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Decision - making of Lane Change Behavior Based on RCS for Automated Vehicles in the Real Environment

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Abstract—**This paper proposes the decision-making framework of lane change behavior based on Hierarchical State Machine (HSM) and we build distributed control system architecture based on RCS (Real-Time Control System) to test the model. Environment perception module, decision planning module and execution control module are put into the distributed system architecture based on RCS to improve real-time and ensure that several modules run simultaneously. Besides, the decision-making framework of lane change behavior consists of two parts: miniature scene information model and decision-making model of lane change behavior based on multi-attribute decision-making. The decision-making model of lane change behavior is based on HSM and it sets two top-level state machines: free lane change model and mandatory lane change model. Free lane change model changes the state by using lane reward model to judge and assess driving condition of each lane, while mandatory lane change model uses strategy of multi-source information fusion to judge whether to lane change. In the end, the unmanned platform BYD Tang using vehicle embedded platform is used to verify the reliability and effectiveness of the lane change decision-making algorithm proposed in this paper in the real road environment.**

***Keywords*—automated vehicle, lane change behavior decision-making model, hierarchical state machine, RCS, real-vehicle tests**

I. INTRODUCTION

With the development of key technologies such as artificial intelligence and machine learning in recent years, automated vehicle has gradually been a promising research area and drawn widespread public attention [1]. Behavior decision-making module is the key for automated vehicles to handle complex, dynamic real urban traffic environment. Also, the fast and accurate behavior decision can reduce accidents, which is of great significance to the personal safety.

In order to achieve automated driving, a number of studies have been conducted. The Odin automated vehicle developed by Virginia tech university [2] subdivided the driving behaviors and scenarios of overtaking, changing lanes, and car-following into different models to deal with them separately. Brechtel S et al. proposed an approach based on solving a continuous POMDP. They considered the sources of uncertainty, such as stochastic behavior of other road users and the measurement process of sensors. Then they models the driving tasks as a continuous POMDP based on the pose and velocities of the involved road users [3]. P. Suresh et al. presented a cognitive decision-making algorithm for automated vehicles which tried to emulate human driver behavior[4]. They used vehicle dynamics model for different traffic scenarios to demonstrate the performance of integration of the control and decision making modules in MATLAB / SIMULINK software environment. Seongjin Choi et.al focused on a lane change probability solutioning finding process based on genetic algorithm(GA) process[5]. They built a virtual road and used macroscopic and microscopic simulation to analyze behavioral changes. Yi Hou[6] et.al combined Bayes classifier and decision-tree into a single hybrid classifier to develop models for mandatory lane changes at lane drops.

In the previous research, we proposed an intention-aware decision-making algorithm for autonomous driving in an uncontrolled intersection [7]. An intention prediction model was built which uses easy observed parameters such as velocity and position to recognize the lateral and longitudinal behaviors of human-driven vehicles. Finally, the model was verified with Prescan which can interact with Matlab/Simulink. We regarded overtaking behavior as a separate driving behavior and presented a decision-making model of overtaking behavior for automated driving on freeways, which was also verified with Prescan/Simulink[8]. We conducted a research on the rules of lane change for vehicles driving autonomously in urban environment [9]. The rough set algorithm was used to process the driving data of human driver and the driving rules were extracted. The safety of the lane change decision algorithm is verified by co-simulation with V-rep and Visual Studio.

Our previous research on the behavior decision- making of automated vehicles is mainly based on the theoretical research and experimental verification in simulation environment. Although some achievements have been made, there is a certain difference between the simulation environment and the real traffic environment. Therefore, the research on behavior decision-making of automated vehicles in real traffic environment is necessary. In the real traffic environment, the control algorithm has higher requirements on real-time performance and requires multiple application modules to work simultaneously. In this paper, we propose a decision-making framework of lane change behavior which consists of miniature scene information model and decision-making model of lane change behavior. What's more, in order to test the framework in the real road, we build the real-time control architecture based on RCS (Real-Time Control System) library under Ubuntu system, which can guarantee the independence and cooperation among several modules. RCS can accomplish the real-time control of complex tasks by breaking down a huge system into simple sub-modules [10]. Therefore, we put environment perception

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module, decision planning module and execution control module into the real-time control platform based on RCS.

