A data-driven chassis coordination control strategy

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Abstract

Collaborative control strategy based on different driving conditions is a challenge for chassis systems with various electronic control units. This paper proposes a chassis cooperative control strategy based on vehicle inertial sensor data. Its novelty lies in the fact that it greatly simplifies the judgment logic while classifying various driving behaviours, and further reduces the possibility of bad control operation caused by misjudgement of driving state through heuristic decision logic. The clustering algorithm based on triaxial acceleration and angular velocity data was used to identify the driving behaviour of the vehicle, and the complex driving conditions were simplified into a single driving condition. The multi-axis weighted fusion method is used to extend the data and improve the generalization performance of the data. In order to improve the stability of steering control, S-type function is used to allocate the weights of AFS and DYC. The proposed control strategy is tested in the CarSim/Simulink co-simulation environment, and the simulation results of two key driving scenarios (double lane change and emergency braking) show that the proposed control strategy can effectively improve the vehicle handling and safety.

1 INTRODUCTION

With the development of the automobile industry and the maturity of the intelligent automobile, the safety performance of automobile driving has been paid more and more attention. An automobile chassis system is crucial for driving safety. There are various control technologies for automobile chassis. According to different control system implementation modes, automobile chassis control system can be roughly divided into three categories: Longitudinal control system, transverse control system and vertical control system [1]. These different control systems improve the riding comfort and handling stability of the vehicle, but the simple superposition of these systems cannot give full play to the potential of their respective control performance, and may even lead to the deterioration of the overall performance of the vehicle; the reason is that different control systems may have contradictory control objectives [2]. Coordinating the relationship between each subsystem can promote the function of each subsystem and achieve better performance [3].

In recent years, the automobile industry has been developing towards electric and intelligent, and the electronic and automatic level of chassis system is also getting higher and higher. Various sensors and electronic systems equipped with intelligent vehicles can replace drivers to complete many complex driving tasks, and these systems are increasingly applied to the advanced chassis of manned or unmanned vehicles. This also means that the cooperative control of the chassis system becomes more and more important [4, 5].

In the past few years, many people have studied the coordination control of vehicles. To improve the safety, stability and comfort of vehicles, many kinds of active safety systems have been applied to modern vehicles, such as active steering system, active suspension system, and active braking system. In general, the hierarchical control method is adopted for collaborative control, and multiple subsystems are coordinated by adding upper controllers to achieve better integration and reliability [6, 7]. In terms of lateral and longitudinal dynamics, research focuses on the coordination of steering and braking systems to improve vehicle stability [8–11] or further improve vehicle braking performance [12–14]. In some other papers, the suspension system was added to the cooperative control to prevent roll-over [15, 16]. In [16], the coordinated control of active steering, differential braking and active suspension is studied, the concept of safety domain and danger domain is established, and the control...
logic of safety domain and danger domain is distributed according to the smooth boundary. In particular, the gradual transition method is adopted to switch between active front-wheel steering (AFS) and differential braking, which effectively improves the smoothness of the control. In our works, a similar smooth transition control switch is used to switch between AFS and direct yaw moment control (DYC). However, this paper focuses more on the upper controller. In the upper controller, the driving behaviour recognition module is introduced to allocate different control logics under different driving states, so that the control is more targeted.

Excellent decision-making ability and control method is an important link to improve the intelligent ability of vehicles, and more intelligent decision-making method is also helpful to ensure more convenient driving [17]. Therefore, in addition to introducing various control subsystems, various decision modules are also the focus of collaborative control research. Some researchers used game theory to establish interaction models between different chassis subsystems [18], while more studies adopted a more direct decision-making method: Identification of vehicle driving behaviour [19–23]. In [19], the researchers judge the driving state of the vehicle through longitudinal and lateral acceleration, and use this as the judgment logic of the control rules. Although only two states of steering and braking are divided, they still achieved good results in the real car test. In other studies, multiple variables such as speed, steering angle, vehicle acceleration, yaw velocity and other variables are judged to achieve the purpose of classifying more kinds of vehicle driving behaviour [20, 21]. This article adopts a data-driven driving behaviour recognition method. It not only divides various driving states but also greatly simplifies the judgment logic. Besides, the heuristic decision logic is introduced to further reduce the possibility of bad control operation caused by misjudgement of driving state.

