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Behavior-Based Anthropomorphic Lane-Changing Decision and Control for Intelligent Vehicles on Highways

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Abstract: *This paper is based on the study of incorporating personalized driver styles in automatic lane changing control technology, to establish a vehicle lane changing trajectory planning and control model considering driver styles as well as to improve the applicability of the lane changing planning control model to drivers with different styles. First, the HighD dataset is screened, and drivers are categorized according to their driving styles using principal component analysis and K-means (K-means) cluster analysis. Secondly, the process of generating drivers' lane changing decisions is fully considered, and human drivers' driving behavior experience is learned through Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) methods that introduce the attention mechanism, so as to improve drivers' acceptance and satisfaction of smart vehicle acceptance and satisfaction, and propose a lane changing decision model that considers the rationality and safety of lane changing. An emergency lane changing control strategy based on Model Predictive Control (MPC) is adopted, and finally, a joint simulation is conducted by Simulink/CarSim software to prove that the lane changing decision-making method based on the driver's style proposed in this study is able to realize the autonomous lane changing task of intelligent vehicles.*

Keywords: *Highway safety, Lane changing, Emergency collision avoidance*

1. Introduction

Intelligent vehicles are one of the hotspots in vehicle engineering research, and their self-driving systems have advantages such as higher safety, comfort, energy saving and pollution reduction compared with traditional vehicles. In order to ensure road safety and smooth traffic flow, self-driving vehicles and manually driven vehicles need to travel together on the road with consistency over a period of time. However, it is not feasible to transform the driver into a machine driving mode. In contrast, it is more practical to make the anthropomorphization of self-driving vehicles technically possible by extracting the driving characteristics of the driver and inputting them into a computer. The purpose of this study is to learn the characteristics of drivers when they perform lane changing normally, and to establish a lane changing decision model as well as a lane changing control model for intelligent vehicles in the case of free lane changing, in order to ensure the safety and ride comfort of self-driving vehicles during lane changing.

Initially, the lane changing decision-making model was based on the rules of the road, and Gipps proposed in the twentieth century that lane changing behavior can be analyzed from three aspects: 1) necessity, 2) safety, and 3) propensity. Yang and others not only considered the probability of lane changing, but also introduced the random error on the basis of Gipps's proposed model. Hidas et al. classified the vehicle lane changing into free lane changing, forced lane changing and collaborative lane changing. Kesting et al. expressed the lane changing gain by acceleration and proposed a MOBLL model based on and speed control. With the development of deep learning and machine learning, more scholars are trying to improve the stability and accuracy of the lane changing decision through this more advanced method. Qiu et al. used Bayesian network to model vehicle lane changing. Motamedidehkordi et al. modeled the lane changing decision through random forests. Shalev-Shwartz S et al. decomposed the decision into two parts, thus ensuring the stability and accuracy of the decision. Decomposed, thus ensuring the safety of the proposed decision while greatly improving the reliability of the decision. Liu M, although using the algorithm of decision tree to realize the modeling of lane changing decision in urban environment, their proposed driving environment is too ideal, and at the same time, there is the

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problem of insufficient consideration of vehicle dynamics constraints. Jin Fan used convolutional neural network to obtain the optimal solution for decision making and verified the migration of the proposed model by using the highway dataset in China. Wang Shubo et al. trained a decision-making system using deep reinforcement learning with environmental state information as input and decision commands as output, but the final training effect was less satisfactory[1-3].

This paper takes driving style as the starting point, classifies driving styles through HighD database, establishes a lane change decision model based on convolutional neural network and long and short-term memory network method which introduces the attention mechanism, establishes a lane change control model based on fuzzy control, and finally verifies the lane change decision and the lane change control model through simulation software and driving simulation platform.

2. Driving Style Classification

In the road traffic environment, in order to complete the driving task, drivers with different driving styles will show different driving behaviors and characteristics, which makes the driver's manipulation of the vehicle differentiated. Therefore, in order for a human-machine co-driving vehicle to fully understand the driver's driving behavior, the driver's driving style needs to be taken into account in order to improve the safety of vehicle lane changing. In this chapter, 13 feature parameters related to driving style were selected and dimensionality reduction was performed using principal component analysis to reduce the existence of certain information redundancy between feature parameters. Based on the results of principal component analysis, the driving styles were categorized into cautious, general and aggressive based on the K-means algorithm.

