Control Strategy of Vehicle Anti-Rollover Considering Driver’s Characteristic

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ABSTRACT In the process of vehicle anti-rollover, the driver’s behavioral characteristics have a great influence on the vehicle rollover stability. However, the existing researches on anti-rollover rarely consider the driver in the human-vehicle-road closed loop system, which may directly affects the rollover dynamics characteristics of the vehicle. Aiming at this problem, this work analyzes the influence of different driver parameters on vehicle dynamics and establishes a driver model considering the vehicle rollover stability. Based on this, a collaborative control strategy of vehicle anti-rollover considering the driver’s characteristics is designed to assist the driving stability requirements of different types of drivers. It includes the upper layer of supervision decision control and the lower layer of cooperative execution control. The supervisory decision control layer sets different rollover constraint boundaries for different types of drivers, and makes six control decision modes combining driver input and vehicle path tracking error. Aiming at different types of drivers, the lower cooperative execution control layer constrains the front wheel angle by the active steering system to reduce yaw rate and the risk of rollover. Moreover, it reasonably distributes the braking force of four tires by the active braking system to reduce the path tracking error while preventing rollover. The simulation results show that, the proposed cooperative control strategy can provide different control effects for different drivers, and ensure the effective anti-rollover control of the vehicle and achieve good path tracking performance.

INDEX TERMS Driver model, rollover, parameter identification, active steering, active braking.

I. INTRODUCTION

With the increase of vehicle ownership, the safety accidents are also increasing. In all traffic accidents, rollover accident has a low occupancy rate but a high fatality rate. According to the statistics of the U.S. highway traffic safety administration, from 2012 to 2017, there are more than 2.1 million traffic accidents in the United States. In 2017, more than 30000 people lost their lives in the accidents, and the fatality rate of rollover accident accounted for 11% [1]. Rollover accident is the second largest traffic accident after collision accident. It indicates that once a rollover accident occurs, it will cause great harm, resulting in serious loss of life and property. Therefore, it is necessary to study the safety performance of rollover.

In recent years, with diversification of driving groups and deepening of urban integration, highway traffic has gradually turned to intensive, high-speed and complex road conditions [2]. Meanwhile, the handling characteristics of different drivers have become the main cause of frequent traffic accidents. Research data shows that 20% - 25% of crashes are caused by subjective causes of drivers. However, the existing researches on anti-rollover rarely consider driver’s characteristics on the rollover dynamics characteristics of the vehicle. They only consider the vehicle-road system, and corrects the vehicle’s driving error by means of state feedback adjustment and error compensation to prevent the vehicle from rollover [3]–[7].

Although there are some scholars who have studied the driver’s steering characteristics, it is rarely associated with rollover and the only ones are basically at the early warning level [8]–[13]. The case in point is that a design method of ideal vehicle model was proposed in [11] to ensure the
good performance of rollover warning even if the driver’s steering characteristics change, while the anti-rollover control is not much involved. Researchers of intelligent driving usually focus on the parameter changes of driver-vehicle system and the rights of steering driving. In a separate study [12], researchers extended the model reference adaptive controller (MRAC) to system parameter changes caused by the compliance of the driver arms. In particular, the author in [13] solved the problem of smooth switching of steering driving rights by using a hybrid control framework.

However, those existing researches ignore the influence of different driver’s behavior characteristics on vehicle stability control, which may directly affect the dynamic characteristics of vehicle rollover. Except a small number of autonomous intelligent vehicles, modern vehicles are mainly controlled by drivers. The safety of vehicles is closely related to the driving behavior of drivers [14]. Therefore, the research on the vehicle rollover stability could not be separated from the operation behavior of drivers themselves. On the one hand, experienced drivers have shorter reaction time and stronger operation ability when driving, and they are more proficient in mastering the vehicle. Therefore, in the face of sudden rollover conditions, they have a strong perception ability and they can make timely manipulation action to avoid rollover. On the contrary, inexperienced drivers may cause improper manipulation, thereby aggravating the risk of rollover. On the other hand, the rollover stability of some vehicles is often in the critical condition. Even for experienced drivers, their physiological and psychological limitations often make them unable to correct the vehicle in time, resulting in vehicle rollover [15]. Therefore, it is necessary to further design the anti-rollover dynamic control system based on the study of the influence of different types of driver’s handling on vehicle stability to improve the safety of vehicle driving and reduce the driver’s operating burden.

Based on the results of our research team as shown in literature [16], this article further aims to assist the driving stability requirements of different types of drivers, and puts forward a vehicle anti-rollover control strategy considering the driver characteristics to ensure that different types of drivers track the ideal path while preventing the vehicle from rollover.

The rest of this article is arranged as follows: Section II establishes the driver model considering rollover stability and identifies the driver parameters of the model. The control strategy of vehicle anti-rollover considering driver’s characteristic is designed in Section III, including supervisory decision control and executive control. Moreover, conclusions are given in Section IV.

II. DRIVER MODEL AND PARAMETER IDENTIFICATION

This section mainly analyzes the influence of different parameters of the driver model on the dynamic behavior of vehicle rollover through the hardware-in-the-loop test platform. The driver model considering rollover stability is established, and the parameters of the model are identified.

A. OVERALL DESIGN OF DRIVER MODELING

Figure 1 shows the overall framework of driver model considering rollover stability. Firstly, based on the driver’s hardware-in-the-loop test platform, the test data of different drivers’ steering control under the double-shift condition is collected, and the drivers with different steering styles are classified by K-means clustering algorithm. Second, a driver model considering the stability of vehicle rollover is established, which includes driver preview and neuro-muscular steering. Finally, the parameters related to rollover dynamics in driver models with different styles are identified by differential evolution algorithm.

B. DRIVER HARDWARE-IN-THE-LOOP TEST

Considering the special research situation of rollover control, it is generally considered that the vehicle may occur rollover under the critical conditions of stability and instability. Therefore, considering the safety and reliability of data acquisition, this work collects different driver characteristics data based on the hardware-in-the-loop test platform. 30 drivers are selected to carry out the test under the double-shift condition, and the test data related to rollover dynamics and path tracking are collected.

The driving simulation platform in this paper is a driving simulator that can simulate the real driving environment, as shown in Figure 2. The vehicle chassis electric control comprehensive test platform adopts Chang’an cs75 model, which integrates the braking system, steering system, sensor system and network communication system of the original vehicle, and constructs the overall hardware system of the test platform. The test system takes NI PXI real-time operating system as the core, and realizes the complete vehicle hardware-in-the-loop simulation environment based on the combination simulation of CarSim software and LabVIEW software.

The double-shift test with multiple participants is designed. The width of pavement is set as 4m and the adhesion coefficient of pavement is 0.85. In order to ensure the validity of the test data, the test fully considers the influence of the driver’s personal age, gender, preference, driving age, etc. 30 drivers with C1 license are selected in the university, among which 26 are male drivers, accounting for 86.7% of the total, and 4 are female drivers, accounting for 13.3% of the total. The age distribution of drivers is between 20-45 years old and the driving age distribution is 1-16 years old, which covers the general classification of the actual driving population. Before the test, every driver needs to be familiar with the operation on the hardware-in-the-loop test platform in advance to ensure that the test is not affected by unfamiliar environment. It takes about 15 minutes for each participant to complete the test. In addition, the drivers are required to track the preset path according to their daily life habits and drive independently for 5 times at the speed of 90km/h to prevent invalid data.

