and the probability of “Safe” level is the highest depend on (6) and (16). The driving conditions of the leftmost lane are satisfactory for the DP-AHT after completing the lane-change at 7.8 s, which avoids frequent lane-change based on the proposed methods. With regard to the DP-APC, left lane has the highest probability to be chosen from the beginning, and the corresponding decision is made at 0.4 s when the risk level becomes “Safe”. After the lane-change, leftmost lane has a greater attraction and the planner decides to keep lanes. The APF planner shows similar performance compared with them in Scenarion 1, as shown in Fig. 8(e). The LEV and LAV in target lane when the autonomous heavy truck tracks the paths generated by DP-AHT, DP-APC and APF, respectively.

The $EV$ will continue changing lane at 1.4 s until arriving at the center of lane. Then, the $EV$ is beyond the influence range of current $PV$ and $FV$ and it keeps lanes with a uniform velocity.

Although the DP-AHT, DP-APC and APF have the same decision in the similar traffic conditions, the path and velocity produced by DP-AHT are closer to those from the human drivers. Besides, the aggressiveness during lane change period is described in Fig. 8(d). The $EV$ tracking the trajectory of DP-AHT has the aggressiveness with mean values of 0.95 for $LAV$ and 0.79 for $LEV$ during LC, which are both lower than those of the DP-APC (with mean values 1.43 and 0.81) and the APF (with mean values 1.03 and 1.07). It attributes to the smoother trajectory of the DP-AHT, and the greater velocity variation of the DP-APC.
3) Dynamics Stability Analysis: The roll and lateral stability performances in two scenarios are also analyzed based on the dynamics model of (21)–(24), when the heavy truck respectively tracks three trajectories generated by the planners of the DP-AHT, DP-APC and APF. The results are shown in Fig. 9. It can be seen that the DP-AHT planner with considering the dynamics constraints of (25)–(27) generates the path with good driving stability, where the maximum values of yaw rate \( r \), lateral velocity \( v_y \) of the trailer and rollover index of the tractor are 1.7 °/s, 0.42 m/s and 0.40 in Scenario 1, and 1.6 °/s, 0.48 m/s and 0.38 in Scenario 2, respectively.

![Dynamic variables by tracking the three planned trajectories](image)

Contrastively, the dynamics parameters when tracking the DP-APC path are much greater in both two scenarios. Although both of them are within the stability region because driving environment is not critical, it is foreseeable that the DP-AHT can generate the path with higher stability that prevents the rollover and lateral sliding for the autonomous heavy trucks in other critical cases. However, a high \( RI \) will occur and the rollover could not be prevented when the heavy truck tracks the path of APF. It shows that the path planned by APF cannot be applied to heavy truck.

4) Discussion: Some findings can be concluded from the results of the two different scenarios.

The DP-APC without considering the specificity of heavy truck focuses more on speed efficiency than driving space for the lane selection. Additionally, the DP-APC has higher variation speed range during lane change execution period, while the DP-AHT basically keeps the constant speed. The aggressiveness index plays a more important role in making decisions for the DP-AHT. Higher aggressiveness makes the DP-AHT generate a more conservative behavior decision and trajectory, and keeping greater distances from other vehicles. Besides, the risk assessment module effectively constrains the potential frequent decision shift.

In terms of the planning process, the DP-AHT spends more time to complete lane change, and the planned path is smoother with a steady velocity compared with the DP-APC and APF. This is because the aggressiveness and the vehicle stability are considered as the constraints in the planning process.

The proposed model captures above findings well, and makes more human-like decisions. Besides, it shows that the proposed model also can be applied to the autonomous passenger cars without including the characteristics of the heavy truck. However, as a passive planning method, the traditional APF plans a lane-change only when the ego vehicle enters the predesigned region of surrounding vehicles. The driving intention and the particularity of heavy truck, such as dynamics stability and aggressiveness, are not considered in APF planner. Thus, it usually generates a sharp lane-change path which is dangerous and infeasible for the autonomous heavy truck.

C. Robustness Analysis

The effectiveness of the proposed model in the normal traffic is demonstrated through the above two scenarios. In this section, two extreme driving scenarios are designed to show the robustness of the decision-making and planning framework, where the lag vehicle in the target lane suddenly accelerates during the ego vehicle’s lane-change execution, and the ego vehicle encounters a cut-in vehicle from the adjacent lane.

1) Scenario 3: The ego vehicle drives on the rightmost lane in the two-lane highway road, and the \( LAV \) in the left lane accelerates to overtake. The results are shown in Fig. 10.

![Simulation results of Scenario 3](image)

The utility of current lane and the selection probability keep decreasing and are lower than those of the left lane at 3.4 s. Simultaneously, the risk assessment results of (16) show that the left lane is “Safe”. Thus, the EV starts the lane-change. At 6 s, the \( LAV \) suddenly speeds up with a large acceleration. As a result, the utility of left lane has a rapid reduction and is less than that of the current lane at 8.6 s. However, the DP-AHT decides to terminate the lane-change maneuver at 6.6 s although both the selection probability and risk level indicate the lane-change conditions are still acceptable. It is because the predicted risk level of left lane is not “Safe” caused by the \( LAV \)’s great acceleration. Thus, the DP-AHT returns to the original lane and slows down to keep a safe distance to the \( PV \).
2) Scenario 4: In the highway with three lanes, the ego vehicle drives on the middle lane and encounters a cut-in vehicle with larger velocity. The results are shown in Fig. 11.

