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Lane changing assistance strategy based on an improved probabilistic model of dynamic occupancy grids*

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Abstract: Lane changing assistance in autonomous vehicles is a popular research topic. Scene modeling of the driving area is a prerequisite for lane changing decision problems. A road environment representation method based on a dynamic occupancy grid is proposed in this study. The model encapsulates the data such as vehicle speed, obstacles, lane lines, and traffic rules into a form of spatial drivability probability. This information is compiled into a hash table, and the grid map is mapped into a hash map by means of hash function. A vehicle behavior decision cost equation is established with the model to help drivers make accurate vehicle lane changing decisions based on the principle of least cost, while considering influencing factors such as vehicle drivability, safety, and power. The feasibility of the lane changing assistance strategy is verified through vehicle tests, and the results show that the lane changing assistance system based on a probabilistic model of dynamic occupancy grids can provide lane changing assistance to drivers taking into consideration the dynamics and safety.

Key words: Occupancy grids; Probabilistic model; Lane changing assistance
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1 Introduction

Collisions are prone to occur during vehicle lane changing. According to the data from the National Highway Traffic Safety Administration (2021), about 500 000 car accidents that involve lane changing occur in the United States every year. Research includes primarily modeling and perception of the driving area and decision-making during lane changing.

1.1 Driving area perception and modeling

Various types of road environmental information are obtained by sensors, such as LiDAR and machine vision, and such information includes lane line recognition and the distance between vehicle obstacles and the vehicle of interest. This information can be effectively expressed by suitable data structures and algorithms. Many vectors can be used to express these data, and the most common is a variation of Bayesian occupancy filters that is simply called an occupancy grid or grid map. This data format provides a means of expressing sensor data to adapt to the types and characteristics of multiple sensors.

Research on occupancy grids has a long history. Moravec (1988) and Elfes (1989) described the use of occupancy grids in sensor fusion and environmental perception. However, the proposed scheme was applied to robots at that time. Coue et al. (2003) developed a Bayesian occupancy filter algorithm, whose primary feature is the fused observation of multiple sensors and the prediction and reasoning of

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the vehicle status through various observed information; thus, an accurate and reliable perception system for road environments was created. With the general application of smart car technology and computer science, various algorithms based on the occupancy grid model and other related models have gradually been developed for intelligent vehicles. Richter et al. (2009) improved the efficiency of generating occupancy grids based on LiDAR data through secondary sampling. Oh and Kang (2016) conducted fast occupancy grid filtering through grid cell clusters from LiDAR and stereovision sensors. Nadarajan and Botsch (2016) investigated vehicle safety applications to predict occupied grids based on the self-encoder and random forest algorithm. Danescu et al. (2011) predicted the probability of occupancy grid estimation via machine learning. Schreier et al. (2016) proposed a compact, free-space, dynamic object mapping scheme that characterizes the dynamic driving environment parameters in an advanced driving assistance system. Nègre et al. (2014) introduced a new representation for the Bayesian occupancy filter that describes the environment through a mixture of static and dynamic occupancy. Sivaraman and Trivedi (2014) proposed a new compact representation of road environments, called "dynamic probabilistic driving map." Their application in helping drivers make predictions and decisions in lane changing systems has been verified. Robbiano et al. (2020) proposed a new occupancy estimation method considering the dependency between the occupancy states of grid cells.

In relation to occupying the storage structure of a grid, Sencan and Temeltas (2018) developed a quantization method (Q-tree) for occupancy grids of autonomous vehicles. Kim et al. (2019) created a dynamic occupancy raster map based on a cascading support vector machine. The occupancy raster map was divided into upper and lower layers. Yatim et al. (2020) used static binary Bayesian filters to construct raster maps and neural networks to interpret the measurement results of adjacent sensors as the occupancy of grid cells.

1.2 Lane changing assistance decision-making for vehicles

There are many studies on lane changing assistance systems through algorithmic perception and modeling of the driving area environment. The methods commonly used in these studies include machine learning, fuzzy logic, and Bayesian networks. With reference to the Bayesian network method, Schubert et al. (2010) developed Bayesian decision diagrams that assist vehicles in making behavioral decisions. Kumar et al. (2013) proposed an online method that predicts lane changing intentions based on a support vector machine and Bayesian filtering. The method regards the multi-class probability output of the support vector machine as the input of the Bayesian filter, and obtains the final prediction of lane changing through the output of the Bayesian filter. Wang et al. (2019) proposed a lane changing decision method based on deep reinforcement learning with rule constraints. This method uses a deep Q-network to map the surrounding environment to the horizontal decision layer. Smirnov et al. (2021) proposed a lane changing behavior model based on non-cooperative dynamic game decision-making. Gao et al. (2019) used a new dimensionality reduction model, i.e., the collaborative representation optimization projection classifier (CROPC), to detect drivers and lane changing behaviors. To this day, research on lane changing decision-making and assistance continues.

2 Problem statement

Under extremely complex and dynamic driving conditions, adopting a reliable environment awareness model and a decision algorithm is crucial in effectively enabling safe and reliable lane changing of vehicles. Certain problems exist in most systems at present. First, combined with the sensor data, the lane changing strategy is established from only a certain algorithm. Moreover, road conditions or scenes posed are relatively simple and ideal. Second, risk estimation of lane changing is mostly for target detection and tracking of static or dynamic objects in the scene, and is derived and verified by data (e.g., the vehicle trajectory). It is generally assumed in the lane changing model that when vehicles in the adjacent lane change lanes, the vehicle in the target lane keeps moving at a constant speed. This assumption is inconsistent with the actual lane changing. Third, the impacts of traffic regulations, vehicle size, dynamic characteristics, and obstacle vehicle behavior prediction on the lane changing decisions of vehicles are not fully considered.

Therefore, two main problems should be addressed: (1) During the lane changing process, all information, including the lane line estimation, obstacle vehicles, and traffic laws, should be comprehensively considered to obtain accurate lane changing results; (2) Behavior prediction of dynamic obstacle vehicles should be conducted, and the probability problem of lane changing safety should be addressed.

An improved dynamic occupancy grid probabilistic model (DGPM) is proposed in this study. Considering the lane changing probability caused by multiple influencing factors on a lane changing decision, DGPM is used to construct a driving strategy that provides lane changing assistance to vehicles.