Figure 3 shows the collected data by drivers 9, 17 and 22 at the speed of 90km/h, including steering wheel angle, yaw
rate, lateral displacement and side inclination angle. From the test results in Figure 3, it can be seen that the drivers with different styles adopt different control methods for the same condition, and the control effect is quite different.
C. CLASSIFICATION OF DRIVER BEHAVIOR CHARACTERISTICS

In order to study the behavior characteristics of different drivers in anti-rollover control, this section classifies the behavior characteristics of different drivers in anti-rollover control based on the collected data in the hardware-in-the-loop test in Section II.B.

1) SELECTION OF CHARACTERISTIC PARAMETERS

The data collected by hardware-in-the-loop test platform cannot be directly used for the classification of driver behavior characteristics, so it is necessary to select characteristic parameters that reflect different drivers’ behavior in anti-rollover control. In this paper, the absolute value of the maximum lateral load transfer rate $\text{LTR}_{\text{max}}$ and the square mean of the path tracking error $e_y$ are selected as the characteristic parameters for clustering analysis.

2) CLUSTERING OF BEHAVIORAL CHARACTERISTICS

At present, there is no prior knowledge that can be referred to for the study of driver’s anti-rollover characteristics. In this section, drivers with the same characteristics need to be classified to build the distribution space of different types of drivers. For behavior characteristics classification, this paper uses K-means clustering algorithm to attribute similar driver behavior characteristics to the same clustering.

Figure 4 shows the process of K-means clustering algorithm designed in this paper, which is mainly divided into five parts:

- **Step 1:** Initialize the program, and select $K$ numbers representative points arbitrarily, written as $\{c_1, c_2, c_3, \ldots c_K\}$;
- **Step 2:** Calculate the distance between sample $X_p$ and cluster $c_i$ using Euclidean square distance algorithm;

$$d_{pi} = \|X_p - c_i\|^2 \quad (1)$$

- **Step 3:** Classify the clusters according to the minimum distance rule;

$$S_i = \{X_p | \|X_p - c_i\|^2 \leq \|X_p - c_j\|^2, \forall j \in Z, 1 \leq j \leq K\} \quad (2)$$

- **Step 4:** The new clustering center $c_i$ is obtained by calculating the mean value of the samples in the cluster $S_i$, as follows:

$$c_i = \frac{1}{|S_i|} \sum_{X_p \in S_i} X_p \quad (3)$$

- **Step 5:** The K-means algorithm recalculates the new clustering center through repeated iterations, and the clustering center is updated accordingly with the iteration. The squared error criterion function is the condition of iteration termination, and the function model is as follows:

$$E = \sum_{i=1}^{K} \sum_{X_p \in S_i} \|X_p - c_i\|^2 \quad (4)$$

If $E$ does not change, or the difference between the two successive calculations is less than the set threshold value, it can be assumed that clustering is complete. Otherwise, go to Step 2 for further iteration.

3) CLUSTERING RESULTS AND ANALYSIS

The absolute value of the maximum lateral load transfer rate $\text{LTR}_{\text{max}}$ and the square mean of the path tracking error $e_y$ in section II.C are used as the characteristic parameters in clustering analysis. After clustering calculations, it is found that when the $K$ value is 3, the driver categories can be divided more effectively. Based on clustering, the three data sets are 19, 59 and 72 respectively.

Figure 5 shows the K-means clustering results. In Figure 5, the drivers represented by the red dot have a relatively small absolute value of the maximum lateral load transfer rate and the mean square value of the path tracking error, which conform to the driving style of the cautious driver, characterized by driving in strict accordance with the preset path and low rollover risk. The drivers represented by the green dot have relatively large vehicle parameters, which conform to the driving style of aggressive drivers. Their driving process deviates from the preset path, and there...
is a greater risk of rollover. The blue dots represent the drivers in between, which conform to the general drivers. Cautious drivers and aggressive drivers are distributed on both sides of the figure, while general drivers are distributed in the middle of the figure. The parameter values of the drivers with the same type are close to each other, and the parameter values of the drivers with different types are quite different. The three black figures in Figure 5 represent the center values of the three clusters, and the specific parameters are shown in Table 1. It can be seen from Table 1 that the vehicle parameters values obtained by different driving styles are quite different. The driver data collected this time are mostly from young people whose driving times are less and their driving process is more cautious, so the number of cautious and general driver data is more. Finally, 30 drivers are divided into three groups, including 14 cautious drivers, 12 general drivers and 4 aggressive drivers. The data statistics are shown in Figure 6.

According to the collected driver data and the drivers’ actual information, it can be divided into three types: the cautious, the general and the aggressive.

D. DRIVER ANTI-ROLLOVER MODEL

This section further studies the driver model to analyze the impact of driver characteristics on vehicle rollover and path tracking performance. The driver model considering the dynamic characteristics of rollover is divided into two parts: the anti-rollover preview model and the neuromuscular model [17]–[20]. The block diagram of the whole driver model is shown in Figure 7.

Rollover accidents often occur at the position where the steering angle suddenly changes greatly. That is, the position where the expected path curvature is large. The optimal preview driver model has the advantages of simple structure, good robustness and high tracking accuracy [21]. In this section, the driver preview model considering rollover characteristics is built according to the optimal preview driver model.

When rollover occurs, the vehicle tends to be at a higher speed, larger steering wheel angle and larger side inclination angle. When the driver feels the danger, he will not blindly decide the optimal steering wheel angle according to the lateral position error and the direction error. Instead, he will consider the rollover error in the preview link and decide the best steering wheel angle according to the lateral position error, the direction error and the rollover error. In this section, the rollover error function is added to the optimal preview driver model to better describe the rollover condition.

The optimal steering wheel angle can be described as the product of the weight of the vehicle displacement error, the directional error and the rollover error, and the operation delay of the driver. The error weight function is as follows:

$$J_e = \sum_{k=0}^{\infty} w_x e_x^2 + w_\phi e_\phi^2 + w_\psi e_\psi^2$$

$$e_\psi = \psi(t) - \psi_{des}$$

where, as is shown in Figure 8, $e_x$, $e_\phi$, and $e_\psi$ are the displacement error, current heading error and roll angle error in the preview pilot model, respectively [22]; $\psi_{des}$ is the desired roll angle; $w_x(X = y, \phi, \psi)$ is the weight function.

With the increase of preview time, the weight ratio of $w_\psi$ will decrease correspondingly. When both the rollover angle and the rollover angular velocity are relatively small, for example, when $LTR < 0.8$, the driver only considers
tracking the expected path and does not consider the rollover characteristics. On the contrary, with the increase of the rollover angle and the rollover angular velocity, for example, when $LTR \geq 0.8$, the coefficient $w_{\psi}$ will also increase, which means that the driver will pay more attention to the rollover characteristics and less consider tracking the corresponding path.

