Adaptive trajectory tracking control strategy of intelligent vehicle

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Abstract
The trajectory tracking control strategy for intelligent vehicle is proposed in this article. Considering the parameters perturbations and external disturbances of the vehicle system, based on the vehicle dynamics and the preview follower theory, the lateral preview deviation dynamics model of the vehicle system is established which uses lateral preview position deviation, lateral preview velocity deviation, lateral preview attitude angle deviation, and lateral preview attitude angle velocity deviation as the tracking state variables. For this uncertain system, the adaptive sliding mode control algorithm is adopted to design the preview controller to eliminate the effects of uncertainties and realize high accuracy of the target trajectory tracking. According to the real-time deviations of lateral position and lateral attitude angle, the feedback controller is designed based on the fuzzy control algorithm. For improving the adaptability to the multiple dynamic states, the extension theory is introduced to design the coordination controller to adjusting the control proportions of the preview controller and the feedback controller to the front wheel steering angle. Simulation results verify the adaptability, robustness, accuracy of the control strategy under which the intelligent vehicle has good handling stability.

Keywords
Trajectory tracking, adaptive sliding mode control algorithm, coordination control, dynamic state, intelligent vehicle

Introduction
Traffic congestion, frequent accidents, environmental pollution, and energy waste become more and more serious with the swift growth of traffic volume and vehicle ownership. The traditional vehicle needs a driver to drive it. Due to the differences of the drivers’ driving skill, physical and mental condition, personality, gender, and so on, the driver’s personal factors are the main cause of traffic accidents. Intelligent vehicle can make people get rid of the “driver–vehicle–road” closed-loop traffic control system, and form “vehicle–road” closed-loop traffic control system to eliminate the influence of the personal factor differences of drivers. In the same traffic environment, the intelligent vehicle can be driven safely, efficiently, and legally with optimal driving strategies and driving techniques, thereby can greatly improve the efficiency of the transportation system, significantly reduce the traffic accident rate, and also can reduce the energy consumption and the exhaust emissions. The key technologies of intelligent vehicle include the environmental perception, the behavioral decision, the path planning, and the motion control. The motion control technology is the basis of other key technologies. The
trajectory tracking is a basic functional, but is vital to ensure that the intelligent vehicle tracks the target trajectory safely and accurately.

The vehicle needs to travel along the target trajectory on a certain width road, so the trajectory tracking control must be highly accurate. The driver determines the appropriate steering wheel angle to control the vehicle to track the target trajectory based on the preview deviation, which is obtained through previewing the trajectory in a certain distance. So, the single-point preview follower theories and multi-point preview follower theories are proposed by CC MacAdam, K-H Guo, RS Sharp and colleagues successively. Due to the characteristics of intelligent vehicle operation and execution, the preview follower theories have been widely applied in trajectory tracking control.

The vehicle dynamics model is the basis of the trajectory tracking control of intelligent vehicle. The vehicle dynamics factors determine performances of the target trajectory tracking which can be improved through comprehensively considering of the vehicle dynamics factors and combining with the advanced and/or fused control algorithms. However, the parameter perturbations and the external perturbations of the vehicle during driving are not considered in these papers. They are the important factors to further improve the tracking control performance.

Some control algorithms with strong robustness and adaptivity are used for these factors on the current research, such as the backstepping control algorithm, the sliding mode control (SMC) algorithm, the H-infinity algorithm, the optimization algorithm, and so on. Considering the parameters uncertainties of the tire-road friction coefficient and the lateral tire stiffness, and the presence of external perturbations, an attitude controller of vehicle is designed based on the lateral dynamic model to track the trajectory. In view of the tire forces saturations, system uncertainties, and the variation of the desired-path curvature, a composite nonlinear feedback control algorithm based on the integral sliding mode is proposed. Considering influence of the tire friction physical limits and the external disturbance on driving conditions, a robust steering controller is designed by the backstepping variable structure control algorithm. The active disturbance rejection control is applied to the steering controller to estimate the uncertainties and the external disturbances in real time and compensate them actively. In view of vehicle nominal cornering stiffness, road–tire adhesion coefficient, inertial parameters, and forward speed, a robust adaptive indirect control method is proposed based on an exponential-like-sliding-mode fuzzy type-2 neural network approach to enhance tracking performance. An adaptive multivariable super-twisting control strategy is proposed to deal with the multiple unknown and mismatched disturbances problem of the steering system. A steering controller based on fuzzy-adaptive preview time for the robust SMC is proposed according to the curvature change and the lateral acceleration of vehicle. A hierarchical lateral control scheme is proposed, where the upper controller is designed by the linear quadratic regulator algorithm based on robust H-infinity to compensate the sensor-induced delays. In view of parametric uncertainties, external disturbances, and over-actuated features, an adaptive hierarchical control framework is proposed which applies an adaptive sliding mode high-level control law to produce a vector of front steering angle and external yaw moment. The learning algorithm is also applied to the motion control gradually. In terms of the problem of model error and tracking dependence, an intelligent vehicle model transfer trajectory planning method is proposed based on the deep reinforcement learning to obtain the effective the control action and trajectory sequences.