3 Creation of DGPM

Prior to DGPM construction, the surrounding environmental information of the vehicle must be redefined through an array of occupancy grids. These grids contain the drivability probability caused by a series of information, such as vehicle size, the maximum steering angle, traffic rules, and obstacle.

A dynamic grid is geometrically modeled in the Cartesian plane rectangular coordinate system together with lane line information. A two-dimensional (2D) image coordinate system model of the lane line is built first. On this basis, occupancy grid modeling of the driving area can be completed, and the effective driving area should be limited.

Under the premise that each equally divided grid (called a driving unit) can accommodate one car, the horizontal width of the grid is set to 3.75 m, and a vertical length of 3.75 m is set for a single lane to form a square grid area. With the vehicle position as the zero point, the vehicle is assumed to be always in the DGPM matrix [0, 0]. The driving area of the vehicle is equally divided according to the following setting principles: vertically −22.5 to 30 m and horizontally −9.375 to 9.375 m; the area is divided into a 5×14 grid map.

Vehicle and environmental information, such as the horizontal and vertical positions of a data point relative to the vehicle, obstacle type, and structural parameters, can be obtained by calculating sensor information, such as radar, camera, and Global Positioning System (GPS) inertial navigation. This information should be embedded in the cell properties, as shown in Fig. 1. Meanwhile, the grid is estimated between two updates, and the model is constantly updated. Table 1 shows the parameter description and acquisition method of DGPM.

To construct the DGPM, it is necessary to obtain environmental information through the vision sensor to form an occupancy grid first. Then, a state lattice

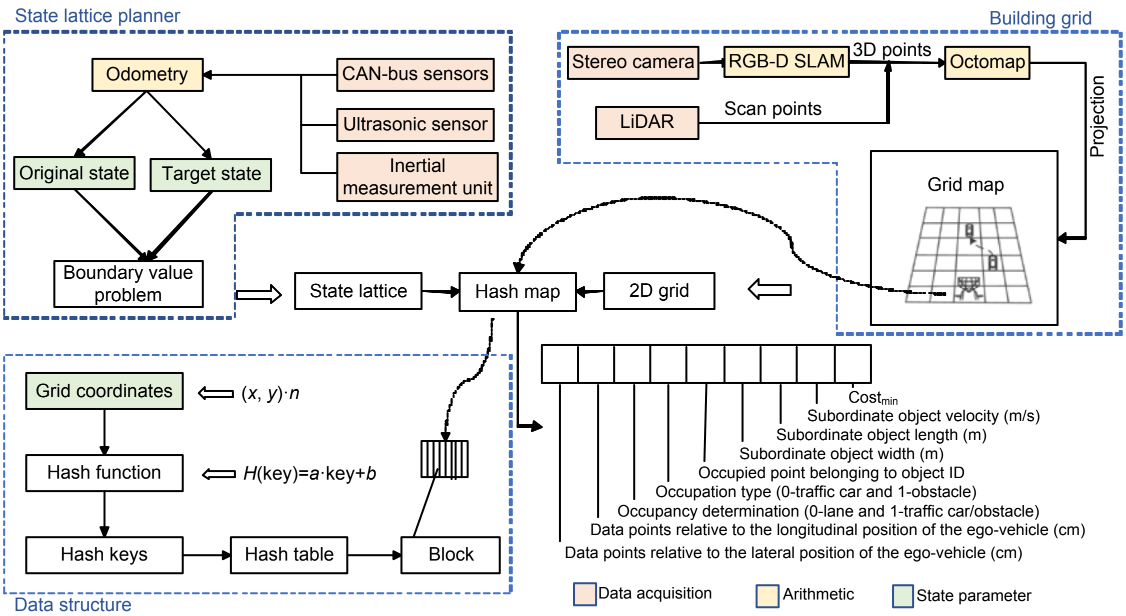

Fig. 1 Architecture of the dynamic occupancy grid probabilistic model (DGPM)

Table 1 DGPM algorithm parameters

Probability	Description	Parameter	Parameter description	Devices used to obtain the parameter
P_1	Motion information of the vehicle	V	Speed of the vehicle	Inertial positioning device
		a	Acceleration of the vehicle	
		θ	Maximum angle of the wheel of the vehicle	Vehicle sensors
		L, W	Vehicle length and vehicle width	Known
		(X, Y)	Vehicle coordinates of the grid	Algorithm update in real time
P_2	Lane line information	n	Current number of detectable lane lines	Camera inertial device
		ID	Identification of the lane of a vehicle at a certain time	
		1, 0	1 for solid line and 0 for dotted line	
		L_i	Horizontal distance of the left and right lane lines of the i^{th} grid to the vehicle	
		C_i	Curvature of the left and right lanes of the i^{th} grid	
P_3	Road vehicle/obstacle information	S_i	Distance from the obstacle vehicle in the i^{th} grid to the vehicle	(1) LiDAR; (2) posterior lateral ultrasonic sensor; (3) camera
		(x_i, y_i)	Obstacle grid position in the i^{th} grid	
P_4	Forecasting information of road vehicles	$L/M/R$	Markov prediction outputs	LiDAR

planner is introduced on the basis of the occupancy grid. Given the vehicle dynamic model, the vehicle driving path is planned using a sampling method in state space. This will make the constructed grid contain not only occupancy information, but also drivability probability data caused by a series of information such as vehicle size, the maximum turning angle, traffic rules, and obstacles.

The dynamic grid is modeled based on the Cartesian plane rectangular coordinate system. First, a 2D image coordinate system model of the lane line is built. Based on this, the occupancy grid modeling of the driving area is completed to define the effective driving area.

The first step is to use a stereo camera which can capture the depth information in addition to the RGB information provided by a normal camera. Then an RGB-D simultaneous localization and mapping (SLAM) algorithm is used to construct the three-dimensional (3D) space environment. The point cloud map of the 3D space environment obtained by the RGB-D SLAM algorithm can accurately describe the surrounding environment of the vehicle. However, the generated point cloud map is very large and occupies a large amount of storage space. Therefore, octomap modeling based on octree is used to transform the 3D point cloud map. The car moves in a plane, so the information of the third dimension of the 3D grid map obtained by octomap modeling is not important. It can be converted into a 2D grid map according to the principle of 3D projection transformation.

