Anti-rollover Motion Planning for Automated Heavy Trucks

Zhilin Jin

Nanjing University of Aeronautics and Astronautics

Jingxuan Li

Nanjing University of Aeronautics and Astronautics

Hong Wang (✉ hong_wang@tsinghua.edu.cn)

Tsinghua University <https://orcid.org/0000-0002-5127-2941>

Jun Li

Tsinghua University

Chaosheng Huang

Tsinghua University

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Title page

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Zhi-Lin Jin, born in 1978, is currently an Associate Professor of Department of Vehicle Engineering at Nanjing University of Aeronautics and Astronautics, China. He received his PhD degree from Nanjing University of Aeronautics and Astronautics, China, in 2008. His research interests include vehicle system dynamics and control.

Tel: +86-13913949581; E-mail: jinzhilin@nuaa.edu.cn

Jing-Xuan Li, born in 1997, is currently a graduate student at *Nanjing University of Aeronautics & Astronautics, China*.

E-mail: 269199917@qq.com

Hong Wang, born in 1986, is currently a research associate professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: hong_wang@tsinghua.edu.cn

Jun Li, born in 1958, is currently a professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: lj19580324@126.com

Chao-Sheng Huang, born in 1972, is currently a research professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: huangchaosheng@tsinghua.edu.cn

Corresponding author: Hong Wang E-mail: hong_wang@tsinghua.edu.cn

ORIGINAL ARTICLE (or REVIEW)

Anti-rollover motion planning for automated heavy trucks

Zhi-lin Jin^{1*} • Jing-xuan Li¹ • Hong Wang^{2*} • Jun Li² • Chao-sheng Huang²

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Abstract: Anti-rollover is an important performance for automated heavy trucks, which has been seldomly considered in the motion planning. This paper proposes an anti-rollover motion planning based on model predictive control (MPC) for automated heavy trucks. Taking the coupling of roll motion of sprung mass of the front axle with that of the drive axle into consideration, a seven degrees of freedom rollover dynamics model is established, and an evaluation index that can accurately describe the rollover motion is derived for heavy trucks. Then, a model predictive control strategy is designed for motion planning that combines the rollover dynamics, the artificial potential field for obstacle avoidance, and the trajectory tracking. In addition, the optimal path is calculated that considers collision avoidance, anti-rollover and vehicle dynamic constraints. Furthermore, three typical scenarios are applied to validate the performance of the proposed motion planning algorithm. The obtained results demonstrate that the proposed anti-rollover motion planning can effectively avoid collisions and reduce the rollover risk simultaneously when confronting edge scenarios.

Keywords: Anti-rollover • Motion planning • Artificial potential field • Model predictive control • Heavy truck

1 Introduction

1.1 Motivation

In the past few decades, the autonomous driving technology has rapidly developed. Fully autonomous vehicles are expected to be on the public roads in the next 30 years, which will not only reflect a country's advanced

technology, but more importantly will help ease the traffic accidents and congestion [1-2]. Motion planning is a key component of autonomous vehicles. Proper motion planning algorithm can significantly reduce traffic accidents caused by fatigue and drunk driving [3]. Majority of the researchers focus on obstacle avoidance in motion planning. Vehicle rollover is the phenomenon of vehicle instability caused by severe steering or external road excitation, especially for heavy trucks due to the long wheelbase, the large unsprung mass and the high center of gravity. In 2016, over 6 million vehicle crashes happened in the United States. Among those crashes, 17.9% of the fatal crashes caused by vehicle rollover, and 8.5% of those came from heavy trucks [4]. Therefore, it is of significantly importance to explore the motion planning mechanism of heavy truck combined with rollover dynamics.

1.2 Related Research

A successful motion planning algorithm can not only drive the vehicle to the destination set by the occupant, but can also respond to extreme situations that the vehicle may encounter, including avoiding collisions and maintaining vehicle stability. The early motion planning algorithms such as Dijkstra algorithm [5], A* algorithm [6] and D* algorithm [7], were mainly based on the graph search approach, which built the environment map into a discrete grid and generated the shortest path. However, the path obtained by the graph search-based algorithm is not continuous, and is difficult to combine with the dynamic characteristics of the vehicle. The samples-based approaches have attracted the attention of scholars, which randomly sample the state space to find the connectivity and quickly realize the path planning, including Rapidly-exploring Random Trees (RRT) [8] and Probabilistic Road Maps (PRM) [9]. To solve the problem

✉ Hong Wang
hong_wang@tsinghua.edu.cn

¹ Department of Vehicle Engineering, Nanjing University of Aeronautics & Astronautics, Nanjing 210016, China

² Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing 100084, China

of path discontinuity, scholars optimized the existing trajectories based on interpolation curves and generated a new set of data using a previous set of nodes to obtain a smoother and more reasonable path, including the polynomial curves [10], the clothoid curves [11], and the bezier curves [12]. The artificial potential field approach is a typical numerical optimization algorithm that constructs the gravitational and the repulsion fields in order to guide the vehicle to the destination avoiding collision [13]. Ji and Wang et al. superimposed the trigonometric function of the road and the exponential function of the obstacle, constructed a 3D virtual danger potential field, generated the ideal collision avoidance trajectory, and used the multi-constraint model predictive control (MMPC) to track the collision avoidance trajectory [14-16]. With the rapid development of artificial intelligence, machine learning is now being used to make decisions on autonomous vehicles. David improved the classical multi-agent reinforcement learning algorithm and used the neural network and the kernel smoothing technology to perform the approximate greedy operation on the unknown environment, which could generate multiple alternative paths [17]. Wolf searched for various extreme conditions through reinforcement learning, learned driving behavior in simulation and trained the autopilot system to plan a safe driving path [18]. To sum up, the path planning algorithm can be categorized into global path planning and local path planning, also known as motion planning. This paper assumes that the global path planning is available and focuses on the design of motion planning.