In the papers mentioned above, the adaptability of the control system to parametric uncertainties and external disturbances is improved through the control algorithms with strong robustness. The vehicle is a highly nonlinear, time-varying, intensive coupling, uncertain, and complex system with time lag. So, it is difficult to establish an accurate vehicle dynamics model. The majority of the papers just take into account a part of dynamics characteristics and uncertainties. Moreover, the dynamic state of intelligent vehicle is changing as the target trajectory, front wheel steering angle, and velocity. Intelligent vehicle may travel in the various dynamic states which lead to the differences of accuracy, handling stability, and so on. Especially, the trajectory curvature which changes a lot will cause some potential hazards. The circumstances of vehicle traveling cannot be fully listed as far as we know, and the control strategies for them cannot be designed correspondingly. So, the extensive adaptive trajectory tracking control method and strategy should be investigated to ensure not only the accuracy of trajectory tracking but also the robustness and adaptability to uncertainties and dynamic states.

Considering the uncertainties and various dynamic state, this article researches a novel robust adaptive trajectory tracking control strategy. The main contributions are summarized as follows: the lateral preview deviation dynamics model of the vehicle system is established involving the parameters perturbations and external disturbances of the system; according to the tracking state variables, the preview control method based on the adaptive sliding mode control (ASMC) algorithm is proposed to realize strong robustness and adaptability of the trajectory tracking control to uncertainties; the coordination control method is proposed to adjust the proportions of the preview controller and the feedback controller to the front wheel steering angle.
in order to improve the adaptability to multiple dynamic states.

This article is organized as follows. In section "Trajectory tracking control strategy," the trajectory tracking control strategy is constructed. The lateral preview deviation dynamics model of the vehicle is established and the preview controller is presented based on the ASMC algorithm in section "Preview controller." In section "Feedback controller," the feedback controller is designed using the fuzzy control algorithm. In section "Coordination controller," the coordination controller is proposed using the extension theory. Simulation studies are provided in section "Simulation results," where the simulation results are presented and analyzed. Conclusions are presented in section "Conclusion."

**Trajectory tracking control strategy**

According to the preview information and the feedback information obtained through the environmental perception system, the trajectory tracking is realized by the hierarchical trajectory tracking control strategy in this article. It consists of a preview control layer, a feedback control layer, and a coordination control layer, as shown in Figure 1. Based on the simplified lateral dynamics model of vehicle, the preview control layer introduces the uncertain factors to establish the lateral preview deviation dynamics model, and uses the ASMC algorithm to design the preview controller to track the target trajectory. In the feedback control layer, the fuzzy control algorithm is adopted to design the feedback controller to eliminate the real-time tracking deviation. The coordination control layer coordinates the control proportions of the preview controller and the feedback controller, and finally outputs the front wheel steering angle to control the vehicle lateral motion.

**Preview controller**

**Preview control model**

Considering that the single-point preview follower theory can meet the accuracy requirement of the trajectory tracking and its calculation amount is small, the single-point preview follower theory is adopted in this article. The preview distance is usually described by the preview time, and should be adjusted in accordance with the vehicle velocity to ensure the accuracy and stability during preview following the target trajectory. To avoid that the preview controller works too frequently or too slowly, the function of the single-point preview distance with vehicle velocity and preview time as variables is designed as follows

\[
L_p(v, t_p) = \begin{cases} 
L_{p\text{min}} & \text{if } v < v_{\text{min}} \\
L_p & \text{if } v_{\text{min}} \leq v \leq v_{\text{max}} \\
L_{p\text{max}} & \text{if } v > v_{\text{max}}
\end{cases}
\]

where \( v \) is the vehicle velocity; \( t_p \) is the preview time; \( L_{p\text{min}} \) and \( L_{p\text{max}} \) are the minimum and maximum preview distances, respectively; \( v_{\text{min}} \) and \( v_{\text{max}} \) stand for the velocity thresholds corresponding to the minimum and maximum preview distances, respectively. K-H Guo et al.\(^{41}\) obtain the driver’s preview time range of \([0.58, 2.072]\) s by identifying the driver model parameters. This article determines that \( t_p \) is 1 s, \( v_{\text{min}} \) is 20 km/h, \( v_{\text{max}} \) is 90 km/h, \( L_{p\text{min}} \) is 6 m, and \( L_{p\text{max}} \) is 25 m.

The vehicle mass center is acted as the reference point of vehicle motion. On the condition that the real-time position and attitude angle \((x_0, y_0, \phi_0)\), velocity \( v \) and the target trajectory curvature \( \rho \) are obtained, the mass center is used as the center of a circle, and \( L_p \) is used as the radius to draw an arc in front of the vehicle. The intersection point of the arc and the extending line of the longitudinal axis of the vehicle stands for the preview point, and the intersection point of the arc and the target trajectory stands for the target point. The positions and attitudes of the vehicle at the two points are described as the preview state \((x_p, y_p, \phi_p)\) and the target state \((x_{t\text{r}}, y_{t\text{r}}, \phi_{t\text{r}})\), respectively. In the preview process of intelligent vehicle, the lateral preview position deviation is the position deviation \( y_r \), and the lateral preview attitude angle deviation is the yaw angle deviation \( \phi_r \). The principle of the single-point preview control is shown in Figure 2.