![Simulation results of Scenario 4](image)

Fig. 11. Simulation results of Scenario 4, (a) The probability of lane selections; (b) The risk level of target lane; (c) The planned path with speed profile.

At the beginning of simulation, the rightmost lane has the maximum probability to be selected, but the DP-AHT generates a lane-keep decision because the risk level of the rightmost lane is “Dangerous” based on (16). Afterwards, the cut-in vehicle starts lane-change maneuver at 4 s. However, the current lane is predominant and the DP-AHT still keeps the lane, because the cut-in vehicle is still located in the leftmost lane. The selected probability of three lanes has a dramatic saltation at 5.8 s when the cut-in vehicle crosses the lane marking and has a small distance to EV. Thus, the rightmost lane becomes the target lane once again, but the lane-change decision is prevented by the results of risk assessment. Consequently, the DP-AHT produces a lane-keeping path, and decelerates to keep a safe distance to the cut-in vehicle. The large speed difference increases the distance between EV and cut-in vehicle. Therefore, the probability of selecting the current lane is the highest after 9 s, and then the EV stays in the middle lane and speeds up slightly.

The planned trajectories in the above two scenarios show that the proposed model DP-AHT can deal with the behavior decision-making and planning problem of the autonomous heavy truck in the dynamic driving environments. When surrounding vehicles speed up or slow down, the DP-AHT is able to capture the variations in the target lane selections and risk assessment, and then adjust the behavior decision and planned trajectory. The DP-AHT also has a correct response for the cut-in maneuver. It is validated in determining which lane the surrounding vehicles locate in and then generating the corresponding driving behavior and path. However, the lane selection probability and risk level vary greatly when the cut-in vehicle crosses the lane marking due to the limitation of the linear prediction. If the cut-in maneuver can be predicted in advance, the DP-AHT can replace the preceding vehicle with the predicted cut-in vehicle before it crosses the lane marking.

V. CONCLUSIONS AND FUTURE WORK

This study proposed a lane-change decision-making and trajectory planning framework for the autonomous heavy trucks to improve driving stability, and decrease the risks for other vehicles. Utility theory was utilized to model the lane change intention and target lane selection. The risks of the target lane were then assessed to determine the feasibility to execute the lane-change. The trajectory was optimized with the dynamics stability envelopes considered. Finally, four driving scenarios extracted from highD dataset were applied to validate the effectiveness and robustness of proposed model. The comparisons were conducted by setting up the benchmark planning model based on APF.

The conclusions are threefold. Firstly, the proposed framework could capture the features of heavy trucks and generate driving behavior decision similar to the human drivers in various interactive driving situations. Secondly, the designed model for the autonomous heavy truck focuses more on traffic regulations and available driving gap rather than speed efficiency, and the risks are thus decreased to the surrounding vehicles. Thirdly, dynamics stability is considered in the trajectory planning for the autonomous heavy truck, and the trajectories are excluded that cannot be executed to guarantee the driving stability. This work is a comprehensive investigation of decision-making and planning for enhancing the safety and stability of autonomous heavy trucks. Moreover, it provides a deep insight into the distinctions between the autonomous heavy trucks and passenger cars.

Linear prediction was used in both target lane selection and risk assessments, and might cause errors in the harsh maneuvers. Thus, a more accurate motion estimation method will be utilized in the future work. Besides, further studies in curve road and using driving simulators or real experiments will be considered in the future work. Moreover, the driving behavior decision-making in different densities of surrounding vehicles will be discussed in the future work.

REFERENCES


Bangji Zhang received the Ph.D. degree in 2010 from Hunan University. He was a Visitor Scholar in University of Technology, Sydney, from 2013 to 2014. He is currently Professor of College of Mechanical and Research Fellow in State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body. His research interests include vehicle dynamics and control in intelligent vehicle.

Amir Khajepour (Member, IEEE) is a Professor of Department of Mechanical and Mechatronics Engineering at the University of Waterloo. He holds the Canada Research Chair in Mechatronic Vehicle Systems, and NSERC/General Motors Industrial Research Chair in Holistic Vehicle Control. His research has resulted in many patents, technology transfers and over 500 journal and conference publications, as well as several books. He is a Fellow of the Engineering Institute of Canada, the American Society of Mechanical Engineers, and the Canadian Society of Mechanical Engineering.

Lei Zeng received the B.S. degree from Nanchang University. He is now working toward the M.S. degree with the College of Mechanical and Vehicle Engineering, Hunan University. His research interests include reinforcement learning, decision-making, and planning in automated driving.

Yang Wu received the B.E. degree in aircraft design and engineering from Xi’an Jiaotong University, in 2011. He received the Ph.D. degree in mechanical engineering from the College of Mechanical and Vehicle Engineering, Hunan University, in 2021. He is currently working as a Post-Doctoral Research Fellow at Tsinghua University. His research interests include nonlinear system control, active vehicle suspensions, autonomous vehicle control, and modelling of driver-vehicle system.