The remainder of this paper is organized as follows: In Section II, we introduce the overview of the framework based on RCS. Section III discusses the specific content of the lane change decision-making framework. Section IV introduces the real traffic environment tests and results based on the embedded hardware platform under different real scenarios. Section V concludes this paper.

II. VEHICLE FRAMEWORK BASED ON RCS

A. Overview of framework of lane change behavior decision-making structure

As shown in the Figure 1, this paper builds a miniature scene information model as the input information of the lane change behavior decision-making model by extracting and screening valid information from real traffic scenarios. The top-level state machines of the lane change decision-making model include free lane change model and mandatory lane change model [11]. Free lane change is the behavior that drivers take the initiative to change lanes to achieve desired speed and wider driving space. Mandatory lane change is the behavior that drivers must change lanes within a certain interval to reach the target lane. The main difference between free lane change and mandatory lane change is whether it is possible to complete a given driving task without changing lanes.

As the middle layer of planning, the decision module is carried out in accordance with the global path planning. This paper only discusses the decision-making part of the lane change behavior, and does not involve with path planning. Following that, the calculation results of planning module are output to the control and executive layer. The control and executive layer generates a specific control volume to control the throttle, brake and steering of the vehicle. Besides, it returns the status quantity to the decision-making module in real time so as to complete the closed-loop control of the automated vehicle.

B. Distributed control system framework based on RCS

The RCS library is a real-time control system based on the C ++ class library, designed primarily for designing real-time distributed applications with the ability to solve cross-platform and cross-network communication problems [12].

We make use of RCS to build a software control architecture for the automated vehicle. The RCS library realizes the real-time control of the complex task system by decomposing tasks. It decomposes the huge system into a plurality of relatively simple sub-modules, each performing its own task independently. In the control architecture based on RCS, modules can cooperate with each other through NML (Neutral Message Language). Therefore, an environment perception module, a decision planning module, and an execution control module are added into the architecture. All three modules have their own sub-modules, constituting distributed control system architecture for the automated vehicles. The higher level module accepts the command information and sends it to its sub-module, while the lower level module sends its own execution information and status information back to the parent module. At the same time, all the modules update their execution status.

Top-level operation module is used to accept the commands of the developer, such as start-up, initialization, suspension and other orders. After analysis, top module send the same command to all the subordinate sub-modules to complete the interaction with the system. When we need to control a single module, for example, we want to only start the environment-perception layer of the module, it is convenient for us to send the start command to the environment-perception layer alone.

III. LANE CHANGE DECISION-MAKING FRAMEWORK

A. Miniature scene information model

For automated vehicles, a comprehensive scenario information model is the basis for the accurate scenario evaluation. The information collected by lidar, camera and other environmental sensing devices is extracted and filtered to form a miniature scene information model which is shown in Figure 2.

As the input information of lane change behavior decision-making model, miniature scene information model consists of three parts: road information model, vehicle information model and other obstacles information model. The road information model extracts the real-time information of the road in the driving scene of the current moment. The vehicle information model extracts the regional distribution, location and speed information of the environment vehicle around the automated vehicle. For example, the presence of the left rear vehicle affects the speed of lane change. The other-obstacles information model reflects the navigable area of automated vehicle in the current driving environment, avoiding collision. This information will help to enhance the understanding of the current traffic environment and make the best decision.

Take the road information model as an example. The environmental sensing module passes the relative position coordinates of the four points: A1(x_1,y_1) and A2(x_2,y_2) forms left lane line of current lane, A3(x_3,y_3) and A4(x_4,y_4) forms right lane line of current lane. X and y are the X-axis and Y-axis coordinate of the point relative to the vehicle body coordinate system (the midpoint of the rear axle of the vehicle). Based on the above conditions, the general formula of the linear equation of the two lane lines in the current lane of the automated vehicle is constructed:

$$a_i x + b_i y + c_i = 0 (i = l, r) \tag{1}$$

Where l represents the left lane line, r represents the right lane line. Then, according to the position coordinates of the four points, the parameters a_i, b_i and c_i of the line equation of the left lane of the lane are calculated. For example,

$$a_l = y_1 - y_2 \tag{2}$$

$$b_l = x_2 - x_1 \tag{3}$$

$$c_1 = y_2(x_1 - x_2) - x_2(y_1 - y_2) \quad (4)$$

After the linear equation of two lane lines is obtained, the reciprocal of slope of the lane line are obtained.

$$k_i = \frac{b_i}{a_i}(i = l, r) \quad (5)$$

B. Lane change Behavior Decision-Making Model Based on Hierarchical State Machine

As shown in Figure 3, the lane change behavior decision-making model is based on HSM. The top-level state machine is divided into free lane change model and mandatory lane change model. Both models has its own sub-states. Besides, free lane change model owns cancel lane change state, which is different from mandatory lane change model.