On the premise that each grid (called the driving unit or unit) obtained by equal division can accommodate a car, the horizontal width of the grid is set to 3.75 m and the longitudinal length of the grid is set to 3.75 m, forming a square grid area. With the position of the vehicle as zero point, the vehicle is always at the matrix [0, 0] of DGPM. The vehicle driving area is divided equally according to the following setting principles: vertically −20–50 m and horizontally −6–6 m, divided into a 5×14 grid map.

The hash map and state lattice planner are introduced based on a 2D grid. The environmental information and state parameters are stored in the hash map, as well as the minimum lane changing cost obtained from the lane changing probability. They can be iterated according to the replacement of the sensor timestamp. As shown in Fig. 1, the model is constantly updated by state estimation and searching for the grid between two updates. With a grid containing multiple information elements, a four-level probability map mode can be pre-computed by the application for each lane changing influencing factor and the minimum lane changing cost is obtained. Then, lane changing decisions are made. The four-layer probability calculation method will be described in detail in Section 4.

4 Improved DGPM construction

A four-layer probability map model is proposed based on the traditional occupancy grid model and dynamic occupancy grid data format. The model comprehensively considers the factors that influence lane changing decisions, and discretizes vehicle driving data, detection information of road vehicles and obstacles, and behavior prediction information of obstacle vehicles to calculate the lane changing cost of a vehicle in accordance with the current environment. The aim is to assist the vehicle's lane changing decision.

The drivability probability of the vehicle lane changing behavior is affected mainly by four factors, namely motion state parameters of vehicles, lane line parameters, occupation of vehicles and obstacles on the road, and road vehicle behavior intentions. The improved DGPM map is divided into four layers, as shown in Fig. 2.

1. First layer: motion information of the vehicle

Given the geometric characteristics of DGPM, the running speed of the vehicle, and the real-time nature of the program, the drivability probability $P_1(i, j)$ of the unit is set to be attenuated in accordance with the distance, and the unit probability values of other locations are selected based on the following principles:

(1) Set $P_1(i, j)$ of the unit that the vehicle cannot actually reach as 0 considering the limit turning angle when the vehicle is moving.

(2) As shown in Fig. 3, when a cell is in the same row as A, B, or C, its probability is gradually reduced in accordance with its distance from $A \rightarrow B \rightarrow C$. The change continues to be significant.

(3) When a row in DGPM does not contain an $A \rightarrow E$ unit, the probability of the row satisfies the following: when $P_1(i_2, j)$ is known and $i_1 < i_2$, we have $P_1(i_1, j) < P_1(i_2, j)$. The first-layer layout is

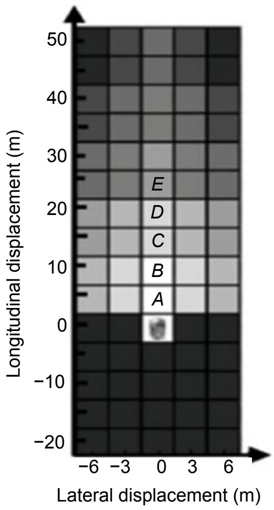

Fig. 3 DGPM initial state diagram

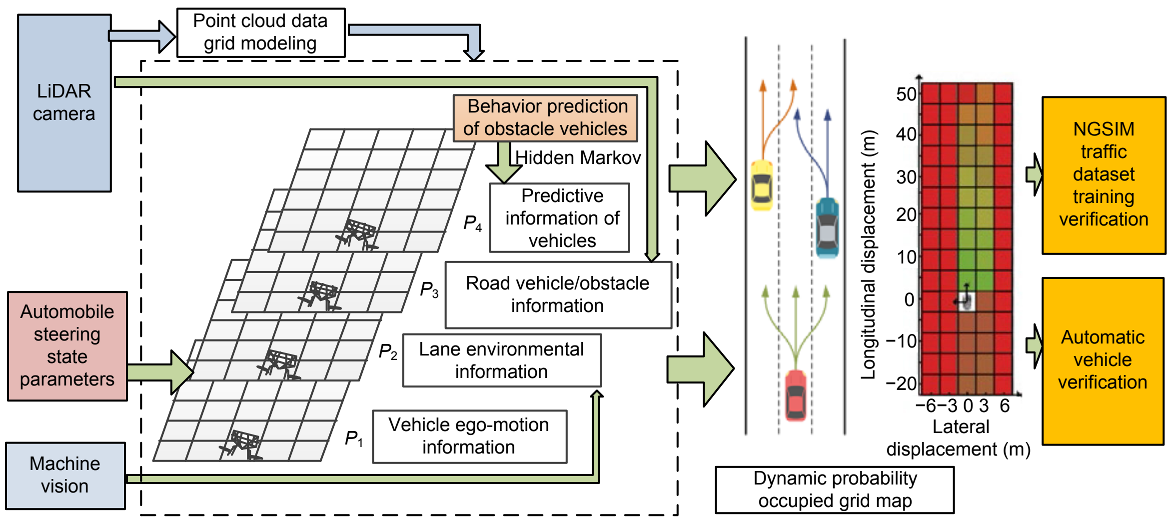

Fig. 2 DGPM algorithm framework

comprehensively selected in accordance with probability $P_1(i, j)$ of the bottom DGPM.

2. Second layer: lane line information

The second layer of the DGPM map is affected mainly by the lane environmental information, which includes the curvature of each lane line and the distance of the vehicle to the left and right lane lines. The work carried out at the second layer is of two types: First, the occupancy grid of the DGPM lane lines is divided, the input value of which is the curvature value of each lane line; Second, the work is in accordance with the drivability probability of the occupancy grid corresponding to the lane line.