The influence of time lag \( \tau \) of the steering system is introduced to the dynamic model. According to the principle of the single-point preview control and the 2-degree-of-freedom (2-DOF) vehicle dynamics model, the front wheel steering angle \( \delta_p \) is considered as the control vector; \( Y = (y_r, \phi_r)^T \) is the output vector; the state vector is \( X = (y_r, \dot{y}_r, \phi_r, \dot{\phi}_r, \delta_p)^T \). Suppose the velocity is approximately equal to longitudinal velocity...
the lateral preview deviation dynamics model is rewritten as

\[
\begin{align*}
\dot{X} &= (A + \Delta A(t))X + (B + \Delta B(t))U + D(t) \\
Y &= CX 
\end{align*}
\]

where \(\Delta A(t)\) and \(\Delta B(t)\) are the parameter perturbation matrixes, and \(D(t)\) is the external disturbance matrix.

**Preview control method**

Since the sliding mode motion has no relations with the parameters and the disturbance of the system, the SMC algorithm has strong robust performance to the unmodeled dynamics, parameter perturbation, and external disturbance of the controlled object. Therefore, the lateral preview deviation dynamics model is used as the controlled system, and the ASMC algorithm is adopted to design the preview controller to realize the preview trajectory tracking in this article.

The lateral preview deviation dynamics system is an uncertain system with parameter perturbations and external disturbances, as shown as formula (4)

\[
\begin{align*}
\dot{x}(t) &= (A + \Delta A(t))x(t) + (B + \Delta B(t))u(t) + D(t) \\
x(t_0) &= h(t_0)
\end{align*}
\]

where \(x(t) \in R^{5 \times 1}\) and \(u(t) \in R^{1 \times 1}\) are the state vector and the control vector, respectively, and \(x(t)\) is obtained from the sensors; \(A \in R^{5 \times 5}\) and \(B \in R^{5 \times 1}\) are the nominal matrixes of the system, respectively, which satisfy the controllable conditions, and \(B\) is a full rank matrix; \(\Delta A(t) \in R^{5 \times 5}\) and \(\Delta B(t) \in R^{5 \times 1}\) are the uncertain matrixes of the parameter perturbations, and \(D(t) \in R^{5 \times 1}\) is the uncertain matrix of the external disturbances. \(\Delta B(t)\) meets the matched conditions of the sliding mode, while \(\Delta A(t)\) and \(D(t)\) don’t; and \(h(t_0)\) is the initial value of the status vector.

Using the method of nonsingular linear transformation, the uncertain matrixes are projected into the matched space and the mismatched space. According to the equation of the lateral preview deviation dynamic system, the matrix \(E\) is selected to be \(I^{5 \times 5}\), and the system is decomposed into two subsystems after the nonsingular linear transformation as follows

\[
\begin{align*}
\dot{z}_1(t) &= (A_{11} + \Delta A_{11}(t))z_1(t) + (A_{12} + \Delta A_{12}(t))z_2(t) + D_1(t) \\
\dot{z}_2(t) &= (A_{21} + \Delta A_{21}(t))z_1(t) + (A_{22} + \Delta A_{22}(t))z_2(t) + (B_2 + \Delta B_2(t))u(t)
\end{align*}
\]

where equations (5) and (6) are the two subsystems projected into the mismatched space and the matched space, respectively. For the subsystem in the mismatched space (equation (5)), uncertain matrixes \(\Delta A_{11}(t)\) and \(\Delta A_{12}(t)\) can be expressed as

\[
\begin{align*}
L_p((a_{k_f} - b_{k_c})/I_{2z}), & \quad a_{23} = -((k_f + k_r)/m) - L_p((a_{k_f} - b_{k_c})/I_z), \\
a_{24} = -((L_p - a_{k_f} + (L_p + b_{k_c})/m - L_p((a(L_p - a_{k_f} - b_{k_c})/I_z), & \quad a_{43} = -(a_{k_f} - b_{k_c})/I_z), \\
a_{44} = -(a_{L_p - a_{k_f}}), & \quad k_f = b(L_p + b_{k_c})/I_{2z}, \\
a_{45} = ak_f/I_z, & \quad a_{55} = -1/\tau_s, \\
a_{53} = 1/\tau_s, d_2 = \rho((L_p - a_{k_f})k_f + (L_p + b_{k_c})/m) + \rho{d_4} = \rho((a(L_p - a)k_f - b(L_p + b_{k_c})/I_z)} + v_2^2
\end{align*}
\]
The switching function. In this article, the switching function is designed in accordance with the mismatched uncertainties and the matched uncertainties of the system. Since the nominal form of the lateral preview deviation dynamic system is a linear system, \( s(t) = Kz(t) \) is chosen as the switching function. The switching function can also be represented as follows

\[
s(t) = [K_0 \quad I]^T [z_1(t) \quad z_2(t)]^T (7)
\]

where \( K \in R^{5 \times 5} \) and \( K_0 \in R^{1 \times 4} \). According to the definition of the switching function, when \( D_1(t) = 0 \), equation (7) can be transformed as \( z_2(t) = -K_0 z_1(t) \).

