

Article

Research on Electric Vehicle Differential System Based on Vehicle State Parameter Estimation

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Abstract

To improve the stability and safety of electric vehicles during medium-to-high-speed cornering, this paper investigates torque differential control for dual rear-wheel hub motor drive systems, extending beyond traditional speed control based on the Ackermann steering model. A nonlinear three-degree-of-freedom vehicle dynamics model incorporating the Dugoff tire model was established. By introducing the maximum correntropy criterion, an unscented Kalman filter was developed to estimate longitudinal velocity, sideslip angle at the center of mass, and yaw rate. Building upon the speed differential control achieved through Ackermann steering model-based rear-wheel speed calculation, improvements were made to the conventional exponential reaching law, while a novel switching function was proposed to formulate a new sliding mode controller for computing an additional yaw moment to realize torque differential control. Finally, simulations conducted on the Carsim/Simulink platform demonstrated that the maximum correntropy criterion unscented Kalman filter effectively improves estimation accuracy, achieving at least a 22.00% reduction in RMSE metrics compared to conventional unscented Kalman filter. With torque control exhibiting higher vehicle stability than speed control, the RMSE values of yaw rate and sideslip angle at the center of mass are reduced by at least 20.00% and 4.55%, respectively, enabling stable operation during medium-to-high-speed cornering conditions.

Keywords: in-wheel motor; torque differential; unscented Kalman filter; sliding mode control



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1. Introduction

For in-wheel motor-driven electric vehicles, electronic differential systems employed during cornering operations can be categorized into speed differential control and torque differential control [1]. Speed differential control calculates the inner/outer wheel speed differential during turning based on the Ackermann steering model. Reference [2] improved the Ackermann steering model to achieve smoother vehicle steering. However, under high-speed conditions, this model still treats the vehicle as a rigid body, failing to account for nonlinear disturbances arising from variations in tire characteristics. Additionally, it lacks the capability to coordinate wheel motor speeds in real-time. Consequently, its applicability remains restricted to low-speed scenarios, with experimental validation limited to speeds below 30 km/h [3,4]. In contrast, torque differential control implements direct torque regulation on in-wheel motors, strategically incorporating slip ratio, sideslip angle at the center of mass, and yaw rate perturbations—either partially or comprehensively—as control variables. This approach optimizes armature current modulation across individual in-wheel

motors to achieve coordinated torque control, with the primary objective of minimizing system disturbances [5]. The execution of electronic differential control requires accurate vehicle parameters, some of which cannot be directly acquired via sensors. Researchers therefore utilize cost-effective sensors to measure easily obtainable parameters, while employing vehicle dynamics models combined with algorithmic estimators for real-time estimation of vehicle state parameters during operation [6]. Typical estimation techniques include Kalman filters, extended Kalman filters, Luenberger observers, sliding mode observers, and other nonlinear observers [7]. Reference [8] combines the advantages of robust estimation, robust adaptive filtering, and particle filtering to perform filtering and estimation of longitudinal/lateral velocities and yaw rate using an adaptive robust unscented particle filter. Reference [9] proposes a robust bias-compensated Kalman filtering algorithm for vehicle state estimation based on an extended Kalman filter framework, incorporating bias compensation and residual covariance matrix weighting to enhance estimation accuracy and robustness. Reference [10] dynamically adjusts measurement noise covariance through fuzzy inference-based factor tuning in cubature Kalman filtering, aligning actual and theoretical residual covariance values to minimize estimation errors. Reference [11] estimates vehicle lateral acceleration using a Luenberger observer based on a bicycle planar model. Reference [12] employs a nonlinear sliding mode observer for vehicle state estimation, with stability rigorously proven through Lyapunov theory. Recent years have witnessed the development of integrated Kalman filters combining different algorithms, such as interactive multiple-model adaptive robust Kalman filters and LSTM-integrated adaptive Kalman filters, to enhance estimation accuracy [13,14].

Leveraging the independent torque controllability of in-wheel motors, torque differential control can be achieved through direct yaw moment regulation. Prevalent methods for computing additional yaw moment include proportional–integral–derivative (PID) control, the linear quadratic regulator (LQR), model predictive control, and sliding mode control (SMC). Reference [15] employs LQR for additional yaw moment calculation, validating control performance through hardware-in-the-loop simulation test bench experiments. Reference [16] develops an adaptive fuzzy controller that dynamically adjusts adaptive parameters according to driving conditions to determine the optimal desired yaw moment. When an in-wheel motor fails, it tends to generate undesired yaw moments. To address this issue, References [17,18] implement a dual-layer fault-tolerant control strategy: the upper-layer MPC computes compensatory yaw moments and the lower-layer torque distribution allocates wheel-specific torque. However, chattering remains a persistent challenge in SMC. To suppress chattering in conventional SMC implementations, reference [19] implements a super-twisting sliding mode controller for yaw moment computation. For stability enhancement, reference [20] categorizes the vehicle phase plane into stable and unstable regions. Within unstable zones, a fuzzy neural network control strategy calculates the corrective yaw moment using the instability degree as the control objective, effectively transitioning vehicle states from unstable to stable domains.

This study focuses on a rear in-wheel motor-driven electric vehicle, utilizing the maximum correntropy criterion (MCC) to improve the unscented Kalman filter (UKF)'s performance in non-Gaussian environments for vehicle state estimation. Speed differential control is realized through the Ackermann steering model, while torque differential control is achieved by computing additional yaw moment with a novel sliding mode reaching law, enhancing vehicle stability during cornering maneuvers.

2. Design of Vehicle State Parameter Estimator

2.1. Vehicle Model

Appropriate vehicle model selection forms the foundation of state parameter estimation, where fewer degrees of freedom (DOFs) generally reduce computational load at the potential cost of accuracy, while higher-DOF models improve precision with increased computational demands. Although high-precision applications may require expanded DOF, practical implementations necessitate balanced model selection tailored to specific requirements. For electronic differential control, which demands accurate characterization of cornering stability alongside computational efficiency, this study adopts a laterally symmetric vehicle assumption with coincident origins of the centroidal frame (OX) and vehicle coordinate system. We further neglect pitch/roll motions, suspension dynamics, and steering system influences [21], establishing a nonlinear three-DOF model encompassing longitudinal, lateral, and yaw dynamics, as depicted in Figure 1.