Furthermore, the neuromuscular model is introduced into the driver’s control model to better explain the driver’s dynamic operation behavior. Therefore, this paper adopts the driver model proposed by Macadam [17], which has less parameters, simple structure and representative attribute. According to the desired angle calculated by the driver’s control model, the simplified neuromuscular model is controlled to output the final steering wheel angle $\delta_{sw}$, which can be expressed by the following formula:

$$\delta_{sw}(s) = \frac{G_h (1 + \tau_L s) e^{-\tau_d s}}{1 + \tau_d s} \delta^*$$

where $\delta^* = \arg\min(J)$; $G_h$ is the steering gain; $\tau_L$ is the differential/lead time constant; $\tau_d$ represents driver neural delay; $\tau_d1$ is the pure delay constant.

Generally, $\tau_L$ and $\tau_d1$ are less than 1s, $1 + \tau_L s$ is the first two terms of the Taylor expansion of $e^{\tau_L s}$, so $1 + \tau_L s$ can be considered as an approximate term of $e^{\tau_L s}$. In addition, $e^{\tau_d s}$ can be simplified as a first-order system $1/(1 + \tau_d s)$. The above equation can be described as follows:

$$\delta_{sw}(s) = \frac{G_h}{a_0 T_d^2 s^2 + 2 \tau_d s + 1} \delta^* + d_4(s)$$

where $\tau_d = \tau_d1 + \tau_d2$ is the delay time; $a_0 = \tau_d1 \tau_d2/T_d^2$; $d_4$ is the model approximate error.

E. PARAMETER IDENTIFICATION OF DRIVER ANTI-ROLLOVER MODEL

In this section, for three kinds of driver data with different styles, differential evolution algorithm is used to identify the relevant parameters of the driver model, and the driver model after parameter identification is verified.

1) PARAMETER IDENTIFICATION OF DRIVERS

Differential evolution algorithm is a kind of adaptive global optimization algorithm, which imitates the natural life and takes survival of the fittest as the criterion. It can solve the problem of parameter identification of complex system.

In this section, five parameters are selected for identification: preview time $T_p$, rollover angle weight function $w_{\psi}$, neuromuscular delay time $\tau_{d1}$, $\tau_{d2}$, and steering gain $G_h$. The algorithm flow chart is shown in Figure 9, and the main parameters set in the differential algorithm are shown in Table 2.

In this section, the parameters waiting for identification are set as a population, and five unknown parameters are set, which are encoded with real numbers, respectively:

$$X = [T_p, w_{\psi}, \tau_{d1}, \tau_{d2}, G_h]$$

The output error criterion is applied in this section, and the formula is expressed as:

$$\varepsilon(k) = y(k) - y_m(k)$$

where $y(k)$ is the actual input of the system; $y_m(k)$ is the output of the model; $\varepsilon(k)$ is the error value.

The error index of the identification can be written as:

$$J = \frac{1}{2} \sum_{k=1}^{N} \varepsilon(k)^2 = \frac{1}{2} \sum_{k=1}^{N} (y(k) - y_m(k))^2$$

where $N$ is the number of test data.

The differential evolution algorithm keeps the excellent individuals, which are the units with small error index, and eliminates the inferior individuals, to approach the optimal solution gradually. The algorithm consists of several steps, as shown below:

Step 1: Generate the initial population, randomly select $M$ individuals in the n-dimensional space, and meet the constraints. The implementation steps are as follows:

$$x_{ij}(0) = rand_i(0, 1) (x_{ij}^U - x_{ij}^L) + x_{ij}^L$$

where $x_{ij}^U$ and $x_{ij}^L$ are the upper and lower bounds of the $j$ chromosome respectively; $rand_i(0,1)$ is a random decimal between $[0,1]$.

The value range of the individuals is as follows [17]:

$$X_{\text{max}} = [2.5, 1, 0.2, 0.5, 2]$$

$$X_{\text{min}} = [0.4, 0.1, 0.01, 0.1, 0.4]$$
Step 2: Evaluate individual fitness, and calculate the fitness of each individual in the initial population.

Step 3: Variation operation: randomly select three individuals \(x_{p1}, x_{p2}, \text{and } x_{p3}\) from the population, \(i \neq p_1 \neq p_2 \neq p_3\), and carry out variation operation. The formula can be expressed as:

\[
h_{ij}(t+1) = x_{ij}(t) + F(x_{p2j}(t) - x_{p3j}(t)) \tag{15}
\]

where \(x_{p2j}(t) - x_{p3j}(t)\) is the differentiation vector; \(F\) is the variation factor; \(p_1, p_2, p_3\) are random integers representing the number of individuals in the population; \(x_{ij}(t)\) is the optimal individual in the current population, and this operation speeds up the whole convergence speed.

Step 4: Cross operation. In order to make the population more diverse, the following steps need to be done.

\[
v_{ij}(t+1) = \begin{cases} 
     h_{ij}(t+1) & \text{rand } l_{ij} \leq CR \\
     x_{ij}(t) & \text{rand } l_{ij} > CR
\end{cases} \tag{16}
\]

where \(\text{rand } l_{ij}\) is a random decimal between \([0,1]\); \(CR\) is the crossover probability, and \(CR\) value is \([0,1]\).

Step 5: Select operation. In order to verify whether \(x_{ij}(t)\) can be the next generation of individuals, the experimental vector \(v_i(t+1)\) and the target vector \(x_i(t)\) need to be compared:

\[
x_i(t+1) = \begin{cases} 
     v_i(t+1) & f(v_i(t+1)) < f(x_i(t)) \\
     x_i(t+1) & \text{others.}
\end{cases} \tag{17}
\]

Step 6: According to step 2 to step 5, repeat the iterative calculation until the number of iterations \(G\) reaches the maximum number of iterations, terminate the operation, and give the optimal solution.

2) THE RESULTS AND ANALYSIS OF PARAMETER IDENTIFICATION

The simulation output curve is collected to verify the differential evolution algorithm. The driver parameters are: \(X_{\text{moni}} = [0.6, 0.5, 0.1, 0.5, 0.5]\). The optimization process of the value of identification error function after the algorithm iteration is shown in Figure 10 (a). The final identification error index is: \(Best J = 0.0032\), and the identification parameters are: \(X_{\text{bianshimoni}} = [0.6, 0.5, 0.08, 0.5204, 0.4958]\). It can be seen from the Figure 10 that the model output values of the optimal individuals are consistent with the change trend of the simulated driver data. The value of the vehicle maximum path error is 0.0946, the value of mean absolute error MAE is 0.041, the value of path error sum variance SSE is 13.1102, the value of mean square error MSE is 1.8104, and the value of root mean square RMSE is 2.5603. Therefore, the differential evolution algorithm can effectively identify the parameters of the driver model.