The main idea to make anti-rollover path planning is to take a rollover index that describes the rollover risk of the vehicle at any time into consideration as the constraint in the motion planning algorithm. The rollover index is used to describe and determine whether the vehicle has reached the critical rollover point. The static stability factor has been defined as a ratio of height of mass center to half-track width to detect the rollover risk [19]. The lateral load transfer ratio (LTR) is widely used in terms of rollover observations by measuring the vertical load of each wheel [20-22]. Time to rollover (TTR) is an efficient indicator for the rollover warning [23]. Zhu proposed a TTR warning algorithm and regulated TTR online by a back-propagation neural network [24]. Currently, some scholars have considered the lateral stability in motion planning process. Li used the roll plane model to obtain the rollover state of the vehicle, and combined it with the 3D occupancy grid to generate a safe path without rollover and collision [25]. Cheng proposed a lateral stability coordinated collision avoidance control system (LSCACS). The LSCACS

obtained the reference values of yaw angle and side deflection angle through the linear two-DOF vehicle model, determined the working mode of the system by combining with Time to Collision (TTC), and finally obtained the corresponding tire force based on the MPC control [26]. He assessed the risk related to collision and instability using the dynamic risk assessment model based on genetic algorithm and used the fifth order polynomial equation to generate the path without collision and with high lateral stability [27].

1.3 Contributions

Despite the large amount of research in path planning, there are few researches on the active anti-rolled-over motion planning algorithm. Therefore, an anti-rollover motion planning algorithm for heavy trucks based on V2V communications is proposed in this paper. The main contributions of this paper are as follows:

1. A seven degrees of freedom rollover dynamics model is established to accurately describe the motion state of heavy truck and a novel rollover index is defined to reveal the rollover mechanism of the heavy truck with flexible frame and solid axle suspension.
2. A motion planning algorithm based on model predictive control (MPC) is proposed, which integrates the active rollover prevention, the obstacle avoidance and the path tracking with multiple dynamic constraints.
3. Three extreme danger scenarios are designed to verify the obstacle avoidance performance and the effect of active rollover prevention of the anti-rollover motion planning algorithm.

1.4 Paper organization

The rest of this paper is organized as follows. In Section 2, the framework of anti-rollover motion planning is described. In Section 3, a nonlinear-coupled rollover model is established, which considers longitudinal, lateral, yaw, and roll motions of unsprung and sprung masses of each axle. Section 4 presents the details of the design of anti-rollover motion planning, which includes the derivation of rollover index, the definition of artificial potential field, and the design of MPC motion planner. In Section 5, some typical scenarios are simulated to verify the performance of the proposed anti-rollover motion planning algorithm. Finally, conclusions are summarized in Section 6.

2 Framework of anti-rollover motion planning for heavy trucks

The overall framework of the proposed anti-rollover motion planning algorithm is demonstrated in Figure 1. The framework includes motion planning, heavy truck dynamic model, state estimator, V2V communications, perception and global planning. The perception module detects and classifies the static obstacle and the road data, determines their location and provides their speed, direction and shape using various sensors including Lidar, Radar, camera, and GPS. The static obstacle and the road data are then sent to the global planning and motion planning modules. The motion planning and the global planning modules acquire the states of the obstacle vehicles through V2V communications. The global planning module combines the environment information and the vehicle state (such as vehicle speed, yaw angular speed, and lateral inclination.) from the state estimator module to generate the global path. Then, the MPC based motion planning module controls the heavy truck to track the global path while avoiding collisions, complying with the road regulations and preventing the rollover. Finally, the decision of the ego-vehicle is broadcast to the obstacle vehicles via V2V communications.

Figure 1 The framework of anti-rollover motion planning

This paper focuses on motion planning for heavy truck. It is assumed that the data of obstacle vehicles and the global path have been obtained from the perception module, V2V communications and the global planning module.

3 The heavy truck model

After obtaining the reference global path, it is necessary to establish an appropriate vehicle dynamic model to conduct the motion planning and the trajectory tracking control for the reference path in order to achieve the smooth running of the automated heavy truck. Due to the characteristics of large mass, high center of gravity and

uneven load distribution, it is easy to rollover in the process of driving. Therefore, this paper considers the roll stability of heavy trucks while conducting path planning. To simplify the modeling process, some idealized assumptions are made for heavy trucks:

1. The pitch and the vertical motion of the vehicle are ignored.
2. The influence of side wind is ignored.
3. The effect of tire aligning torque is ignored.
4. Only the characteristics of the pure side-slip linear tire are considered, while the horizontal and the vertical coupling relationship of the tire is ignored.
5. Only front wheel steering is considered.

Considering the roll coupling between the front and the rear sprung systems, an ideal torsion bar with fixed torsional stiffness and no mass is used to link the front and the rear sprung systems. Since the unsprung mass of heavy trucks is large, its influence on the roll motion cannot be ignored. Hence, a seven-degree-of-freedom dynamic model can be obtained, as shown in Figure 2:

Figure 2 A seven degree of freedom dynamic model for heavy truck

According to D'Alembert's principle, the motion equation of each degree of freedom is as follows:

Longitudinal motion:

$$m(\dot{u} - vr) = F_{xT} - F_r \quad (1)$$

Lateral motion:

$$ma_y - m_{sf} h_f \ddot{\phi}_{sf} - m_{sr} h_r \ddot{\phi}_{sr} = 2F_{Y1} \cos \delta_f + 2F_{Y2} \quad (2)$$

Yaw motion:

$$I_z \dot{r} = 2aF_{Y1} \cos \delta_f + 2bF_{Y2} \quad (3)$$

Roll motion of the front sprung mass of the front axle:

$$I_{Xf} \ddot{\phi}_{sf} = m_{sf} h_f a_y + m_{sf} g h_f \phi_{sf} - k_f (\phi_{sf} - \phi_{uf}) - l_f (\dot{\phi}_{sf} - \dot{\phi}_{uf}) + k_b (\phi_{sf} - \phi_{sr}) \quad (4)$$

