Intelligent Assisted Driving Method Based on Mathematical Modeling and MPC Algorithm

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Abstract: With the continuous increase in the number of vehicles,traffic accidents are occurring more frequently, which poses a great threat to peoples` lives and to property safety. In order to improve improve driving safety, an intelligent assisted driving method based on mathematical modeling and model predictive control is proposed. This method applies clustering algorithms and Bayesian networks for identifying the driving styles and evaluating the road adhesion level. In addition, the results of the simulations which were carried out could be applied to the construction of mathematical models for vehicle driving, combined with model predictive control methods for achieving the control of assisted driving systems. The obtained results show that the vehicle tracking accuracy of the proposed assisted driving method remains within the range of 0.4m, and the response time is only 0.64s. To that, the average value for the passenger comfort assessment exceeded 90 points out of a maximum score of 100 points. This indicates that the proposed assisted driving method can effectively enhance the user's assisted driving experience, by achieving a higher accuracy and enabling a safer intelligent driving.

Keywords: Mathematical modelling, MPC, Clustering, Intelligent driving, Assistance.

1. Introduction

With the rapid advancement of autonomous driving technology, intelligent assisted +driving systems are playing an increasingly important role in improving road safety and driving comfort (Chen et al., 2023; Hu et al., 2022; Watson et al., 2022). The vehicle following control system can effectively maintain a safe distance between vehicles. However, the existing vehicle tracking control system is still inadequate in handling traffic flow changes and responding to emergencies (Yan et al., 2023). Most intelligent driving technologies do not consider the driver's environmental perception and personalised characteristics (Çimen & Yalçın, 2022). Intelligent driving is a research direction that involves multiple disciplines, including but not limited to control theory, computer vision, machine learning, and artificial intelligence. In recent years, many researchers have been committed to developing more efficient and reliable intelligent assisted driving systems (Guo et al., 2022; Wu et al., 2022). Liang et al. (2022) found that in order to improve the timeliness of target detection schemes in intelligent transportation systems and reduce energy consumption, a detection system based on edge cloud collaboration and reconstructed convolutional neural network was proposed. The system is lightweight due to a pruning operation and network compression. The results show that the number of network parameters in the system is reduced by 60% (Liang et al., 2022). Lyu et al. (2022) proposed a driving style recognition method that utilised machine learning and driving data to develop personalised driving strategies for specific drivers and improve traffic safety. The classifier is integrated by reinforcement learning to classify and predict driving styles. The findings indicated that applying this method to intelligent driving could improve the driving comfort of drivers.

With the development of computer technology, the model predictive control (MPC) algorithm is being widely used in the field of intelligent driving. The MPC algorithm, as an advanced control strategy, can predict the system behavior in the future and achieve the expected output by optimising the control input. It has wide applications in various fields (Long et al., 2022). Wang, Ren & Zheng (2023) artificially improved the predictive control accuracy of nonlinear system event models with bounded perturbations, and proposed an adaptive event triggering mechanism.

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The trigger threshold of this mechanism adapts to the changes of the system state. The trigger mechanism is applied to the MPC algorithm to further reduce the computational complexity of the optimisation problem at each trigger time. The results showed that this method can solve optimal problems with less computing time (Wang, Ren & Zheng, 2023). Mathematical modeling is the foundation of intelligent assisted driving systems. By constructing vehicle dynamics models and environmental perception models, the behavior of vehicles under different road conditions can be accurately described, providing the necessary predictive information for MPC algorithms (Skrynkovskyy et al., 2022). Ali et al. (2023) developed a fitting mathematical model to analyse the probability of HIV-1 patients being infected with CD4+T cells, which used the finite difference method for numerical research. The results indicated that this mathematical model could effectively assist in analysing cell infection and further improve analysis efficiency.

Based on the above content, it can be seen that mathematical modeling can be applied to various problem solving fields to provide decision support for the system. The current intelligent driving technology does not consider the road environment and driver characteristics in the dynamic driving environment, and the vehicle brake control is not accurate. As such, the applicability of the existing driving assistance system is not high, which results in its infrequent use. To solve this problem, an intelligent driving assistance method based on mathematical modeling and a MPC algorithm is proposed. The purpose of this study is to ensure the safety and comfort of driving and avoid the occurrence of traffic accidents such as rear-end collisions. The innovation of this research lies in further improving the intelligence and applicability of assisted driving by introducing environmental perception and driver style recognition into the construction of the vehicle dynamics model. This paper aims to enable a more intelligent and more accurate assisted driving, and further maintain the driving safety during car driving.

The remainder of this paper is structured as follows. Section 2 describes the design process and outlines the technical details of the intelligent driving assistance method based on mathematical modeling and the MPC algorithm. Section 3 includes an experimental analysis, during which the performance and practical application of the proposed intelligent driving assistance method are tested and analysed. Finally, Section 4 provides the conclusion of this paper and possible future research directions.