Research on vehicle driving behaviour recognition (VDBR) is booming. Considering the diversity of road sections and the different driving habits of drivers, data-based driving behaviour identification will be a more effective method. Through data-based classification and coordination algorithms, complex driving conditions can be transformed into a single control problem [22, 23]. Under the increasingly excellent computing conditions and increasingly important data-driven background, the scheme has a wider application space and a more intelligent future. In previous years, some researchers used the inertial sensor in smartphones to detect the driving behaviour of vehicles [24, 25], and proposed a variety of methods to improve the classification accuracy. [26] points out that data classification and recognition based on the inertial sensor is a major VDBR method, which also proves the feasibility of using an inertial sensor to identify driving behaviour in this article.

The main contribution of this article is to propose a chassis cooperative control strategy driven by on-board accelerometer and gyroscope data. This strategy can effectively recognize different driving behaviours and make corresponding control decisions through heuristic decision logic. For complex operating conditions, the classification algorithm can classify them into the most similar driving behaviour, and then make the relative optimal decision. The strategy is divided into two layers of control system: the upper layer is used for classification and decision, and the lower layer is composed of various control subsystems. In order to improve the generalization performance of the data in the classification module, the multi-axis weighted fusion (MAWF) algorithm [26] is used to enhance the data. It can not only keep the main features of the samples undistorted, but also expand the dataset to ensure the diversity of the samples and improve the generalization performance. Then, based on heuristic strategy, function assignment is carried out on the sub-system. The lower controller consists of three subsystems: Steering, suspension and braking. The control system scheme is verified by CarSim/Simulink co-simulation.

This article is organized as follows: Section 2 describes the architecture of the control strategy, and introduces the model and details of each layer architecture. Section 3 tests the effect of the classification algorithm, and verifies the effect of the control strategy through the simulation of two scenarios. Finally, conclusions of this research are given in Section 4.

2 \ CHASSIS COORDINATION CONTROL STRATEGY

2.1 \ Control system architecture

The control system is divided into two levels: the upper controller recognizes driving behaviour and gives instructions to the lower controller on how to coordinate; the lower controller receives the instruction from the decision level and controls the corresponding control target. As shown in Figure 1.

The upper controller uses the samples after data enhancement through a multi-axis weighted fusion algorithm, classifies the driving state according to the signals collected by the inertial sensor during the current driving, makes online decisions according to different driving states, and regulates the parameters of the lower controller in real-time. Since the main problems faced by different driving states are different, different driving states also correspond to different control indexes.

2.2 \ Upper-level controller

The upper controller is divided into two parts: the driving behaviour recognition module and the control decision logic module. First, the VDBR module identifies and classifies the vehicle based on the data of triaxial acceleration and angular velocity, and then the decision module makes logical judgment according to different working conditions to determine the cooperative mode of the control subsystem.

2.2.1 \ VDBR module

The VDBR module uses kNN algorithm to cluster the inertial sensor data to identify driving behaviour. KNN algorithm is one of the concise and effective classification algorithms in machine learning. Its goal is to solve the position of each group of
vectors that need to be recognized to the adjacent k points, and to determine which kind of label the recognized vector belongs to by judging the number of labels. The implementation of the algorithm is as follows:

First, a training dataset is given:

$$T = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), ..., (x_N, y_N)\},$$  \hspace{1cm} (1)

and

$$x_i \in X \subseteq \mathbb{R}^6,$$  \hspace{1cm} (2)

$$y_i \in Y = \{c_1, c_2, ..., c_K\},$$  \hspace{1cm} (3)

where $x_i$ is a 6-dimensional instance vector consisting of triaxial acceleration and triaxial angular velocity and $y_i$ is the class of the instance. The driving state in this paper is divided into 5 categories, as shown in Table 1.