According to the three types of driver data in Section II.C, the driving data of one driver close to the clustering center is selected randomly to identify and fit the parameters. Considering that in the double-shift condition, the reference significance of vehicle data in straight line driving is small, so only lane change data is selected as identification data. The data of a driver close to the clustering center from the cautious drivers is selected, and the optimization process of the identification error function value after the algorithm iteration is completed is shown in Figure 11 (b). The final identification error index is: \(Best J = 0.0676\), and the optimal individual value of the corresponding model is: \(X_{\text{best–jinsheng}} = [0.6, 0.3, 0.0985, 0.1523, 0.5078]\). For general drivers, the driver data close to the clustering center is also selected, and the optimization process is shown in Figure 11 (c). The final identification error index is: \(Best J = 0.0899\), and the optimal individual value of the corresponding model is: \(X_{\text{best–jinsheng}} = [0.5, 0.1, 0.0825, 0.2451, 0.7469]\). For aggressive drivers, the optimization process is shown in Figure 11 (d). The final identification error index is: \(Best J = 0.0173\), and the optimal individual value of the corresponding model is: \(X_{\text{best–jinsheng}} = [0.4, 0.02, 0.0842, 0.3017, 0.8953]\). The above identification results conform to the analysis results in Section II.D. The parameters of cautious drivers are preview time \(0.6s\), rollover weight \(0.3\), neuromuscular delay \(0.0985s\), \(0.1523s\), and steering gain \(0.5078\). The preview time \(T_p\) is moderate and sensitive to the rollover response \(w_y\). The neuromuscular delay \(T_d\) is small. Moreover, the steering gain
$G_h$ is appropriate, which can track the expected path well and reduce the risk of rollover. The parameters of aggressive drivers are preview time 0.4s, roll weight 0.02, neuromuscular delay 0.0842s, 0.3017s, and steering gain 0.8953. The preview time $T_p$ is short and insensitive to rollover response $w_\psi$. The neuromuscular delay $T_d$ is large. The steering gain $G_h$ is large, the tracking path effect is poor and the risk of rollover is increased.

### III. VEHICLE ANTI-ROLLOVER CONTROL STRATEGY CONSIDERING DRIVER’S CHARACTERISTICS

According to the three different types of driver models established in the Section II, based on the active steering and active braking system, this section designs a vehicle anti-rollover cooperative control strategy considering the driver’s characteristics.

#### A. CONTROLLER OVERALL DESIGN

The anti-rollover control strategy designed in this section is to prevent the rollover of vehicles operated by different types of drivers, and ensure that the vehicles can effectively track the expected path. Figure 12 shows the framework of vehicle anti-rollover control considering different driver characteristics, which is divided into two layers: the upper layer of supervision decision control and the lower layer of cooperative execution control. The upper layer sets different rollover constraint boundaries for different types of drivers, and makes six control decision modes combining them with driver input and vehicle path tracking error. Aimed at different types of drivers, the lower layer constrains the front wheel angle through the active steering system to reduce the yaw rate and roll risk. Meanwhile, through the braking system, it reasonably distributes the braking force of four tires to reduce the path tracking error while preventing rollover.

#### B. UPPER SUPERVISION DECISION CONTROL

The upper supervisory decision control layer is mainly responsible for detecting the driver’s input signal and the...
body status signal, and determining the driver’s anti-rollover critical safety supervision area. The path tracking error is the difference between the actual lateral position and the ideal lateral position, and the critical safety area is the relationship between the vehicle velocity and the path considering the steering constraints and rollover constraints.

1) CRITICAL SAFETY SUPERVISION AREA
The critical safety supervision area layer is mainly to find a relationship between vehicle velocity and path curvature considering the maximum steering angle and different driving rollover thresholds. In the critical steering safety area, the driver’s tracking trajectory will not be affected by the dynamic characteristics of the vehicle, and the vehicle will not have the risk of rollover. Through setting up the security constraints, the scopes of danger and safety area can be drawn, which lays a foundation for the design of the next decision control mode.

**a: STEERING CRITICAL SAFETY AREA**
The driver may be constrained by the vehicle dynamics when tracking the path. Within this constraint, the driver has the ability to track the expected trajectory. When this constraint is exceeded, the expected goal can only be achieved by reducing the vehicle velocity.

With reference to the published paper of our own research team [16], the vehicle meets the driver’s requirements in the driving process, which is constrained by the vehicle dynamics and handling dynamics characteristics.

\[
R = \frac{(\frac{mb}{k_f(a+b)} - \frac{ma}{k_r(a+b)}) \cdot v_x^2 + (a+b)}{\delta_f} \tag{18}
\]

where \( R \) is the driving radius of the vehicle; \( v_x \) is the longitudinal speed; \( \delta_f \) is the front wheel steering angle; \( a, b \) is the distance from the center of front and rear axle to the center of mass; \( k_f, k_r \) is the tire lateral stiffness; \( m \) is the mass of vehicle.

According to Equation (18), the steering safety boundary can be calculated by the maximum front wheel angle \( \delta_{MAX} \) and vehicle velocity.

\[
n_1 = \frac{1}{R} \leq \frac{\delta_{MAX}}{(\frac{mb}{k_f(a+b)} - \frac{ma}{k_r(a+b)}) v_x^2 + (a+b)} \tag{19}
\]

Then the boundary constraint of steering critical safety area can be obtained as shown in Figure 13 (a).

**b: ROLLOVER BOUNDARY CONSTRAINT**
According to the rollover evaluation index PTLTR [16], the boundary constraints for preventing the rollover of the vehicle can be obtained. Considering that the risk of vehicle rollover is also different under different drivers’ operation, this section sets the aggressive driver rollover boundary as \( LTR_b = 0.8 \), the general driver rollover boundary as \( LTR_b = 0.9 \), and the cautious driver rollover boundary

\[
\text{LTR}_b = 1.0, \text{ which is expressed as:}
\]

\[
\begin{align*}
LTR^* &= \frac{2(m_d a_y h_z + K_\phi \phi + C_\psi \dot{\phi} + m_s a_{ys} (h - e))}{mgT} \\
\phi &= a_y R_\phi / g
\end{align*}
\]

where \( m_d, a_y, h_z \) is the mass, acceleration and center height of the unsprung parts; \( K_\phi, C_\psi \) is roll stiffness and damping respectively; \( m_d, a_{ys}, h \) is the mass and lateral acceleration and centroid height of the sprung parts; \( e \) is distance from sprung mass to roll center; \( T \) is wheelbase; \( R_\phi \) is the roll velocity gain.

Then the vehicle rollover boundary can be expressed as Equation (21) by the rollover index threshold and the vehicle velocity.

\[
n_2 = \frac{1}{R} \leq \frac{LTR_b \cdot mgT}{2v_x^2 m_s (e R_\phi + h)} \tag{21}
\]

Figure 13 (b) is the vehicle rollover boundary constraint obtained by Equation (21). In Figure 13 (b), the red dotted line is the rollover constraint boundary of the aggressive driver, and the blue dotted line is the rollover constraint boundary of the general driver. The black solid line is the rollover constraint boundary of the cautious driver.