Roll motion of the sprung mass of the rear axle:

$$I_{Xr} \ddot{\phi}_{sr} = m_{sr} h_r a_y + m_{sr} g h_r \phi_{sr} - k_r (\phi_{sr} - \phi_{ur}) - l_r (\dot{\phi}_{sr} - \dot{\phi}_{ur}) - k_b (\phi_{sr} - \phi_{sf}) \quad (5)$$

Roll motion of the unsprung mass of the front axle:

$$2F_{Y1} h_c + m_{uf} (h_{uf} - h_{cf}) a_y = -m_{uf} g (h_{uf} - h_{cf}) \phi_{uf} - k_f (\phi_{sf} - \phi_{uf}) - l_f (\dot{\phi}_{sf} - \dot{\phi}_{uf}) + k_{uf} \phi_{uf} \quad (6)$$

Roll motion of the unsprung mass of the virtual rear axle:

$$2F_{Y2} h_c + m_{ur} (h_{ur} - h_{cr}) a_y = -m_{ur} g (h_{ur} - h_{cr}) \phi_{ur} - k_r (\phi_{sr} - \phi_{ur}) - l_r (\dot{\phi}_{sr} - \dot{\phi}_{ur}) + k_{ur} \phi_{ur} \quad (7)$$

where the lateral acceleration of the sprung mass is:

$$a_y = \dot{v} + ur \quad (8)$$

The state of longitudinal and lateral motion of heavy truck are:

$$\dot{X} = u \cos \psi - v \sin \psi \quad (9)$$

$$\dot{Y} = u \sin \psi + v \cos \psi \quad (10)$$

where, m denotes the total mass of heavy truck, $* \in \{f, r\}$ denote the front and rear axles, m_{s*} and m_{u*} represent the equivalent sprung and unsprung masses, respectively, a , and b are the longitudinal distances from the CG to the

front axle and the rear axle, respectively, h_* is the height between the center of sprung mass and the roll center, h_{c*} and h_{u*} are the heights of the roll center and the center of the unsprung mass, measured upwards from the road, respectively, F_{xT} is the longitudinal force, F_r is the wheel rolling resistance, F_{Y1} , and F_{Y2} are the lateral forces of the tires at the front axle and the rear axle, respectively, I_{X*} is the roll inertia of the sprung mass, I_z is the yaw inertia of the heavy trucks, g is the gravitational acceleration, k_* and k_{u*} are the equivalent roll stiffness coefficients of the suspension and the unsprung mass, respectively, l_* is the equivalent roll damping coefficient of the suspension, k_b is the torsion stiffness coefficient of vehicle frame, r denotes the yaw rate of the sprung mass, u is the longitudinal speed, and v denotes the lateral velocity. X is the longitudinal displacement, Y is the lateral displacement, δ_f is front wheel steering angle, ϕ_{s*} and ϕ_{u*} are the roll angles of the sprung and the unsprung masses, respectively and ψ denotes the heading angle.

The lateral forces in Eqs. (2) and (3) mainly depend on the corresponding side slip angles β_f and β_r .

The side slip angles of the tire can be expressed as:

$$\beta_f = \arctan\left(\frac{v + ar}{u}\right) - \delta_f \quad (11)$$

$$\beta_r = \arctan\left(\frac{v - br}{u}\right) \quad (12)$$

Assuming that the yaw velocity and the lateral velocity are small relative to the vehicle speed, Eqs. (11)-(12) can be linearized as follows:

$$\beta_f = \left(\frac{v + ar}{u}\right) - \delta_f \quad (13)$$

$$\beta_r = \left(\frac{v - br}{u}\right) \quad (14)$$

Simplify the tire model by considering the cornering stiffness of the tires as constant, the lateral forces of tires can be obtained:

$$F_{Y1} = -K_f \beta_f \quad (15)$$

$$F_{Y2} = -K_r \beta_r \quad (16)$$

where, K_f and K_r are the cornering stiffnesses of the front and the rear wheels, respectively.

4 The anti-rollover motion planning

This section introduces the design of the anti-rollover motion planning for automated heavy truck. The process includes the derivation of rollover index of the heavy truck, the establishment of the artificial potential field, and the generation of MPC based motion planning

4.1 Rollover index of the heavy truck

$$LTR = \frac{F_L - F_R}{F_L + F_R} \quad (17)$$

It can be considered from Eq. (17) that the vehicle will rollover when the absolute value of LTR is more than one. However, the vertical load is hard to measure or estimate in real-time, especially in tripped rollover and emergency case [28]. Therefore, the LTR should be transformed to another expression to evaluate the rollover.

The difference between left and right vertical forces of each axle of the vehicle is expressed as Eq. (18).

$$\begin{cases} F_{L1} - F_{R1} = -k_f(\varphi_{sf} - \varphi_{uf}) - l_f(\dot{\varphi}_{sf} - \dot{\varphi}_{uf}) \\ F_{L2} - F_{R2} = -k_r(\varphi_{sr} - \varphi_{ur}) - l_r(\dot{\varphi}_{sr} - \dot{\varphi}_{ur}) \end{cases} \quad (18)$$

In addition, the total vertical load of each axle of the vehicle can be achieved as:

$$\begin{cases} F_{L1} + F_{R1} = m_f g \\ F_{L2} + F_{R2} = m_r g \end{cases} \quad (19)$$

