

Study on Anthropomorphic Lane Changing Decision Making for Smart Trucks Based on Driving Behavior

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Abstract: In order to improve the applicability of the lane change decision model to different styles of drivers, especially for trucks with less flexibility and stability of their own, safe and reasonable lane change decisions are more important. In this paper, based on the research of integrating personalized driver styles in automatic lane change control technology, a vehicle lane change decision model considering driver styles is established. Firstly, the HighD dataset is screened and the drivers are classified by driving style using principal component analysis and K-means (K-means) cluster analysis. Secondly, we propose a lane change decision model that takes into account the rationality and safety of lane change by learning human drivers' driving behavior experience through Long Short-Term Memory (LSTM) method, so as to improve drivers' acceptance and satisfaction of smart cars. Finally, the joint simulation by Simulink/CarSim/PreScan software proves that the lane change decision method based on the driver's style proposed in this study can realize the autonomous lane change task of smart cars.

Keywords: Highway safety, Curved section, Lane changing, Emergency collision avoidance, Minimum safe distance.

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 human-driving vehicles need to travel together on the road and maintain 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 model the lane changing decision of intelligent trucks in free lane changing situations to ensure the safety and ride comfort of self-driving vehicles when changing lanes.

Initially, the lane changing decision-making model was based on the rules of the road, and Gipps[1] proposed in the twentieth century that lane changing behavior can be analyzed from three aspects: 1) necessity, 2) safety, and 3) propensity. Yang[2] 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[3] et al. classified the vehicle lane changing into free lane changing, forced lane changing and collaborative lane changing. Kesting[4] 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 [5] et al. used Bayesian network to model vehicle lane changing. Motamedidehkordi [6] et al. modeled the lane changing decision through random forests. Shalev-Shwartz S[7] 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[8], 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 problem of insufficient consideration of vehicle dynamics constraints. Jin Fan[9] 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[10] et al. used environmental state information as input and decision commands as output to train the decision-making system using deep reinforcement learning, but the final training effect was less satisfactory.

At present, deep learning has been widely recognized as an effective means to improve the perceptual ability of automatic driving, and there are still some limitations from the point of view of the research object and means: firstly, the research object of vehicle lane-changing decision-making is mainly for sedans, while the research for heavy trucks is still relatively small; secondly, an important research direction in the area of decision-making and planning tasks is the anthropomorphism of automatic driving decision-making, which doesn't need to provide its own A lot of driving rules, as long as the system is given enough driving data, the neural network model can automatically learn the driving skills under different traffic conditions. Therefore, the design of lane-changing decision-making models using neural networks plays an important role in realizing anthropomorphic decision-making for self-driving cars.

Trucks play a very important role in land transportation because of the large amount of cargo they carry. It is due to the large amount of loaded cargo leads to its own characteristics of large mass and high center of gravity, which greatly increases the possibility of vehicle destabilization due to continuous steering during high-speed lane changing, thus leading to major traffic accidents [11]. In order to improve the safety of intelligent trucks as well as to improve the efficiency of access, it is necessary to improve the lane changing ability of intelligent trucks.

In this paper, we take driving style as the starting point, categorize driving styles through HighD database, establish a lane changing decision model based on LSTM neural network, and finally verify the lane changing decision through simulation software and driving simulation platform.

2. Driving Style Classification

Driving style refers to the relatively stable driving behavior characteristics presented by a person in the process of driving a vehicle, reflecting the driver's mastery of the vehicle's habitual maneuvering behavior [12]. There are many factors that can influence driving style, including the driver's personality, gender, driving age and driving experience, as well as road and environmental factors. Therefore, driving styles have been studied in order to improve the comfort of drivers with different styles when riding smart trucks as well as to enhance the safety level of smart trucks.

2.1. Introduction to the HighD Vehicle Dataset

In this paper, the HighD vehicle trajectory open source dataset is used as the data source [13]. This dataset is vehicle information extracted by UAVs photographing German highways at high altitude, and Figure 1 shows a bird's eye view view of the UAV capturing a length of about 420m.

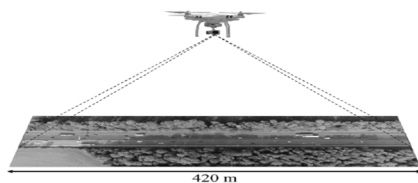


Figure 1. Drone captures road map

2.2. Categorizing Driving Styles

In this paper, 13 feature parameters related to driving style are selected to reflect the driver's driving behavior. In this paper, principal component analysis [14] (PCA) is used for dimensionality reduction. In the PCA dimensionality reduction process, variables that may be correlated are first extracted, and then these correlated feature variables are converted into a set of fewer and linearly uncorrelated variables by orthogonal transformation to replace the original variables.