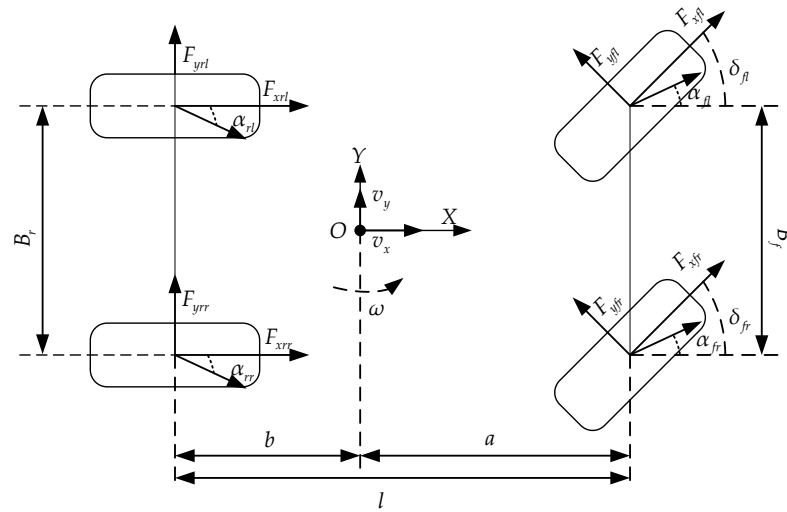


Figure 1. Nonlinear 3-degree-of-freedom vehicle model.

As shown in Figure 1, F_{xfl} , F_{xfr} , F_{xrl} , and F_{xrr} represent the longitudinal forces of the left-front, right-front, left-rear, and right-rear wheels, respectively; F_{yfl} , F_{yfr} , F_{yrl} , and F_{yrr} denote the corresponding lateral forces; α_{fl} , α_{fr} , α_{rl} , and α_{rr} indicate the sideslip angles. The parameters a and b correspond to the distances from the center of mass to the front and rear axles, l is the wheelbase, B_f and B_r represent the front and rear track widths, δ_{fl} and δ_{fr} are the steering angles of the left and right front wheels, v_x and v_y signify the longitudinal and lateral velocities, and ω denotes the yaw rate.

Longitudinal dynamic equation:

$$m(\dot{v}_x - \omega v_y) = F_{xfl} \cos \delta_{fl} + F_{xfr} \cos \delta_{fr} - F_{yfl} \sin \delta_{fl} - F_{yfr} \sin \delta_{fr} + F_{xrl} + F_{xrr} - F_w \quad (1)$$

Lateral dynamic equation:

$$m(\dot{v}_y + \omega v_x) = F_{xfl} \sin \delta_{fl} + F_{xfr} \sin \delta_{fr} + F_{yfl} \cos \delta_{fl} + F_{yfr} \cos \delta_{fr} + F_{yrl} + F_{yrr} \quad (2)$$

Yaw dynamic equation:

$$\begin{aligned} I_z \dot{\omega} = & a \left(F_{xfl} \sin \delta_{fl} + F_{xfr} \sin \delta_{fr} + F_{yfl} \cos \delta_{fl} + F_{yfr} \cos \delta_{fr} \right) \\ & + \frac{B_f}{2} \left(F_{xfr} \cos \delta_{fr} - F_{xfl} \cos \delta_{fl} + F_{yfl} \sin \delta_{fl} - F_{yfr} \sin \delta_{fr} \right) \\ & + \frac{B_r}{2} (F_{xrr} - F_{xrl}) - b (F_{yrl} + F_{yrr}) \end{aligned} \quad (3)$$

In the above equations, m represents the total vehicle mass and F_w denotes the aerodynamic drag. The longitudinal and lateral accelerations can be respectively expressed as:

$$a_x = \dot{v}_x - \omega v_y \quad (4)$$

$$a_y = \dot{v}_y + \omega v_x \quad (5)$$

The sideslip angle at the center of mass can be expressed as:

$$\beta = \frac{v_y}{v_x} \quad (6)$$

2.2. Tire Model

This paper adopts the Dugoff tire model [22], where the longitudinal and lateral forces can be expressed as:

$$F_x = \mu F_z C_x \frac{\lambda}{1 - \lambda} f(L) \quad (7)$$

$$F_y = \mu F_z C_y \frac{\tan \alpha}{1 - \lambda} f(L) \quad (8)$$

$$f(L) = \begin{cases} (2 - L)L, & L < 1 \\ 1, & L \geq 1 \end{cases} \quad (9)$$

$$L = \frac{(1 - \lambda) \left(1 - \zeta v_x \sqrt{(C_x \lambda)^2 + (C_y \tan \alpha)^2} \right)}{2 \sqrt{(C_x \lambda)^2 + (C_y \tan \alpha)^2}} \quad (10)$$

In the above equations, F_x and F_y represent the longitudinal and lateral forces, respectively. F_z denotes the vertical load, C_x and C_y are the longitudinal slip stiffness and cornering stiffness of the tire, λ is the tire slip ratio, α is the tire slip angle, μ signifies the road–tire friction coefficient, ζ is the velocity influence factor, and L defines the boundary value.

2.3. Design of Maximum Correntropy Criterion Unscented Kalman Filter Estimator

For general nonlinear systems, the state and measurement equations can be expressed as:

$$\begin{cases} \dot{x}(t) = f(x(t), u(t)) + w(t) \\ z(t) = h(x(t), u(t)) + v(t) \end{cases} \quad (11)$$

In the above formulation, $x(t)$ and $z(t)$ represent the system's state vector and measurement vector, respectively. $u(t)$ denotes the input variable, while $w(t)$ and $v(t)$ signify the process noise and measurement noise, both following Gaussian distributions and being mutually independent. For the vehicle state estimator, the state variables are defined as $x(t) = [v_x, \beta, \omega]^T$, the measurement vector is $z(t) = [a_x, a_y, \omega]^T$, and the input vector is $u(t) = [\delta_{fl}, \delta_{fr}]^T$. The state equation for vehicle state estimation can be expressed as:

$$\dot{x}(t) = \begin{pmatrix} \dot{v}_x \\ \dot{\beta} \\ \dot{\omega} \end{pmatrix} = \begin{pmatrix} \omega \beta & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} v_x \\ \beta \\ \omega \end{pmatrix} + \begin{pmatrix} f_1 \\ f_2 \\ f_3 \end{pmatrix} - \begin{pmatrix} \frac{1}{m} \\ 0 \\ 0 \end{pmatrix} F_w(t) + w(t) \quad (12)$$

where f_1 , f_2 , and f_3 can be expressed as

$$f_1 = \frac{F_{xfl} \cos \delta_{fl} + F_{xfr} \cos \delta_{fr} - F_{yfl} \sin \delta_{fl} - F_{yfr} \sin \delta_{fr} + F_{xrl} + F_{xrr}}{m} \quad (13)$$

$$f_2 = \frac{F_{xfl}\sin\delta_{fl} + F_{xfr}\sin\delta_{fr} + F_{yfl}\cos\delta_{fl} + F_{yfr}\cos\delta_{fr} + F_{yrl} + F_{yrr}}{mv_x} \quad (14)$$

$$f_3 = \frac{a(F_{xfl}\sin\delta_{fl} + F_{xfr}\sin\delta_{fr} + F_{yfl}\cos\delta_{fl} + F_{yfr}\cos\delta_{fr})}{I_z} + \frac{B_f}{2} \frac{(F_{xfr}\cos\delta_{fr} - F_{xfl}\cos\delta_{fl} + F_{yfl}\sin\delta_{fl} - F_{yfr}\sin\delta_{fr})}{I_z} + \frac{B_r}{2} \frac{(F_{xrr} - F_{xrl}) - b(F_{yrl} - F_{yrr})}{I_z} \quad (15)$$