2.1. Real Vehicle Track Data Screening

In order to provide a good data base for driving style analysis, the raw data need to be preprocessed. The original data set contains feature parameters such as longitudinal velocity, longitudinal acceleration, transverse acceleration, minimum headway, and the inverse of the collision time parameter to obtain the feature parameter matrix.

2.2. Classification of driving styles

In order to reflect the driving style characteristics more comprehensively, 13 feature parameters related to driving style were selected to reflect the driver's driving behavior. The principal component analysis (PCA) was used to realize the dimensionality reduction of the original feature parameters to provide data input for the subsequent driving style clustering.

The principal component contribution ratio and cumulative contribution ratio were calculated respectively, and according to the calculation results, the cumulative contribution ratio of the first four principal components was 84.527%, and the eigenvalues were all greater than 1. Thus, the first four principal components were extracted as the input variables for data analysis. In this paper, the first 4 principal components are used instead of the original 13 principal components. The feature vectors of the original data and the principal components are obtained. The expression for the common factor can be calculated.

$$\begin{aligned}
F_1 &= -0.255X_1 - 0.369X_2 + 0.422X_3 - 0.121X_4 \cdots - 0.049X_{10} + 0.069X_{11} + 0.027X_{12} + 0.026X_{13} \\
F_2 &= 0.29X_1 + 0.2X_2 + 0.172X_3 + 0.432X_4 \cdots - 0.13X_{10} - 0.17X_{11} - 0.17X_{12} - 0.322X_{13} \\
F_3 &= -0.03X_1 - 0.062X_2 + 0.08X_3 - 0.256X_4 \cdots + 0.475X_{10} + 0.54X_{11} + 0.547X_{12} - 0.08X_{13} \\
F_4 &= 0.51X_1 + 0.44X_2 + 0.112X_3 - 0.386X_4 \cdots + 0.153X_{10} + 0.05X_{11} + 0.115X_{12} + 0.399X_{13}
\end{aligned} \tag{1}$$

Where F1 is the "acceleration factor" F2 is the "transverse factor" F3 is the "follow-through factor" F4 is the "longitudinal factor".

2.3. Driving style k-means clustering

The k-means algorithm was applied to analyze the clustering of the four factors. Define the number of cluster center k as 3, and get the cluster center factor value and the number of each category as shown in Table 1. Combining the sample attributes, it can be obtained that there are 51 groups of cautious driving data, 147 groups of general driving data and 94 groups of aggressive driving data in the experimental

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data.

Table 1: Factor Score Coefficient Matrix Clustering Center Factor and Number of Categories.

Typology	F1	F2	F3	F4	Amount
1	-18.148	12.451	1.019	33.125	94
2	-3.877	4.054	4.022	15.333	51
3	-14.22	9.98	2.045	25.998	147

3. Autonomous Lane-Changing Behavioral Decision Making for Intelligent Vehicles

3.1. Driving style k-means clustering

The network structure of the Attention-based CNN-LSTM driver lane-changing decision-making method proposed in this paper is shown in Fig. 1, which mainly consists of a convolutional layer, an LSTM layer, an Attention layer and a fully connected layer.

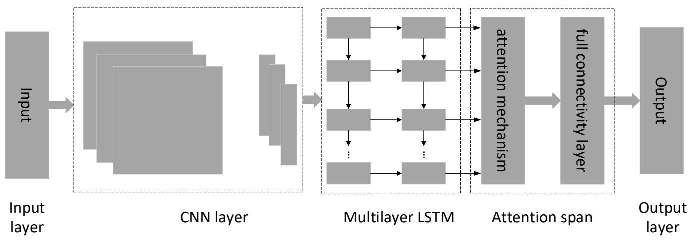

Figure 1: Structural schematic.

In this paper, we propose a lane-changing decision-making method that introduces the attention mechanism of convolutional neural network and long and short-term memory network, firstly, the model is trained by a large amount of driver lane-changing data, so that the model learns the behavioral characteristics of driver lane-changing, and then the trained model is used for lane-changing decision-making of intelligent vehicles, it should be noted that the model does not analyze inputs one by one in each time step, but rather, it analyzes a small segment of the data sequence, so that the model can make a reliable prediction[4-5].

3.2. Model training

The change of loss during the training process of CNN-LSTM-Attention network model is shown in Fig. 2, and the convergence of CNN-LSTM-Attention model is judged by observing the curve change.