The safe area distribution in the coordinates of vehicle velocity and road curvature can be obtained by combining the boundary constraint of steering critical safety area and rollover boundary constraints, as shown in Figure 14. In Figure 14, the blue area I is a non-hazardous area, which is composed of the area within the range of A-B-C1-B1-A1. There is no risk of rollover in this area, and the driver is not
affected by the dynamic characteristics of the vehicle. That is, the driver’s steering operation is unlimited by the mechanical structure of the vehicle and kinematics, and the driver can better track the expected trajectory. The gray area II is composed of the areas within the range of B-D-C and B1-C1-D1. In this area, the vehicle has a certain rollover risk. The driver is not affected by the dynamic characteristics of the vehicle and has the ability to track the expected trajectory. The above two areas are the areas where the vehicle is prone to rollover during actual driving. In Area III, which is composed of two white areas, b-e-f-d and b1-e1-f1-d1, the driver cannot track the expected track due to the influence of vehicle dynamic characteristics. The white area IV is composed of areas within the range of A-E-B and A1-B1-E1. Although the vehicle has no rollover risk, considering the low velocity of the area and the large curvature of the path, the performance of the vehicle itself is difficult to track path. The above two areas are not easy to appear during vehicle driving.

2) DECISION CONTROL MODE
In this section, the six modes of decision-making are established, which provide the basis for the weight distribution between the executive controller based on active steering and active braking and the driver. Through the switching control strategy shown in Figure 15, the output of the lower cooperative execution control is changed to assist different types of drivers to effectively track the expected trajectory and prevent vehicle rollover.

In Figure 15, Mode 1 is within the area IV. According to the above analysis, it is difficult for vehicle in this area to reach the expected path due to the limitation of their own performance, and the vehicle is no rollover risk. In this mode, the vehicle velocity \( v_x \) is set to 0 and \( \varepsilon_1 = 0, \varepsilon_2 = 1, \varepsilon_3 = 0 \), where \( \varepsilon_1 \) is the weight of steering controller, \( \varepsilon_2 \) is the weight of driver, \( \varepsilon_3 \) is the weight of braking controller.

Mode 2 is within the area I, in which the vehicle has no rollover risk. In addition, the path tracking error is greater than \( L_c \), which represents the minimum allowable path tracking error. In this mode, \( \varepsilon_1 = L_Y, \varepsilon_2 = 1 - L_Y, \varepsilon_3 = 0 \) is set. \( L_Y \) represents the lateral deviation degree of the vehicle trajectory, which is represented by the ratio of the lateral deviation value \( d_Y \) at the current moment to the maximum allowable lateral deviation value \( d_{Y,\text{max}} \) at the current moment. The values of \( L_c \) and \( d_{Y,\text{max}} \) of drivers with different driving styles are different [22]. The parameters corresponding to aggressive drivers are set as 0.1m and 0.5m respectively; the parameters corresponding to general drivers are set as 0.2m and 1m respectively; the parameters corresponding to cautious drivers are set as 0.3m and 1.5m respectively.

Mode 3 is within the area I. In this mode, the vehicle has no rollover risk and the path tracking error is smaller than \( L_c \). In addition, there is no need to intervene with the driver in this mode, and then \( \varepsilon_1 = 0, \varepsilon_2 = 1, \varepsilon_3 = 0 \) are set.

Mode 4 is within the area III. In this mode, the vehicle has a high rollover risk, and the driver is unable to track the expected trajectory due to the impact of the vehicle dynamic characteristics. It is difficult to correct the vehicle body attitude only by the driver’s operation, and it is easy to generate greater danger. Therefore, in this mode, the driver should be deprived of control, \( \varepsilon_1 = 1, \varepsilon_2 = 0, \varepsilon_3 = 1 \), so that the vehicle can return to area II or I as soon as possible.

Mode 5 is within the area II. In this mode, the vehicle has rollover risk and the path tracking error is greater than \( L_c \). Then \( \varepsilon_1 = L_Y, \varepsilon_2 = 1 - L_Y, \varepsilon_3 = L_y \) are set. \( L_y \) represents the rollover risk degree of the vehicle, which is represented by the current rollover value and the rollover boundary \( \text{LTR}_{b} \):

\[
L_y = \frac{\text{PTLTR} - \text{LTR}_{b}}{1 - \text{LTR}_{b}}.
\]

Mode 6 is within the area II. In this mode, the vehicle has rollover risk and the path tracking error is smaller than \( L_c \). Then \( \varepsilon_1 = 0, \varepsilon_2 = 1, \varepsilon_3 = L_y \) are set.

C. LOWER COOPERATIVE EXECUTION CONTROL CONSIDERING DRIVER CHARACTERISTICS
On the basis of the content of upper supervisory decision control, this section further proposed the lower cooperative control strategy for three different types of drivers according to the published paper [16] of our own research team. On the one hand, the yaw rate and rollover risk are reduced by restricting the front wheel angle to track the expected path of different drivers. On the other hand, the additional yaw moment caused by uneven distribution can be offset by distributing the braking force of four tires reasonably to prevent rollover and reduce the impact on path tracking.

It should be noted that the corresponding dynamic models used in this section could refer to the published paper of our own research team [16].

1) ACTIVE STEERING CONTROLLER DESIGN
The design objective of the active steering controller is as follows. When the driver deviates from the expected path, the driver is assisted to better track the expected trajectory by providing the vehicle with an additional front wheel angle [23]. This section designs an active steering controller based on model predictive control (MPC).

Figure 16 shows the MPC control system structure. MPC control needs to discretize the reference trajectory signal.
According to the dynamic model established in the published paper of our own research team [16], the lateral and yaw motions of the vehicle are considered, and the longitudinal velocity of the vehicle is assumed a constant. Then, the motion equation of the model is:

\[
\begin{align*}
\dot{v}_y &= -mv_t \theta + F_{sf} \cos \delta_f + F_{yr} \\
I_\ell \dot{\omega} &= aF_{sf} \cos \delta_f - bF_{yr} \\
\dot{Y} &= v_t \phi + v_y + d_3
\end{align*}
\]  

(22)

where \(\phi, \omega, \dot{\omega}\) is yaw angle, yaw rate and yaw acceleration; \(F_{sf}, F_{yr}\) is lateral force of front and rear tires; \(I_\ell\) is the yaw moment of inertia; \(\dot{Y}\) is the velocity in Y direction in geodetic coordinates.