The measurement equation for vehicle state estimation can be expressed as:

$$z_1(t) = \begin{pmatrix} a_x \\ a_y \\ \omega \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} v_x \\ \beta \\ \omega \end{pmatrix} + \begin{pmatrix} f_1 \\ f_2 \\ 0 \end{pmatrix} - \begin{pmatrix} \frac{1}{m} \\ 0 \\ 0 \end{pmatrix} F_w(t) + v(t) \quad (16)$$

Building upon the conventional unscented Kalman filter (UKF), this paper integrates the maximum correntropy criterion (MCC) to estimate vehicle state parameters [23–25], with the filtering process illustrated in Figure 2.

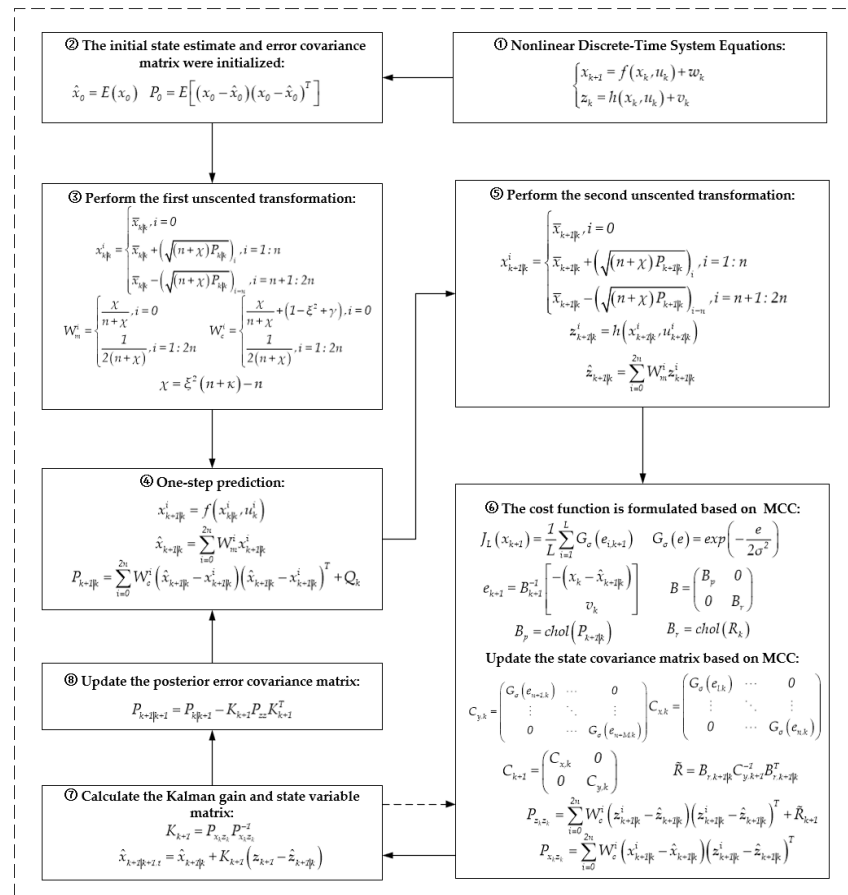


Figure 2. The filtering process of the MCCUKF.

If the following condition is satisfied, set $\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k+1,t}$; otherwise, set $t+2 = t+1$, and proceed to the next iteration by repeating steps ⑥ and ⑦ in Figure 2.

$$\frac{\|\hat{x}_{k+1|k+1,t} - \hat{x}_{k+1|k+1,t-1}\|}{\hat{x}_{k+1|k+1,t-1}} \leq \varepsilon, \varepsilon > 0 \quad (17)$$

3. Design of Speed Differential and Torque Differential Controllers

3.1. Speed Differential Control

The speeds of the two rear drive wheels can be calculated based on the Ackermann steering model [26], as shown in Figure 3.

$$\begin{cases} v_{in} = \frac{v_1 \left(\frac{l}{i \tan \delta} - \frac{B_f}{2} \right)}{\sqrt{a^2 + \left(\frac{l}{i \tan \delta} \right)^2}} \\ v_{out} = \frac{v_1 \left(\frac{l}{i \tan \delta} + \frac{B_f}{2} \right)}{\sqrt{b^2 + \left(\frac{l}{i \tan \delta} \right)^2}} \end{cases} \quad (18)$$

Figure 3. Ackermann steering model.

In this context, v_1 denotes the vehicle speed, v_{in} and v_{out} represent the rotational speeds of the inner and outer wheels during cornering, respectively, and δ is the steering angle of the front wheels. It is assumed that the steering angles of both front wheels are equal, i.e., $\delta_{fl} = \delta_{fr} = \delta$.

3.2. Torque Differential Control

Torque differential control is achieved through direct yaw moment control of the vehicle. This is implemented by calculating an additional yaw moment and distributing it between the two rear-drive in-wheel motors, thereby enabling torque differentiation. The schematic diagram of the torque differential control principle is shown in Figure 4.

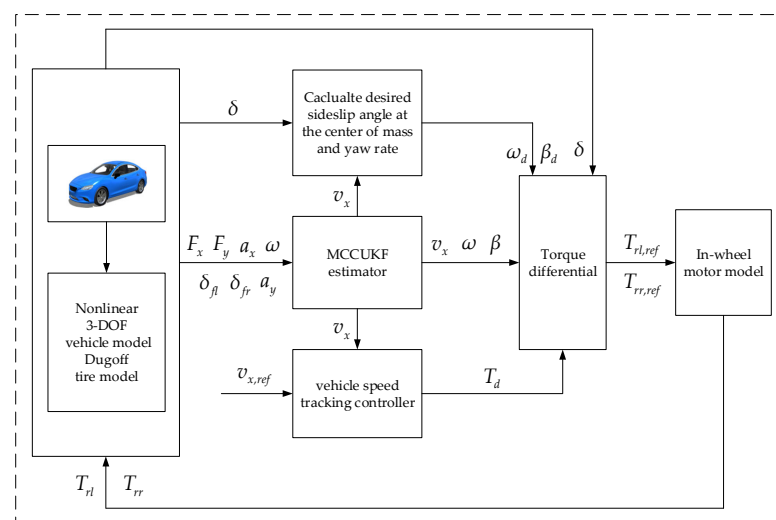


Figure 4. Schematic diagram of torque differential control principle.