The drivability probability of the second layer in DGPM is defined as $P_2(i, j)$, which considers the observation value of the lane lines and is determined by detailed lane lines. The detailed definition is shown below:

$$P_2(i, j)=\begin{cases}0, & \text{solid or unavailable lane line,}\\ 1, & \text{dotted lane line.}\end{cases} \tag{1}$$

3. Third layer: road vehicle/obstacle information

The presence of road vehicles or obstacles in the corresponding grid unit inevitably affects the drivability probability of the vehicle from the perspective of safety and power. The probability of lane changing affected by the occupation of road vehicles or obstacles is defined as $P_3(i, j)$. The solution of $P_3(i, j)$ is determined by the occupation point information at the current moment, and the specific occupation point information is obtained through the grid map:

$$P_3(i, j)=\begin{cases}0, & \text{the vehicle/obstacle part is}\\ & \quad\text{detected in this cell,}\\ 1, & \text{otherwise.}\end{cases} \tag{2}$$

The vehicle occupies a certain area in the dynamic probabilistic grid. Assuming that S_v represents the occupied area of the vehicle and that S_g represents the occupied area of cell g, the total occupied area of the vehicle and the cell is expressed as

$$S=S_\mathrm{v}\cup S_g,\quad S_\mathrm{v}\cap S_g\neq\varnothing. \tag{3}$$

The occupied area of the vehicle under the grid model can be approximately described by the Gauss formula, and the occupancy probability P_v at time t is expressed as

$$P_\mathrm{v}(t)=\oint_S -\frac{\exp(z_\mathrm{v}-z_\mathrm{g})^2}{\sqrt{2\pi}\sigma}\mathrm{d}s, \tag{4}$$

where z_v and z_g represent the coordinates of the vehicle and the occupancy grid unit respectively, and σ represents the standard deviation. Algorithm 1 is as follows:

Algorithm 1 Occupancy grid status and occupation situation of the vehicle

```
1  Initialize P=100%
2  Parameterize the grid quadrilateral cell
3  Calculate the vehicle coordinates in the grid
4  Select the i^th edge of the cell
5  Define the parameter of the line equation corresponding to
   the cell
6  Define the inner product of the line segment and occu-
   pancy point inner
7  If inner<0, P=0
8     Else Output the value of P
9  End if
```

The influence of vehicles/obstacles on the road within a safe distance on the probability parameters in the occupancy grid is the only concern. In Fig. 4, V_1, V_2, and V_3 represent three obstacle vehicles on the three lanes. All grid cells included in the safety distance are confirmed. This task is completed using Hui et al. (2018)'s algorithm.

We use the distance of vehicle V to obstacle vehicle V_3 as an example. In accordance with the state of the cell within the safe distance, the probabilities of the three states (occupied, empty, and dangerous) are determined as

$$\begin{cases}P_\mathrm{O}=\dfrac{1}{n}\sum\limits_m P_{\mathrm{O}m},\\ P_\mathrm{E}=\dfrac{1}{n}\sum\limits_m P_{\mathrm{E}m},\\ P_\mathrm{D}=\dfrac{1}{n}\sum\limits_m P_{\mathrm{D}m},\end{cases} \tag{5}$$

where P_O, P_E, and P_D are the probabilities of the occupied, empty, and dangerous states respectively, $P_{\mathrm{O}m}$, $P_{\mathrm{E}m}$, and $P_{\mathrm{D}m}$ are the probability values of the occupied, empty, and dangerous states in cell m respectively, signified as g_m (m=0, 1, …, 7), and n is the number of units belonging to the current lane within a safe distance.

The driving probability of the third layer in the grid map (road vehicle/obstacle information) is

$$P_3(i, j) = \max\{P_{\rm E}, P_{\rm O}, P_{\rm D}\}. \quad (6)$$

4. Fourth layer: forecasting information of road vehicles

The Markov prediction algorithm, hidden Markov model (HMM), is used to analyze the trajectory of the tracked vehicle and to predict whether the vehicle will change lanes. As shown in Fig. 5, the drivability probability generated under this situation is defined as $P_4(i, j)$. This information will be used to update the overall DGPM.

The Markov model λ can be expressed as λ={$\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{\pi}$, S, O}, where $\boldsymbol{A}$ represents the state transition probability matrix, $\boldsymbol{B}$ represents the state observation output probability matrix and $\boldsymbol{B}$=[$b_i(O_k)$] (here, b_i represents the probability that the output variable is O_k when the state of the preceding vehicle is s_i, i=1, 2, 3), $\boldsymbol{\pi}$ represents the probability vector at the initial state and $\sum \pi_i = 1$, S represents the number of hidden states, and O represents the number of observed variables. The hidden states of the obstacle in front of the vehicle are set to three types, namely left lane changing, lane keeping, and right lane changing (i.e., S=3). The number of observed variables is 3, which means O=3. The state transition probability matrix $\boldsymbol{A}$ is composed of the three state transition probabilities of left lane changing, lane keeping, and right lane changing. The state observation output probability matrix $\boldsymbol{B}$ is composed of the output probability of