Moreover, the difference between left and right vertical forces of each axle of the vehicle can be obtained from Eqs. (4) and (5)

$$\begin{cases} F_{L1} - F_{R1} = \frac{2}{T_{wf}} [I_{Xf} \ddot{\varphi}_{sf} - m_{sf} h_f a_y - m_{sf} g h_f \varphi_{sf} + k_b(\varphi_{sf} - \varphi_{sr})] \\ F_{L2} - F_{R2} = \frac{2}{T_{wr}} [I_{Xr} \ddot{\varphi}_{sr} - m_{sr} h_r a_y - m_{sr} g h_r \varphi_{sr} + k_b(\varphi_{sr} - \varphi_{sf})] \end{cases} \quad (20)$$

When only taking the front axle steering into account, the yaw rate gain can be described as follows.

$$\begin{cases} RI_f = \frac{-\frac{2}{T_{wf}} [I_{Xf} \ddot{\varphi}_{sf} - m_{sf} h_f a_y - m_{sf} g h_f \varphi_{sf} + k_b(\varphi_{sf} - \varphi_{sr})]}{m_f g} \\ RI_r = \frac{-\frac{2}{T_{wr}} [I_{Xr} \ddot{\varphi}_{sr} - m_{sr} h_r a_y - m_{sr} g h_r \varphi_{sr} + k_b(\varphi_{sr} - \varphi_{sf})]}{m_r g} \end{cases} \quad (21)$$

In terms of the above results, a novel rollover index (NRI) is defined to reveal the rollover mechanism of the heavy truck with flexible frame and solid axle suspension, as shown in Eq. (22). Compared with the problem that the LTR is difficult to measure in real-time, the state quantity in NRI can be obtained through the sensor to ensure real-time performance. Next, the accuracy of the NRI is verified by conducting simulations under typical rollover conditions,

$$NRI = \begin{cases} -1 & (aRI_f + bRI_r) \leq -L \\ \frac{aRI_f + bRI_r}{L} & -L < (aRI_f + bRI_r) < L \\ 1 & L \leq (aRI_f + bRI_r) \end{cases} \quad (22)$$

where, L is the wheelbase.

To verify the accuracy and the feasibility of the NRI in evaluating the rollover of the heavy truck, three cases and a “2A truck” model in TruckSim are used.

Fishhook is a worst untripped rollover maneuver. In this case, the amplitude of steering angle is set to five degrees. The results of NRI and LTR of the heavy truck at different running speeds are illustrated in Figure 3.

Figure 3 Results of *NRI* and *LTR* of heavy truck in Fishhook maneuver. (a) $u = 55$ km/h; (b) $u = 65$ km/h.

4.2 Artificial potential field for obstacles description

The basic idea of Artificial Potential Field (*APF*) is to construct a field including the repulsion and the attractor poles. In this paper, the trigonometric and the exponential functions are used to define an *APF* that can accurately and comprehensively reflect the integration of vehicle and road in dangerous driving state according to the information of road structure parameters, traffic running conditions and the positions of the obstacles. The *APF* includes non-crossable area (P_{NC}), crossable area (P_C), and road markers or boundaries (P_R), as shown in Eq. (23).

$$APF = \sum_i P_{NC_i} + \sum_j P_{C_j} + \sum_q P_{R_q} \quad (23)$$

where i , j , and q represent the indices of the non-crossable area, the crossable area and the road markers or boundaries, respectively.

Next, the *APF* is described in detail:

1) *Non-crossable Area*: A non-crossable area means the obstacles that the vehicle must avoid, such as vehicles and pedestrians. In this paper, the potential field of non-crossable area is defined as [29]:

$$P_{NC_i}(X, Y) = \frac{a_i}{s_i \left(\frac{dX}{X_{si}}, \frac{dY}{Y_{si}} \right)^{b_i}}$$

$$X_{si} = X_0 + uT_0 + \frac{\Delta u_{ai}^2}{2a_n}, Y_{si} = Y_0 + (u \sin \theta + u_{oi} \sin \theta)T_0 + \frac{\Delta v_{ai}^2}{2a_n} \quad (24)$$

where a_i and b_i are the parameters of the P_{NC} , respectively, a_n is the comfortable acceleration, dX and dY denote the distances between the obstacle and the ego-vehicle in longitudinal and lateral directions,

respectively, T_0 denotes the safe time gap, X_0 and Y_0 are the minimum longitudinal and lateral distances, respectively, X_{si} and Y_{si} are the safe longitudinal and lateral distances, u_{oi} is the velocity of the obstacles, θ is the heading angle towards each other, and Δu_{ai} and Δv_{ai} are the longitudinal and the lateral approaching velocities, respectively.

2) *Crossable area*: The potential field of crossable area which is less dangerous is generated by the exponential function and the safe distance s_j between the ego-vehicle and the crossable obstacles:

$$P_{C_j}(X, Y) = a_j e^{-b_j s_j \left(\frac{dX}{X_{si}}, \frac{dY}{Y_{si}} \right)} \quad (25)$$

where a_j and b_j are the parameters of P_C .

3) *Road markers or boundaries*: In addition to the lane changes, the vehicles should follow the lane center line and do not cross the road boundaries. The potential field of road markers or boundaries is defined by quadratic form function:

$$P_{R_q}(X, Y) = \begin{cases} a_q (s_{Rq}(X, Y) - D_a)^2 & s_{Rq}(X, Y) < D_a \\ 0 & s_{Rq}(X, Y) \geq D_a \end{cases} \quad (26)$$

where a_q is the intensity parameter of P_R , D_a is the permitted distance from the road boundary, and s_{Rq} is the safe distance between the ego-vehicle and the road boundaries.

An example of the potential field of non-crossable area is shown in Figure 4 (a), and the compound potential field of P_{C_j} and P_{R_q} of the two-lane road is shown in Figure 4 (b).