2. Research Methodology

This paper presents an intelligent driving assistance model based on mathematical modeling and a MPC algorithm. The model first evaluates the vehicle attachment and the driver's driving style, and then constrains the kinematic model according to the evaluation results. Finally, a MPC algorithm is used for intelligent control of assisted driving to achieve an intelligent assisted driving.

2.1 Assessment Method for the Driver`s Driving Style and the Road Adhesion Condition

If the assisted driving system directly controls the vehicle according to the established program, it may cause significant changes in driving speed, driving direction, etc. (Wei & Shi, 2022; Tan et al., 2024). To improve the driver's acceptance of the vehicle system in the process of intelligent assisted driving, it is necessary to determine the driver's driving style and imitate it. The specific process related to the driver`s driving style recognition method proposed in the study is shown in Figure 1.

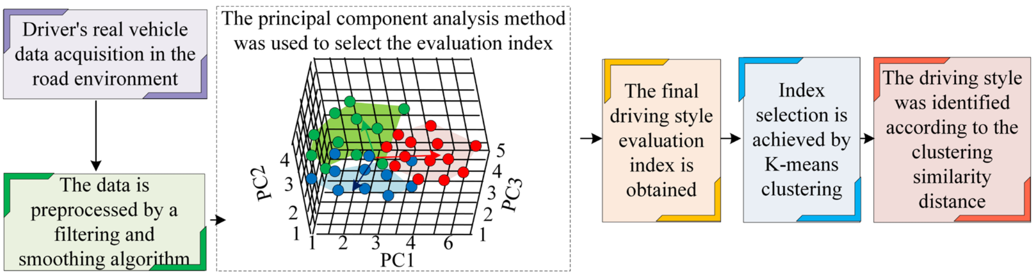


Figure 1. Driving style recognition based on the principal component analysis and the clustering algorithm

As it can be seen in Figure 1, this study first uses the Principal Component Analysis (PCA) to extract the main indicators for driving style evaluation, and then uses clustering methods to recognise driving styles. After clustering and the PCA analysis, the study focused on using the driver's braking frequency, lane changing frequency, acceleration, average speed, etc. within one minute as evaluation indicators. During the research process, it was found that directly applying these indicators to identify the drivers' driving styles will result in excessive noise, leading to a low recognition accuracy. In response to this, the study focused on the use of filtering and smoothing algorithms for data preprocessing to reduce the impact of noise. The filtering process is expressed by equation (1):

$$\begin{cases} X(t_i) = \frac{1}{z}\sum_{k=i-D}^{i+D} X(t_k) exp\left(-\frac{|i-k|}{\xi}\right) \\ z = \sum_{k=i-D}^{i+D}\left(-\frac{|i-k|}{\xi}\right) \\ D = min(3\xi, i-1, N-i) \\ \xi = \frac{T}{dt} \end{cases} \tag{1}$$

In equation (1), D is the width of the filtering window, dt is the inter-frame interval, t_i is the current time, i is the initial filtering window, $X(t_i)$ is the vehicle fitting value, and T is the sampling period of the data. The wheel speed period was set at 0.1s, the acceleration period to 0.4s, ξ is the time coefficient, and z is the integer coefficient. After denoising the data and using the PCA algorithm for further evaluation index screening and dimensionality reduction, the K-means clustering algorithm was used for clustering and partitioning, and a driving style recognition model was established based on the partitioning results. The principal components after dimensionality reduction are three driving styles, each of which contains six evaluation indicators. The cluster center coordinates of each driving style were determined through the clustering algorithm. The distance to the cluster center for aggressive, conservative and average drivers is expressed by equation (2):

$$\begin{cases} dis_1 = \sqrt{(Y_1-x_1)^2+(Y_2-y_1)^2+(Y_3-z_1)^2} \\ dis_2 = \sqrt{(Y_1-x_2)^2+(Y_2-y_2)^2+(Y_3-z_2)^2} \\ dis_3 = \sqrt{(Y_1-x_3)^2+(Y_2-y_3)^2+(Y_3-z_3)^2} \end{cases} \tag{2}$$

In equation (2), (x_1, y_1, z_1) represent the cluster center coordinates for aggressive drivers, Y_1, Y_2, and Y_3 are the three values of the principal component reference index, and dis_1 is the distance between the analysed sample and the cluster center for aggressive drivers. dis_2 and dis_3 are the distances between the current point and the cluster centers of normal driving and conservative drivers, respectively, while (x_2, y_2, z_2) and (x_3, y_3, z_3) are the coordinates of the cluster centers of average and conservative drivers. The driver's driving style is the one featuring the smallest distance among the three. When the car is not yet started, its road adhesion coefficient and driving stage are different, and different calculation methods need to be considered. A calculation method has been determined through testing and analysis. The slip rate of the vehicle is first calculated through front and rear wheel speed difference, and then road conditions and vehicle dynamics information are combined to determine the current adhesion level to the road surface using an adhesion coefficient estimation model. During the vehicle driving phase, the road adhesion level is calculated through the slip rate and by Bayesian estimation. The process flow of the road adhesion assessment method is shown in Figure 2.