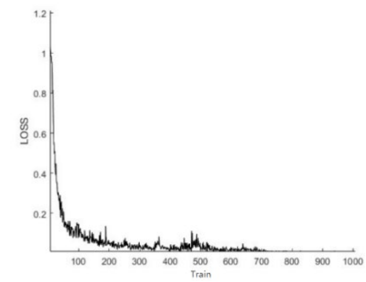

Figure 2: Model Loss Decline Curve.

The proposed CNN-LSTM-Attention neural network model is trained several times and Table 2 shows the classification accuracy results of the trained model on the test sample dataset.

Table 2: Model training results

Model	Accuracy
Test 1	96.76%
Test 2	95.68%
Test 3	96.30%
Test 4	94.14%
Test 5	97.14%

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4. Lane change trajectory planning

The minimum safe distance for a vehicle to make a lane change is shown in equation (2):

$$D_{MSS}(M, Lo) = max\{X_m - X_{Lo} + 2L_x + W\sin(\varphi)\} =$$

$$\max\left\{\int_0^t\int_0^\lambda\left[a_M(\tau) - a_{Lo}(\tau)\right]d_\tau d_\lambda + v_M(0) - v_{Lo}(0)t + 2L_x + W\sin(\varphi)\right\}, \tag{2}$$

$$\forall\, t \in (t_{in}, t_c)$$

Where: X, v, a are longitudinal displacement, velocity and acceleration respectively,t_{in} indicates the moment of commencement of the changeover, ,t_c denotes the moment of critical collision,λ, τ are integral variables.

In this paper, a fifth-degree polynomial is used to plan the lane change trajectory, and the constructed trajectory function is shown in Eq. (3), and Eqs. (4) and (5) are the velocity and acceleration functions, respectively, i.e.

$$\left.\begin{aligned} X(t) &= a_5t^5 + a_4t^4 + a_3t^3 + a_2t^2 + a_1t + a_0 \\ Y(t) &= b_5t^5 + b_4t^4 + b_3t^3 + b_2t^2 + b_1t + b_0 \end{aligned}\right\} \tag{3}$$

$$\left.\begin{aligned} v_X(t) &= 5a_5t^4 + 4a_4t^3 + 3a_3t^2 + 2a_2t + a_1 \\ v_Y(t) &= 5b_5t^4 + 4b_4t^3 + 3b_3t^2 + 2b_2t + b_1 \end{aligned}\right\} \tag{4}$$

$$\left.\begin{aligned} a_X(t) &= 20a_5t^3 + 12a_4t^2 + 6a_3t + 2a_2 \\ a_Y(t) &= 20b_5t^3 + 12b_4t^2 + 6b_3t + 2b_2 \end{aligned}\right\} \tag{5}$$

The critical collision moment t_c under each driving style is calculated by making $Y(tc) = W\cos(\varphi)$. The safety distance D_{MSS} is obtained by substituting X(t) in Eq. (3) into Eq. (2), and the results are shown in Table 3.

Table 3: Critical collision moments and minimum safe distances for lane changing for different styles of drivers

	t_c/s	D_{MSS}/m
Cautious type	3.97	12.21
Normal type	3.68	10.79
Radicalization type	3.38	9.21

5. Kinetic modeling

Model predictive control (MPC) is a control method for solving optimization problems with constraints on a rolling basis. Its biggest advantage is that it can add multiple constraints in the control process, which can control the vehicle more rationally and efficiently, and also further simplify the results and improve the reliability of the control system.

The model used in this paper is a three-degree-of-freedom vehicle model with lateral, transverse and longitudinal motions. The following idealized assumptions are made for the vehicle[6-7].

(1) Assuming that the car is driven only on a flat road surface and that the suspension system and the vehicle are rigid, the vertical motion of the vehicle and the effect of the suspension are neglected.

(2) Neglecting the effect of air resistance.

(3) Assuming that the vehicle speed changes slowly, the change of tire characteristics and the change of correction moment due to the change of left and right tire loads are ignored.

(4) The vehicle is assumed to be front-wheel drive, the effect of the steering system is ignored, and the front wheel angle is taken as an input.

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Based on the above four assumptions, the planar motion vehicle has only three directions of motion, i.e., longitudinal, transverse and transverse pendulum motion. The vehicle model is equivalent to a monorail model by replacing the front and rear wheels with an equivalent front wheel and an equivalent rear wheel, respectively. The model is shown in Fig. 3.