As shown in Figure 4, T_{rl} and T_{rr} denote the driving torques of the left rear wheel and right rear wheel, respectively; $T_{rl,ref}$ and $T_{rr,ref}$ denote left wheel reference torque and right wheel reference torque, respectively; ω_d and β_d denote the desired yaw rate and sideslip angle at the center of mass; T_d is the total driving torque and $v_{x,ref}$ is the reference vehicle speed.

3.2.1. Design of a Novel Sliding Mode Controller

During vehicle operation, the sideslip angle at the center of mass (β) and yaw rate (ω) constitute two critical parameters characterizing vehicular stability. When β remains small, ω predominantly determines the vehicle's dynamic state; however, at elevated β values, the vehicle experiences irreversible loss of controllability [27]. Consequently, torque differential control is implemented to enforce rigorous tracking of desired β and ω reference values, thereby ensuring stable vehicle operation through coordinated regulation of these stability indices.

The desired sideslip angle at the center of mass and yaw rate can be derived from linear two-degree-of-freedom (2-DOF) equations, with the linear 2-DOF model illustrated in Figure 5.

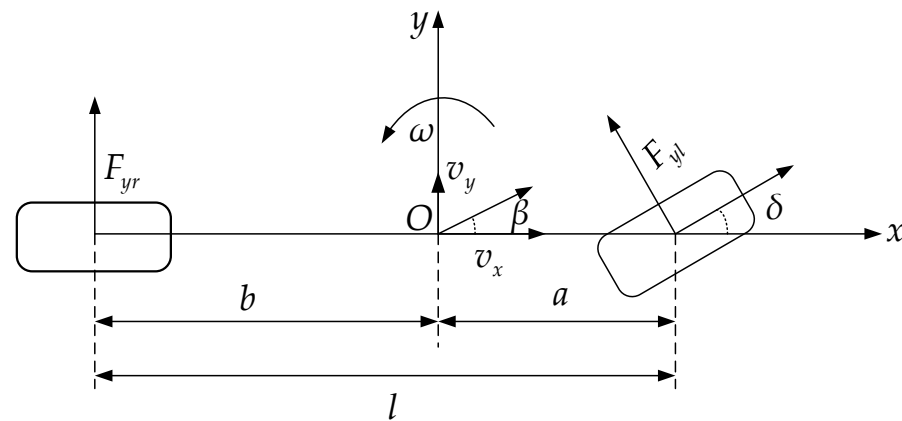


Figure 5. Linear 2-DOF model.

From the linear two-degree-of-freedom (2-DOF) vehicle dynamics equations, the following relationships can be derived:

$$\begin{cases} \dot{\beta} = \frac{c_f + c_r}{mv_x} \beta + \left(\frac{ac_f - bc_r}{mv_x^2} - 1 \right) \omega - \frac{c_f}{mv_x} \delta \\ \dot{\omega} = \frac{ac_f - bc_r}{I_z} \beta + \frac{a^2 c_f + b^2 c_r}{I_z v_x} \omega - \frac{ac_f}{I_z} \delta \end{cases} \quad (19)$$

where c_f and c_r represent the tire cornering stiffness of the front and rear axles, respectively. Based on the above equations, the desired sideslip angle at the center of mass and yaw rate can be derived as follows [28]:

$$\begin{cases} \omega_d = \min \left(\left| \frac{v_x}{l(1 + Kv_x^2)} \delta \right|, 0.85 \frac{\mu g}{v_x} \right) \text{sgn}(\delta) \\ \beta_d = 0 \end{cases} \quad (20)$$

where $K = \frac{m}{l^2} \left(\frac{a}{c_r} - \frac{b}{c_f} \right)$ is the stability factor.

As sliding mode control (SMC) constitutes a nonlinear control methodology with inherent strong robustness, it is employed to compute the additional yaw moment. However,

conventional SMC exhibits inherent chattering phenomena. To mitigate chattering while accelerating reaching-phase convergence, this study proposes a novel reaching law:

$$\begin{cases} \dot{s} = -k_1 e^{-k_2 s^2} s(s) - k_3 s - k_4 |s|^{k_5} s(s) \\ s(s) = \frac{2}{\pi} \arctan(e^{k_s s} - e^{-k_s s}) \end{cases} \quad (21)$$

In this design, $k_1 > 0$, $0 < k_2 < 1$, $k_3 > 0$, $k_4 > 0$, $k_5 > 0$ and $k_s > 0$, while the switching functions $s(s)$ is constructed as continuously smooth functions. As the system approaches the sliding manifold, the influence of the linear term $e^{-k_2 s^2}$ diminishes to mitigate chattering, while the terminal term $|s|^{k_4}$ dominates to enhance convergence speed. Specifically, the composite switching function:

To prove the stability of the proposed sliding mode reaching law, a Lyapunov function is constructed as follows:

$$V = \frac{1}{2} s^2 \quad (22)$$

Differentiating the above equation yields:

$$\dot{V} = s\dot{s} = s \left[-k_1 e^{-k_2 s^2} s(s) - k_3 s - k_4 |s|^{k_5} s(s) \right] \leq 0 \quad (23)$$

Therefore, it can be concluded that the proposed reaching law ensures system stability. To further eliminate steady-state errors, an integral sliding surface is adopted:

$$s = e + c \int e dt \quad (24)$$

where $c > 0$, and e denotes the error.

Rewriting Equation (19) as:

$$\begin{cases} \dot{\beta} = \frac{c_f + c_r}{mv_x} \beta + \left(\frac{ac_f - bc_r}{mv_x^2} - 1 \right) \omega - \frac{c_f}{mv_x} \delta \\ \dot{\omega} = \frac{ac_f - bc_r}{I_z} \beta + \frac{a^2 c_f + b^2 c_r}{I_z v_x} \omega - \frac{ac_f}{I_z} \delta + \frac{\Delta M_z}{I_z} \end{cases} \quad (25)$$

where ΔM_z denotes the additional yaw moment.