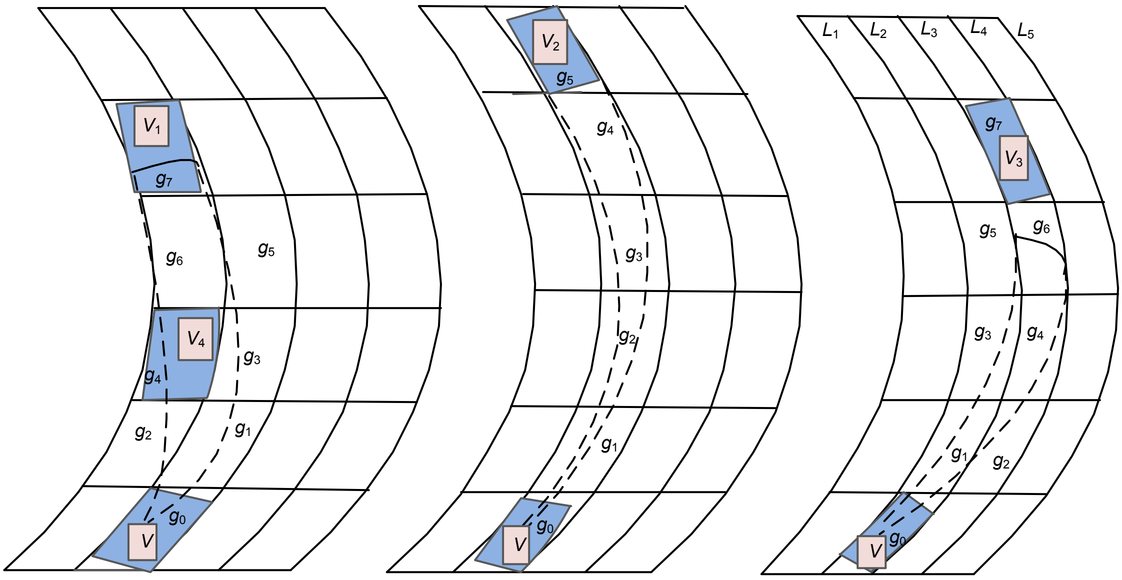

Fig. 4 Determination of occupied cells in the grid

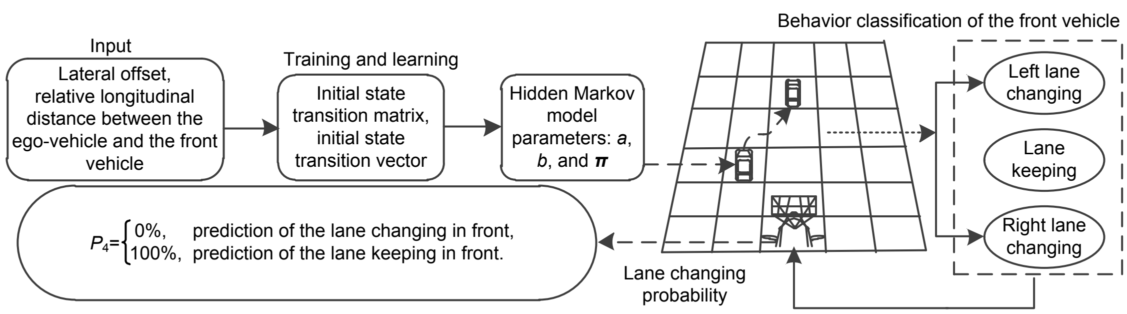

Fig. 5 Obstacle vehicle behavior prediction process

relatively lateral and longitudinal velocities in the dynamic grid and the observation value of the preceding vehicle on the $(i, j)^{\text{th}}$ grid. The initial state probability vector $\boldsymbol{\pi}$ is set using the mean method, and $\boldsymbol{\pi}$=[1/3, 1/3, 1/3].

The model is trained by the Baum-Welch algorithm to obtain the Markov model parameters. Then the Viterbi algorithm is used to predict the hidden state sequence, thereby predicting the lateral state of the preceding vehicle at the next moment. To avoid collision with the vehicle in front, the lane changeable driving probability is calculated based on the predicted lateral status information of the front vehicle and the dynamic grid probability model is updated in real time.

As shown in Fig. 6, at 1.52 s, the vehicle in front is about to change lanes, and the probability of changing to the right lane changes significantly from 0 to 100% in a short time. The opposite circumstance (i.e., the probability of changing lanes to the left is always zero) is observed for the remaining vehicles on the original lanes. In this process, the vehicle's intention to change lanes becomes increasingly clear.

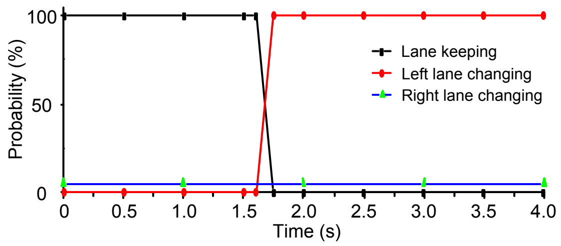

Fig. 6 Recognition probability of the right lane changing behavior

Logical judgment is made based on the probability output: it is stipulated that the confidence threshold of lane changing to the left and right is 80%, and that the confidence threshold of lane keeping is 70%. When the confidence level of lane changing intention is greater than the corresponding confidence threshold, it is determined to be the correct type. Therefore, there are only two results of the lane changing probability of this vehicle, obtained by predicting the behavior of the preceding vehicle by HMM. The output is zero when the obstructing vehicle has the intention to change lanes, and is 100% when the obstructing vehicle remains in the lane. In accordance with the prediction result of the preceding car, the probability of the vehicle lane changing is obtained as P_4:

$$P_4=\begin{cases}0\%, & \text{prediction of lane changing in front,}\\ 100\%, & \text{prediction of lane keeping in front.}\end{cases} \tag{7}$$

The following formula is provided to obtain the driving probability $P(i, j)$ of the overall cell of DGPM:

$$P(i,j)=\min\left\{P_1(i,j),P_2(i,j),P_3(i,j),P_4(i,j)\right\}. \tag{8}$$

At this point, the probability calculation method for DGPM has been introduced. After DGPM construction, the following problem emerges: how can this model give accurate advice on lane changing to drivers? A vehicle behavior decision cost equation is established from the perspectives of vehicle power and safety in this study. Drivability cost is obtained based on the DGPM as follows:

$$\text{Cost}_{\text{speed}}=\frac{\sum_{t=0}^{t=t_{\text{obj}}} t^2\left|v_{\text{ref}}-v_{\text{ego}}\right|}{\sum_{t=0}^{t=t_{\text{obj}}} t^2+\varepsilon}(1-P(i,j)), \tag{9}$$

$$\text{dist}_{\text{safe}}=\begin{cases}s_{\text{obstacle}}-\text{buffer}_{\text{yield}}-s_{i,j}, & s_{i,j}\le s_{\text{obstacle}}-\text{buffer}_{\text{yield}},\\ s_{i,j}-s_{\text{obstacle}}-\text{buffer}_{\text{yield}}, & s_{i,j}> s_{\text{obstacle}}-\text{buffer}_{\text{yield}}.\end{cases} \tag{10}$$

The parameters in Eqs. (9) and (10) are described in Table 2. The vehicle lane keeping cost $\text{Cost}_{\text{keep}}$ and the lane changing cost $\text{Cost}_{\text{chan}}$ are calculated:

$$\text{Cost}_{\text{keep}}=\frac{\sum_{t=0}^{t=t_{\text{obj}}}\exp\left[-(s_{\text{obstacle}}-\text{buffer}_{\text{yield}}-s_{i,j})\right]^2}{\sum_{t=0}^{t=t_{\text{obj}}}\exp\left[-0.5(s_{\text{obstacle}}-\text{buffer}_{\text{yield}}-s_{i,j})\right]^2}, \tag{11}$$

$$\text{Cost}_{\text{chan}}=\frac{\sum_{t=0}^{t=t_{\text{obj}}}\exp\left[-(s_{i,j}-s_{\text{obstacle}}-\text{buffer}_{\text{yield}})\right]^2}{\sum_{t=0}^{t=t_{\text{obj}}}\exp\left[-0.5(s_{i,j}-s_{\text{obstacle}}-\text{buffer}_{\text{yield}})\right]^2}. \tag{12}$$

Therefore, we have

$$\text{Cost}_{\min}=\min\left\{\text{Cost}_{\text{keep}},\text{Cost}_{\text{chan}}\right\}. \tag{13}$$