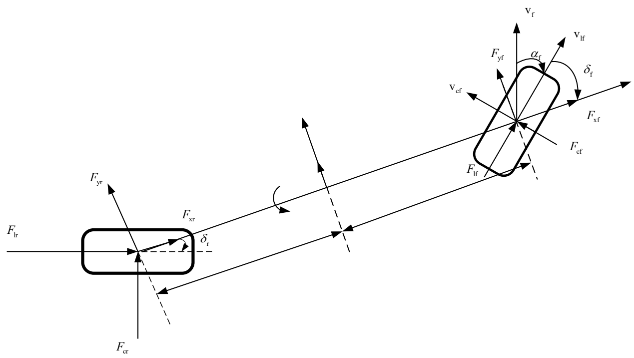

Figure 3: Three-degree-of-freedom vehicle model.

Based on the assumption of small angle of front wheel turning angle, the force relationship along x and y coordinate axes and the moment relationship around the center of mass of the car are obtained by analyzing the force on the car as follows:

$$\begin{cases} \mathrm{m}\dot{\mathrm{x}} = \mathrm{m}\dot{\mathrm{y}}\dot{\varphi} + 2F_{\mathrm{xf}} + 2F_{\mathrm{xr}} \\ \mathrm{m}\ddot{\mathrm{y}} = -\mathrm{m}\dot{\mathrm{x}}\dot{\varphi} + 2F_{\mathrm{yf}} + 2F_{\mathrm{yr}} \\ I_{\mathrm{z}}\ddot{\varphi} = 2\mathrm{l}_{\mathrm{a}}F_{\mathrm{yf}} - 2\mathrm{l}_{\mathrm{b}}F_{\mathrm{yr}} \end{cases} \tag{6}$$

The Pacejka magic tire model was used to represent the longitudinal and lateral tire forces, and the tire forces were approximated by a linear function:

$$\begin{cases} F_1 = C_1 s \\ F_c = C_c \alpha \end{cases} \tag{7}$$

Based on the assumption of small angle of tire side deflection, the calculation of tire side deflection is expressed as:

$$\begin{cases} \alpha_f = \delta_f - \dfrac{\dot{y} + a\dot{\varphi}}{\dot{x}} \\ \alpha_r = \dfrac{\dot{y} + b\dot{\varphi}}{\dot{x}} \end{cases} \tag{8}$$

Ultimately, the established three-degree-of-freedom vehicle dynamics model can be expressed as:

$$\begin{cases} m\ddot{y} = -m\dot{x}\dot{\varphi} + 2\left[C_{cf}\left(\delta_f - \dfrac{\dot{y} + a\dot{\varphi}}{\dot{x}}\right) + C_{cr}\dfrac{b\dot{\varphi} - \dot{y}}{\dot{x}} \right] \\ m\ddot{x} = m\dot{y}\dot{\varphi} + 2\left[C_{lf}s_f + C_{cf}\left(\delta_f - \dfrac{\dot{y} + a\dot{\varphi}}{\dot{x}}\right)\delta_f + C_{lr}s_r \right] \\ I_s\ddot{\varphi} = 2\left[aC_{cf}\left(\delta_f - \dfrac{\dot{y} + a\dot{\varphi}}{\dot{x}}\right) - bC_{cr}\dfrac{b\dot{\varphi} - \dot{y}}{\dot{x}} \right] \end{cases} \tag{9}$$

$$\begin{cases} \dot{X} = \dot{x}\cos\varphi - \dot{y}\sin\varphi \\ \dot{Y} = \dot{x}\sin\varphi + \dot{y}\cos\varphi \end{cases}$$

6. Simulation test

In this paper, CarSim/Simulink is used to conduct a joint simulation test on lane change planning and tracking control for different driving styles. The effect of lane change trajectory planning and tracking control is evaluated by analyzing the transverse error, traverse angle error and other indexes under each working condition.