C. Free Lane Change Model Based On Lane Reward Value Evaluation Model

As shown in Figure 4, the free lane change model consists of three states. The migration condition between different states is essentially an evaluation of the quality of driving conditions in different lanes. We build the free lane change sub-state machine based on lane reward value evaluation model. It makes a final decision by comparing the reward values of different lanes.

$$Decision = Max(R_l, R_m, R_r) \quad (6)$$

R_l, R_m and R_r represents the reward value of left lane, ego lane and right lane of the current moment respectively. Ego lane is current lane of automated vehicle. Based on this, the reward value functions for three lanes are defined as follows:

$$R_l = R_{l\_vehicle} C_{l\_area} C_{stability} C_{l\_law} \quad (7)$$

$$R_m = R_{m\_vehicle} \quad (8)$$

$$R_r = R_{r\_vehicle} C_{r\_area} C_{stability} C_{r\_law} \quad (9)$$

Take the left lane as an example, we introduce these sub-functions. $R_{i\_vehicle(i=l,m,r)}$ is environmental vehicles reward value based on front vehicle information of left, ego and right lane, respectively.

$$R_{l\_vehicle} = \begin{cases} M, v_{LF} > v_{\max} \text{ or no left front car} \\ k_1 y_{LF} + k_2 v_{LF}, \quad \text{other situation} \end{cases} \quad (10)$$

v_{max} is the highest expected speed in the current driving environment set by the automated vehicle. v_{LF} is the speed of the left front car. K_1 and k_2 are custom factors indicating that the reward value is related to the longitudinal relative position y_{LF} and the absolute speed v_{LF} of the left front car. M is much larger than $k_1 y_{LF}+k_2 v_{LF}$ to ensure that the left lane has a high priority when there is no left front car or the speed of left front car is greater than the maximum expected speed of the automated vehicle.

Considering that the current driving lane and the adjacent lane are both in good condition, in order to ensure the safety and stability of the automated vehicle, the lane keeping state should be maintained, so M + 1 is of great value.

$$R_{m\_vehicle} = \begin{cases} M+1, v_{MF} > v_{\max} \text{ or no front car} \\ k_1 y_{MF} + k_2 v_{MF}, \quad \text{other situation} \end{cases} \quad (11)$$

C_{area} is the lane change area limit value. Lane change area limit value of left lane C_{l_area} is defined as follows:

$$C_{l\_area} = \begin{cases} 1, \text{Left car does not exist} \\ 0, \quad \text{Left car exists} \end{cases} \quad (12)$$

$C_{stability}$ is defined as the stability limit value based on the reciprocal of the slope of the straight line equation of the lane line in the body coordinate system.

$$C_{l\_stability} = \begin{cases} 1, |k_l| < K \text{ and } |k_r| < K \\ 0, \quad \text{other situation} \end{cases} \quad (13)$$

k_l, k_r is the reciprocal of slope of left and right lane line equations formula 3.5. K is the threshold of the angle between the lane line and heading angle of the vehicle. When the absolute value of k_i $(i=l,r)$ is greater than K, it indicates that the vehicle currently has not been tracking lane center line stably, which is not suitable for change.

C_{l_law} is the limit value for determining whether to allow lane change to left lane according to the traffic laws and regulations. It is defined as follows:

$$C_{l\_law} = \begin{cases} 1, \text{The left lane line is a dotted line.} \\ 0, \text{The left lane line is a solid line.} \end{cases} \quad (14)$$

When all the subfunctions of the reward value model have been calculated, the reward values of the three lanes need to be compared.

$$Decision = Max(R_l, R_m, R_r) = \begin{cases} \text{Left lane, } R_l > R_m + H \\ \text{Right lane, } R_r > R_m + H \\ \text{Ego lane, other situation} \end{cases} \quad (15)$$

Where H is a constant, which regulates the ease of triggering the change path. Because there is a cost of execution for the automatic vehicle to change lane, it is possible to make a lane-change decision only when the adjacent lane is higher than the reward value of the ego lane.