To facilitate the use of probabilistic map data to carry out lane changing decision-making, we use the hash table for data operation. The hash table provides convenient key-value functions of data storage and search. We can design a hash function such that the keyword of each element corresponds to a function value. It can be simply interpreted as sorting each element by keyword and storing it in a place that corresponds to the corresponding "class," called a block (Fig. 7). Here, we first use it to store the coordinate values of the 2D grid map and then receive each state parameter obtained by the state grid planner. The specific method is to map (x, y) of the 2D grid into a hash key-value by the hash function. We use the direct addressing method to construct the hash function, and take the key or a linear function value of the key as the hash address. Then a hash table dependent on the hash key-value is obtained, through which blocks of the grid map are stored. Each block can store the environmental information of the corresponding raster and various state parameters obtained by sensors such as radar, camera, and GPS inertial navigation, as well as the minimum lane changing cost calculated based on various lane changing probabilities. Using the hash function, the key is mapped to different blocks for storage. So, a grid corresponds to a hash table, and the entire grid map can be turned into a hash map. The best path of data can be searched quickly by breadth-first search, and the efficiency of the forwarding query can be improved.

5 Realization of the lane changing assistance strategy

The current collision time is calculated based on the position and speed of the vehicle in the longitudinal direction $\boldsymbol{v}$ to evaluate whether the lane changing strategy of DGPM entails a collision risk. Forward collision risk (FCR) is introduced as a prerequisite for vehicle behavior conditions. The FCR coefficient characterizes the risk coefficient of the collision between the vehicle and the obstacle in front. The calculation of FCR is as follows:

$$\mathrm{FCR} = \mathrm{TTC}^{-1} = \frac{V_{\mathrm{rel}}}{s_{\mathrm{obstacle}}} = \frac{V_{\mathrm{ego}} - V_{i,j}}{s_{\mathrm{obstacle}}}, \tag{14}$$

where TTC is the collision response time, V_{rel} is the

Table 2 Drivability cost parameter description of DGPM

Parameter	Description
$P(i, j)$	Drivability probability of the $(i, j)^{\mathrm{th}}$ grid of the DGPM
t_{obj}	Time elapsed for the vehicle to reach the target point
v_{ref}	Reference velocity
v_{ego}	Evaluated velocity
ε	Weighting factor
$\mathrm{dist}_{\mathrm{safe}}$	Collision safety distance
s_{obstacle}	Distance from the ego-vehicle to the obstacle vehicle
$\mathrm{buffer}_{\mathrm{yield}}$	Longitudinal collision buffer
$s_{i,j}$	Track distance from the vehicle to the $(i, j)^{\mathrm{th}}$ point in the DGPM map
$\mathrm{Cost}_{\mathrm{speed}}$	Dynamic evaluation parameter

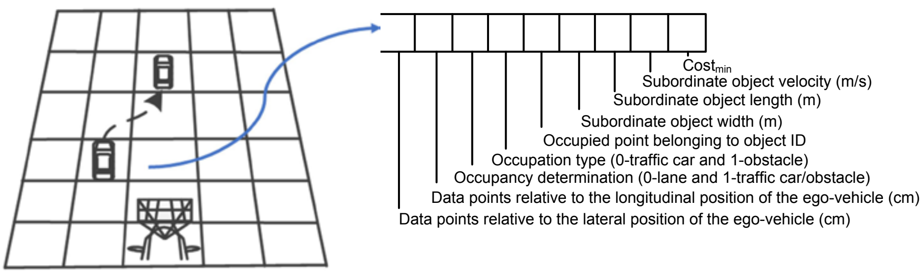

Fig. 7 Data unit of DGPM

relative speed of the vehicle to the obstacle ahead, s_{obstacle} is the real-time longitudinal distance between the ego-vehicle and the obstacle, V_{ego} is the velocity of the vehicle, and $V_{i,j}$ is the vehicle velocity at the $(i, j)^{\text{th}}$ grid.

In this study, the minimum cost is calculated for various behavior operations under different paths of the vehicle using the established DGPM, and the problems are identified and resolved. First, the system traverses the DGPM unit longitudinally in the five cells in front of the vehicle and makes a preliminary judgment about the FCR coefficient. Second, the current safety distance between the vehicle in front and the subject vehicle is calculated, and the vehicle behavior decision costs for the vehicle reaching the unit by acceleration, deceleration, or lane changing are separately computed. Third, the behavior costs of each unit under different path selections are iteratively calculated by the dynamic programming algorithm, and the current path that can generate the least cost is identified. Lastly, the current minimum cost is compared with a preset threshold. When the current minimum cost is lower than the threshold, the driver is advised to drive, and the recommended behavior and recommended acceleration are given; otherwise, the recommendation is considered invalid, and no driving recommendations are returned. The strategy's flow chart is shown in Fig. 8.

6 Vehicle test and verification

The tested vehicle used in this study is a Haval H7 passenger vehicle platform. The sensors include a four-wire LiDAR installed in the front and rear the vehicle, a millimeter-wave radar installed in front of the vehicle, a binocular camera, a GPS device, and an inertial navigation system (Fig. 9). The creation of the DGPM and the decision-making on the driving assistance behavior are completed through the collection of various sensor information (Fig. 10).

To verify the effectiveness of the dynamic occupancy raster probability model proposed in this study, the DGPM strategy is compared with the traditional vehicle lane changing decision.

The advantages of the DGPM strategy are demonstrated in Figs. 11 and 12. The blue curve in