For the data vectors to be classified $x \subseteq \mathbb{R}^6$, the closest point is:

$$g_k(x) = \arg \min \{d(x, x_i)\},$$  \hspace{1cm} (4)

where $d(x, y)$ is defined by:

$$d(x, y) = \sqrt{\sum_{j=1}^{6} (x_j - y_j)^2}.$$  \hspace{1cm} (5)

The classification tag $y$ of $x$ is determined according to the rule of majority voting:

$$y = \arg \max \sum_{i=1}^{k} I(y, \epsilon),$$  \hspace{1cm} (6)

$$I(x, y) = \begin{cases} 1, & \text{if } x = y \\ 0, & \text{if } x \neq y \end{cases},$$  \hspace{1cm} (7)

The dataset uses the inertial sensor data in the CarSim software for the vehicle under different driving conditions on different roads. Considering that not all variables of the vehicle have the same importance under different driving states, the main feature axes of the data are determined by analyzing the data feature axes that are mainly affected under different driving states, and by multi-axis weighting fusion (MAWF) [27] algorithm to increase the sample size and increase the diversity of samples, at the same time also can better increase the authenticity of the simulated driving scene.

According to the analysis method in [27], the main characteristic axis and non-main characteristic axis of each driving behaviour can be obtained, as shown in Table 1:

| Category number | Driving behaviour                | Main characteristic axis                                      |
|-----------------|---------------------------------|--------------------------------------------------------------|
| 1               | Straight driving at constant speed | No main characteristic axis                                   |
| 2               | Acceleration/braking           | Acceleration (X-axis)                                        |
| 3               | Emergency braking              | Acceleration (X-axis); angular velocity (Y-axis)            |
| 4               | Cornering                      | Acceleration (Y-axis); angular velocity (Z-axis)            |
| 5               | Fast /wide cornering           | Acceleration (Y-axis); angular velocity (Z-axis)            |

Find the k points closest to x in $T$, and the neighbourhood containing these k points will be called $N_k(x)$. In $N_k(x)$, the classification tag $y$ of $x$ is determined according to the rule of majority voting:

$$y = \arg \max \sum_{i=1}^{k} I(y, \epsilon),$$  \hspace{1cm} (6)

$$I(x, y) = \begin{cases} 1, & \text{if } x = y \\ 0, & \text{if } x \neq y \end{cases},$$  \hspace{1cm} (7)
fused by MAWF algorithm is $D_{\alpha}$, the amount of data to be fused is $k_{\alpha}$, and the MAWF algorithm is as follows [27]:

$$D_{\alpha} = [D_{mi}, D_{\alpha}] f = 1 : k_{\alpha},$$

(8)

$$D_{n,mi} = [\omega_1 D_{mi} + \omega_2 D_{str}, D_{mil}],$$

(9)

$$\omega_1 + \omega_2 = 1$$

(10)

The sample data under various driving behaviours in the original data were weighted and fused, and finally, 150 sets of new sample data were obtained as the expanded data, which together with the original data were used as the reference data in the kNN algorithm.

2.2.2 Heuristic logic decision module

In order to achieve the coordination of the three control subsystems, the decision logic needs to decide the following two questions: (1) Whether the current driving state is dangerous; (2) Whether the control state of each control subsystem needs to be changed. In order to complete the decision-making task, we establish the following decision principles:

1. Safety priority: When the driving state is judged to be dangerous, the control state of the subsystem should be changed immediately to obtain safe driving guarantee; when the driving state is safe, handling stability is preferred.
2. The number of simultaneously enabled control subsystems is as small as possible.
3. The control state should be as stable as possible: the control state should not have frequent runout changes, such as repeated switching of some subsystems in a short time.
4. Try to balance comfort and maneuverability.

So in the decision-making module, in addition to the classification signal of vehicle driving, it also needs additional import of front-wheel angle input, and to record the time of the current driving behaviour, to avoid the control state runout because of fine-tuning of speed or direction and some errors (such as the classification error or brief changes in driving behaviour caused by external transient disturbance input).

Each driving behaviour has its own combination of control subsystems. After receiving the driving behaviour signal, the decision-making module decides whether to be in a dangerous state according to the changes in driving behaviour, and decides whether to change the control behaviour and controller parameters. The rules are as follows:

First, for each control subsystem, there are switch variables $k_{str}$, $k_{mil}$, $k_{heh}$ representing the switches of steering, suspension and brake control subsystems respectively. For each switch variable, there are:

$$k_{\alpha} = \begin{cases} 
0 & \text{subsystem off} \\
1 & \text{subsystem on} 
\end{cases}$$

(11)

Then, the driving behaviour is used to determine whether it is a safe driving state. To simplify the description, 0 and 1 respectively represent the safety state and the dangerous state.

Next, determine whether the control state needs to be switched. For dangerous scenarios, the system will immediately switch to the corresponding state.