After comparing the three lanes' reward values, free lane change sub-state machine switches the decision state from lane keeping to lane change preparing state if the result is an adjacent lane. When it is in lane change preparing state, it is also necessary to calculate and compare the reward value of each lane. If the result is the current target lane and continued T seconds, the free lane change sub-state machine is ready to switch the state into lane change state. If not, free lane change sub-state machine switches the state back to lane keeping and restart lane calculation and comparison.

When it is in lane change state, the automated vehicle still needs to continuously evaluate the driving environment of the target lane to determine its own driving state. Function used to evaluate the driving situation of the target lane during the lane change is as follows. Take the left lane as the target lane for example.

$$TTC_{lr} = \frac{y_{host} - y_{lr}}{v_{y\_host} - v_{y\_lr}} \quad (16)$$

$$Estimate_1 = \begin{cases} \text{cancel lane change, } TTC_{lr} < T_{safe} \\ \text{continue lane change, other situation} \end{cases} \quad (17)$$

Among them, y_{host} and v_y_host are the current longitudinal position and longitudinal speed of the vehicle, y_{lr} and v_{y_host} are the current longitudinal position and longitudinal velocity of the left rear vehicle. $TTC_{l,r}$ is the collision time between the rear vehicle in the target lane and the automated vehicle. T_{safe} is the safety collision time threshold. When it is not suitable to continue the lane change, free lane change sub-state machine switches to cancel lane change state. When arriving at the destination lane, free lane change sub-state machine switches the lane change state to lane keeping state.

D. Mandatory lane change sub-state machine based on multi-source information fusion

The mandatory lane change sub-state machine based on the road information model is due to the law or other reasons. Crossing crossroads is a typical mandatory lane change scene. When there is a certain distance from the lane change area (the lane line is a dashed line), the decision-making module will switch to the mandatory lane change state and confirm the target lane and whether it is currently in the target lane. If so, autonomous vehicle will remain in the current lane until it crosses the intersection. If not, when approaching the mandatory lane change area, the forced lane-changing sub-state machine enters the lane changing preparation state. At this time, the automated vehicle travels in the current lane, and turns on the turn signal light as the interaction information with the environmental vehicle to transmit the lane change intention of the own vehicle. The automated vehicle calculates the collision time TTC between the rear vehicle in the target lane and the automated vehicle and compares it with the safe collision time T_{safe}. When TTC is less than T_{safe}, the automatic vehicle slows down and turns on the signal for information interaction until completing lane change. When the automated vehicle reaches the target lane, the mandatory lane change state machine change into the state of lane keeping until it passes through the intersection.