In Figure 2, the use of the adhesion coefficient plays a very important role in estimating road adhesion (Lubin et al., 2023; Wang et al., 2022). During the vehicle's driving phase, it is necessary

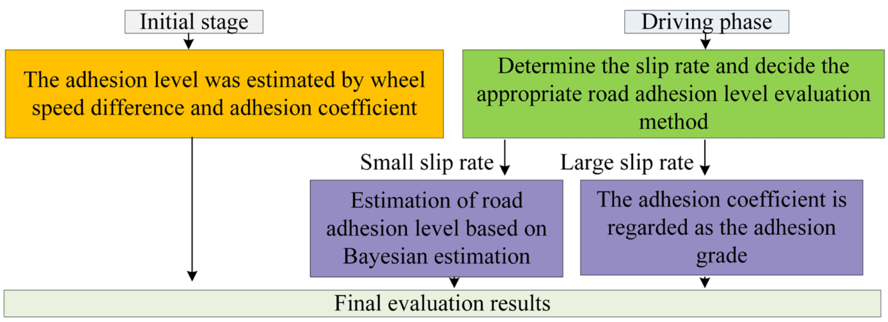


Figure 2. The road adhesion assessment method process flow

to use the slip rate to determine which evaluation method to use. The variation curves of the slip rate and road adhesion coefficient on different roads are different. Therefore, four different mathematical models of slip rate using the adhesion curve were established in this study, as shown in equation (3):

$$\begin{cases} \mu_1 = 1.40\left(1-e^{-23.99s}\right) - 0.52s \\ \mu_2 = 0.86\left(1-e^{-33.53s}\right) - 0.35s \\ \mu_3 = 0.20\left(1-e^{-92.28s}\right) - 0.06s \\ \mu_4 = 0.04\left(1-e^{-324.45s}\right) - 0.001s \end{cases} \tag{3}$$

In equation (3), μ_1, μ_2, μ_3, and μ_4 are the four adhesion coefficient functions for dry, slippery, snowy, and icy road surfaces, respectively. s is the overall slip rate of the vehicle. The overall slip rate of a vehicle is denoted by the average slip rate of the left and right drive wheels. When the slip rate is less than 0.4, a Bayesian theorem is used to calculate the posterior probability of the adhesion coefficient using the adhesion coefficient of the drive wheel. When the slip rate is greater than 0.4, the adhesion coefficient value will not be equated with the road adhesion coefficient value. If the final adhesion coefficien is below 0.4, this will be considered a low adhesion level. If the adhesion coefficient is within the range of [0.4, 0.7], it will be judged as a medium adhesion level. If the adhesion coefficient is higher than 0.7, it is judged as a high adhesion level.

2.2 Intelligent Assisted Driving Based on Mathematical Modeling and a MPC Algorithm

After determining the road adhesion coefficient and the drivers` driving styles, the study applies them to the establishment of vehicle kinematic models. In the process of assisted driving, the car following system is the most common means of assisted driving (Zhan et al., 2024; Li & Wang, 2023; Iancu et al., 2022). But during the car following process, it is easy to experience rear end collisions due to the distance between the vehicles being too small. To address this issue, the study applies road adhesion and driver driving style recognition outcomes for the establishment of a safe distance model (Simo et al, 2023; Dahmad et al., 2024; Li & Yao, 2024). The calculation method for the minimum distance between vehicles when they are stationary is shown in equation (4):

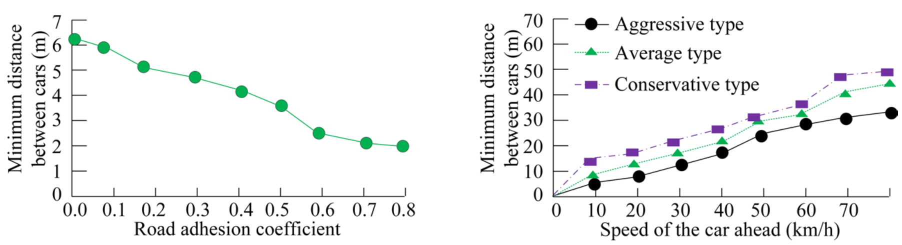
$$c_0 = k\frac{c}{\mu + b} \tag{4}$$

In equation (4), k represents the driving style level, 1.5 for the aggressive type, 1.0 for the average type, 0.6 for the conservative type, c and c_0 represent a constant coefficient and the minimum distance between vehicles at rest, respectively, μ is the road adhesion coefficient, and b is a constant coefficient. The distance between vehicles with different adhesion coefficients and drivers` driving styles is shown in Figure 3.