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Figure 4 shows the results of lane changing trajectory planning and tracking for different driving styles, and the results show that the actual trajectory is smoother and can track the desired trajectory better during the whole tracking process. Figure 5 shows the lateral errors of different driving styles in tracking the lane change trajectories, and the results show that the overall trend of the lateral errors is to increase and then decrease, and then increase and then decrease in the reverse direction. Figure 6 shows the tracking transverse error of lane changing trajectories of different driving styles. The maximum transverse error and the maximum transverse angle error in Figures 5 and 6 both occur near the maximum curvature of the lane changing trajectory, which indicates that the error increases with the increase of curvature. Comprehensive Figs. 4-6 show that the designed trajectory tracking controller is able to track the desired trajectory better, with smaller transverse error and traverse swing angle error, and the errors are all within the acceptable range. Figure 7 shows the lateral acceleration of tracking trajectories for different styles of drivers changing lanes. From Fig. 7, it can be seen that the curve does not have a large sudden change, and the maximum lateral acceleration is less than $2\,m \cdot s^{-2}$, which can ensure the driver's comfort in the process of changing lanes. Figure 8 shows the longitudinal speed and speed tracking error for different driving styles. From Fig. 8, it can be seen that the speed tracking error under each working condition is small and negligible relative to the desired speed, indicating that the speed tracking controller designed in this paper can track the desired speed of different styles of drivers better.

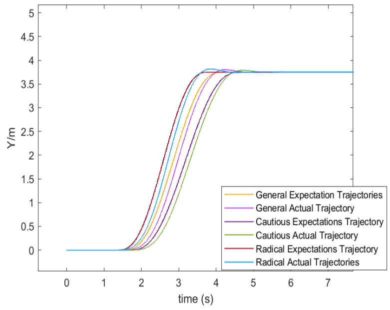

Figure 4: Lane change trajectory tracking results.

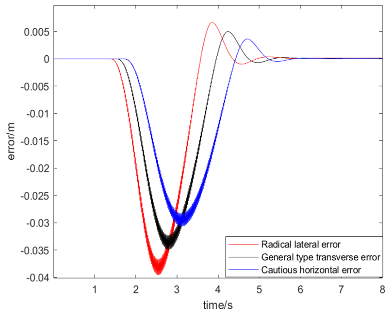

Figure 5: Lateral Error.

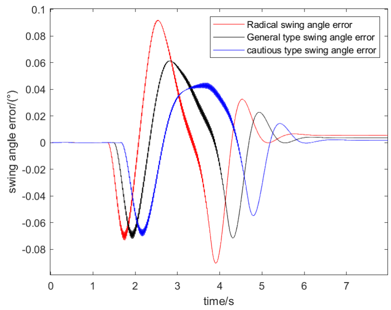

Figure 6: Pendulum Angle Error.

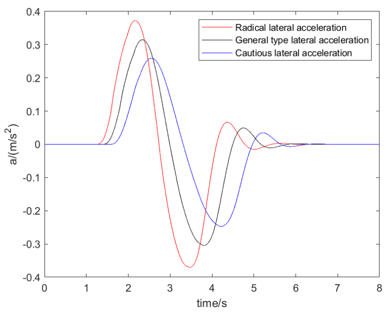

Figure 7: transverse acceleration.

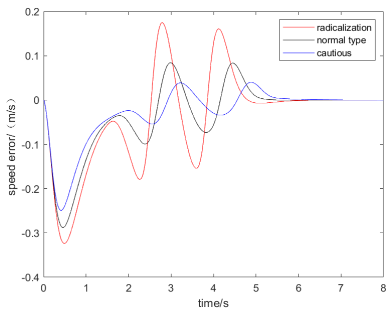

Figure 8: Longitudinal speed tracking error.

7. Conclusions

(1) This paper integrates personalized driver style in automatic lane changing control technology, establishes a vehicle lane changing trajectory planning and control model considering driver style, and the results of the study can provide a reference for the study of lane changing considering driver style.

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(2) The data screened in the HighD database are analyzed by principal component analysis and K-means clustering, so as to classify the data according to driving styles, and the characteristics of lane changing behaviors of drivers with different styles are obtained by analyzing the driving data of drivers with different driving styles.

(3) A decision-making method for autonomous lane-changing behavior of smart cars is proposed, in which the characteristic factors affecting the lane-changing behavior of smart cars are taken as conditional attributes and the driving behavior of smart cars is taken as decision-making attributes, and the driving experience of drivers is imitated and learned based on CNN-LSTM-Attention neural network, and a lane-changing decision-making model is established by the trained neural network, so as to complete the design and development of an autonomous lane-changing behavior decision-making model for smart cars. The design and development of autonomous lane-changing behavioral decision-making model for intelligent vehicles is completed.

(4) CarSim and MATLAB/Simulink are used to conduct joint simulation tests on lane changing planning and tracking control for different driving styles, and the results show that the lane changing trajectory tracking model designed in this paper, which takes the driver into account, has a small tracking error and can satisfy the lane changing needs of different drivers.

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