Because the subsystem (equation (5)) is not directly related to the variable \( u(t) \), the state variable \( z_2(t) \) of the subsystem (equation (6)) is acted as the virtual control vector of the subsystem (equation (5)), then \( z_2(t) = -K_0 z_1(t) \) is substituted into the subsystem (equation (5)). Considering the uncertain factors, the reduced-order system state equation can be expressed as

\[
\dot{z}_1(t) = (A_{11} + \Delta A_{11}(t))z_1(t) - (A_{12} + \Delta A_{12}(t))K_0 z_1(t) (8)
\]

where \( A_{11} \) and \( A_{12} \) are obtained through nonsingular linear transforming of the nominal matrix \( A \). They satisfy the controllable conditions because \( A \) satisfies the controllable conditions. Therefore, the system (equation (8)) can be made asymptotically stable by selecting an appropriate value of \( K_0 \). The Lyapunov function is selected as \( V(t) = z_1^T(t)Qz_1(t) \), where \( Q \) is a symmetric positive definite matrix. \( z_1(t) = 0 \) is not considered here. The sufficient condition for the asymptotic stability of the system (equation (8)) is that \( \dot{V}(t) < 0 \), that is to say, the sufficient condition can be expressed as

\[
P + (J_1 - J_2 K_0)^T H^T(t) H(t) < 0 (9)
\]

where \( P = (A_{11} - A_{12} K_0)^T Q + Q (A_{11} - A_{12} K_0) \). When \( H(t) \) satisfies the condition \( H^T(t) H(t) \leq I \), equation (9) is valid, and the system (equation (8)) is asymptotically stable.

The control function. The switching method is used to design the SMC function. The control function consists of an equivalent control function \( u_{eq}(t) \) and a switching control function \( u_m(t) \), which represent the controls for certainties and uncertainties of system, respectively. It can be expressed as formula (10)

\[
u(t) = u_{eq}(t) + u_m(t) (10)
\]

After nonsingular linear transformation, the switching function of the lateral preview deviation dynamics system is expressed as \( s(t) = Kz(t) \). The derivative of \( s(t) \) is obtained that

\[
\dot{s}(t) = K \dot{z}(t) = K_0 (A_{11} z_1(t) + A_{12} z_2(t)) + A_{21} z_1(t) + A_{22} z_2(t) + B_2 u(t) + \xi(t) (11)
\]

where \( \xi(t) = K_0 (\Delta A_{11}(t) z_1(t) + \Delta A_{12}(t) z_2(t)) + \Delta A_{21}(t) z_1(t) + \Delta A_{22}(t) z_2(t) + \Delta B_2 u(t) + K_0 D_1(t) \).

The equivalent control function is designed without considering parameter uncertainties and external disturbances. The switching control function is used to eliminate parameter perturbations and external disturbances. The external disturbances of the lateral preview deviation dynamic system have not been considered in the analysis of the subsystem (equation (5)). The external disturbance matrix \( D_1(t) \) is a mismatched matrix which is mainly determined by the curvature of the target trajectory, and is the direct influence factor of the vehicle lateral movement. The purpose of the vehicle lateral movement is to travel along the target trajectory. Therefore, it is necessary to estimate the external disturbance and introduce it into the control function.

Assumption 1. There are positive constants \( \gamma_0 \) and \( \gamma_1 \) to make any state vector \( z(t) \) and external disturbances \( D_1(t) \) meet the inequality condition

\[
\| K_0 \| D_1(t) \| \leq \gamma_0 \| z(t) \| \|z(t)\|^{\frac{3}{2}}
\]

\( \tilde{\gamma}_0(t) \) and \( \tilde{\gamma}_1(t) \) are the estimate values of \( \gamma_0 \) and \( \gamma_1 \), whose corresponding estimation errors are \( \hat{\gamma}_0(t) \) and \( \hat{\gamma}_1(t) \). The adaptive law is designed as follows

\[
\left\{ \begin{array}{l}
\hat{\gamma}_0(t) = r_0^{-1} \| s(t) \|
\hat{\gamma}_1(t) = r_1^{-1} \| s(t) \| \| z(t) \|
\end{array} \right. (12)
\]
According to the reachable condition of the sliding mode surface, the Lyapunov function is constructed as shown as formula (13)

\[ V(t) = \frac{1}{2} s^2(t) + \frac{1}{2} r_0 \bar{y}_0^2(t) + \frac{1}{2} r_1 \bar{y}_1^2(t) \]  

(13)

The derivative of \( V(t) \) is

\[ \dot{V}(t) = s^T(t) \dot{s}(t) + r_0 \bar{y}_0 \dot{\bar{y}}_0(t) + r_1 \dot{\bar{y}}_1(t) \]  

(14)

Finally, the equivalent control function and the switching control function can be expressed as

\[ u_{eq}(t) = \frac{-B_2^{-1}}{1 + \lambda_3} \left[ K_0(A_{11} \dot{z}_1(t) + A_{12} \dot{z}_2(t)) + A_{21} \dot{z}_1(t) + A_{22} \dot{z}_2(t) \right] \]  

(15)

\[ u_{sw}(t) = \frac{-s(t)B_2^{-1}}{1 + \lambda_3} s(t) \left[ \|K_0G\| + |J_1| + \lambda_1 \|B_2\| \|z_1(t)\| \
+ \|K_0G\| |J_2| + \lambda_2 \|B_2\| \|z_2(t)\| \
+ (\dot{\bar{y}}_0(t) + \dot{\bar{y}}_1(t)) \|z(t)\| + \xi_1 \right] \]  

(16)

where \( \xi_1 > 0 \).