In order to describe the driver-vehicle model in the form of state space, it is assumed that the steering angle of the front and rear wheels is small and the course angle of the vehicle is small. Equation (22) can be rewritten as follows:

\[
\begin{align*}
\dot{v}_y &= -mv_t \theta + \frac{1}{m} \left( F_{sf} + F_{yr} \right) + d_1 \\
\dot{\omega} &= \frac{1}{I_\ell} \left( aF_{sf} - bF_{yr} \right) + d_2 \\
\dot{Y} &= v_t \phi + v_y + d_3
\end{align*}
\]  

(23)

where

\[
\begin{align*}
d_1 &= \frac{1}{m} \left[ F_{sf} (\cos \delta_f - 1) + F_{yr} (\cos \delta_r - 1) \right] \\
d_2 &= \frac{1}{I_\ell} \left[ aF_{sf} (\cos \delta_f - 1) - bF_{yr} (\cos \delta_r - 1) \right] \\
d_3 &= v_t (\sin \phi - \phi) + v_y (\cos \phi - 1)
\end{align*}
\]

According to the driver model in Section II, for the convenience of modeling, the rollover weight function is ignored here.

\[
\begin{align*}
\delta_{sw} &= \frac{G_h(Y_p(s)e^{T_p s} - Y(s)(T_p s + 1))}{a_0 T_d^2 s^2 + T_d s + 1} + d_4(s)
\end{align*}
\]  

(24)

where \(Y_p\) is preview point and \(Y\) is current status point.

Assuming that the transmission ratio from the steering wheel to the front wheel is \(R_\ell\), the driver’s control to the front wheel angle is \(\delta_{ed} = R_\ell \delta_{sw}\). Then Equation (24) can be described in the form of the following differential Equation (25) [24].

\[
\begin{align*}
\dot{\delta}_{ed} &= \frac{-\delta_{ed}}{a_0 T_d^2} + \frac{\delta_{ed} + R_\ell G_h}{a_0 T_d^2} \left[ Y_p - (Y + T_p v_t \phi) \right] + d_4
\end{align*}
\]  

(25)
In the design of active steering controller, combining Equation (23) and Equation (25), the state equation of vehicle in global coordinate is:

$$\begin{align*}
\dot{x} &= Ax + B_1 u + B_2 w + d \\
y &= cx
\end{align*}$$

(26)

where $x = [x_1, x_2, x_3, x_4, x_5, x_6], x_1 = \dot{v}, x_2 = \dot{\phi}, x_3 = \phi, x_4 = Y, x_5 = \delta_d, x_6 = \delta_d, u = \delta_c, w = Y_p; \delta_c$ is the additional front wheel angle calculated by the controller, then the front wheel angle $\delta_f = \delta_c + \delta_d; d = [d_1 \ d_2 \ 0 \ d_3 \ 0 \ d_4]^T$;

$$B_1 = \begin{bmatrix} -\frac{k_f}{m} & -\frac{k_f a}{m} & 0 & 0 & 0 & 0 \end{bmatrix}^T;$$

$$B_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & \frac{R_{g} G_h}{a_0 T_d^2} \end{bmatrix}^T;$$

$$c = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

$$A_{11} = \begin{bmatrix} \frac{mv_x}{a_k} & -v_x + \frac{ak_f - bk_f}{a_k} \\ \frac{mv_x}{a_k} & \frac{ak_f - bk_f}{a_k} \end{bmatrix},$$

$$A_{12} = \begin{bmatrix} 0 & -\frac{k_f}{m} \\ 0 & -\frac{ak_f}{T_z} \end{bmatrix},$$

$$A_{21} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 0 \end{bmatrix},$$

$$A_{22} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{R_{g} G_h T_z v_x}{a_0 T_d^2} & -\frac{R_{g} G_h}{a_0 T_d^2} & -1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. $$

Neglecting the simplified error $d$ of the system model, the controller and the controlled system are written in the form of augmented matrix, as shown in Equation (27).

$$\dot{x} = A(t)x(t) + [B_1(t) B_2(t)] \begin{bmatrix} u(t) \\ w(t) \end{bmatrix}$$

(27)

The first-order difference quotient method is used to discretize Equation (27), and the discrete state space expression is obtained.

$$x(k + 1) = A_{dyn}(k)x(k) + B_{dyn}(k)u_{K}(k)$$

(28)

where $A_{dyn}(k) = I + T_i A_{dyn}(t); B_{dyn}(k) = T_i B_{dyn}(t)$; $x(k)$ is the state quantity at moment $k$; $u_{K}(k)$ is the augmented system input quantity at moment $k$; $I$ is the unit matrix with the same order of $A$ matrix; $T_i$ is the discretization time.

The objective of model predictive control belongs to an optimal control method, and its objective function is as follows:

$$J(x_{dyn}(t), u_{dyn}(t - 1), \Delta u_{dyn}(t)) = \sum_{i=1}^{N_p} \left\| y_{dyn}(t + i \mid t) - y_{dyn, ref}(t + i + 1) \right\|^2_Q + \sum_{i=1}^{N_c} \left\| \Delta u_{dyn}(t + i \mid t) \right\|^2_R + pe^2$$

(29)

where $N_p$ and $N_c$ are prediction time domain and control time domain respectively; $y_{dyn, ref}(t + i \mid t) i = 1, \ldots, H_p$ is reference output; $Q$ and $R$ are weight matrix; $p$ is relaxation factor weight coefficient; $e$ is relaxation factor.

When the trigger signal is turned on, the optimal control quantity of the next cycle is calculated and the above process is repeated. According to this cycle, the trajectory tracking of the vehicle can be realized.

2) ACTIVE BRAKE CONTROLLER DESIGN BASED ON SLIDING MODE VARIABLE STRUCTURE CONTROL

The previous section proposes an active steering control to reduce the rollover risk by restricting the front wheel angle. However, when the vehicle rollover risk is high, simply providing additional front wheel angle is not enough to reduce the rollover risk while tracking the path effectively. At this time, it is necessary to reduce the vehicle velocity through active braking, and then combined with active steering control to track the path and prevent the occurrence of rollover accident. Sliding mode variable structure control (SMC) has less dependence on mathematical model, and does not need to identify system variables online [25], so it can accurately calculate the required braking force. Therefore, this section uses the sliding mode control method to design the active braking controller.

SMC is a control method that designs the switching hyperplane of the system according to the expected dynamic characteristics of the system [26], [27]. Then it uses the sliding mode controller to make the system state from the outside of the switching hyperplane to the switching hyperplane. Its basic structure is shown in Figure 17. Through the pre-designed switching function $s(x)$ and the required switching rules, the system control quantity $u$ switches freely between two different control modes. In the whole control process,
two control modes switch continuously according to the control requirements to make the control quantity \( u \) constantly change until the system reaches the stable equilibrium point.

The reference model receives the PTLTR signal measured by the system. When PTLTR reaches the defined threshold value \( LTR^* \), the reference model is triggered to calculate the ideal vehicle velocity in the rollover critical state:

\[
v_s = \frac{LTR^* \cdot mgT}{2m_1(eR_y + h)r}
\]  

(30)

The expected vehicle velocity can be obtained by braking force \( \Delta F_s \), and the dynamic equation on the x-axis is as follows:

\[
v_s = F_{xf} + F_{yg} \cos \delta_f - F_{yg} \sin \delta_f + mv_s r - \Delta F_s
\]  

(31)

Since the front wheel angle is small, Equation (31) can be rewritten as the derivative form of speed.

\[
\dot{v}_s = \frac{1}{m}(F_{xr} + F_{yg}\delta_f - F_{yg}\delta_f) + v_r r - \frac{1}{m}\Delta F_s
\]  

(32)

In order to obtain the desired braking force, the nonlinearity of the system is considered, and the sliding mode variable structure control method is adopted. The surface is defined as follows [28]:

\[
s = v_s - v_{s,des}
\]  

(33)

where \( v_{s,des} \) is desired longitudinal velocity.

