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A Probabilistic Method for Behavior Prediction of Intelligent and Connected Vehicles in Freeway

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Abstract: The rapid developing technology of mobile communication and autonomous driving makes the intelligent and connected vehicle a new hotspot nowadays. How to improve the vehicle's ability to understand the driving environment itself is an important issue in recent years. In this paper, a Bayesian prediction model based on human driving cognitive process model is proposed for freeways with special structures, which can inference the driving intention and predict the trajectory of the target vehicle. On the basis of considering the historical trajectory of the target vehicle, the motion states of the surrounding vehicles and values reflecting the characteristic of the road structure which are discretized by Chi-Merge algorithm improved the inference performance. The experimental results show that, compared with Naive Bayes Classifier, the Kalman Filter and the LSTM network, the accuracy of the maneuver reasoning results is significantly improved, and the RMSE value of the trajectory prediction results of the prediction model we propose is significantly reduced.

1. Introduction

The rapid developing technology of mobile communication and autonomous driving makes the intelligent connected vehicle a new hotspot nowadays. Intelligent connected vehicles need to understand the surrounding driving environment and predict the behavior of other traffic participants like human drivers[1]. With the research in related fields, researchers have realized that how to predict the motion behavior of vehicles accurately and efficiently is one of the most challenging issues in realizing fully autonomous driving of intelligent vehicles. Commonly used vehicle behavior prediction methods include motion model prediction methods, deep learning prediction methods, machine learning prediction methods[2].

The prediction methods based on the motion model assume that the motion parameters of the vehicle remain unchanged during the prediction period, and use kinematics and dynamics knowledge to directly deduce the motion behavior of the vehicle, including the uniform linear motion model and the uniform angular velocity curve motion model [3- 6]. Some researchers have noticed the good performance of recurrent neural networks in sequence analysis and processing complex modelling problems, and have applied its classic network and improved structure to trajectory prediction. Su [14] from Carnegie Mellon University used the LSTM network structure to identify and predict the lane-changing behavior of vehicles. Nachiket [15] from the University of California, San Diego proposed a convolutional social pooling layer structure to process the interaction between the predicted vehicle and its surrounding vehicles.

In view of the disadvantage that motion model prediction methods usually fail to predict accurately for long periods of time, researchers have proposed prediction methods based on machine learning, which use more complex data models to describe vehicle motion behaviors, including Gaussian process models, Gaussian mixture models, Bayesian and dynamic Bayesian network, Markov chain, hidden Markov model [9-13]. Among these models, the probabilistic graphical model represented by Bayesian network is commonly used in vehicle behavior prediction tasks. Gindele [7] from Karlsruhe Institute of Technology used dynamic Bayesian networks to clarify the interactions between vehicles, achieve a comprehensive understanding of the driving scene, and model the causal relationships between factors. With description. Schreier [8] from the Technical University of Darmstadt added causal criteria and diagnostic criteria to the Bayesian network structure, allowing the network to detect unreasonable driving behaviors.

During years of related research, researchers have achieved a lot in predicting vehicle behavior. However, traditional vehicle behavior prediction methods still have certain shortcomings. Efficient and accurate prediction of vehicle behavior is still a challenge. **The shortcomings of current vehicle behavior prediction methods mainly include the inability to reflect the multi-modal characteristics of human driving behavior, and limitations in the representation of interactive relationships in the driving environment.**

The contributions of this paper are as followed:

1) We propose a behavior prediction method for vehicles in highway using Bayesian network based on the structural characteristics of the human driving cognitive process model.

2) The prediction trajectory is generated from intention inference and kinematic states of surrounding vehicles in the past. The vehicle status and road structure feature, which are discretized with Chi-Merge algorithm, have improved the inference accuracy significantly.

3) The predicting ability of the model have been tested using the natural driving data from NGSIM data set with MATLAB, indicating its accuracy and robustness in different road sections.

The contents and the structure of this article are as follows: In Section 2 we introduce the human driving cognitive process model and the Bayesian prediction model. In Section 3 we test the performance of the proposed model using natural driving data from different highway sections. In Section 4 we summarize the structure and the predicting performance of the Bayesian model and put forward prospects for the limitations.

2. Behavior Prediction Model based on Probabilistic Graph

2.1. Driving Cognitive Process Model

In a common driving environment, the human driver's driving cognitive process includes three levels: target perception, situation understanding, and decision making [11]. Inspired by this process model, we divide the vehicle behavior prediction task in the intelligent network environment into three levels, which are the target detection period, the environment understanding period, the intention reasoning and result prediction period as shown in Figure 1. Among them, the environment understanding, the intention reasoning and the execution result prediction periods correspond to the main research content of this article. The human driving cognitive process and vehicle behavior prediction can be abstracted into a multi-variable uncertainty problem containing multiple sets of causal relationships. For this kind of uncertainty problem with conditional dependence, we choose the Bayesian network as the basic structure of the prediction model.