In Figures 3(a) and 3(b), after curve fitting, the sum values for aggressive drivers were 0.15 and 6, for average drivers they were 0.12 and 6, and for conservative drivers they were 0.10 and 6, respectively. After comprehensive consideration, the vehicle safety distance model is shown in equation (5):

$$S = \begin{cases} 1.2v_1 + k\dfrac{c_1}{\mu + b_1} \\ 1.6v_2 + k\dfrac{c_2}{\mu + b_2} \\ 1.8v_3 + k\dfrac{c_3}{\mu + b_3} \end{cases} \tag{5}$$

In equation (5), S is the safe distance between vehicles, v_1, v_2, and v_3 are the speeds of the three types of drivers, c_1, c_2, and c_3 are the values of c coefficients for the three types of drivers, and b_1, b_2, and b_3 are the values of b coefficients for the three types of drivers. In the process of vehicle following control, it is also necessary to consider the tracking



(a) Workshop spacing of different road adhesion coefficients

(b) Workshop spacing for different driving styles

Figure 3. Experimental spacing for different road adhesion coefficients and driving styles

performance and driving comfort for the vehicle (Li et al., 2024). Therefore, in this study the maximum vehicle speed is constrained to be lower than 120 km/h and the distance between vehicles is greater than the minimum safe distance established in the previous distance model. In addition, in the following state, the distance between the vehicles ahead and behind should satisfy equation (6):

$$L_1 = q_1 \Delta s_e(n)^2 + q_2 \Delta v_r(n)^2 \tag{6}$$

In equation (6), L_1 is the distance between vehicles, $\Delta S_e(n)$ and $\Delta v_r(n)$ are the following distance error and relative vehicle speed, q_1 and q_2 are weight coefficients, and n is the current time. The rate of acceleration change should vary between [-2.5m/s^3, 2.5m/s^3], and the range of acceleration values should also be kept within [-3m/s^2, 3m/s^2]. The calculation method for the acceleration change rate is expressed in equation (7):

$$j(k) = \frac{a(n+1) - a(n)}{T_s} \tag{7}$$

In equation (7), $a(n)$ represents the current acceleration of the vehicle, $a(n+1)$ represents the acceleration at the next moment, and T_s represents the system sampling time. After establishing a vehicle kinematic model and setting certain constraints, this paper focuses on using MPC controllers to control the vehicle assisted driving system. The MPC control principle is shown in Figure 4.

As it can be seen in Figure 4, the objective function and constraint conditions are input into the MPC controller, and the parameters are adjusted according to the predicted results. The output sequence includes the distance between the vehicles ahead and behind, the relative speed for the two vehicles, the speed of the vehicle itself, the acceleration of the vehicle itself, and the amount of system interference. The MPC algorithm is predictive, includes constraints and is a real-time algorithm, due to which it can achieve the precise control of the driving system. According to the pre-designed prediction model, the future system state is predicted, and the optimal control sequence is obtained according to the predicted results. In the face of a complex and changeable driving environment, it can respond in advance to improve the stability and safety of the driving system. In the intelligent driving assistance system, it is necessary to consider many constraints such as vehicle tracking performance, driving comfort and safe distance. The MPC algorithm can take these constraints into account in the process of optimisation, and ensure that the control sequence can be optimised under the premise of satisfying the constraints. In the process of vehicle driving, the driving environment is changing in real time, requiring the control system to respond quickly and make adjustments. Through rolling optimisation, the MPC algorithm can update the control sequence at each sampling time to adapt to the changes of the environment and achieve real-time control. Therefore, the MPC algorithm is chosen as the control algorithm for intelligent driving. The specific scheme for the input-output constraint values and parameter values set in the MPC controller is shown in Figure 5.

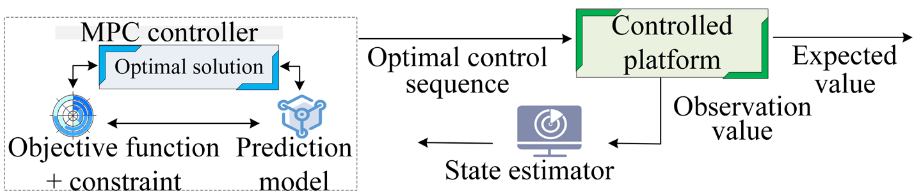


Figure 4. The principle of MPC control

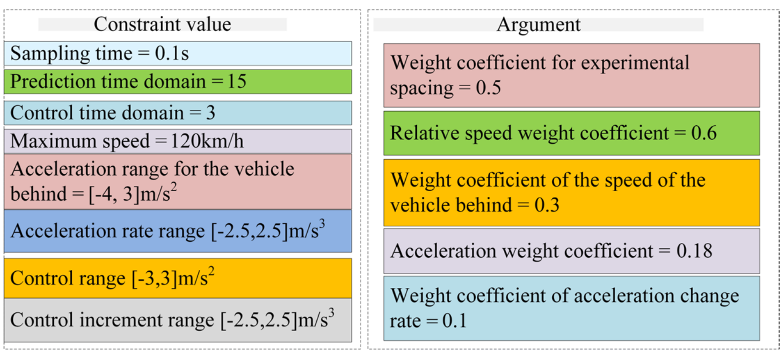


Figure 5. The input and output constraint values and the parameter values set for the MPC controller