Considering the disturbance of the vehicle when it is running and the temporary adjustment of the driver for acceleration, braking and steering, the control state will not be switched directly in the safe working condition, but the time length $t$ after the switching state will be introduced. When the working condition lasts for a period of time, that is, $t > t_{\theta}$, then the control state will be switched, and $t_{\theta}$ is the threshold of switching time length. Considering such disturbance and the safety of the vehicle, $t_{\theta} = 0.1$ is taken for the switching between a safe state and another safe state, and $t_{\theta} = 0.15$ is taken for the switching between the dangerous state and the safe state.

Finally, the operation signal of each controller is transmitted to the corresponding child controller. Table 2 shows the decision rules for different driving behaviours.

| Driving behaviour | Whether it is in a critical state | Whether needs $t$ | $k_{str}$ | $k_{mil}$ | $k_{heh}$ |
|-------------------|----------------------------------|------------------|---------|---------|---------|
| Straight driving at constant speed | 0 | Y | 0 | 0 | 0 |
| Acceleration/braking | 0 | N | 0 | 1 | 0 |
| Emergency braking | 1 | N | 0 | 1 | 1 |
| Cornering | 0 | Y | 1 | 0 | 0 |
| Fast/wide cornering | 1 | N | 1 | 1 | 0 |

In addition, AFS can maintain the vehicle speed and driving comfort when the steering sub-controller is turned on, while DYC has the disadvantage of making the driver uncomfortable when activated. The coordination of the two can improve the overall comfort, handling and lateral stability [28]. Therefore, the decision module will weigh the two parts of the steering sub-controller according to the driver input and assign the corresponding weight coefficient. The weight coefficients are allocated according to the S-shaped function, and Figure 2 shows the weight allocation operation of this strategy.

$$k_{str,AFS} = 1 - \frac{1}{1 + e^{-\xi (|\delta| - \delta_{0})}}$$

(12)

$$k_{str,DYC} = \frac{1}{1 + e^{-\xi (|\delta| - \delta_{0})}}.$$  

(12)

The parameter $\xi$ in the weight coefficient function is a constant that controls the weight change speed, and $\delta_{0}$ is the control threshold of the steering angle. In this control strategy, take:

$$[\xi, \delta_{0}] = [3, 2.5].$$  

(13)
2.3 Controller models

For different driving behaviours, each control subsystem is not always on at the same time. In other words, the final control output is:

\[ u^*_c = k_u k_c u, \]  

where, \( u^*_c \) is the final control output of the controller, and \( k_c \) is the weight coefficient of the controller. \( u \) represents the output of the controller before the switching variable \( k_u \) and the weight variable \( k_c \) are applied, that is, \( u_{str}, u_{sur}, \) and \( u_{brk} \) in the following text. The controllers for each subsystem are described below.

2.3.1 Steering subsystem controller

The steering subsystem consists of two parts, AFS and DYC, which are described together in this paragraph because their control target is the vehicle’s yaw-angular rate.

First, a reference model of vehicle lateral movement is established. The desired dynamic reference model of the driving vehicle can be generated by the bicycle model of the vehicle. The bicycle model can greatly simplify the vehicle movement model and generate a reference model that the driver expects without any external interference, as shown in Figure 3 [16].

The 2-DOF reference model can be described by the following formula [28]:

\[
\begin{align*}
mv_x (\dot{\beta} + \gamma) &= F_{yf} \cos \delta_f + F_{yr}, \\
I_x \dot{\gamma} &= aF_{yf} \cos \delta_f - bF_{yr},
\end{align*}
\]

where \( \gamma \) and \( \beta \) are vehicle yaw rate and slip angle, respectively, and \( \delta_f \) is the front-wheel angle of the vehicle. Considering the non-linear characteristics of tires, reference values should be limited to the following areas for safety reasons [28]:

\[ |\gamma_{ref}| \leq \left| \frac{0.85 \mu g}{v_x} \right|, \]

where \( \delta_{str}, M_{bek}, M_{bek}, \) and \( \delta_{AFS} \) are the steering wheel input, DYC braking moment, AFS braking moment, and AFS steering wheel compensation angle, respectively. AFS generates an additional front-wheel compensation angle caused by the steering wheel, \( \delta_{AFS} \) represents the additional front-wheel compensation angle generated by the AFS, and \( k_{c,AFS} \in (0, 1) \) is the gain coefficient assigned by the decision level to the AFS subsystem. The DYC subsystem generates an additional yaw moment by applying a braking moment to the front-wheel to eliminate yaw angular velocity deviation as much as possible.
Similar to AFS, there is $k_{e,DYC} \in (0, 1)$, which is the gain coefficient assigned to the DYC subsystem by the decision level. Both AFS and DYC subsystems use PID controllers:

$$u = k_p \left( e_y + \frac{1}{T_i} \int e_y dt + T_d \frac{de_y}{dt} \right),$$ \hspace{1cm} (25)