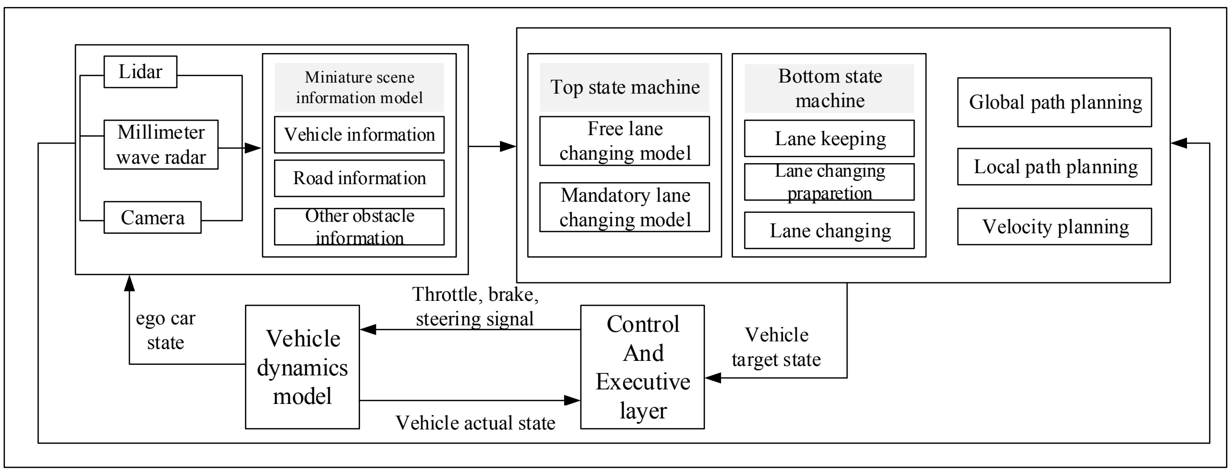


Figure 1 Lane change behavior decision-making control structure

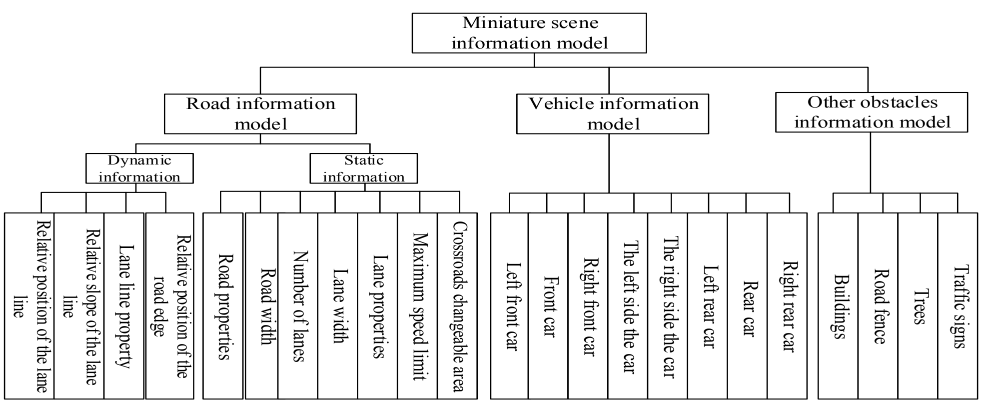


Figure 2 Miniature scene information mod

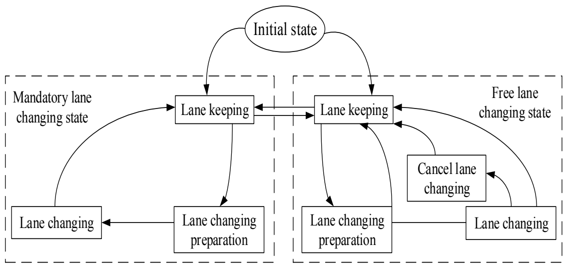


Figure 3 Lane change Behavior Decision-Making Model

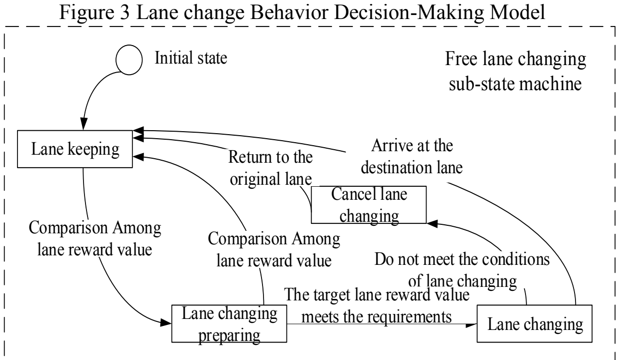


Figure 4 Free lane change sub-state machine

IV. EXPERIMENT AND ANALYSIS

In order to verify the reliability and effectiveness of the lane change decision-making model, the tests are conducted according to different scenarios. Actual vehicle test road environment is as follows. Two main tests are presented.