The control function \( u(t) = u_{eq}(t) + u_{sw}(t) \) is brought into formula (14), and then the results are obtained as follows

\[ \dot{V} \leq \xi_1 \|s(t)\| \leq 0 \]  

(17)

Inequality (equation (17)) shows that the control function \( u(t) \) can make the derivative of Lyapunov function negative semi-definite. That is, \( u(t) \) can make the lateral preview deviation dynamic system satisfy the reachable condition of the sliding mode surface from any state and reach the sliding mode surface in limited time.

**Feedback controller**

The preview control belongs to the feedforward control. It is used to eliminate the position and attitude deviations at the preview point, but it can’t completely eliminate the real-time deviations of position and attitude between the vehicle and the target trajectory. Therefore, the feedback controller is needed as a supplement to the preview controller.

The article seeks the two points of the target trajectory which are nearest to the intelligent vehicle. Then, a line is used to connect the two points. The position and attitude angle deviations between this line and the vehicle are used as the feedback information. The trajectory tracking deviation feedback principle is shown in Figure 3. The vehicle position and attitude angle at the mass center \( P_1 \) are expressed as \( (x_0, y_0, \phi_0) \) which is obtained by the positioning system and the posture sensor. The two points \( L_{ef} \) and \( L_{fr} \) are closest to the lateral centers of the front and rear axles of the vehicle through searching the target trajectory in real time. The two points coordinates are \( (x_{ef}, y_{ef}) \) and \( (x_{fr}, y_{fr}) \), respectively. The vertical distance from the point \( P_i \) to the connecting line is the position deviation \( e_y \), and the angle between the longitudinal axis of vehicle and the connecting line is the attitude angle deviation \( e_\phi \), as shown as formulas (18) and (19), respectively.

\[ e_y = \frac{kx_0 - y_0 - k_{x_{ef}} + y_{ef}}{\sqrt{1 + k^2}} \]  

(18)

\[ e_\phi = \varphi_0 - \varphi_f \]  

(19)

where \( k = ((y_{ef} - y_{fr})(x_{ef} - x_{fr})); \varphi_f = ac \tan (k) \).

The feedback controller is mainly made of the position fuzzy controller and the attitude fuzzy controller. The control principle is shown in Figure 4.

The abscissa values of points on the target trajectory are set to be 0. According to the lane width in the road, the discourse domains of \( e_y \) and \( \dot{e}_y \) are set to \((-1.87, 1.87) \) m and \((-5, 5) \) m/s, respectively. Assuming that the vehicle is traveling forward on the road, the discourse domains of \( e_\phi \) and \( \dot{e}_\phi \) are set to \((-90, 90) \) and \((-20, 20) \) \(^\circ\)/s, respectively. The discourse domain of the front wheel steering angle is set to \((-10, 10) \)\(^\circ\).

Fuzzy subsets of input and output variables are defined as \{NB, NM, NS, ZO, PS, PM, PB\}, and are fuzzified by the Gaussian curve membership function. The control rules of the position fuzzy controller and the attitude fuzzy controller are designed as shown in Tables 1 and 2, and Mamdani method is used to fuzzy reason.

Then, the article method is used to defuzzify to obtain the control variable \( \delta_y \) of the position fuzzy controller and the control variable \( \delta_{\phi y} \) of the attitude fuzzy controller. Since they are equally important for the trajectory tracking, the weight coefficients \( \lambda_y \) and \( \lambda_\phi \) of \( \delta_y \) and \( \delta_{\phi y} \) are set to 0.5. Finally, the control variable \( \delta_{ef} \) of the feedback controller is shown as
Coordination controller

The preview controller is used to eliminate the deviation of the preview position and attitude. The feedback controller is used to eliminate the deviation of the real-time position and attitude. However, the dynamic state is time-variable as vehicle traveling, such as the stable state, the extreme state, the unstable state, and so on, which may cause the large real-time position deviations, real-time attitude deviations, and/or lateral motion to make vehicle dangerous. So, the accuracy, handling stability, safety of trajectory tracking need to improve. The extension theory is adopted to design the coordination controller to adjust the preview controller and feedback controller to improve these performances. The yaw rate $\omega$ and the real-time position deviation $\dot{e}_y$ are selected as the characteristic variables. The extension set is divided into classical domain C, extension domain E, and non-domain N, as shown in Figure 5. Different domains correspond to different proportion strategies of the preview controller and the feedback controller.

Domain boundary

The relation curves of the lateral forces and the sideslip angles of the tire are linear in the condition that the lateral force is smaller than $\mu F_z/3$ and the lateral force.

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**Figure 4.** Control principle of the feedback controller.