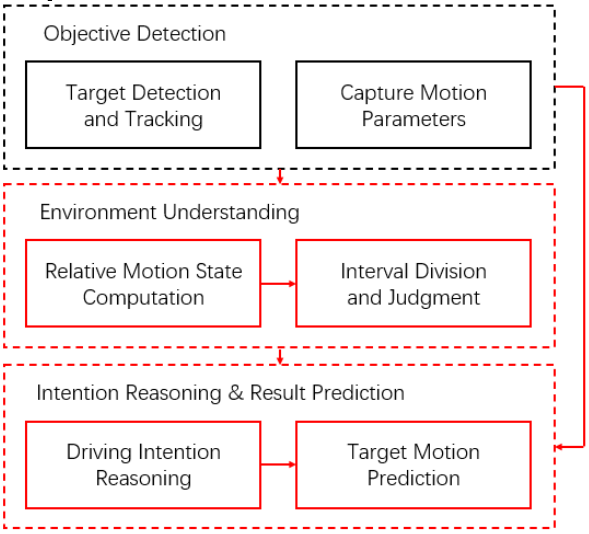

Figure 1: The reasoning model for vehicle behavior prediction task.

2.2. Bayesian Behavior Inference and Prediction Model

Bayesian network is a classic probabilistic graphical model, which applies probabilistic statistical methods to uncertainty reasoning and data analysis problems in complex fields. It is currently one of the most popular methods for expressing uncertainty knowledge and reasoning uncertain problems. Based on the human driving cognitive process model, this study established a prediction model with a Bayesian network as the basic structure as shown in Figure 2. The squares and circles in the Figure 2 represent network nodes whose corresponding variables are discrete variables and continuous variables respectively. Solid and dashed directed edges respectively represent the conditional dependency and unconditional dependence mapping relationships between two nodes.

The prediction model includes three layers: the input layer, the inference layer, and the output layer. It can also be divided into intention inference module and trajectory generation module. Based on the driving cognitive process model, it can be assumed that human drivers tend to be with better driving conditions during driving, which is also expressed that when the current driving conditions cannot meet driving needs such as target speed and interval distance between vehicles, the driver will take the corresponding lane change intention.

The intention inference module is used to obtain the inference result of the target vehicle's driving intention based on the discretized relative motion status of vehicles around the target vehicle and the road structure feature values, and transmits the longitudinal speed and lateral position prediction values to the trajectory generation module along the conditional dependency relationship. The inputs to the input layer of the trajectory generation module include the current and historical motion status of the target vehicle and the relative motion status between it and surrounding vehicles. The output after processing by the inference layer is the predicted value of the target vehicle's longitudinal velocity and lateral position. The final prediction result of the lateral position will directly adopt the inference result of the probabilistic inference, while the final prediction result of the longitudinal position is based on the assumption of average speed and is obtained recursively through the uniform speed motion model.

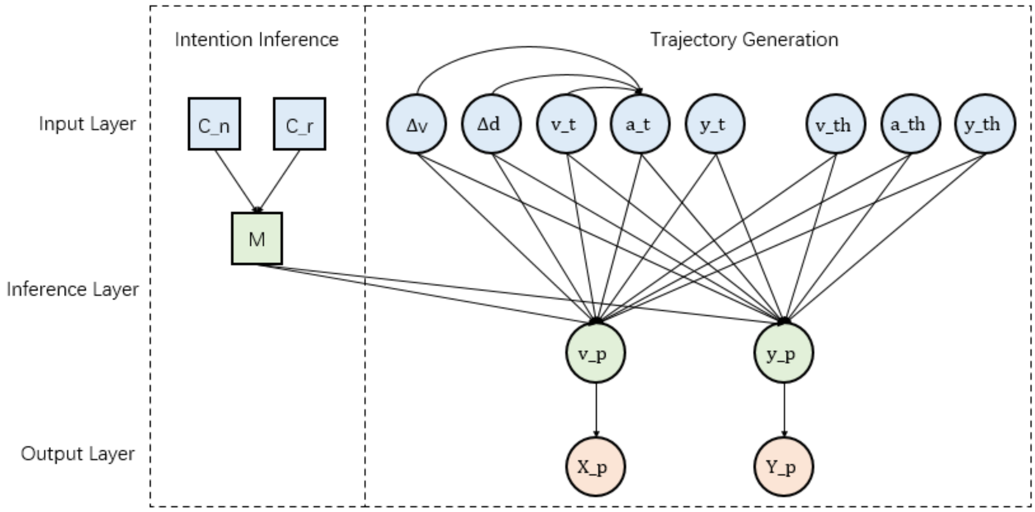

Figure 2: Vehicle behavior prediction model based on Bayesian network.