$e_y$ is the error between measured yaw rate and the reference:

$$e_y = \dot{\gamma} - \dot{\gamma}_{ref}.$$ \hspace{1cm} (26)

After many times of simulation debugging, the PID parameters in AFS and DYC subsystems are designed as:

$$\{AFS : [k_p, T_i, T_d] = [0.156, 5.778, 0, 0028]\}$$

$$\{DYC : [k_p, T_i, T_d] = [3072, 65.362, 0]\}. \hspace{1cm} (27)$$

For the DYC subsystem, the output control variable is the braking moment of the front wheel. Therefore, after obtaining the expected additional yawing moment, according to the lateral dynamics of the vehicle:

$$M_{DYC} = F_{x,DYC} \cdot d,$$ \hspace{1cm} (28)

$$M_{brk} = F_{x,DYC} \cdot R,$$ \hspace{1cm} (29)

$$\begin{align*}
M_{DYC} > 0 & \rightarrow \text{Front left wheel brake} \\
M_{DYC} < 0 & \rightarrow \text{Front right wheel brake}\end{align*} \hspace{1cm} (30)$$

where $M_{DYC}$ is the expected additional yawing moment generated by a PID controller; $F_{x,DYC}$ is the extra longitudinal force of the tyre produced by the braking torque; $d$ is half of a vehicle’s tread; $M_{brk}$ is the front-wheel braking torque; $R$ is tire radius.

At the same time, the braking moment on the other side is 0, therefore, the braking moment in the final DYC subsystem is

$$M_{brk} = k_{e,DYC} \cdot u_{DYC} \cdot R \cdot \frac{R}{d}.$$ \hspace{1cm} (31)

### 2.3.2 Suspension subsystem controller

The active suspension system adopts the fuzzy control mode, similarly, after considering the decision level, there is:

$$u_{act} = k_u \cdot u_{act},$$ \hspace{1cm} (32)

$$u_{act} = \{u_{act,fr}, u_{act,fl}, u_{act,rl}, u_{act,rr}\}. \hspace{1cm} (33)$$

The fuzzy logic controller has two inputs: $\epsilon_\phi$ and $\phi$, are the errors of the roll angle and the pitch angle, respectively. We want the angle of roll and pitch to be as small as possible, so their expected values are set to zero here. Through the input of the two errors, the fuzzy controller can make fuzzy decisions according to the fuzzy rule table after fuzzing the two inputs, and then calculate the main power provided by the active suspension at the four wheels by anti-fuzzing.

The two input and output fuzzy variables are shown below:

$$\{\epsilon_\phi\} = \{NB, NM, NS, Z, PS, PM, PB\}$$

$$\{\phi\} = \{NB, NS, Z, PS, PB\}$$

$$\{F_{sus}\} = \{NB, NM, NS, Z, PS, PM, PB\}$$

Here, nine fuzzy sets are defined including negative big (NB), negative moderate (NM), negative small (NS), negative zero (NZ), zero (Z), positive zero (PZ), positive small (PS), positive moderate (PM), and positive big (PB).

Tables 3 and 4 show the fuzzy rules of active suspension control.