According to Figure 5, various weight coefficients, constraint conditions, and other parameters are input into the MPC controller to effectively adjust the real-time motion state of the vehicle. To ensure the safety and comfort of the vehicle during the vehicle following control process, a vehicle state estimation module was also introduced in this study, which can monitor the dynamic parameters of the vehicle in real time, and feed back these parameters to the MPC for the intelligent control of the vehicle. The objective function of MPC is expressed in equation (8):

$$\begin{cases} J = \left[\Delta U(n)^T \varepsilon\right]^T H_t \left[\Delta U(n)^T \varepsilon\right] + G_t \left[\Delta U(n)^T \varepsilon\right] \\ H_t = \begin{bmatrix} \Theta^T Q_e \Theta & 0 \\ 0 & \rho \end{bmatrix}, G_t = \left[2E_p(n+1|n)^T Q_e \Theta \quad 0\right] \end{cases} \tag{8}$$

In equation (8), ΔU is the set of expected accelerations, and H_t and G_t are matrices of 2×2 and 1×2, respectively. ε is the relaxation factor, Θ is the union of expected and actual values, Q_e is the matrix of objective function weight coefficients, E_p is the output deviation, ρ is the weight coefficient, and J is the control sequence in the control time domain. In order to apply the simulation results to actual driving, tests were first carried out to ensure that the mathematical model and the MPC algorithm in the simulated environment were equally valid for the actual vehicle. This included a thorough testing of the driving assistance system for different road, weather and traffic conditions to verify its stability and reliability. By embedding the simulation results into the control system of the vehicle, the real-time control of the auxiliary driving function is achieved. The sensors are used to collect information about the environment around the vehicle in real time, and then the information is input into the verified mathematical model and the MPC algorithm to calculate the optimal driving strategies and implement these strategies through the vehicle's executive mechanism. In addition, in order to ensure the safety and reliability of the auxiliary driving system, it is necessary to establish a sound monitoring and fault diagnosis system. When the system detects an abnormal situation or a failure, it can immediately take the appropriate measures, such as issuing an alarm, slowing down or stopping, to avoid potential dangers.

3. Results and Discussion

To test the assisted driving effectiveness of the raised intelligent assisted driving method, this study analysed and discussed its performance through simulation and real-world scenario testing.

3.1 Analysis of the Assisted Driving System Performance Under Different Vehicle Conditions

The research uses MATLAB as the simulation platform to carry out the simulation test. In the simulation test, four different driving situations were simulated: steady-state vehicle following, emergency braking of the preceding vehicle, adjacent vehicle entry, and the start stop function of the preceding vehicle. The assisted driving methods proposed by the research were applied during the testing process. With respect to road conditions, the medium road adhesion level was considered, and the speed changes under the four different traffic conditions are shown in Figure 6. The phrase "Front vehicle speed" indicates the forward speed of the vehicle in front of the reference vehicle during the car following.

As shown in Figure 6(a), in the steady-state car following scenario, the vehicle entered a stable following state after decelerating and approaching the preceding vehicle for about 10 seconds, and the lag time of the vehicle speed change remained within 0.5 seconds after applying the assisted driving method. In Figure 6(b), in the case of emergency braking of the preceding vehicle, the vehicle rapidly decelerated when it detected a decrease in the speed of the preceding vehicle, with a lag time of about 0.18s in speed change. In Figures 6(c) and 6(d), the proposed assisted driving method exhibited a good response speed and stability with a lag time of less than 0.3 seconds for vehicle speed changes under the conditions of adjacent vehicle entry and front vehicle start and stop function.

To further validate the application effect of the proposed method under the four different traffic conditions, the changes in the distance between vehicles were recorded, and the specific results are shown in Figure 7.

As shown in Figures 7(a), 7(b), 7(c), and 7(d), under four different driving conditions, the car can keep running stably and avoid accidents such as side falling and rear-end collisions. Under the four vehicle conditions, the tracking error between the following distance and the safe distance is not higher than 0.5m.