The tracking error is defined as a linear combination of the yaw rate error and the sideslip angle error at the center of mass [29]:

$$e = \lambda_1 (\beta - \beta_d) + (1 - \lambda_1) (\omega - \omega_d) \quad (26)$$

where $\lambda_1 (0 < \lambda_1 < 1)$ is the weighting factor. Differentiating the above equation yields:

$$\dot{e} = \lambda_1 \dot{\beta} + (1 - \lambda_1) (\dot{\omega} - \dot{\omega}_d) \quad (27)$$

The additional yaw moment can be solved as:

$$\Delta M_z = I_z \left\{ \begin{aligned} & \frac{-k_1 e^{-k_2 s^2} s(s) - k_3 s - k_4 |s|^{k_5} s(s)}{1 - \lambda_1} \\ & - \left[\frac{\lambda_1 (c_f + c_r)}{(1 - \lambda_1) mv_x} + \frac{ac_f - bc_r}{I_z} \right] \beta \\ & - \left[\frac{\lambda_1}{1 - \lambda_1} \left(\frac{ac_f - bc_r}{mv_x^2} - 1 \right) + \frac{a^2 c_f + b^2 c_r}{I_z v_x} \right] \omega \\ & - \left[\frac{\lambda_1}{1 - \lambda_1} - \frac{c_f}{mv_x} - \frac{ac_f}{I_z} \right] \delta + \frac{\lambda_1}{1 - \lambda_1} \dot{\beta}_d + \dot{\omega}_d - \frac{\lambda_1 c e}{1 - \lambda_1} \end{aligned} \right\} \quad (28)$$

3.2.2. Torque Distribution Strategy

To determine the driving torque for each wheel, it is essential to first compute the total driving torque, which is obtained from the vehicle speed tracking controller. To ensure

the actual vehicle speed tracks the desired speed, a PID controller is implemented. The PID controller takes the tracking error between the actual and desired vehicle speeds as its input and outputs the total driving torque. By combining the derived total driving torque with the additional yaw moment, the driving torques for the two wheels can be calculated using the following equations [30]:

$$\begin{cases} T_{rlrl,ref} = \frac{T_d}{2} - \frac{\Delta M_z r}{W} \\ T_{rrrr,ref} = \frac{T_d}{2} + \frac{\Delta M_z r}{W} \end{cases} \quad (29)$$

where W represents the track width, with the assumption that the front and rear track widths are equal (i.e., $W = B_f = B_r$).

By applying the calculated driving torques of the two rear wheels to the respective rear in-wheel motors, torque differential control is effectively realized. This study employs permanent magnet synchronous motors as the in-wheel motors, whose torque outputs are governed by their torque-speed characteristics.

4. Simulation Analysis

4.1. Simulation of Vehicle State Parameter Estimation

In the simulation of vehicle state parameter estimation, both process noise and measurement noise are considered as non-Gaussian noises following mixed Gaussian distributions. The covariance matrices for the process noise and measurement noise are denoted as $Q_k = \text{diag}([0.028, 10^{-5}, 10^{-4}])$ and $R_k = \text{diag}([0.028, 0.028, 0.028])$, respectively. A comparative analysis is conducted between the UKF and the MCCUKF. The Root Mean Square Error (RMSE) is employed as the metric to evaluate the estimation accuracy of both algorithms. The RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_0} (\hat{\sigma} - \sigma_0)^2}{n_0}} \quad (30)$$

In the equation, n_0 represents the number of sampled data points, $\hat{\sigma}$ denotes the estimated value, and σ_0 is the actual value. A smaller RMSE value indicates higher estimation accuracy.

The vehicle parameters employed in this study are presented in Table 1.

Table 1. Vehicle parameters.

Parameter	Value
Total vehicle mass/kg	1412
Distance from center of mass to front axis/m	1.015
Distance from center of mass to rear axis/m	1.895
Yaw moment of inertia/(kg·m ²)	1536.7
Track width/m	1.675
Height of center of gravity/m	0.54
Tire rolling radius/m	0.325

4.1.1. Double Lane Change

Under the double lane-change maneuver, the simulation was configured with a vehicle speed of 100 km/h, a tire–road friction coefficient of 0.8, and a simulation duration of 10 s. Figure 6 illustrates the estimation results.

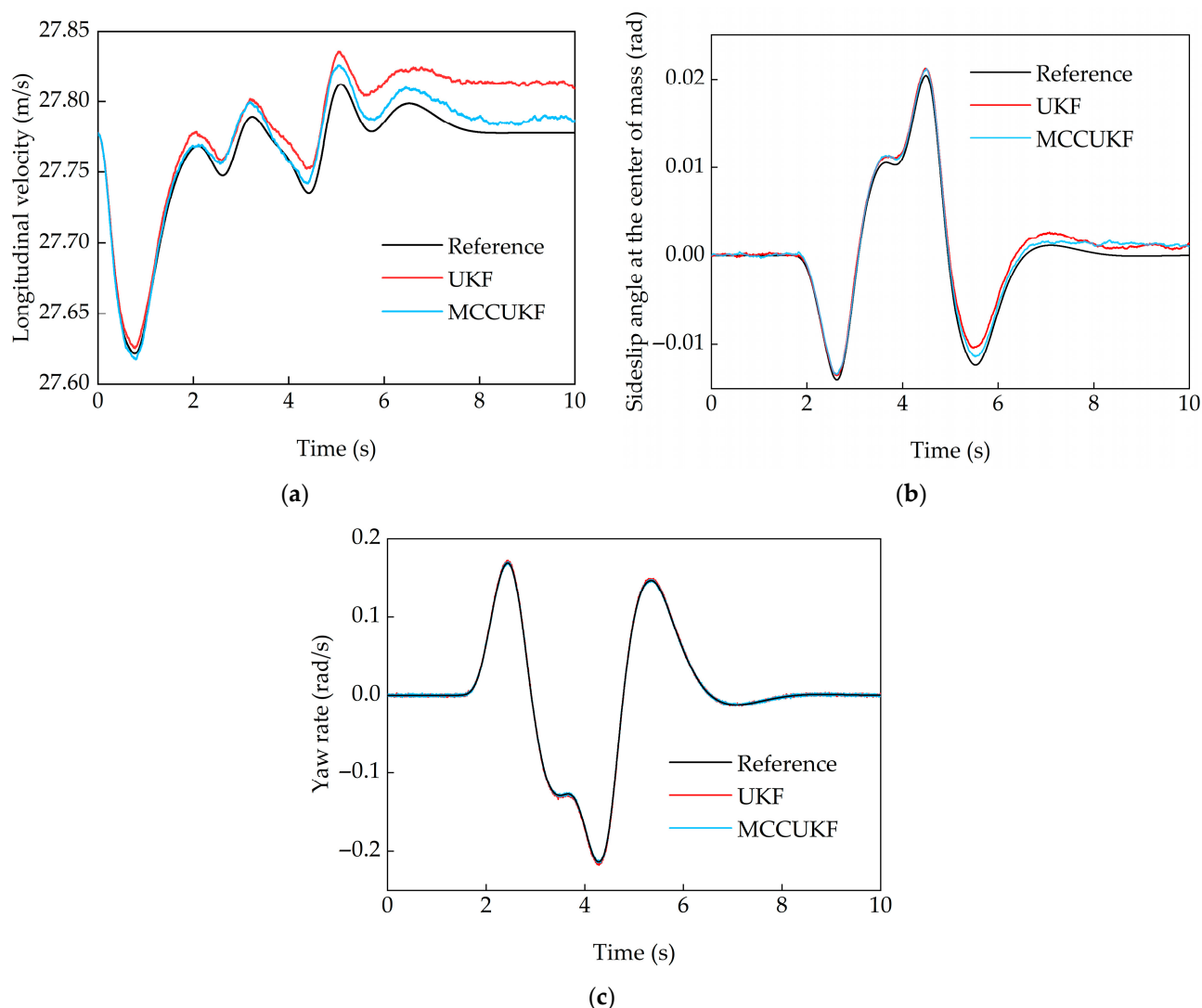


Figure 6. Double lane-change estimation results: (a) longitudinal velocity; (b) sideslip angle at the center of mass; (c) yaw rate.