Table 1: Definition of variables in the Bayesian-based prediction model.

Variables	Definition and descriptions
C_n	Discretized relative motion status value, including relative longitudinal speed and relative longitudinal distance
C_r	The road structure characteristic value is the discretized longitudinal distance of the target vehicle relative to special structures such as ramps and merges.
M	Type of driving intention of the target vehicle
v_t	The longitudinal speed of the target vehicle at the current moment
a_t	The longitudinal acceleration of the target vehicle at the current moment
y_t	The lateral position coordinates of the target vehicle at the current moment
Δv	The relative longitudinal speed of the target vehicle at the current moment and the surrounding vehicles
Δd	The relative longitudinal distance between the target vehicle and surrounding vehicles at the current moment
v_th	The longitudinal speed of the target vehicle within 3 seconds from the current moment
a_th	The longitudinal acceleration of the target vehicle within 3 seconds from the current moment
y_th	The lateral position coordinates of the target vehicle within 3 seconds from the current moment
v_tp	The predicted longitudinal speed of the target vehicle in the next 5 seconds from the current moment
y_tp	The predicted lateral position coordinates of the target vehicle in the next 5 seconds from the current moment
X_tp	The longitudinal position prediction result of the target vehicle in the next 5 seconds from the current moment
Y_tp	The prediction result of the lateral position of the target vehicle in the next 5 seconds from the current moment

It can be seen from the description in Table 1 that the driving intention of the target vehicle is a discrete variable, which has three values: go straight, left lane-change, and right lane-change, while the original vehicle relative motion state obtained in the environment understanding layer is continuous variable. Bayesian networks have certain limitations when conducting discrete variable inference based on continuous variables, and have difficulty in accurately predicting [11]. Therefore, we use the Chi-Merge algorithm to discretize continuous variables. The Chi-Merge algorithm is a supervised statistical algorithm proposed by Kerber in 1992 [15]. Compared with the equal-width discretization method, the Chi-Merge algorithm takes into account the category information to which the data instances belong and can discretize them according to the degree of correlation of the data. Based on the discretized surrounding vehicle motion states C_n and discretized road structure characteristic value C_r, the model can not only reflect the behavior decision-making process in the predicted scene, but also adapt to the road structural characteristics represented by the characteristic value, thereby improving the prediction model's prediction accuracy and algorithm robustness in dynamic traffic scenes and road with specific structure.

According to the conditional dependence between Bayes' theorem and the variables of this module, we can get the conditional probabilities of variables v_tp and variables y_tp in the trajectory generation module as:

$$P(v\_tp) = P(v\_tp \mid M, \Delta v, \Delta d, v\_t, a\_t, v\_th, a\_th) \cdot P(\Delta v, \Delta d, v\_t, a\_t) \cdot P(v\_th) \cdot P(a\_th) \cdot P(M \mid C\_n, C\_r) \cdot P(C\_n) \cdot P(C\_r) \tag{1}$$

$$P(y\_tp) = P(y\_tp \mid M, \Delta v, \Delta d, v\_t, a\_t, y\_t, v\_th, a\_th, y\_th) \cdot P(\Delta v, \Delta d, v\_t, a\_t) \cdot P(v\_th) \cdot P(a\_th) \cdot P(y\_th) \cdot P(M \mid C\_n, C\_r) \cdot P(C\_n) \cdot P(C\_r) \tag{2}$$

Taking the lateral position as an example, the conditional probability distribution of variable y_p a at time i can be obtained as:

$$p(y\_tp(i+j) \mid M, \Delta v(i), \Delta d(i), v\_t(i), a\_t(i), y\_t(i), v\_th(i), a\_th(i), y\_th(i)) = \frac{1}{\sqrt{2\pi}\sigma_{y\_tp}(m)} e^{-\frac{(y\_tp(i+j) - \mu_{y\_tp}(m) - \omega_{y\_tp}(m) \cdot A_{y\_tp}(i))^2}{2\sigma^2_{y\_tp}(m)}} \tag{3}$$

$$A_{y\_tp}(i) = [\Delta v(i) \quad \Delta d(i) \quad v\_t(i) \quad a\_t(i) \quad y\_t(i) \quad v\_th(i) \quad a\_th(i) \quad y\_th(i)]^{\mathrm{T}} \tag{4}$$

$$\omega_{y\_tp} = [\omega_{\Delta v} \quad \omega_{\Delta d} \quad \omega_{v\_t} \quad \omega_{a\_t} \quad \omega_{y\_t} \quad \omega_{v\_th} \quad \omega_{a\_th} \quad \omega_{y\_th}] \tag{5}$$

μ_{y_tp} and σ_{y_tp} are the mean and standard deviation of y_tp separately. $\omega_{\Delta v}$, $\omega_{\Delta d}$, ω_{y_t} , ω_{v_t} , ω_{a_t} , ω_{y_th} , ω_{v_th} , ω_{a_th} are the weight coefficients of Δv, Δd, y_t, v_t, a_t, v_th, a_th, y_th separately, m represent the value of M.