**Table 1.** Control rules of the position fuzzy controller.

| $\delta_{ff}$ | $\dot{e}_y$ | $\delta_{ff}$ |
|---------------|-------------|---------------|
|               | NB          | NM            | NS            | ZO            | PS            | PM            | PB            |
| $\dot{e}_y$   | NB          | PB            | PB            | PM            | PM            | PS            | PS            | ZO            |
|               | NM          | PB            | PM            | PM            | PS            | PS            | ZO            | NS            |
|               | NS          | PM            | PM            | PS            | PS            | ZO            | NS            | NS            |
|               | ZO          | PM            | PS            | PS            | ZO            | NS            | NS            | NS            |
|               | PS          | PS            | ZO            | NS            | NS            | NM            | NM            | NM            |
|               | PM          | PS            | ZO            | NS            | NS            | NM            | NM            | NM            |
|               | PB          | ZO            | NS            | NS            | NM            | NM            | NB            | NB            |

**Table 2.** Control rules of the attitude fuzzy controller.

| $\delta_{fs}$ | $\dot{e}_u$ | $\delta_{fs}$ |
|---------------|-------------|---------------|
|               | NB          | NM            | NS            | ZO            | PS            | PM            | PB            |
| $\dot{e}_u$   | NB          | PB            | PM            | PM            | PM            | PS            | PS            | ZO            |
|               | NM          | PM            | PM            | PM            | PS            | PS            | ZO            | NS            |
|               | NS          | PM            | PM            | PS            | PS            | ZO            | NS            | NS            |
|               | ZO          | PM            | PS            | PS            | ZO            | NS            | NS            | NS            |
|               | PS          | PS            | ZO            | NS            | NS            | NM            | NM            | NM            |
|               | PM          | PS            | ZO            | NS            | NS            | NM            | NM            | NM            |
|               | PB          | ZO            | NS            | NS            | NM            | NM            | NM            | NB            |

\[
\delta_{ff} = \lambda_1 \delta_{ff} + \lambda_2 \delta_{fs} \tag{20}
\]
acceleration is smaller than 0.4g, where μ is the road adhesion coefficient, and $F_z$ is the vertical load of the tire. In this condition, the dynamic state is stable as the ideal state, and the vehicle model can be linearized. Assuming that the vehicle is on an ideal state, the ideal yaw rate $\omega_{des}$ can be obtained based on the 2-DOF vehicle dynamics model, as shown in equation (21)

$$\omega_{des} = \frac{v_x}{R} = \frac{v_y \delta_f}{a + b + \frac{mv_1^2(b_3 - ab_1)}{2k_e(a + b)}}$$  \hspace{1cm} (21)$$

The $\omega_{des}$ is often regarded as the ideal target of vehicle lateral motion control. Due to the yaw rate changes with road adhesion coefficient, front wheel steering angle, and velocity, the ideal yaw rate is difficult to realize. The adhesive force of the tire to road surface is the base of vehicle motion. The force which the road surface can apply against the tire cannot exceed the road adhesive force. So, the road adhesion coefficient is introduced to the vehicle dynamics model.

The relationship between the road adhesion coefficient $\mu$ and the lateral acceleration of the vehicle should be $a_y = \mu g$. The lateral acceleration can be expressed as the function of the yaw rate and the sideslip angle of mass center, as shown in function (equation (22))

$$a_y = v_x \omega + \tan(\beta) v_y + \frac{v_y \dot{\beta}}{\sqrt{1 + \tan^2(\beta)}}$$  \hspace{1cm} (22)$$

where $v_x$ is lateral velocity of vehicle; $\beta$ is the sideslip angle of the mass center.

As the sideslip angle of mass center and its differential value are very small, the contribute ratio of the second and third parts is generally set to 15% to the overall lateral acceleration. Therefore, the upper limit of the yaw rate on the extreme state is shown in equation (23)

$$\omega_{upper-limit} = 0.85 \frac{ug}{v_x}$$  \hspace{1cm} (23)$$

This upper limit of the yaw rate is used as extension domain boundary $\omega_2$. Because the trajectory accuracy is lower in this domain, the extension domain boundary $e_{2y}$ is set to 1.6 m. The yaw rate which is $\min(\omega_{des} , 0.4u/g/v_x)$ is set as the classical domain boundary $\omega_1$, and the classical domain boundary $e_{3y}$ is set to 0.8 m.

**Correlation degree and measure mode**

In the characteristic plane $\omega - e_y$, the original point is $O(0, 0)$. $S(\omega, e_y)$ stands for a point in the characteristic plane, and $L = |SO|$ stands for the distance between the point $S$ and the original point $O$. The rays $OS$ passes from the original point $O$ to the point $S$, and intersects with the boundaries of the classical domain C and the extension domain E at the point $S_1$ and the point $S_2$, respectively. The distances from the two intersection points to the original point $O$ are $L_1 = |S_1O|$ and $L_{-1} = |S_2O|$, respectively. The Correlation degree function is designed as

$$R(S) = \begin{cases} 
1 - L/L_1 & S \in C \\
(L_1 - L)/(L_{-1} - L_1) & S \notin C 
\end{cases} \hspace{1cm} (24)$$

According to the Correlation degree function, when $R(S) \in [0, 1]$, the characteristic state of $S(\omega, e_y)$ belongs to the classical domain; when $R(S) \in [-1, 0)$, it belongs to the extension domain; when $R(S) \in (-\infty, -1)$, it belongs to the non-domain.