Figure 4 Examples of the potential field. (a) Potential field of non-crossable area; (b) The potential field of crossable area and road boundaries

4.3 MPC design for anti-rollover motion planning

In this section, the motion planning and the trajectory tracking are realized based on MPC. To avoid the obstacles, follow the road regulations, actively prevent rollover and track the global path, the cost function of MPC is integrated with the *NRI*, the *APF* and the trajectory tracking. According to the vehicle model proposed in Section III, the dynamic characteristics of the heavy truck for a period of time in the future are predicted. Then the cost function is optimized using the nonlinear optimal solver to obtain the control output of longitudinal force (F_{xT}) and steering angle δ_f .

In order to embed into the MPC as a prediction model, the above-mentioned nonlinear vehicle model needs to be linearized.

Synthesizing Eqs. (1)-(10), the nonlinear model can be converted into state space form as

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}, \mathbf{u}) \\ \mathbf{y} &= \mathbf{g}(\mathbf{x})\end{aligned}\quad (27)$$

where,

$$\begin{aligned}\mathbf{x} &= [u \quad v \quad r \quad X \quad Y \quad \psi \quad \dot{\varphi}_{sf} \quad \dot{\varphi}_{sr} \quad \varphi_{sf} \quad \varphi_{sr} \quad \varphi_{uf} \quad \varphi_{ur}]^T \\ \mathbf{u} &= [F_{xT} \quad \delta_f]^T \\ \mathbf{y} &= [u \quad v \quad r \quad Y \quad \dot{\varphi}_{sf} \quad \dot{\varphi}_{sr} \quad \varphi_{sf} \quad \varphi_{sr}]^T\end{aligned}$$

The linearized model state space equation is as follows;

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}, \quad \mathbf{A} = \frac{\partial \mathbf{f}}{\partial \mathbf{x}}, \mathbf{B} = \frac{\partial \mathbf{f}}{\partial \mathbf{u}} \\ \mathbf{y} &= \mathbf{C}\mathbf{x}, \quad \mathbf{C} = \frac{\partial \mathbf{g}}{\partial \mathbf{x}}\end{aligned}\quad (28)$$

where, $\frac{\partial \mathbf{f}}{\partial \mathbf{x}}$ and $\frac{\partial \mathbf{f}}{\partial \mathbf{u}}$ denote the partial derivation of vector $\mathbf{f}(\mathbf{x}, \mathbf{u})$ with respect to the vectors $\mathbf{x}$ and $\mathbf{u}$, respectively, and $\frac{\partial \mathbf{g}}{\partial \mathbf{x}}$ denotes the partial derivation of vector $\mathbf{g}(\mathbf{x})$ with respect to the vector $\mathbf{x}$.

According to the first order differential quotient method, the discrete state-space equation can be described as follows:

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{A}_k \mathbf{x}(k) + \mathbf{B}_k \mathbf{u}(k) \\ \mathbf{y}(k) &= \mathbf{C}_k \mathbf{x}(k)\end{aligned}\quad (29)$$

where, $\mathbf{A}_k = \mathbf{E} + t_s \mathbf{A}$, $\mathbf{B}_k = t_s \mathbf{B}$, $\mathbf{C}_k = t_s \mathbf{C}$, $\mathbf{E}$ is the unit matrix with same matrix order as $\mathbf{A}$, and $t_s = 0.001$ is discrete sampling time.

To design model predictive controller, set $\boldsymbol{\chi}(k) = [\mathbf{x}(k) \quad \mathbf{u}(k)]^T$, the state-space equation of prediction model can be transformed into,

$$\begin{aligned}\boldsymbol{\chi}(k+1) &= \hat{\mathbf{A}}_k \boldsymbol{\chi}(k) + \hat{\mathbf{B}}_k \Delta \mathbf{u}_k \\ \mathbf{y}(k) &= \hat{\mathbf{C}}_k \boldsymbol{\chi}(k)\end{aligned}\quad (30)$$

where,

$$\hat{\mathbf{A}}_k = \begin{bmatrix} \mathbf{A}_k & \mathbf{B}_k \\ \mathbf{0}_{1 \times 12} & \mathbf{1}_{1 \times 2} \end{bmatrix}, \hat{\mathbf{B}}_k = \begin{bmatrix} \mathbf{B}_k \\ \mathbf{1}_{1 \times 2} \end{bmatrix}, \hat{\mathbf{C}}_k = [\mathbf{C}_k \quad \mathbf{0}]$$

Therefore, the output prediction equation is

$$\mathbf{Y}(k) = \boldsymbol{\Psi}(k) \boldsymbol{\chi}(k) + \boldsymbol{\Theta}(k) \Delta \mathbf{U}(k) \quad (21)$$

where,

$$\begin{aligned}
Y(k) &= \begin{bmatrix} y(k+1) \\ y(k+2) \\ \dots \\ y(k+C_h) \\ \dots \\ y(k+P_h) \end{bmatrix}, \psi(k) = \begin{bmatrix} \hat{C}_k \hat{A}_k \\ \hat{C}_k \hat{A}_k^2 \\ \dots \\ \hat{C}_k \hat{A}_k^{C_h} \\ \dots \\ \hat{C}_k \hat{A}_k^{P_h} \end{bmatrix}, \\
\Theta(k) &= \begin{bmatrix} \hat{C}_k \hat{B}_k & 0 & 0 & 0 \\ \hat{C}_k \hat{A}_k \hat{B}_k & \hat{C}_k \hat{B}_k & 0 & 0 \\ \dots & \dots & \ddots & \dots \\ \hat{C}_k \hat{A}_k^{C_h-1} \hat{B}_k & \hat{C}_k \hat{A}_k^{C_h-2} \hat{B}_k & \dots & \hat{C}_k \hat{B}_k \\ \hat{C}_k \hat{A}_k^{C_h} \hat{B}_k & \hat{C}_k \hat{A}_k^{C_h-1} \hat{B}_k & \dots & \hat{C}_k \hat{A}_k \hat{B}_k \\ \vdots & \vdots & \ddots & \vdots \\ \hat{C}_k \hat{A}_k^{P_h-1} \hat{B}_k & \hat{C}_k \hat{A}_k^{P_h-2} \hat{B}_k & \dots & \hat{C}_k \hat{A}_k^{P_h-C_h-1} \hat{B}_k \end{bmatrix} \\
\Delta U(k) &= [\Delta u(k) \quad \Delta u(k+1) \quad \dots \quad \Delta u(k+C_h)]^T
\end{aligned}$$