As can be observed from the figure, both the UKF and the MCCUKF algorithms are capable of tracking the longitudinal velocity, sideslip angle at the center of mass, and yaw rate. However, the estimation results under MCCUKF align more closely with the reference values, demonstrating superior estimation accuracy. The RMSE values for each estimated parameter are presented in Table 2.

Table 2. RMSE of estimated parameters.

Parameter	UKF	MCCUKF	Difference
Longitudinal velocity	0.02350	0.00890	0.01460
Sideslip angle at the center of mass	0.00100	0.00078	0.00022
Yaw rate	0.00120	0.00079	0.00041

As shown in the table, the RMSE values of parameters v_x , β , and ω under MCCUKF are reduced by 62.13%, 22.00%, and 31.17%, respectively, compared to UKF, demonstrating MCCUKF's enhanced capability in resisting non-Gaussian noise.

4.1.2. Slalom Test

Under the slalom test conditions, the simulation vehicle speed is set to 70 km/h, the tire–road friction coefficient is 0.8, and the simulation duration is configured to 18 s. The estimation results are illustrated in Figure 7.

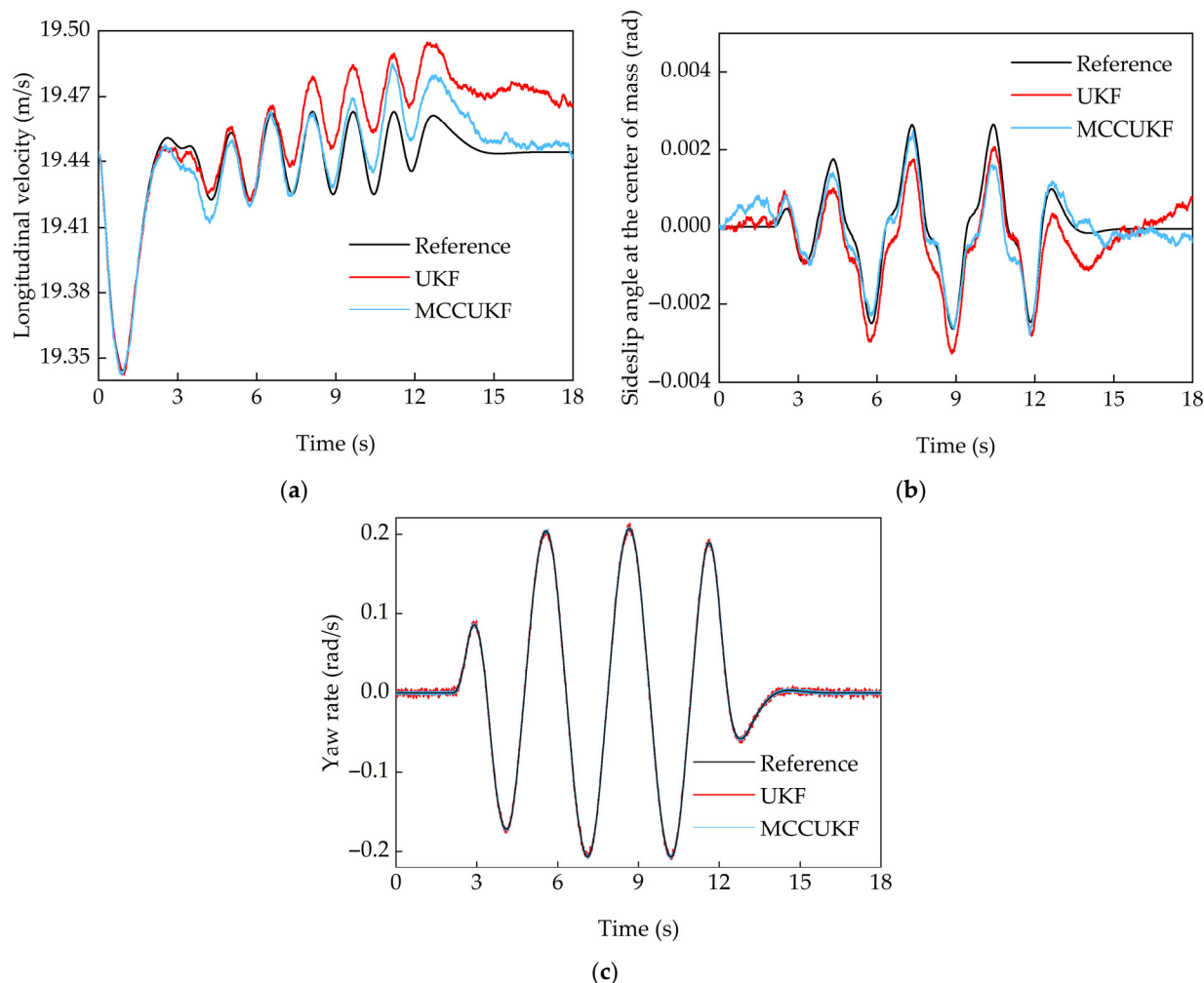


Figure 7. Slalom test estimation results: (a) longitudinal velocity; (b) sideslip angle at the center of mass; (c) yaw rate.

Under slalom test conditions, both algorithms achieve reasonably accurate estimations of vehicle parameters. Similarly, the MCCUKF demonstrates superior estimation performance, with the RMSE values of each estimated parameter listed in Table 3.

Table 3. RMSE of estimated parameters.

Parameter	UKF	MCCUKF	Difference
Longitudinal velocity	0.02020	0.00870	0.01150
Sideslip angle at the center of mass	0.00053	0.00038	0.00015
Yaw rate	0.00220	0.00083	0.00137

From the table above, it can be observed that the RMSE values of the longitudinal velocity, sideslip angle at the center of mass, and yaw rate under MCCUKF are reduced by 56.93%, 28.30%, and 62.27%, respectively, compared to UKF, demonstrating significantly enhanced robustness against non-Gaussian noise.