**Coordination of the control proportions**

The Correlation degree function is used to calculate $\gamma_p$ and $\gamma_f$ which are the control proportions of the preview controller and the feedback controller to the front wheel steering angle. The design principles of the control proportions are due to the good handling stability and the minor deviation of real-time position in the classical domain C, the trajectory tracking is realized by the preview controller; as the handling stability and tracking accuracy decreases in the extension domain E where the vehicle is on the extreme state and is potentially dangerous, the control proportion of the feedback control gradually increases and that of the preview controller gradually decreases; because the handling stability and the tracking accuracy are worse in the non-domain N where the vehicle is on the unstable state and is very dangerous, the trajectory tracking is controlled by the feedback controller. $\gamma_p$ and $\gamma_f$ are determined as shown

$$\begin{cases} 
(\gamma_p, \gamma_f) = (1, 0) & S \in C \\
(\gamma_p, \gamma_f) = (1 - LR_{sgn}(R)/L_{-1}, LR_{sgn}(R)/L_{-1}) & S \in E \\
(\gamma_p, \gamma_f) = (0, 1) & S \in N 
\end{cases} \hspace{1cm} (25)$$
Simulation results

In this section, two simulation tests which are the straight trajectory tracking test and the double lane change test are investigated to verify the effectiveness of the proposed control method and control strategy. The uncertainties of the lateral preview deviation dynamics model of the vehicle system are set as follows: the perturbations of the tire cornering stiffnesses are set to $0.03 \cos(0.1t)$ and $0.03 \cos(0.1t)$, respectively, and the time lag perturbation is set to $0.02 \cos(0.1t) t$.

Straight trajectory tracking test

The performance of straight trajectory tracking belongs to the basic traveling performance of intelligent vehicle. By giving the initial lateral position and attitude angle of intelligent vehicle and the straight trajectory, the performance of traveling into and along the straight trajectory of the preview controller is tested. The simulation test conditions are set as follows: the initial position and attitude angle are set to $(0, 0, 0)$; the straight trajectory is $y = 1$ m; the vehicle is traveling with the uniform velocity of 20 m/s. Besides, the preview controller based on the sliding mode control algorithm which is denoted as “SMC” is introduced as the comparison method.

In Figure 6, it can be found that ASMC preview controller without uncertainties has the best tracking accuracy, and it yields the traveling trajectory whose convergence rate is the fastest. For SMC preview controller with uncertainties, the tracking accuracy decreases largely and the convergence rate of the traveling trajectory is slower than that without uncertainties. The tracking accuracy of ASMC preview controller is influenced by uncertainties slightly, and its convergence rates of the traveling trajectories on the two conditions are almost the same. The front wheel steering angle curves of the two preview controllers on the two conditions are shown in Figure 7. Although the maximum angle of SMC preview controller with uncertainties is close to that without uncertainties, the front wheel steering angle curve of the former condition fluctuates significantly in the process of vehicle traveling into the straight target trajectory. The maximum angle of ASMC preview controller without uncertainties is $1.48^\circ$, and that with uncertainties increases to $3.17^\circ$, but the two front wheel steering angle curves are similar and stable.

The values of the four state variables which are the lateral preview position deviation, the lateral preview velocity deviation, the lateral preview attitude angle deviation, and the lateral preview attitude angle velocity deviation of the preview controller are shown in Figures 8–11.

When the dynamics model with uncertainties, the each variable curves of SMC and ASMC preview controllers are both affected by uncertainties. It can be seen from Figure 8 that the curve of the lateral preview position deviation under ASMC preview controller is less affected by the uncertainties than that under SMC preview controller, and converge rapidly to zero. As shown in Figure 9, the variational trends of the lateral preview velocity deviation curves under ASMC preview controllers with uncertainties and without uncertainties are approximately consistent and smooth. As can be seen from Figure 10, the uncertainties have a little effect on the curve of the lateral preview attitude angle deviation under ASMC preview controller, but have a great effect on that under SMC preview controllers and cause the fluctuation. In Figure 11, the maximum value of the curve of the lateral preview attitude angle velocity deviation under ASMC preview controller with uncertainties increases, but the trend and the
The convergence rate of this curve are similar to that without uncertainties. The curve of the lateral preview attitude angle velocity deviation under SMC preview controller with uncertainties fluctuates significantly. The ASMC preview controller makes the state variables curves converge more quickly and stably, so that adjusts vehicle position and attitude to obtain better performance of the straight trajectory tracking.

The yaw rate curves of vehicle are shown in Figure 12. Although the maximum value of the curve under ASMC preview controller with uncertainties is larger than that without uncertainties, it is lower than those under SMC preview controllers with and without uncertainties. And the curves under ASMC preview controller are more stable and smoother. There is a large oscillation of the curve under SMC preview controller with uncertainties. So, the handling stability under ASMC preview controller is finer than that under SMC preview controller.