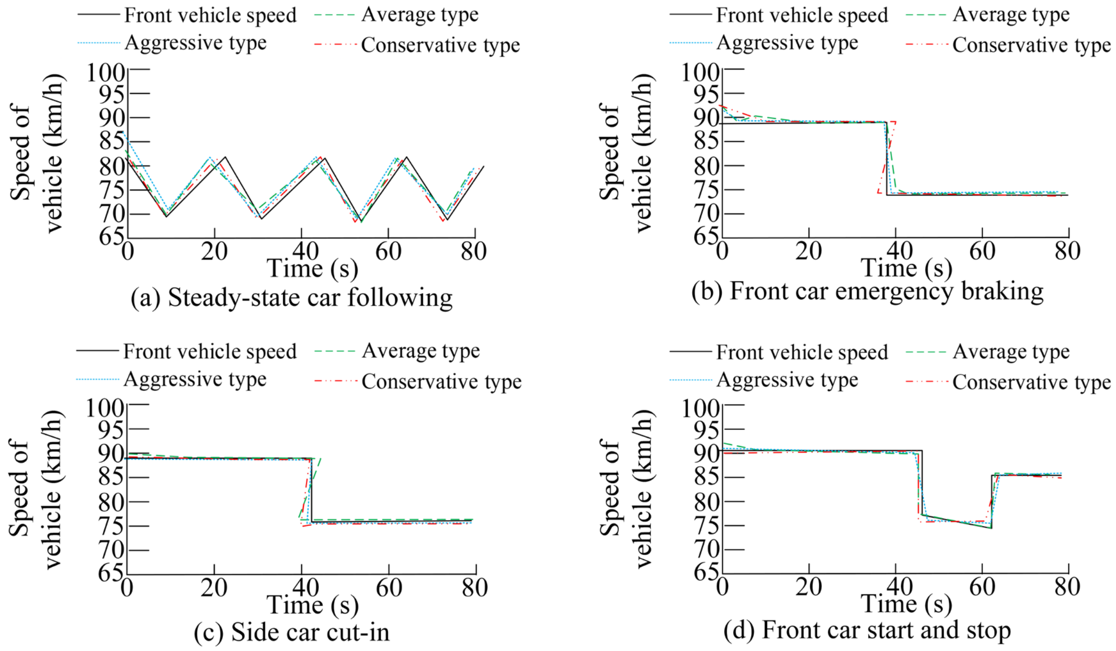


Figure 6. The speed change in the four traffic conditions

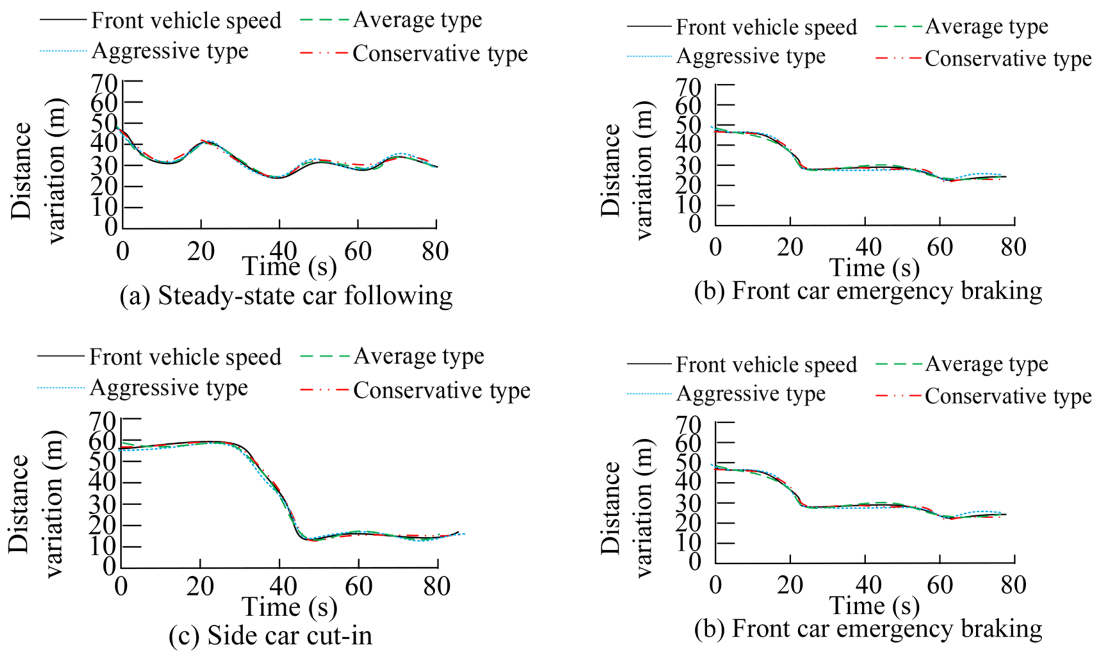


Figure 7. The relative distance change for each of the four traffic conditions during the application of the assisted driving method

3.2 Analysis of the Effectiveness of Driving Style Recognition and Road Adhesion Assessment Methods

To test the effectiveness of the driving style recognition and road adhesion assessment methods proposed in the study, the driving effectiveness of different drivers under the same vehicle conditions was compared. 258 drivers with different driving experiences were involved in the test, including beginners, experienced drivers, and professional racing drivers. Their driving styles were identified by analysing their driving data under four different vehicle conditions: steady-state car following, emergency braking of the preceding vehicle, adjacent vehicle side entry, and start stop of the preceding vehicle. The method employed for comparison purposes was the commonly used driving style recognition algorithm based on convolutional neural networks.