Considering the feasibility of motion planning, the kinematics and the dynamics constraints of the heavy truck should be added to the model predictive controller. Firstly, the outputs of MPC-based motion planner, namely longitudinal force F_{xT} and the front wheel steering angle δ_f , need to satisfy the constraints of vehicle dynamics, as follows:

$$\begin{aligned}
F_{xT} &\leq F_{xT_max} = \frac{T_{max}}{R} \\
|\delta_f| &\leq \delta_{fmax} \\
|\Delta \delta_f| &\leq \Delta \delta_{fmax}
\end{aligned} \quad (32)$$

where, F_{xT_max} denotes the maximum longitudinal force, T_{max} denotes the maximum driving moment, R is the radius of the wheels, δ_{fmax} is the maximum steering angle, and $\Delta \delta_{fmax}$ is the maximum increment of steering angle.

In addition, the longitudinal and the lateral forces of the tire should conform to the friction ellipse limitation [30]. For brevity, the details of the specific derivation of the friction ellipse will not be expanded here.

$$\left(\frac{F_{xT}}{F_{xT_max}} \right)^2 + \left(\frac{F_{y\bullet}}{F_{y\bullet_max}} \right)^2 \leq \mu^2 \quad (33)$$

where, $F_{y\bullet_max}$, for $\bullet=1,2$, is the maximum lateral force of the tire and μ is road adhesion coefficient.

After adding the vehicle dynamic constraints in the

process of motion planning, the cost function of MPC motion planner incorporating the *NRI*, the *APF* and the path tracking is designed as:

$$\begin{aligned}
J = \sum_{k=1}^{P_h} & \left(\|Y(t+k) - Y_{ref}(t+k)\|_{Q_1}^2 + \|u(t+k) - u_{ref}(t+k)\|_{Q_2}^2 \right) \\
& + \sum_{k=1}^{C_h-1} \left(\|APF(t+k)\|_{Q_3}^2 + \|NRI(t+k) - NRI_{ref}(t+k)\|_{Q_4}^2 \right) \\
& + \sum_{k=1}^{C_h-1} \|\Delta u(t+k)\|_R^2 + \rho \varepsilon^2
\end{aligned} \quad (34)$$

where, P_h and C_h are the prediction and the control horizons, respectively, Q_1 , Q_2 , Q_3 and Q_4 denote the output state coefficient matrices, R is the control weight coefficient matrix, ε is the relaxation factor, and ρ is its weight coefficient.

In combination with the vehicle constraints shown in Eqs. (32) and (33), the nonlinear solver **fmincon** is called to optimally solve the cost function and a series of control increments in the control time domain are obtained as follows:

$$\Delta U^*(k) = [\Delta u^*(k) \quad \Delta u^*(k+1) \quad \dots \quad \Delta u^*(k+C_h)]^T \quad (35)$$

After obtaining the sequence of the control increments, the first element of the control sequence can be applied to the system as the actual control input increment,

$$u(k) = u(k-1) + \Delta u^*(k) \quad (36)$$

The system performs this control until the next moment. Then, the control system predicts the output of the next cycle according to the state information, and produces a new control increment sequence, and so on, until the control process is completed. Thus, the anti-rollover motion planning is completed.

5 Case study

To validate the performance of the proposed anti-rollover motion planning algorithm based on MPC, some typical scenarios are simulated. The parameters of a heavy truck (ego-vehicle) are listed in Table 1.

Table 1 Parameters of a triaxle bus

Symbol	value	unit	Symbol	value	unit
a	3.106	m	I_{xf}	2372	kg.m ²
b	1.384	m	I_{xr}	5323.5	kg.m ²
m_{sf}	1960	kg	I_z	30782.4	kg.m ²

m_{sr}	4400	kg	K_f	69252	N/rad
m_{uf}	500	kg	K_r	114829	N/rad
m_{ur}	760	kg	k_f	888433	N.m/rad
h_{cf}	0.1	m	k_r	588843	N.m/rad
h_{cr}	0.1	m	k_{uf}	489978	N.m/rad
h_f	1.1	m	k_{ur}	489978	N.m/rad
h_r	1.1	m	l_f	3444	N.m.s/rad
h_{uf}	0.51	m	l_r	3444	N.m.s/rad
h_{ur}	0.528	m	T_{wf}	2.03	m
k_b	4×10^5	Nm/rad	T_{wr}	1.863	m

Scenario 1: Emergency obstacle avoidance. The ego-vehicle is traveling at a constant speed of 80km/h on lane 1. Suddenly, a car (vehicle 1) directly in front of the ego-vehicle slows down to 40km/h. On lane 2, vehicle 2 is running with a constant speed of 50km/h at a horizontal distance of 10m from the vehicle 1 (red car), as shown in Figure 5

Figure 5 Positions of ego-vehicle and obstacle vehicles in Scenario 1.

In Figure 6, the red box and the red line represent the ego-vehicle and its trajectory. The blue box and the blue line are the vehicle 1 and its trajectory, while the green box and the green line represent the vehicle 2 and its trajectory. When $t=1s$, the ego-vehicle is still behind the vehicle 1. In order to avoid rear-end collision with the vehicle 1, the ego-vehicle has changed to lane 2, and there is no collision with the car during lane change, as shown at $t=2s$ and $t=2.5s$. Finally, the ego-vehicle makes lane change back to lane 1 to complete a safe overtaking. The planned path is compared with that of the motion planning without the anti-rollover, as shown in the dotted pink line. In terms of obstacle avoidance, the proposed anti-rollover motion planning is not as good as the motion planning without anti-rollover. However, it can still ensure collision avoidance.