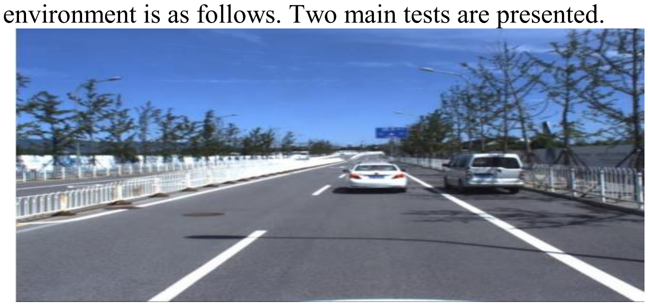


Figure 5 Actual vehicle test road environment

A. Free lane change test

As shown in the Figure 6, the unmanned vehicle is traveling at a constant speed in the middle lane. There are two social vehicles A and B in front of the right lane at a constant speed, and there is no vehicle in the left lane. Because the social vehicle B limits the speed and driving space of the social vehicle A, the social vehicle A decelerates and changes lane to the middle lane. In this case, the unmanned vehicle detects the presence of the vehicles in front of the current lane and the right lane. The left lane still does not have any vehicle. Eventually the unmanned vehicle changes lane to the left lane.

The experimental data are shown in Figure 7.

The real-time status display interface of the lane change decision-making module in the testing process is shown in Figure 8.

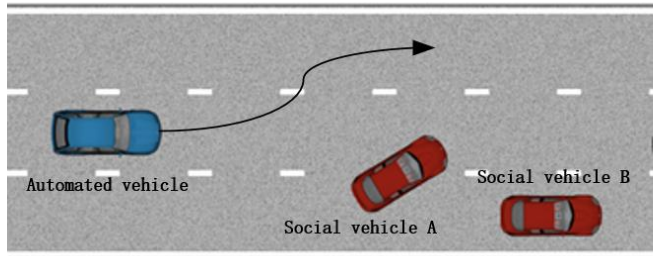
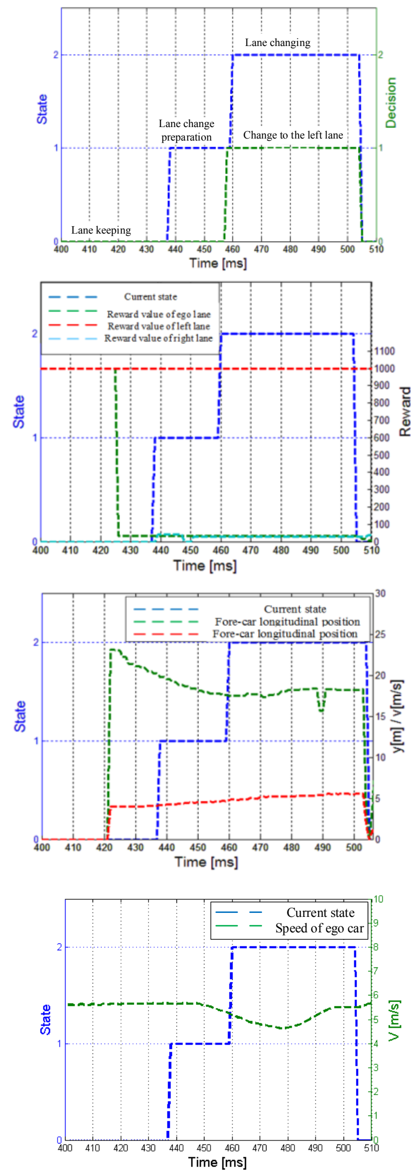


Figure 6 Free lane change test schematic diagram



(a) Decision result and execution state (b) Three lane rewards and status (c) Middle lane front car position and speed (d) Speed and condition of the car

Figure 7 Free lane change test data analysis

B. Mandatory lane change test

The specific scene is shown in Figure 9. The automated vehicle is driving straight ahead on the right turn lane before passing the crossroads. When automated vehicle needs to turn left at the crossroads, it decides to turn to the left turn lane in the mandatory lane change area until passing the crossroads.

(a) lane change preparing state (b) lane change state
(c) lane change completion state
Figure 8 Free lane change decision-making process

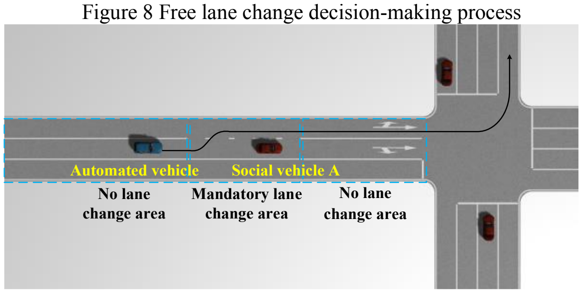
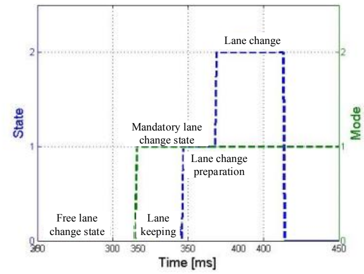