The contribution rate of different principal components and the cumulative contribution rate can be obtained through calculation, and the calculation results are shown in Table 1.

Table 1. Factor analysis related data

Number	eigenvalue	Rate%	Cumulative contribution%
1	4.574	33.442	33.442
2	3.648	21.112	54.554
3	2.756	19.225	73.779
...
11	0.051	0.309	99.657
12	0.040	0.279	99.936
13	0.008	0.064	100.000

Get the original data and the principal components of the eigenvectors. According to the coefficient matrix, we can get the expression of the common factor: where F1 is the "acceleration factor", F2 is the "transverse factor", F3 is the

"follow-up factor", F4 is the "longitudinal factor". F4 is the "longitudinal factor".

$$\begin{cases} F_1 = -0.26X_1 - 0.363X_2 + B + 0.027X_{13} \\ F_2 = 0.286X_1 + 0.206X_2 + B - 0.319X_{13} \\ F_3 = -0.021X_1 - 0.051X_2 + B - 0.08X_{13} \\ F_4 = 0.494X_1 + 0.404X_2 + B + 0.401X_{13} \end{cases} \quad (1)$$

2.3. Driving style k-means clustering results

The k-means algorithm was applied for cluster analysis and from the above it is clear that 4 factors were selected for the analysis. The number of cluster centers selected is 3. The number of three types obtained and the factor values are shown in Table 2. The comparison shows that type 1 is aggressive driver, type 2 is cautious driver and type 3 is average driver. The experimental data includes 51 groups of cautious data, 94 groups of aggressive data, and 201 groups of general data.

Table 2. Factor Score Coefficient Matrix Clustering Center Factor

F1	F2	F3	F4	amount
-19.235	13.615	1.019	32.088	94
-4.937	3.921	3.216	15.265	51
-15.140	10.193	1.475	26.059	201

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

In order to make the lane changing decision more anthropomorphic, this paper adopts neural network to learn the lane changing decision, the method can use the driver's lane changing driving behavior data to imitate the driver's driving experience to learn, so as to make the driving decision of the intelligent trucks more similar to the real drivers, and this paper proposes an architecture of an autonomous lane changing decision-making method for intelligent trucks.

3.1. Model Input Definitions

The raw data are processed to extract the following feature parameters as inputs to the lane changing decision model:

- 1) The travel distance of this vehicle with respect to the vehicles before and after it;
- 2) The collision time of this vehicle relative to the vehicles before and after it;
- 3) The headway time distance of this vehicle relative to the vehicles before and after it;
- (4) Longitudinal velocity, acceleration V_x , a_x , and lateral velocity, acceleration V_y , a_y of the vehicle;
- 5) The front sight distance d_f and rear sight distance d_b of this vehicle with respect to the vehicle in front and behind.
- (6) Driving behavior label.

3.2. Model training and evaluation

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

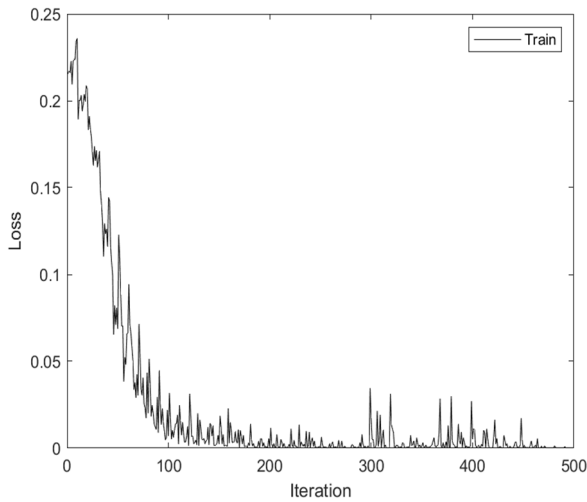


Figure 2. LSTM Model Loss Decline Curve

In order to verify the effectiveness of the lane changing decision-making model proposed in this paper, comparison tests are conducted with the lane changing recognition model based on Support Vector Machine, Hidden Markov Model, and Back Propagation Neural Network on the same dataset, respectively, and the experimental results are shown in Table 3, which indicate that the performance of the model based on the LSTM neural network proposed in this study has a significant advantage.