In order to make the control target \( s = 0 \), select the following control rule to achieve:

\[
\frac{1}{2} \frac{d}{dt} s^2 = \ddot{s} s \leq -\kappa |s|
\]  

(34)

where \( \kappa \) is a positive number.

The derivative of \( s \) is:

\[
\dot{s} = \dot{v}_s - \dot{v}_{s,des}
\]  

(35)

Substituting Equation (32) into Equation (35):

\[
\dot{s} = \frac{1}{m}(F_{xr} + F_{yg}\delta_f - F_{yg}\delta_f) + v_r r - \frac{1}{m}\Delta F_s - \dot{v}_{s,des}
\]  

(36)

From Equation (36), in order to make \( s = 0 \), the control rules can be expressed by:

\[
\Delta F_{x,eq} = (F_{xr} + F_{yg}\delta_f - F_{yg}\delta_f) + m(v_r r - \dot{v}_{s,des})
\]  

(37)

\[
\Delta F_x = \Delta F_{x,eq} - K \text{sgn}(s)
\]  

(38)

Substituting Equation (36) into Equation (34), the expression of sliding mode law can be written as:

\[
\dot{s} = \frac{1}{m}(F_{xr} + F_{yg}\delta_f - F_{yg}\delta_f) + v_r r - \frac{1}{m}\Delta F_s - \dot{v}_{s,des}
\]  

(39)

In order to eliminate the high frequency chattering caused by the high-frequency components of the control input, the saturation function \( \text{sat}(s) \) is used to replace the function \( \text{sgn}(s) \) in the ideal sliding mode. The final expected braking force is as follows:

\[
\Delta F_x = \Delta F_{x,eq} - K \cdot \text{sat}(s)
\]  

(40)

### TABLE 3. Simulation parameters of vehicle model.

| Parameters | Values | Unit |
|------------|--------|------|
| \( m_1 \) | 1592   | kg   |
| \( m_s \) | 270    | kg   |
| \( h_s \) | 300    | mm   |
| \( h_r \) | 350    | mm   |
| \( h \)  | 1000   | mm   |
| \( T \)  | 1575   | mm   |
| \( K_e \)| 57300  | Nm/rad |
| \( D_s \)| 6000   | Nms/rad |
| \( a \)  | 1180   | mm   |
| \( b \)  | 1770   | mm   |

\[
\text{sat}(s) = \begin{cases} 
1 & s > \Delta \\ 
ks & |s| < \Delta, \quad k = \frac{1}{\Delta} \\ 
-1 & s < -\Delta 
\end{cases}
\]  

(41)

The desired braking force is calculated by SMC, and then the lower control algorithm controls each wheel to brake to track the required speed and prevent the vehicle from generating additional yaw moment.

### IV. SIMULATION AND ANALYSIS OF CONTROL SYSTEM

In order to verify the effectiveness of the designed controller, this section selects ISO standard double-shift trajectory conditions for joint simulation verification, which is based on CarSim and Matlab/Simulink software. In the simulation analysis, the initial speed is set as 75 km/h and the road adhesion coefficient is 0.85. The main parameters of the vehicle model are shown in Table 3. In the simulation result diagrams, Driver represents the driver’s individual control, and Driver + con represents the collaborative control.

Considering that the actual driving process of the vehicle is very complicated, it is difficult to express it with a mathematical formula. Reference [22] gives the maximum allowable deviation data such as the trajectory tracking, steering angle and steering rate. Inspired by it, this section uses five indicators: mean square values of trajectory tracking deviation and directional angle error, driver’s workload and mental load, and the risk of rollover. The specific description form is as follows:

\[
\begin{align*}
J_Y &= \frac{1}{T_f} \int_0^{T_f} \left( \frac{(Y(t) - Y_d(t))^2}{\Delta Y_{th}} \right) dt \\
J_\psi &= \frac{1}{T_f} \int_0^{T_f} \left( \frac{(\psi(t) - \psi_d(t))^2}{\Delta \psi_{th}} \right) dt \\
J_\delta &= \frac{1}{T_f} \int_0^{T_f} \left( \frac{\delta^2}{\Delta \delta_{th}} \right) dt \\
J_\beta &= \frac{1}{T_f} \int_0^{T_f} \left( \frac{\beta^2}{\Delta \beta_{th}} \right) dt \\
J_\psi &= \frac{\text{PTLTR}_{\text{max}}}{\text{LTR}_1}
\end{align*}
\]  

(42)

(43)

where \( J_Y \) is the mean square value of trajectory tracking deviation; \( Y_d(t) \) is the horizontal coordinate of the desired trajectory; \( Y(t) \) is the horizontal coordinate of the actual trajectory; \( \Delta Y_{th} \) is the maximum lateral displacement error.
and its value is defined as 1m; $J_\psi$ is the mean square value of directional angle tracking deviation; $\psi_d(t)$ is the direction angle of the desired trajectory; $\psi(t)$ is the direction angle of the actual trajectory; $\Delta \psi_{th}$ is maximum error of direction angle and its value is defined as 5 deg; $J_\delta$ is the workload of the driver; $\delta$ is the actual steering wheel angle; $\Delta \delta_{th}$ is the capability of the driver’s maximum steering angle and its value is defined as 187 deg; $J_\delta$ is the mental load of the driver; $\delta$ is the actual steering wheel angle rate; $\Delta \delta_{th}$ is the capability of the driver’s maximum steering angle rate and its value is defined as 746 deg/s; $J_\psi$ is the risk of rollover; PTLTR$_{max}$ is the actual maximum rollover value and LTR$_1$ indicates a rollover index of 1.

### A. ANALYSIS OF ANTI-ROLLOVER PERFORMANCE

In this section, PTLTR and the roll angle-roll angular rate phase diagram are used to analyze the anti-rollover performance of the vehicle under the driver’s individual control and the cooperative control proposed in this paper.

Figure 18 shows the PTLTR value and the roll angle-roll angular rate phase diagram of the cautious, general and aggressive driver. It can be seen from Figure 18 that with the addition of a collaborative controller, the driver’s vehicle rollover evaluation index and roll phase diagram are similar to the case without the collaborative controller. The maximum value of vehicle rollover evaluation index PTLTR under the operation of general driver alone is 0.94. After adding the collaborative controller, PTLTR is reduced to 0.92, and the vehicle’s roll angle-roll angular rate operated by general drivers can converge more quickly and finally reach stability. Moreover, the maximum value of vehicle rollover evaluation index PTLTR under the operation of aggressive driver alone is 1. After the MPC collaborative controller (driver + con) is added, PTLTR is reduced to 0.8, and the system changes from divergent to stable, which can achieve better control effect. On the contrary, PID collaborative controller (driver + PID) is difficult to produce a marked effect for its PTLTR once reached 1 and took a long time to recover.