According to Figure 8 (a) and Figure 8 (b), the recognition accuracy of both methods was above 95%, but the recognition time for the convolutional neural network-based recognition method was 1.88 seconds, and for the proposed method it was only 1.21 seconds. This indicated that the proposed method could achieve a high-precision driving style recognition at a faster speed.

To verify the relevance of road adhesion assessment in assisted driving, different road adhesion conditions were selected for testing, including dry, slippery, snowy, and icy road surfaces. The results are included in Table 1.

According to Table 1, the stability control response time and braking distance increased with the road adhesion conditions becoming harder, while the lateral control accuracy decreased. Under dry surface conditions, the system performed best with the fastest response time and the shortest braking distance.

3.3 The Practical Application Effect of the Intelligent Assisted Driving Method Based on Mathematical Modeling and the MPC

To test the assisted driving effectiveness of the proposed method (Method 1) under different road conditions, the vehicle following scenario was compared and studied under four actual road conditions: dry asphalt, slippery, snowy, and icy road surfaces. The comparative analysis also included the intelligent assisted driving method in (Ju, Wang & Dou, 2023) (Method 2), the intelligent assisted driving method in (Li et al., 2022) (Method 3), and the intelligent assisted driving method in (Wang et al., 2023) (Method 4). The car following speed and following distance changes for the four methods during a 1-hour driving process are shown in Figure 9.

As shown in In Figures 9(a) and 9(b), the car following speed and following distance variation for the four analysed methods were within an acceptable range. Method 1 performed the best, keeping the distance between vehicles within a safe 0.5m error range, and keeping the car following speed within 1.5m/s of the preceding vehicle.

To further validate the proposed method, the comparative analysis also included the tracking accuracy, response time, and passenger comfort. The passenger comfort level is based on the survey questionnaire results recorded for the testers after the experiment, with a maximum score of 100. The specific findings are included in Table 2.

As shown in Table 2, Method 1 performed well with regard to tracking accuracy, response time, and passenger comfort under the four different

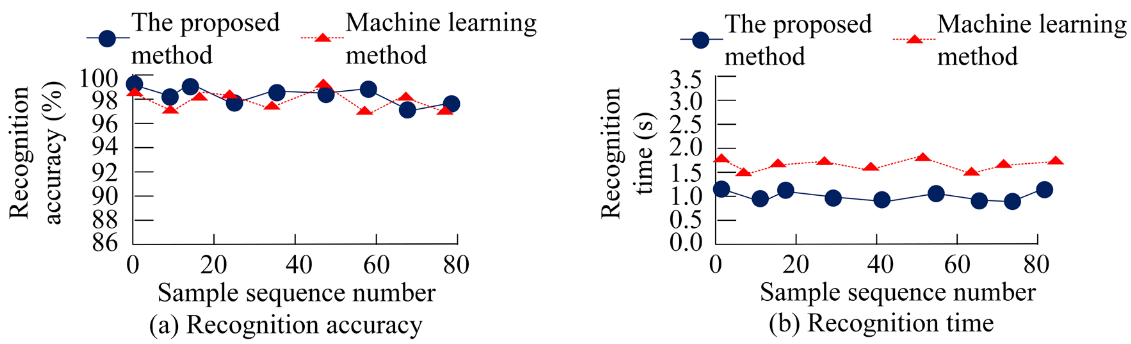


Figure 8. Driving style recognition performance comparison

Table 1. Influence of road adhesion conditions on the assisted driving performance

Road adhesion condition	Stability control response time (s)	Braking distance (m)	Lateral control accuracy (%)
Dry	0.2	10.2	95.47
Slippery	0.3	11.7	92.88
Snowy	0.5	15.4	88.40
Icy	0.7	20.0	85.07