Table 3. Model training results

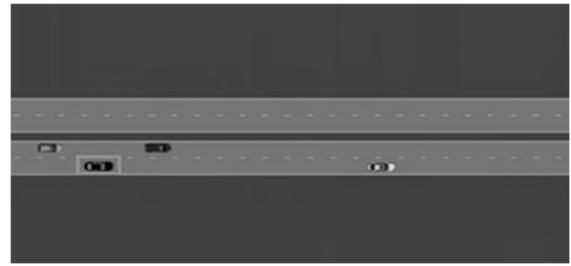
Mould	Accuracy
LSTM Test 1	96.76%
LSTM Test 2	95.68%
LSTM Test 3	96.22%
LSTM Test 4	95.14%
SVM	70.04%
Back Propagation	90.55%
Hidden Markov	88.27%

4. Validation and Analysis of Anthropomorphic Lane Change Decision Models

4.1. Validation of the lane change decision model

In this paper, PreScan/Simulink/CarSim is used to verify the feasibility of lane changing decision. The simulation results of this experiment are shown in Fig. 3, the intelligent car is traveling in the right lane of the highway, the vehicle located in front of the car is traveling slowly, the speed is low, and the speed of the vehicle in front of the left lane is higher than the speed of the car, the distance of the vehicle behind the left lane is farther and the speed is close to that of the car, therefore, the driving conditions of the left lane are better, and the judgment is that the conditions of the lane change are satisfied at the present time, and the vehicle starts to execute

the left lane change.



(a) Start of simulation



(b) Change of channel decision implementation

Figure 3. Simulation process for lane change decision making

4.2. Validation of Lane-Changing Decision Model Based on Different Driving Styles

The driving simulation platform built in this paper consists of a host computer equipped with Virtual Test Drive (VTD) simulation software, a high-definition display, and driving simulation equipment.

The lane-changing simulation condition is shown in Fig. 3, where the scene is built in VTD and six drivers are recruited for simulated driving experiments, and the driving styles of the drivers have been tested and categorized accordingly before the experiments.

Since the driving styles of drivers are different, the requirements for the environmental conditions in the lane changing process will also be different. Different drivers' attitudes, thinking styles and habitual driving behaviors have an impact on driving vehicles. Compared to other driving behaviors, when changing lanes, it is important to observe not only the situation in front of you but also the traffic conditions behind and to the side, and to make lane-changing decisions based on the observed information. Drivers with different styles pay attention to different traffic conditions when changing lanes, and they have different lane-changing thresholds. Therefore, this paper establishes a lane-changing decision-making model for drivers with different driving styles to ensure the performance of the model in terms of decision-making safety and comfort, and to further improve the accuracy of the decision-making model.

Through the simulation experiments of the drivers, and after collecting as well as processing the obtained data, the comparison graphs of lane changing moments, lane changing times and decision-making models of drivers with different driving styles are made as shown in Fig. 4.



Figure 4. Comparison chart of experimental results

By analyzing different driver data, we obtained the corresponding types of lane change decisions. As a result, corresponding variations in lane change moments and lane change times were observed, as shown in Fig. 4. In terms of lane change moments, the lane change moments of aggressive drivers' decisions are 0.25 seconds earlier than those of average drivers, while the lane change moments of cautious drivers' decisions are 0.31 seconds later than those of average drivers. In terms of lane change time, the lane change time of the aggressive driver decision decreased by 0.49 seconds compared to the average driver, while the lane change time of the cautious driver decision increased by 0.6 seconds compared to the average driver.

As mentioned above, the data collected by the driving simulator is extracted and analyzed, and a lane-changing decision-making model is established based on the long and short-term neural networks, and the driving styles are added into it so as to improve the applicability as well as the comfort of drivers with different styles to the lane-changing decision-making model proposed in this paper.

5. Conclusion

The manuscript should include a conclusion. In this section, summarize what was described in your paper. 1) In this paper, we investigated how to incorporate personalized driver styles in automated lane changing decision making, and developed a vehicle lane changing decision making model that considers driver styles. The data in the HighD database were analyzed using principal component analysis and K-means clustering in order to classify the data according to driving style. By analyzing the driving data of drivers with different styles, the characteristics of lane changing behavior of drivers with

different styles were obtained.

(2) In this paper, an anthropomorphic autonomous lane changing decision-making method for smart trucks is proposed to learn the driver's behavior based on LSTM neural network in order to build a lane changing decision-making model, which is found to have a high accuracy rate. Simulink/CarSim/PreScan joint simulation is used to verify the feasibility of the lane changing decision.

(3) Through the simulated driving environment constructed, different styles of drivers are recruited to perform lane changing under the set working conditions, and compared with the lane-changing decision of introducing driving styles proposed in this paper, and the comparison results show that the effect is better. Finally, the design and development of the autonomous lane-changing behavioral decision-making model for intelligent trucks is completed. Authors are strongly encouraged not to reference multiple figures or tables in the conclusion; these should be referenced in the body of the paper.

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