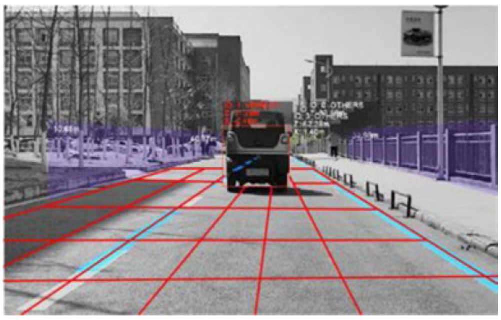

Fig. 9 Obstructing the normal movement of vehicles

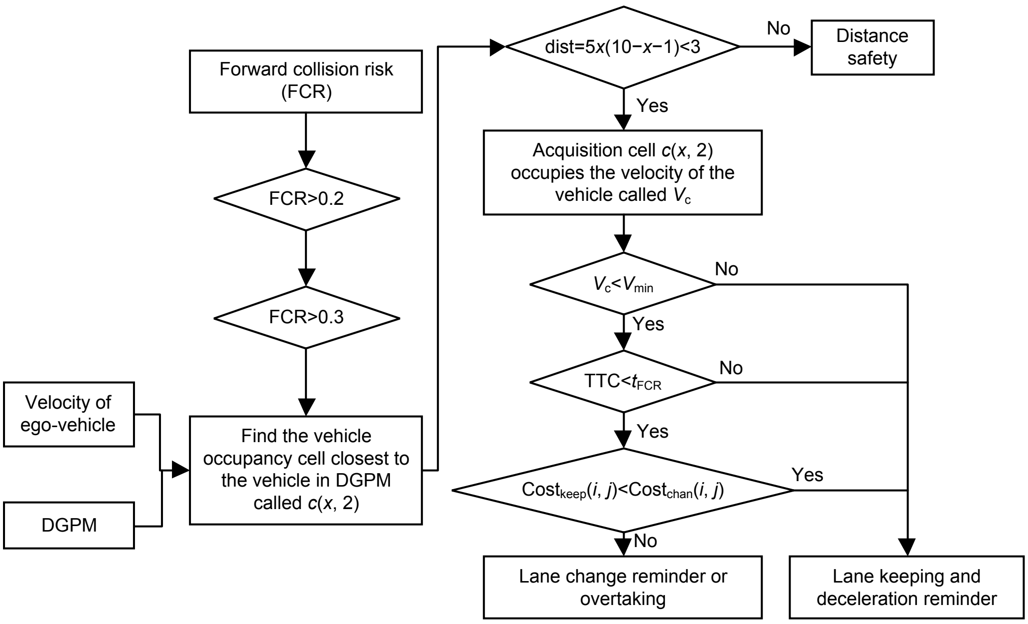

Fig. 8 Flow chart of the assisting lane changing strategy

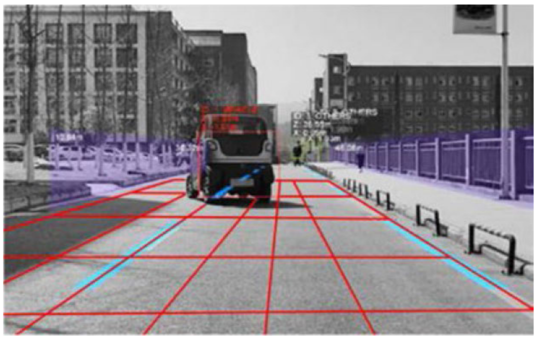

Fig. 10 Obstacle vehicle lane changing behavior

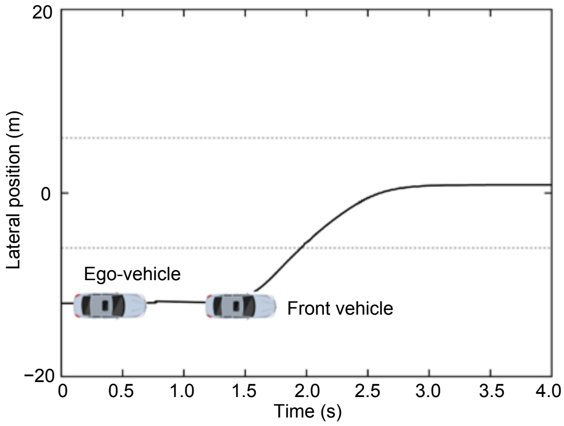

Fig. 11 Vehicle lane changing diagram

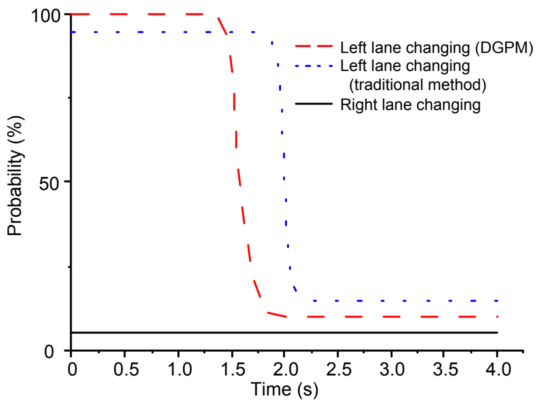

Fig. 12 Vehicle changing lane decision comparison
References to color refer to the online version of this figure

Fig. 12 shows that the traditional lane changing strategy considers only lane line information and obstacles, so the probability of the lane changing decision is 100% during 0–2 s, and the "lane changes not allowed" decision is made only after the obstructing vehicle enters the lane changing area. The red curve in Fig. 12 shows that DGPM takes into account the predicted behavior of the vehicle in front of the obstacle, so the "lane changes allowed" decision can be made at about 1.5 s to avoid actions such as emergency braking.

A typical behavior interaction scene of road vehicle driving is shown in Fig. 13. The fourth layer in DGPM, that is, the prediction probability of lane changing for obstacle vehicles on the road, is paid special attention. In the vehicle test, the initial speed of the vehicle is 36 km/h. The obstacle vehicle on the left lane (ID=01) exceeds the vehicle at a speed of 56 km/h from the left lane and performs lane changing. During the test, a change in the lane changing probability is detected by the DGPM (Fig. 14). The system detects that the vehicle ID=01 intends to change to the right lane at t=1.5 s.

Taking into account all the influencing factors of DGPM, the probability curves of vehicle lane changing assistance can be obtained (Fig. 15).

In accordance with the lane changing decisions based the DGPM, the recommended acceleration and speed changes of the car are shown in Figs. 16 and 17, respectively. At t=1.5 s, the system detects that the vehicle ID=01 intends to change to the right lane. At this time, although the vehicle is on the adjacent lane, it would inevitably exert an impact on the driving behavior and driving safety of the subject vehicle when it changes to the same lane as the subject vehicle, because the longitudinal distance of the two vehicles is too short. The system implements the minimum cost solution based on the DGPM and gives recommendations for deceleration or acceleration.

7 Conclusions

1. An improved DGPM is proposed in this study. The model fully considers various influencing factors, such as roads, vehicles, and traffic laws and regulations, and can accurately and effectively express the environmental information around intelligent vehicles.

2. The Markov model is introduced to predict and recognize the behavior of road vehicles. The behavior of a traffic vehicle can be effectively predicted by observing the lateral deviation of the vehicle and its probability of lane changing, thereby enhancing the robustness of the lane changing assistance driving strategy.