Overall, both UKF and MCCUKF achieve accurate estimations of vehicle state parameters. However, MCCUKF exhibits smaller RMSE values for all state parameters across all test conditions, indicating its superior precision and adaptability in non-Gaussian environments compared to UKF.

4.2. Vehicle Stability Simulation

4.2.1. Double Lane-Change Maneuver on Road Surfaces

The vehicle follows a double lane-change maneuver with an initial tire–road friction coefficient of 0.8, which is reduced to 0.4 after 5 s of travel. The simulation is conducted at a vehicle speed of 100 km/h over a duration of 10 s. Figure 8 illustrates the trajectory tracking results.

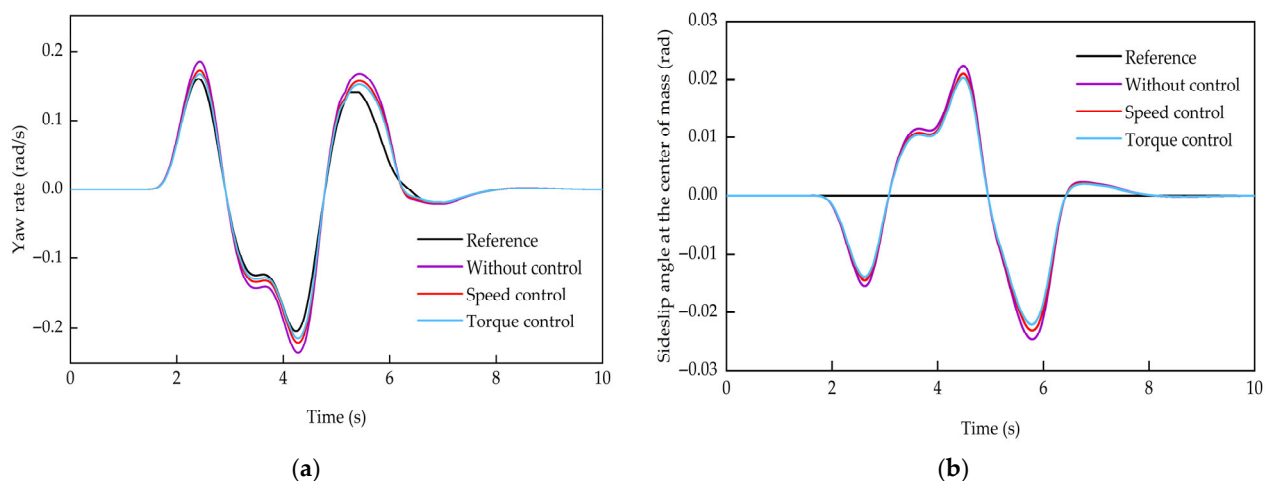


Figure 8. Double lane-change tracking results on road surfaces: (a) yaw rate; (b) sideslip angle at the center of mass.

As can be observed from the figure, the yaw rate and sideslip angle under no control, speed control, and torque control conditions all track the desired yaw rate and sideslip angle variations, indicating that the vehicle maintains stable operation under all three control algorithms in this scenario. However, torque control demonstrates superior tracking performance with the minimum sideslip angle magnitude, suggesting the highest vehicle stability under torque control. The tracking effectiveness of different algorithms can be quantitatively evaluated using the RMSE, as summarized in Table 4.

Table 4. RMSE values under different control algorithms.

Parameter	Without Control	Speed Control	Torque Control
Yaw rate	0.0166	0.0115	0.0092
Sideslip angle at the center of mass	0.0094	0.0088	0.0084

As shown in the table, for the yaw rate, the RMSE value under torque control is reduced by 44.58% and 20% compared to no control and speed control, respectively. For the sideslip angle at the center of mass, the RMSE values are decreased by 10.64% and 4.55%, respectively.

4.2.2. Double Lane-Change Maneuver Under Low Tire–Road Friction Coefficients

The vehicle follows the same double lane-change maneuver, maintaining a speed of 100 km/h, while the tire–road friction coefficient is reduced to 0.3. The simulation spans 10 s, with the results illustrated in Figure 9.

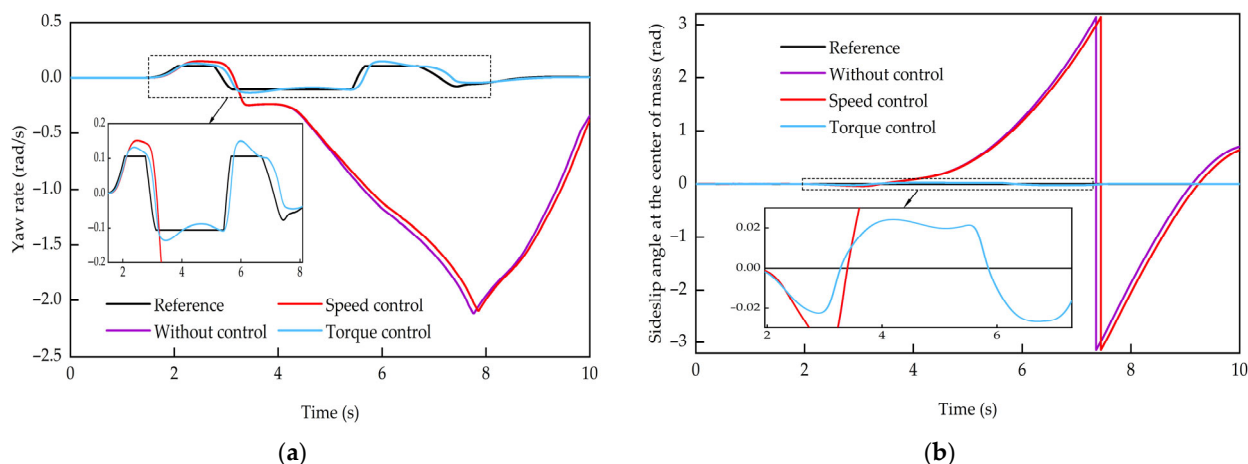


Figure 9. Double lane-change tracking results under low tire–road friction coefficients: (a) yaw rate; (b) sideslip angle at the center of mass.

As evident from the figure, during vehicle cornering, the yaw rate and sideslip angle at the center of mass under speed control and without control rapidly deviate from the desired values, indicating vehicle instability under these conditions. In contrast, the torque-controlled system maintains tracking of the ideal yaw rate and sideslip angle throughout the maneuver. Albeit with minor deviations, torque control ensures stable vehicle operation across the entire process.

4.2.3. Slalom Test on Composite Road Surfaces

The vehicle follows a slalom test with an initial tire–road friction coefficient of 0.8, which is reduced to 0.4 after 5 s of travel. The simulation is conducted at a vehicle speed of 70 km/h over a duration of 20 s. Figure 10 illustrates the trajectory tracking results.