In conclusion, the risk of rollover $J_\psi$ is 0.9, 0.94 and 1.0 corresponding to the cautious, general, and aggressive drivers without the collaborative controller. After adding the controller, $J_\psi$ changes to 0.9, 0.92 and 0.8, of which the last two values have increased by 2.13% and 20% respectively.

### B. ANALYSIS OF PATH TRACKING PERFORMANCE

This section uses lateral displacement, lateral displacement error and the phase diagrams of yaw angle and yaw rate to...
analyze the path tracking performance of the vehicle under the driver’s individual control and the cooperative control. Figure 19 shows the trajectory and path tracking errors at the center of mass, when the cautious, general, and aggressive drivers operate the vehicle.

It can be seen from Figure 19 that by adding a collaborative controller, the cautious driver’s vehicle trajectory at the center of gravity is similar to the case without the collaborative controller. Under the operation of general drivers, the maximum value of the vehicle’s path error has been reduced from 0.2m to 0.17m. Meanwhile, the path error of the vehicle under the cautious and aggressive driver operation have greatly reduced, whose maximum values decrease from 0.6m to 0.4m and 1m to 0.5m separately. The mean square value of trajectory tracking deviation $J_Y$ is 0.0054, 0.0243 and 0.1158 corresponding to the cautious, general, and aggressive drivers without the collaborative controller. After adding the controller, $J_Y$ changes to 0.0053, 0.0106 and 0.0352, of which the values have increased by 1.8%, 56.37% and 69.6% respectively.

Figure 20 is the yaw angle-yaw rate phase diagram and the front wheel angle of the aggressive drivers. As can be seen from it, after the intervention of PID and MPC controllers, the aggressive driver-vehicle system has different response performance.

When the MPC collaborative controller works, the vehicle yaw angle is maintained in a small range, which changes from the uncontrolled divergence state to the convergent state and makes the system tend to be stable. PID collaborative controller also has the same function, but the yaw angle amplitude is larger.

The directional angle tracking deviation mean square $J_\psi$ of single driver, PID coordination and MPC coordination controllers are 16.056, 10.754 and 4.810. Compared with the single driver control, coordination controllers of PID and MPC have increased by 33% and 70% respectively. Although not many, the same MPC controller can also improve the vehicle performance with cautious and general drivers, corresponding to a reduction of 1.3% and 1.2% respectively.

C. ANALYSIS OF DRIVING OPERATION LOAD
This section uses the front wheel angle, in Figure 20 (b), and wheel cylinder pressure to analyze the driving operation load under the driver’s individual control and cooperative control. The cautious and general driver’s front wheel angle trends are basically unchanged, thus were simply analyzed here.

![Figure 19](image1.png)

**FIGURE 19.** Trajectory and path tracking errors at the center of mass under double-shift condition: (a), (c) and (e) are centroid trajectory diagrams of cautious, general and aggressive driver respectively; (a), (c) and (e) are path tracking errors diagrams of cautious, general and aggressive driver respectively.
As can be seen from Figure 20 (b), after the MPC collaborative controller joins the aggressive driver control, the front wheel angle response is closer to the ideal front wheel angle, and its maximum value changes from 15 deg/s to 5 deg/s, which is 4 deg/s smaller than that of PID collaborative controller. For the vehicle control system with cautious and general driver, both the front wheel angle responses are improved, and the curve is smoother.

The workload $J_3$ is 0.5605, 0.6708 and 3.8261 corresponding to the cautious, general, and aggressive drivers without the collaborative controller. After adding the MPC controller, $J_3$ changes to 0.5490, 0.6317 and 0.5702, of which the values have increased by 2.1%, 5.8% and 85.1% respectively. With the MPC controller, similarly, the value of mental load $J_3$ changes from 0.0118, 0.0176 and 0.1078 to 0.0113, 0.0157 and 0.0245, increased by 4.2%, 10.8%, and 77.2% respectively. Curve comparison results show that MPC can better adjust the driver’s operation and reduce the operation load compared with PID control, especially in the case of aggressive driver’s anti roll failure.

FIGURE 21. Pressure change of wheel cylinder under the double-shift condition: (a) wheel cylinder of general driver; (b) wheel cylinder of aggressive driver.

Table 4 is the main objective performance index of different driver types. Date in Table 4 show that the cautious drivers have less physical and mental load than the aggressive drivers do. However, with the help of collaborative controller, the physical and mental load of the aggressive driver is close to the cautious driver. This means that the workload of the aggressive driver has reduced significantly, and the collaborative controller has helped the aggressive driver more.

| Driver Type | Control Mode | $J_1$ | $J_2$ | $J_3$ | $J_4$ | $J_5$ |
|-------------|--------------|-------|-------|-------|-------|-------|
| cautious    | Driver       | 0.005 | 4.186 | 0.560 | 0.012 | 0.9   |
|             | Driver+con   | 0.005 | 4.126 | 0.549 | 0.011 | 0.9   |
| general     | Driver       | 0.024 | 4.386 | 0.671 | 0.018 | 0.96  |
|             | Driver+con   | 0.011 | 4.334 | 0.632 | 0.016 | 0.9   |
| aggressive  | Driver       | 0.116 | 16.056| 3.826 | 0.108 | 1.0   |
|             | Driver+con   | 0.035 | 4.810 | 0.570 | 0.024 | 0.8   |
|             | Driver+PID   | 0.086 | 10.754| 0.927 | 0.076 | 1.0   |

V. CONCLUSION

This article aims to assist different types of drivers to achieve driving stability requirements, and designs anti-rollover control strategy based on active steering and active braking to ensure that different types of drivers track the ideal path and prevent vehicle rollover at the same time.

The influence of different driver parameters on the dynamic behavior of the vehicle is analyzed through the hardware-in-the-loop test platform, the test data of different drivers steering control under the double-shift condition is collected, and the drivers with different steering styles are classified by K-means clustering algorithm; a driver model considering the stability of vehicle rollover is established.
Then differential evolution algorithm is used to identify the parameters related to rollover dynamics in different driver models. Based on the active steering and active braking system, we design an anti-rollover cooperative control strategy, which is composed of two layers: the upper supervision decision layer and the lower cooperative execution layer. According to different types of drivers, the supervisory decision control layer sets different rollover constraint boundaries and makes six control decision modes. The lower cooperative execution control layer aiming at different types of drivers reduces the yaw rate and rollover risk by restricting the front wheel angle through the active steering system. Meanwhile, active braking system reduces the path tracking error. The simulation results show that the proposed cooperative control strategy for different types of drivers can ensure the effective anti-rollover control of the vehicle and achieve good path tracking performance. The research content of this article is to further expand the existing research on vehicle anti rollover, which can provide theoretical basis and technical support for the design and development of vehicle active anti rollover system.

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