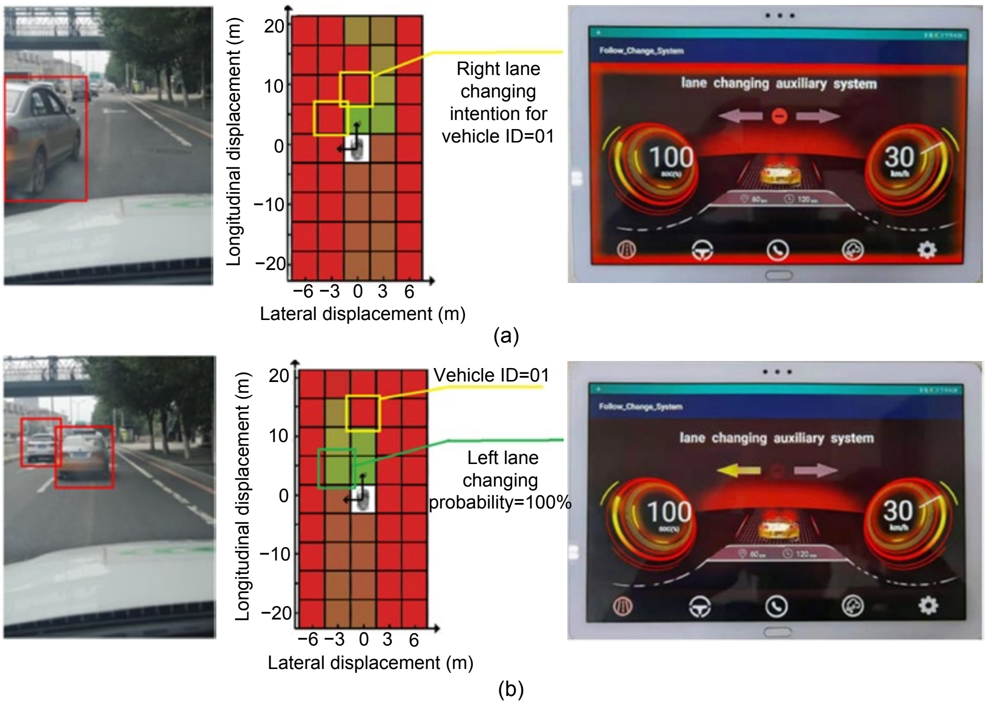

Fig. 13 Vehicle lane changing operation based on DGPM

In (a), the obstacle vehicle ID=01 in front has the intention to change lanes to the right. At this time, the probability that the ego-vehicle can change lanes is 0. In (b), the lane changing behavior of the obstacle vehicle ID=01 ahead ends, and the probability of lane changing from the left becomes 100%

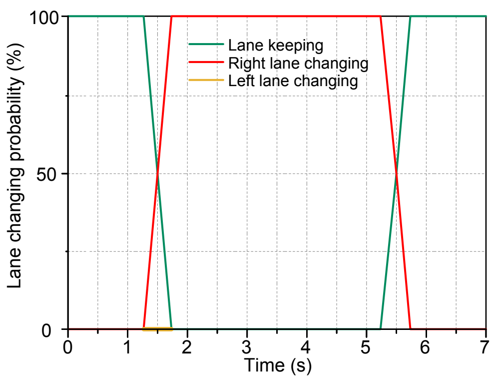

Fig. 14 Prediction of the lateral lane changing intention of vehicle ID=01

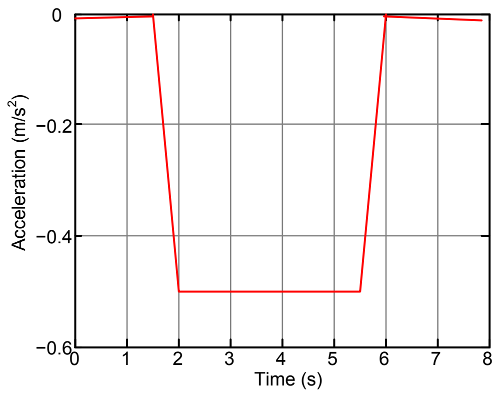

Fig. 16 Recommended acceleration based on DGPM

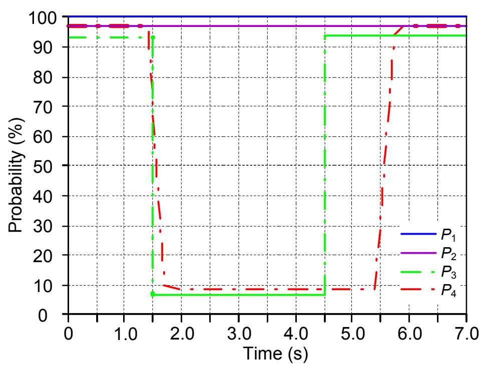

Fig. 15 Probability curves of DGPM

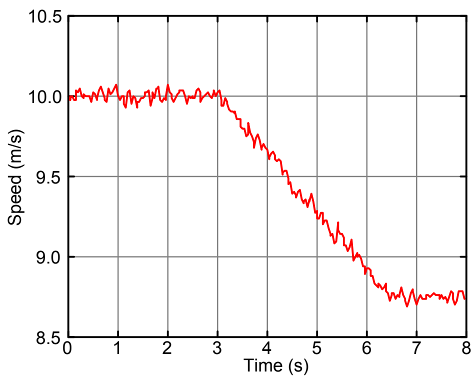

Fig. 17 Speed change of the ego-vehicle

3. A set of vehicle lane changing driving assistance strategies is constructed through the driving area modeling algorithm based on the DGPM of an intelligent vehicle. The vehicle behavior decision cost equation is established based on a comprehensive consideration of the vehicle's drivability, safety, and power factors. A dynamic programming algorithm is used to calculate iteratively the behavior cost of each cell under different path selections, thereby guaranteeing the correctness and enforceability of the strategy.

Contributors

Zhenhai GAO designed the research. Zhengcai YANG, Xinyu WU, and Lei HE completed the tests. Zhengcai YANG and Fei GAO processed the data and drafted the manuscript. Zhengcai YANG revised and finalized the paper.

Compliance with ethics guidelines

Zhengcai YANG, Zhenhai GAO, Fei GAO, Xinyu WU, and Lei HE declare that they have no conflict of interest.

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