### 2.3.3 Brake subsystem controller

The braking subsystem is designed to ensure that the vehicle can brake as quickly and safely as possible. The high slip rate in braking will cause the vehicle to lose control. The sliding mode controller is used to control the slip rate of the wheel around the optimal slip rate all the time to improve the safety during braking. The control variable of the braking subsystem is the gain of braking master cylinder pressure. The deviation between the actual slip rate $\lambda$ and the optimal slip rate $\lambda_0$ is defined as:

$$\lambda = \lambda - \lambda_0.$$ \hspace{1cm} (34)
The rate of change of error is:
\[ \dot{\lambda} = \dot{\lambda} - \dot{\lambda}_0. \] (35)

The sliding surface is taken as:
\[ s = c\dot{\lambda} + \dot{\lambda}. \] (36)

Sliding mode controller is designed as:
\[ u_{\text{slc}} = - (\alpha |\dot{\lambda}| + \beta |\dot{\lambda}| + \varepsilon) \text{sgn}(s) - kr. \] (37)

To reduce chattering, the saturated function \( \text{sat}(s) \) is used instead of the symbolic function \( \text{sgn}(s) \), and the expression is as follows:
\[
\text{sat}(s) = \begin{cases} 
1 & s > \delta \\
 s/\delta & |s| < \delta \\
-1 & s < -\delta 
\end{cases}.
\] (38)

After a lot of debugging, the parameters of the controller are set as follows:
\[ [\varepsilon, \alpha, \beta, \varepsilon, k, \delta] = [2.9, 0.95, 5.0, 1.03, 12.6, 0.02]. \] (39)

3 | SIMULATION ANALYSIS AND EVALUATION

3.1 | Verification of classification algorithm

For verifying the effect of the classifier, a set of test conditions was selected for verification. In order to get the expected classification output easily, some simple conditions that are easy to distinguish were used for superposition of the test conditions. Specifically, the vehicle went straight at a speed of 40 km/h, a front-wheel angle of a sine function with an amplitude of 7 was given at 1 s, the angle was maintained for 1.5 s when it reached a \(-7^\circ\) angle at the 6th s, and then the front-wheel angle at 8.5 s descended to \(0^\circ\) and went straight; at 9 s, the vehicle began to accelerate and reached 60 km/h at 13 s. Thereafter, the front-wheel rotation angle increased linearly to \(3^\circ\) and remained at 1.5 s, then returned to zero at 16 seconds. At 16.5 s, the vehicle started to brake, and at 19 s the speed decreased to 30 km/h, and then went straight at a constant speed. Figure 4 shows the relationship between the front-wheel angle and the longitudinal speed of the vehicle over time in this process.

Obviously, the expected classification results include straight travel, braking, steering, and large-angle steering. It should be noted that when selecting the reference data of the kNN algorithm, it is considered that the front-wheel angle is greater than \(5^\circ\) at 50 km/h speed is the large-angle steering. Therefore, in the setting of the desired output, it is still considered that when the front-wheel angle is greater than \(5^\circ\), it enters a large-angle steering state.

The model parameters are selected as \( k = 30 \), and the simulation results are shown in Figure 5. It can be seen that the predicted output and the expected value are the same, and there are only partial deviations when the steering is just performed. Considering the actual driving conditions, these errors are acceptable.
3.2 Control strategy verification

This section is divided into three parts. First, the coordination strategy in the steering subsystem is simulated, and then the overall control strategy is simulated and verified through two test scenarios.

3.2.1 Co-control simulation of AFS and DYC

The control strategy of the steering subsystem was tested. In the test scenario, a double-lane change condition was adopted and the vehicle was tested at a speed of 50 km/h. The synergies between AFS and DYC were compared in the test results. It should be noted that in this test condition, the decision level is not used to classify the conditions, that is, only the steering subsystem is tested separately.

Figures 6–9 show the simulation results of the double-lane change test at 50 km/h. The weight allocation of AFS and DYC is shown in Figure 6. However, it should be noted that at about 4 s, although the weight of AFS is 1, the steering wheel input at this time is actually 0, which means it is in a straight line state, so AFS does not play a role at this time. Figure 7 shows the longitudinal and lateral velocity comparison under uncontrolled, only AFS or DYC control and coordinated control states, and it can be found that the difference between control states is not great.
In Figures 8 and 9, it is obvious that the coordinated control of
yaw rate is significantly lower than that without control, and can
better track the reference yaw angular velocity, and the coordi-
nated control effect will be better in terms of lateral acceleration.

3.2.2 Test scenario 1: Double lane change, 110 km/h

The first test condition of the overall control strategy is the
double-shift condition at 110 km/h speed. Obviously, due to the
high speed, the vehicle will enter the dangerous condition that
is prone to cartwheel. Therefore, the evaluation indexes include
not only yaw angular velocity, but also lateral acceleration and
roll angle. Figures 10–15 show the simulation results of the test
scenario, in which Figure 10 is the comparison of the driving
state classification results of the decision layer before and after
adding control, and Figure 11 is the control switch variable sig-
nal sent by the decision layer to the control subsystem.