The results of the simulation test verify that ASMC preview controller has strong adaptivity and robustness, and can make intelligent vehicle accurately, rapidly, and stably travel into and along the straight target trajectory and have good handling stability.

Double lane change test
In the process of double lane change test, the dynamic state of intelligent vehicle alternates between stable state, extreme state, and unstable state. It is investigated for the verifications of adaptability of the proposed control strategy. In this simulation test, the intelligent
vehicle travels at high velocity of 25 m/s. The simulation results are shown in Figures 13–17.

From the results in Figure 13, the preview controller and the coordination controller which embodies the proposed control strategy both well complete the double lane change test. And the vehicle under the proposed control strategy has better tracking accuracy. According to the vehicle state, the proposed control strategy adjusts the control proportions of the preview controller and the feedback controller through the coordination controller. In Figure 14, the control proportions under the coordination controller present that the preview controller is the main and the feedback controller is the auxiliary which works when the real-time lateral position deviation or/and the yaw rate beyond the classical domain. The front wheel steering angles are shown in Figure 15. In comparison with the preview controller, the front wheel steering angle curve under the proposed control strategy appears large changes when the vehicle is in the extreme state and the unstable state, where the control proportion of the feedback controller increases and that of the preview controller decreases to adjust vehicle state as shown in Figure 14.

Given that the vehicle should travel along the trajectory of double lane change test, there must be large real-time lateral position deviation and large yaw rate. In the light of the domain boundaries, the dynamic state of the vehicle is transferring between the stable state, the extreme state, and the unstable state under the preview controller. But through the proposed control strategy, the vehicle doesn’t undergo the unstable
state, and the real-time lateral position deviation and the yaw rate decrease dramatically. Compared with the preview controller, the maximum value of the real-time lateral position deviation on the right reduces 0.32 m, and that on the left reduces 0.44 m in Figure 16. Under the proposed control strategy, the maximum values of the yaw rate decline $9.94 \, \text{rad/s}$ on the right and $13.19 \, \text{rad/s}$ on the left in Figure 17.

It clearly found that the proposed control strategy can effectively improve handling stability and tracking accuracy in tracking process. It has strong adaptivity to multiple dynamic states.

**Conclusion**

The article investigates the adaptive trajectory tracking control strategy for intelligent vehicle. Considering the parameters perturbations and external disturbances of the vehicle system, according to the tracking state variables, the preview control method based on the ASMC algorithm is proposed to realize the accuracy, robustness, and adaptability of trajectory tracking. The feedback control method is designed based on the fuzzy control algorithm to reduce the real-time tracking deviation. In order to further improve the accuracy and handling stability of trajectory tracking on the multiple dynamic states, the coordination control method is proposed to adjust the preview controller and the feedback controller to enhance adaptability to multiple dynamic states. The simulation results of the straight trajectory tracking test and the double lane change test show that the proposed control strategy has strong adaptivity and robustness to the uncertainties, has strong adaptivity to multiple dynamic states, can make intelligent vehicle accurately, rapidly, and stably travel along the target trajectory and have good handling stability.

In this article, we assume that the intelligent vehicle travels at uniform velocity. But the actual velocity of intelligent vehicle is controllable and variable. The variable velocity isn’t considered in the proposed control strategy. In the future, we intend to introduce the velocity control to improve the trajectory tracking control strategy, which can further enhance the adaptability to the dynamic states during trajectory tracking through the coupling control of the lateral and longitudinal motions.

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**Appendix 1**

**Notation**

\[ a, b \] \hspace{1cm} \text{distances from the front and rear axles to the mass center}

\[ a_y \] \hspace{1cm} \text{lateral acceleration of the mass center}

\[ g \] \hspace{1cm} \text{gravitational constant}

\[ I_z \] \hspace{1cm} \text{moment of inertia around the z-axis}

\[ k_f, k_r \] \hspace{1cm} \text{tire cornering stiffnesses of the front and rear wheels}

\[ L_p \] \hspace{1cm} \text{single-point preview distance}

\[ m \] \hspace{1cm} \text{cross weight}

\[ t_p \] \hspace{1cm} \text{preview time}

\[ v \] \hspace{1cm} \text{vehicle velocity}

\[ v_x \] \hspace{1cm} \text{longitudinal velocity of the mass center}

\[ v_y \] \hspace{1cm} \text{lateral velocity of the mass center}

\[ \beta \] \hspace{1cm} \text{sideslip angle of the mass center}

\[ \delta_{ff} \] \hspace{1cm} \text{front wheel steering angle which is the control variable of the feedback controller}

\[ \delta_{fp} \] \hspace{1cm} \text{front wheel steering angle which is the control vector of the lateral preview deviation dynamics model}

\[ \gamma_p, \gamma_f \] \hspace{1cm} \text{control proportions of the preview controller and the feedback controller under the coordination controller}

\[ \mu \] \hspace{1cm} \text{road adhesion coefficient}

\[ \rho \] \hspace{1cm} \text{target trajectory curvature}

\[ \tau_t \] \hspace{1cm} \text{time lag in the steering system}

\[ \omega \] \hspace{1cm} \text{yaw rate of the mass center}