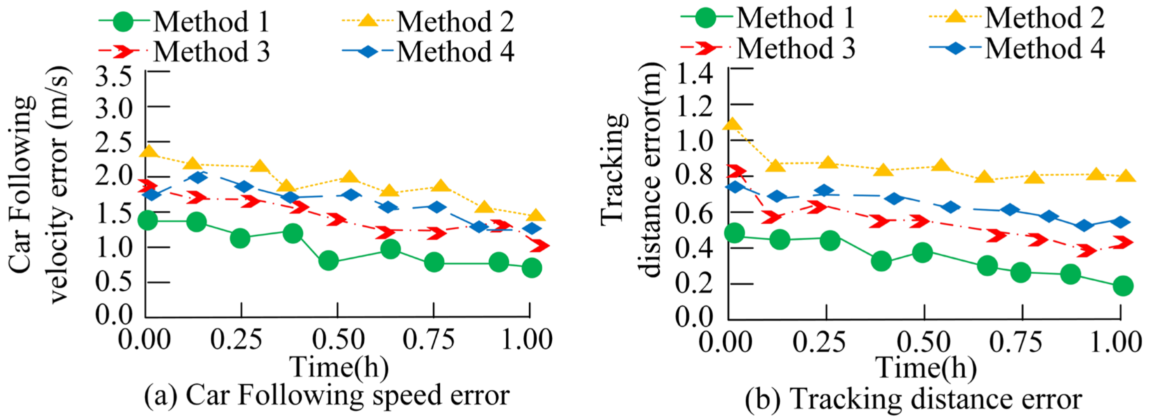


Figure 9. Tracking accuracy changes of four methods during 1h driving

Table 2. Comparison of performance indicators for the proposed method and the other three employed methods

Performance indicator	Method 1	Method 2	Method 3	Method 4
Tracking accuracy (m)	0.33	0.47	0.38	0.40
Response time (s)	0.63	0.88	0.72	0.68
Passenger comfort	91.44	85.88	88.94	87.47

road conditions. Specifically, the average values of the three indicators were 0.335m, 0.635s, and 91.44 points, which were significantly better than the values obtained by the other three methods. The passenger comfort ratings for the other three methods were all below 90 points, and the tracking accuracy exceeded 0.4m for Methods 2 and 4.

To verify the application effect for the employed MPC algorithm, a comparative experiment was conducted, involving the more popular control algorithms. The comparative methods included a PID control algorithm based on deep learning (algorithm 1), a Q-learning control algorithm based on reinforcement learning (algorithm 2) and the traditional fuzzy control algorithm (algorithm 3). In order to comprehensively evaluate the performance of each algorithm in the actual driving environment, a variety of complex road scenarios were selected for this study including straight driving, curve driving, emergency braking and ramp driving. During the experiment, the control accuracy, response time, energy consumption and vehicle distance deviation for each algorithm were recorded and analysed. The specific results are shown in Table 3.

As it can be seen from Table 3, the MPC algorithm proposed in this study proved to be superior to the other three algorithms with regard to all of the four evaluation indices, namely control accuracy, response time, energy consumption and vehicle distance deviation. The control accuracy of the MPC algorithm reached 0.28m, the response time was only 0.55s, the energy consumption was 14.8kWh/100km, and the vehicle distance deviation was kept at 0.32m. The application of the MPC algorithm in intelligent driving control is remarkable, as it not only performs well with regard to control accuracy, response speed and vehicle stability, but it also effectively reduces vehicle energy consumption.

Table 3. Comparison of the four control algorithms in the context of intelligent driving

Control Algorithm	Control Accuracy (m)	Response Time (s)	Energy Consumption (kWh/100km)	Vehicle Distance Deviation (m)
MPC	0.28	0.55	14.8	0.32
Algorithm 1	0.42	0.78	16.2	0.47
Algorithm 2	0.39	0.72	15.5	0.45
Algorithm 3	0.45	0.85	17.1	0.51

4. Conclusion

To improve the driving accuracy and passenger comfort for intelligent driving assistance systems, an intelligent driving assistance method based on mathematical modeling and a MPC algorithm was developed. The experimental outcomes indicated that the proposed assisted driving method could stabilize the car following state in about 10 seconds under different vehicle conditions, and the lag time for the vehicle speed changes remained within 0.5 seconds. To that, under four different vehicle conditions, the tracking error between the following distance and the safe distance should not exceed 0.5m. In comparison with the conventional machine learning-based driving style recognition method, the proposed method maintained a recognition accuracy of over 95% and it achieved a recognition time of only 1.21 seconds, which was shorter than that obtained by the machine learning-based method. Further on, under different road conditions, the average values of the tracking accuracy, response time and passenger comfort indices of Method 1 were 0.335m, 0.635s and 91.44 points, respectively, which are obviously better than the values obtained by the other three methods. This indicated that the raised method could effectively cope with various complex road conditions and provide drivers with a safer and more comfortable driving experience. Future research could incorporate more factors that affect the driving process into the proposed model, such as vehicle load, wind speed, weather conditions, etc., in order to further enhance the performance and reliability of assisted driving systems. In addition, the collaborative work with other intelligent transportation systems could be explored to achieve higher-level autonomous driving capabilities.

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