Figure 9 shows the real-time status display interface of lane change decision-making module in the process of mandatory lane change test

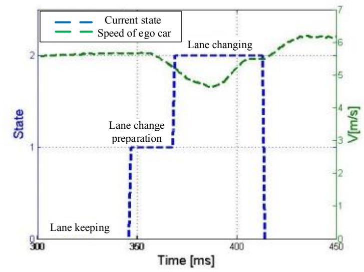
The test data is shown in Figure 10. It can be seen that when the automated vehicle approaches the intersection area, the lane change behavior decision-making model switches to the mandatory lane change state and finishes lane change action (cf. Figure 10 (a)). When changing lane, the vehicle reduces speed to ensure driving safety. After lane change, the speed is restored to the speed of lane keeping (cf. Figure 10(b)). The experiment verifies the feasibility of mandatory lane change model in real traffic environment.

V. CONCLUSION

In this paper, we propose a lane change behavior decision-making framework based on HSM and set up a distributed control system architecture based on RCS. The miniature scene information model works as the input of the decision-making model. The lane change behavior decision-making model based on the HSM is divided into two top-level state machines: free lane change sub-state machine using lane reward value model to evaluate lanes and mandatory lane change sub-state machine based on multi-source information fusion method, each having its own sub-state. Finally, the vehicle embedded platform on BYD-TANG is used to verify the models in real urban traffic environment.



（a）Some parameters in the mandatory lane change



（b)Decision result and execution state
Figure 10 Mandatory lane change test data

REFERENCES

[1] Wei J, Snider J M, Gu T, et al. A behavioral planning framework for autonomous driving[C]// Intelligent Vehicles Symposium Proceedings. IEEE, 2014:458-464.

[2] Bacha A, Bauman C, Faruque R, et al. Odin: Team victor Tango's entry in the DARPA urban challenge [J]. Journal of Field Robotics, 2008, 25 (8): 467-92

[3] Brechtel S, Gindele T, Dillmann R. Probabilistic decision-making under uncertainty for autonomous driving using continuous POMDPs[C]. Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on. IEEE, 2014: 392-399.

[4] Suresh P, Manivannan P V. Human driver emulation and cognitive decision making for autonomous cars[C]// International Conference on Robotics: Current Trends and Future Challenges. IEEE, 2017:1-6.

[5] S. Choi and H. Yeo, "Framework for simulation-based lane change control for autonomous vehicles," 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, 2017, pp. 699-704.

[6] Y. Hou, P. Edara and C. Sun, "Modeling Mandatory Lane Changing Using Bayes Classifier and Decision Trees," in IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 2, pp. 647-655, April 2014.

[7] Song W, Xiong G, Chen H. Intention-Aware Autonomous Driving Decision-Making in an Uncontrolled Intersection[J]. Mathematical Problems in Engineering,2016,(2016-5-3), 2016, 2016:1-15.

[8] Gong J, Xu Y, Lu C, et al. Decision-making model of overtaking behavior for automated driving on freeways[C]// IEEE International Conference on Vehicular Electronics and Safety. IEEE, 2016.

[9] Gong J, Yuan S, Yan J, et al. Intuitive decision-making modeling for self-driving vehicles[C]// IEEE, International Conference on Intelligent Transportation Systems. IEEE, 2014:29-34.

[10] Moore M L, Gazi V, Passino K M, et al. Complex control system design and implementation using the NIST-RCS software library[J]. Control Systems IEEE, 1999, 19(6):12, 14 - 28.

[11] C.B. Erik, Olsen, E.L. Suzzanne, W. Walter. Analysis of Distribution, Frequency, and Duration of Naturalistic Lane Changes. The Human Factors and Ergonomice Society 46th Annual Meeting, 2002:740~741

[12] Kwon J, Hailes S. MIREA: Component-based middleware for reconfigurable, embedded control applications[C]// IEEE International Symposium on Intelligent Control. IEEE, 2010:2385-2390