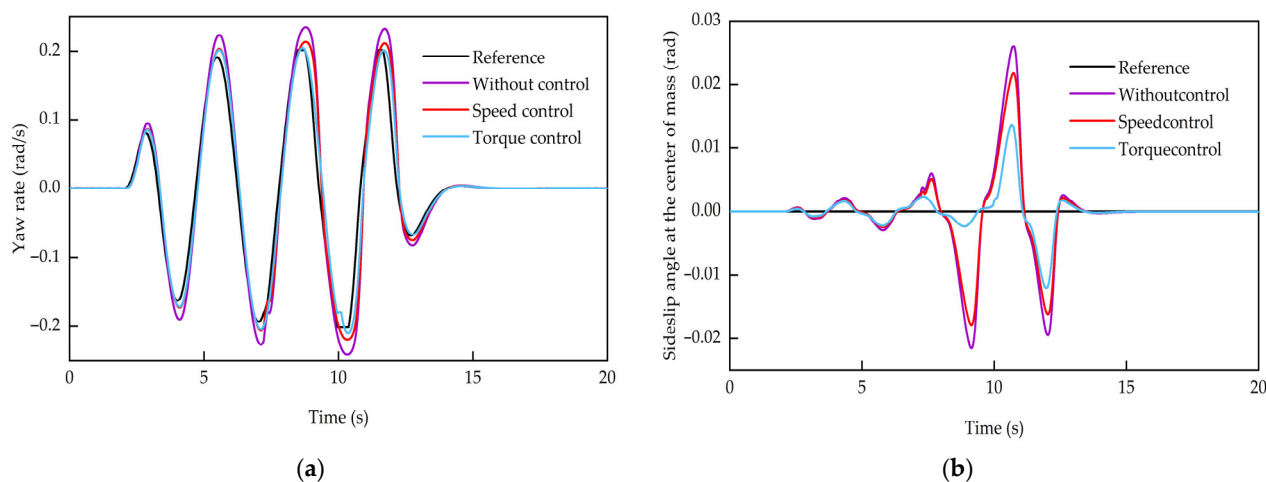


Figure 10. Interface road slalom test tracking results: (a) yaw rate; (b) sideslip angle at the center of mass.

Comparative analysis reveals that all three control algorithms successfully maintained vehicular stability during the slalom path tracking scenario, with the torque control method demonstrating superior stabilization performance. The RMSE metrics corresponding to each control strategy are quantitatively compared in Table 5.

Table 5. RMSE values under different control algorithms.

Parameter	Without Control	Speed Control	Torque Control
Yaw rate	0.0316	0.0254	0.0203
Sideslip angle at the center of mass	0.0065	0.0054	0.0028

As quantitatively demonstrated in Table 5, the torque control method achieved significant error reduction in both key stability parameters. For the yaw rate, the RMSE exhibited a 35.76% decrease compared to uncontrolled conditions and a 20.08% improvement over conventional speed control. Similarly, regarding the sideslip angle at the center of mass, the RMSE values were reduced by 56.92% and 48.15% relative to the uncontrolled scenario and speed control strategy, respectively.

4.2.4. Slalom Test Under Low Tire–Road Friction Coefficients

The vehicle follows the slalom test, maintaining a speed of 70 km/h, while the tire–road friction coefficient is reduced to 0.3. The simulation spans 20 s, with the results illustrated in Figure 11.

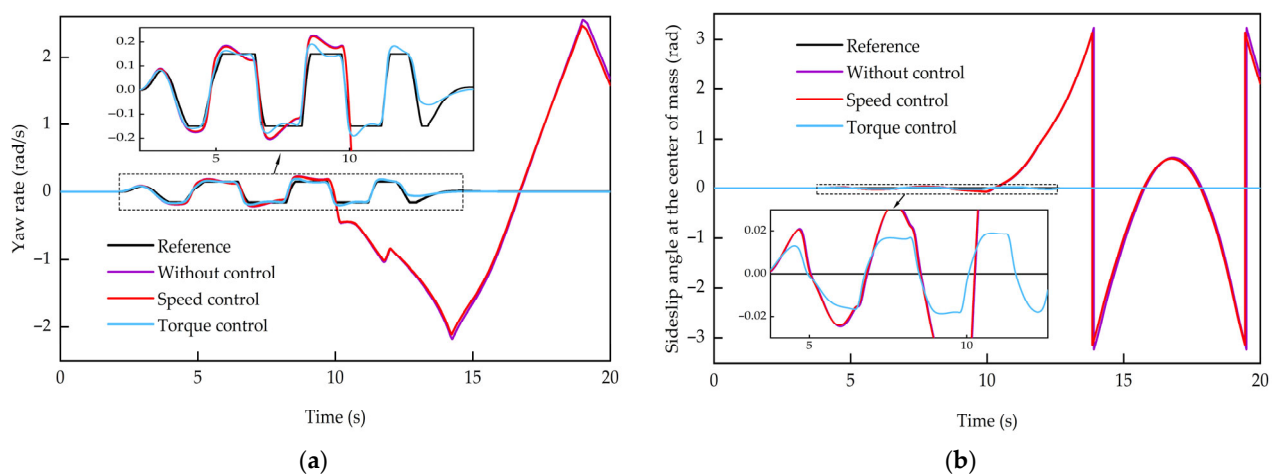


Figure 11. Slalom test change tracking results under low tire–road friction coefficients: (a) yaw rate; (b) sideslip angle at the center of mass.

During the initial phase of the maneuver, all three control algorithms demonstrated competent reference tracking capability. However, as the slalom test progressed through consecutive steering reversals, both uncontrolled and speed-controlled configurations exhibited rapid escalation in yaw rate and sideslip angle at the center of mass, culminating in loss of directional stability. In contrast, the torque-controlled vehicle maintained bounded tracking errors while preserving stable navigation throughout the complete test cycle.

5. Conclusions

This study establishes a nonlinear 3-DOF vehicle–tire dynamics model as the foundation for state estimation. Fundamentally, the synthesis of the maximum correntropy criterion (MCC) with the unscented Kalman filter (UKF) addresses the intrinsic limitation of the Gaussian noise assumption in conventional nonlinear filters. The developed MC-CUKF algorithm demonstrates enhanced robustness against non-Gaussian disturbances through entropy-weighted kernel adaptation, achieving at least a 22.00% RMSE reduction in longitudinal velocity, sideslip angle, and yaw rate estimation compared to standard UKF.

Comparative analysis between speed differential control and torque differential control under various operational conditions demonstrates distinct stability outcomes. Specifically,

speed-differential control fails to ensure vehicle stability on low-adhesion surfaces due to inherent limitations of the Ackermann steering model, which neglects transient tire–road interactions. Conversely, torque-differential control maintains robust directional stability through real-time active modulation of wheel torque, enabling stable vehicle operation during medium-to-high-speed cornering maneuvers.

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