Figure 12 is the comparison curve of yaw rate, which is
respectively compared with the reference yaw rate (Ref.), the
yaw rate without control, the yaw rate when only the steering
subsystem (Str) or suspension system (Sus) are involved in con-
trol, and the yaw rate curve under coordinated control. In the
figure, the yaw rate curve of uncontrolled is similar to that of the

active suspension control, which indicates that the active sus-
pension control alone cannot effectively improve the yaw rate,
while the steering and cooperative control can well track the ref-
ence value. It should be noted that Str fluctuates greatly when
the steering wheel corner is just back to zero, but this prob-
lem can be improved in collaborative control. It can be clearly
seen in Figure 13 that the improvement of coordinate control is
especially obvious compared with the single control. The peak
transverse acceleration is reduced from 0.8 g to 0.6 g, which can-
not be achieved by the single control. Figures 14 and 15 show
the simulation results of roll angle and roll rate. After adding

FIGURE 14 Comparison of roll angle

FIGURE 15 Comparison of roll rate

FIGURE 10 Comparison of driving behaviour signals in test scenario 1

FIGURE 11 Control subsystem switch variables

FIGURE 12 Comparison of yaw rate

FIGURE 13 Comparison of lateral acceleration
active suspension control, the peak of roll angle is reduced by 35.06%, while coordinated control can further reduce this value to 46.75% and reduce the fluctuation of roll angle when turning at a large angle. In terms of roll rate, coordinated control can also improve the violent fluctuation caused by active suspension, and has lower variance and peak value compared with the single control of the steering subsystem.

3.2.3 Test scenario 2: Emergency braking

In test scenario 2, emergency braking is performed at an initial speed of 100 km/h. Figures 16–21 show the simulation results of this test scenario. Figure 16 shows the comparison of driving state signals before and after coordinated control during emergency braking.

Figures 17–19, respectively, show the left front-wheel slip rate in emergency braking conditions and pitch angle and pitch rate of the vehicle, the simulation results show that compared with only slip rate control, the slip rate of coordinated control has tiny fluctuations but the coordination control also guarantees the slip rate good. The pitch angle of steady-state value by 55.51%, effectively improve the ride comfort compared to the emergency brake. In order to compare the braking effect, the change of speed over time and the braking distance of vehicles are analyzed. The simulation results are shown in Figures 20 and 21. It can be seen that both the coordinated control and the single slip rate control can significantly reduce the braking
time and braking distance compared with the control without control. Compared with the single slip rate control, the collaborative control has no great advantage in this respect, only slightly better than the single control. But on the whole, the advantage of coordinated control lies in that it can significantly reduce the vehicle’s pitch angle while further improving the braking efficiency, thus significantly improving the ride comfort during emergency braking.

4 | CONCLUSIONS

This article proposes a chassis comprehensive cooperative control strategy based on vehicle acceleration and angular velocity data. Based on the cluster analysis of inertial sensor data by the upper controller, the driving behaviour of the vehicle is distinguished, and the parameters of the lower controller are updated online by heuristic decision logic according to the driving behaviour signal of the vehicle, so as to realize targeted coordinated control under different working conditions.

The proposed control strategy was analyzed and evaluated by CarSim/Simulink co-simulation:

Firstly, based on a combination of various simple working conditions, the kNN algorithm at the decision level is tested by using its inertial sensor data as the test set without control. The test results show that the kNN algorithm can obtain the expected classification results.

Then, the coordinated strategy of AFS and DYC in the steering subsystem is simulated. The simulation results show that, compared with the single control, the cooperation between AFS and DYC can further improve the vehicle operating stability. It is necessary and meaningful to apply the coordinated control of AFS and DYC in the steering control subsystem.

Finally, two test scenarios (DLC and emergency braking) are used to verify the proposed control strategy; the results show that compared with the control of each subsystem alone, the strategy can further improve the control stability and significantly reduce the vehicle’s roll angle to reduce the risk of rolling over, and its roll rate is also effectively inhibited. In emergency braking, coordinated control can greatly reduce the pitch angle while maintaining the optimal slip rate, effectively reduce the braking distance, and ensure the safety of the vehicle.

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