Figure 6 Trajectories of ego-vehicle and obstacle vehicles in Scenario 1

Figure 7 shows the anti-rollover performance of the anti-rollover motion planning. According to the path obtained by the motion planning algorithm without considering the rollover, the *NRI* value of the ego-vehicle is 1 and one wheel is off the ground at 2.8s. However, the anti-rollover motion planning algorithm significantly reduces the rollover risk. As shown in Figure 7 (b), the steering angle output by the anti-rollover motion planning algorithm satisfies the constraints of vehicle dynamics. And the anti-rollover motion planning algorithm outputs smaller steering angle to complete obstacle avoidance and significantly reduces the rollover risk.

Figure 7 Anti-rollover performance of the anti-rollover motion planning algorithm in *Scenario 1*. (a) Comparison of *NRI*; (b) Comparison of steering angle.

Figure 8 analyzes the longitudinal control effect of the anti-rollover motion planning algorithm. The speed of ego-vehicle tends to slow down when it starts to turn. In order to ensure that the ego-vehicle runs at the target speed, the motion planning algorithm responds to the appropriate longitudinal force in time. Since the steering angle of motion planning without anti-rollover is larger, the descend range of the speed is relatively large and the longitudinal force is also larger than the anti-rollover motion planning. This has a relatively large impact on the handling stability of the vehicle. In summary, the anti-rollover motion planning algorithm better considers both the obstacle avoidance ability and the lateral stability.

Figure 8 Longitudinal control effect of the anti-rollover motion planning algorithm in *Scenario 1*. (a) Longitudinal force; (b) Longitudinal speed.

Scenario 2: Obstacle avoidance on curved road. As shown in Figure 9, the ego-vehicle is travelling on lane 1 at an initial speed of 80km/h, and the vehicle 1 is travelling with a constant speed on lane 2. There is a fixed obstacle of 1m in length and width in the curve part of lane 1. The ego-vehicle needs to make an emergency lane change and slow down to avoid rear-end collision with vehicle 1 in lane 2.

Figure 9 Positions of ego-vehicle and obstacle vehicle in *Scenario 2*

In Figure 10, the red box and the red line represent the ego-vehicle and its trajectory, while the blue box and the blue line are the vehicle 1 and its trajectory. The green box represents the fixed obstacle in lane 1. When $t=1s$, the

ego-vehicle has not yet detected the fixed obstacle and runs normally along lane 1. Then at $t=3s$, the ego-vehicle identifies the fixed obstacle, slows down and gradually moves to lane 2. The vehicle successfully avoids the obstacle at $t=4s$, and there is no rear-end collision with vehicle 1 in the lane changing process. The dotted pink line indicates the path planned by the MPC-based motion planning algorithm, which does not consider the risk of rollover. As can be seen, this path performs better at avoiding obstacles, but cannot guarantee the stability of vehicle.

Figure 10 Trajectories of ego-vehicle and obstacle vehicle in *Scenario 2*

Figure 11 analyzes the anti-rollover performance of the anti-rollover motion planning in *Scenario 2*. Similar to *Scenario 1*, the proposed anti-rollover motion planning algorithm performs well in active rollover prevention, reducing the amplitude of NRI by about 0.2. The steering angle increases gradually, which is consistent with the actual driving condition. The steering angle obtained by the proposed motion planning algorithm is slightly less than that without anti-rollover. From the results in Figures 11, it can be illustrated that the algorithm proposed in the steering process can avoid obstacles smoothly and reduce the rollover risk of the ego-vehicle.

Figure 11 Anti-rollover performance of the anti-rollover motion planning algorithm in *Scenario 2*. (a) Comparison of NRI ; (b) Comparison of steering angle.

The longitudinal control effect of the anti-rollover motion planning algorithm in *Scenario 2* is illustrated in Figure 12. In the first second, the vehicle has not detected the obstacle. Therefore, the longitudinal force is the driving force to overcome the resistance and maintain the vehicle at a speed of 80km/h. Then, to avoid collision with obstacle and adjacent vehicle 1, the longitudinal force is the braking force that gradually increases and reduces the speed to 50km/h, which is slightly less than the speed of motion planning without anti-rollover. The reduction of vehicle speed can also improve the rollover stability. This shows that the algorithm still puts up a good performance in longitudinal control under *Scenario 2*.

Figure 12 Longitudinal control effect of the anti-rollover motion planning algorithm in *Scenario 2*. (a) Longitudinal force; (b) Longitudinal speed.

Scenario 3: Extreme turning conditions. To further validate the proposed anti-rollover motion planning algorithm, a more urgent working condition is used as shown in Figure 13. The heavy truck is passing through a two-way lane at a speed of 50km/h, which has two large detours in the lane. When the ego-vehicle is 15 meters away from the first curve, a fixed obstacle of 1 meter in length and width suddenly appears on the lane 1. Similarly, another fixed obstacle with length and width of 1 meter appears on the lane 1, when the car is 15 meters away from the second curve.

Figure 13 Positions of ego-vehicle and obstacles in *Scenario 3*

Figure 14 shows the trajectories of ego-vehicle and the fixed obstacles in *Scenario 3*. The green box denotes the two fixed obstacles. As shown in dotted red line, the path generated by the anti-rollover motion planning algorithm successfully avoids the fixed obstacles and passes the two curves safely without any rollover. The dotted pink line indicates the path planned by the MPC motion planning algorithm, which does not consider the risk of rollover. The trajectory of the ego-vehicle disappears as it crosses the first curve, meaning it has rollover. Thus, the anti-rollover motion planning provides more safety.

Figure 14 Trajectories of ego-vehicle and fixed obstacles in *Scenario 3*.

Figure 15 shows that under extreme turning conditions, the absolute value of NRI of the vehicle driven by the MPC motion planning without anti-rollover reaches 1 at 7 seconds and then rolls over. However, when the ego-vehicle travels according to the anti-rollover motion planning, although the absolute value of NRI of the ego-vehicle is

also large at 8 seconds, it is quickly adjusted and no rollover is occurred. The steering angle calculated by the anti-rollover motion planning is smaller than that calculated by without anti-rollover, as shown in Figure 15 (b). This also shows that the proposed algorithm emphasizes on the lateral stability of ego-vehicle while ensuring safe avoidance of fixed obstacles.

Figure 15 Anti-rollover performance of the anti-rollover motion planning algorithm in *Scenario 3*. (a) Comparison of *NRI*; (b) Comparison of steering angle.

Figure 16 shows the longitudinal control effect of the anti-rollover motion planning algorithm. When the ego-vehicle passes the curves, the vehicle speed decreases slightly, then the driving force output of the anti-rollover motion planning algorithm increases appropriately, and the speed is stabilized again at the target speed of 50km/h. The path generated by the MPC motion planning algorithm without anti-rollover leads to rollover. Thus, the vehicle speed drops rapidly and finally disappear

Figure 16 Longitudinal control effect of the anti-rollover motion planning algorithm in *Scenario 3*. (a) Longitudinal force; (b) Longitudinal speed

In conclusion, the simulation analysis of three dangerous scenarios verifies the obstacle avoidance and the anti-rollover abilities of the proposed anti-rollover motion planning algorithm. It can be considered that the proposed algorithm can make vehicles, especially, heavy truck, travel safely.

6 Conclusions

In this paper, an anti-rollover motion planning algorithm based on model predictive controller (MPC) is proposed, which can generate a collision-free and anti-rollover path. Firstly, a 7 degrees of freedom vehicle rollover model is established for heavy trucks. As a prediction model for designing the MPC, it can predict the

future motion state of the vehicle. A novel rollover index (*NRI*) is developed that can accurately and effectively evaluate the rollover risk of the heavy truck. The motion states of the obstacles are obtained through the perception module and V2V communications. Then the artificial potential field (*APF*) including non-crossable area, crossable area and road markers or boundaries is established to avoid the obstacles. Finally, an MPC motion planner is designed that combines the *NRI*, the *APF* and the path tracking.

The performance of the proposed anti-rollover motion planning algorithm is analyzed by simulating three dangerous scenarios. The obtained results show that the algorithm performs well in obstacle avoidance and rollover prevention, which verifies its robustness and effectiveness.

7 Declaration

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

Authors' contributions

The author's contributions are as follows: Zhi-lin Jin was in charge of the whole trial; Jing-xuan Li wrote the manuscript; Hong Wang, Jun Li and Chao-sheng Huang assisted with sampling and laboratory analyses.

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The authors declare no competing financial interests.

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Biographical notes

Zhi-Lin Jin, born in 1978, is currently an Associate Professor of *Department of Vehicle Engineering at Nanjing University of Aeronautics and Astronautics, China*. He received his PhD degree from *Nanjing University of Aeronautics and Astronautics, China*, in 2008. His research interests include vehicle system dynamics and control.

Tel: +86-13913949581; E-mail: jinzhilin@nuaa.edu.cn

Jing-Xuan Li, born in 1997, is currently a graduate student of *Department of Vehicle Engineering at Nanjing University of Aeronautics & Astronautics, China*.

E-mail: 269199917@qq.com

Hong Wang, born in 1986, is currently a research associate professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: hong_wang@tsinghua.edu.cn

Jun Li, born in 1958, is currently a professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: lj19580324@126.com

Chao-Sheng Huang, born in 1972, is currently a research professor at *Tsinghua Intelligent Vehicle Design and Safety Research Institute, Tsinghua University, Beijing, China*.

E-mail: huangchaosheng@tsinghua.edu.cn

Figures

Figure 1

The framework of anti-rollover motion planning

Figure 2

A seven degree of freedom dynamic model for heavy truck

Figure 3

Results of NRI and LTR of heavy truck in Fishhook maneuver. (a) $u = 55$ km/h; (b) $u = 65$ km/h.

Figure 4

Examples of the potential field. (a) Potential field of non-crossable area; (b) The potential field of crossable area and road boundaries

Figure 5

Positions of ego-vehicle and obstacle vehicles in Scenario 1.

Figure 6

Trajectories of ego-vehicle and obstacle vehicles in Scenario 1

(a)

(b)

Figure 7

Anti-rollover performance of the anti-rollover motion planning algorithm in Scenario 1. (a) Comparison of NRI; (b) Comparison of steering angle.

(a)

(b)

Figure 8

Longitudinal control effect of the anti-rollover motion planning algorithm in Scenario 1. (a) Longitudinal force; (b) Longitudinal speed.

Figure 9

Positions of ego-vehicle and obstacle vehicle in Scenario 2

Figure 10

Trajectories of ego-vehicle and obstacle vehicle in Scenario 2

Figure 11

I Anti-rollover performance of the anti-rollover motion planning algorithm in Scenario 2. (a) Comparison of NRI; (b) Comparison of steering angle.

Figure 12

Longitudinal control effect of the anti-rollover motion planning algorithm in Scenario 2. (a) Longitudinal force; (b) Longitudinal speed.

Figure 13

Positions of ego-vehicle and obstacles in Scenario 3

Figure 14

Trajectories of ego-vehicle and fixed obstacles in Scenario 3.

Figure 15

Anti-rollover performance of the anti-rollover motion planning algorithm in Scenario 3. (a) Comparison of NRI; (b) Comparison of steering angle.

Figure 16

Longitudinal control effect of the anti-rollover motion planning algorithm in Scenario 3. (a) Longitudinal force; (b) Longitudinal speed