For uncertain problems abstracted from real systems, the corresponding Bayesian network parameters are usually unknown. Therefore, the network parameters need to be identified based on data. Here we use the maximum likelihood estimation (MLE) method to predict the model output. The likelihood function of output variables is:

$$J = \ln\left(\left(\prod_{j=1}^{k}\prod_{i=1}^{N} v\_tp(i+j)\right)\left(\prod_{j=1}^{k}\prod_{i=1}^{N} y\_tp(i+j)\right)\right) \tag{6}$$

N represents the sample size, and k represents the maximum prediction step size, which is determined by the maximum prediction time domain range and data collection frequency

According to the output result of the inference layer, the final output result of the prediction model in the output layer is the position prediction value X_tp and Y_tp of the target vehicle in the next 5 seconds from the current moment. The lateral position of the vehicle directly adopts the output result of the inference layer. The vehicle lateral position coordinate at time $i+j$ is:

$$Y\_tp(i+j) = y\_tp(i+j) \tag{7}$$

Differently, the longitudinal position of the vehicle is obtained by using the prediction results of the longitudinal speed of the target vehicle and using the average speed calculation method to prevent data saturation and increase in prediction errors caused by excessive longitudinal distance range. The formula is:

$$X\_tp(i+j) = X\_tp(i) + \frac{1}{2}\sum_{k=0}^{j-1}(v\_tp(i+k) + v\_tp(i+k+1))\Delta t \tag{8}$$

$X\_tp(i)$ represents the longitudinal position coordinate of the vehicle at the current i moment, $X\_tp(i+j)$ represents the longitudinal position coordinate of the vehicle at the $i+j$ moment in the future, Δt indicates the time interval between two adjacent steps determined by the sampling frequency of vehicle trajectory data, which is 0.1s.

3. Simulation Results and Analysis

In order to verify and evaluate the reasoning and prediction capabilities of the proposed prediction model, the natural driving data was processed with MATLAB to perform parameter training and result reasoning for the prediction model, and the intent reasoning ability and trajectory prediction ability of the prediction model were comparatively evaluated. The training data and validation data were gathered from the I-80 intercontinental highway data and Highway 101 data in the NGSIM natural driving data set. For the intention reasoning task and the trajectory prediction task, the naive Bayes classifier (NBC), the Bayesian network containing flexible maximum transfer function nodes (BNS), and the constant velocity model Kalman filter and long short-term memory network (LSTM) are used as comparison models to compare and analyze intention inference results and trajectory prediction results.

3.1. Evaluation Index for Behavior Prediction

The intermediate variables and output results of the prediction model are mainly located in the inference layer and output layer. For the judgment of the intention inference results and the accuracy of the trajectory prediction results, the prediction accuracy and the root mean square error value were selected as evaluation indicators respectively. The formula for accuracy is:

$$ACC = \frac{TP}{TP + FP} \tag{9}$$

TP and FP are the number of samples with correct and incorrect vehicle intention inference results respectively.

In the natural driving data set, the vast majority of vehicle driving intention samples are straight driving samples, and lane-change samples account for only a small proportion. Timely and accurate judgment and reasoning about lane changing behavior are crucial for vehicle behavior prediction tasks especially in highway scenarios, which is an inevitable requirement put forward by the prediction model. Therefore, we additionally use the lane change intention inference accuracy in addition to examine the prediction model's inference accuracy for lane change samples. The formula is:

$$ACC\_LC = \frac{TP\_LC}{TP\_LC + FP\_LC} \tag{10}$$

TP_LC and FP_LC are the number of samples with correct and incorrect inference results among all lane-changing samples respectively.

The evaluation index of driving trajectory prediction is the root mean square error value, and its formula is:

$$RMSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(y_i - \hat{y}_i)^2} \tag{11}$$

k is the maximum prediction step size, y_i and $\hat{y}_i$ are respectively the true value and the predicted value of the vehicle position coordinates at step i.

3.2. Intention Inference Results for Discretized Inputs

Figure 3 and Figure 4 show the intention inference results of different models under each data set, where PM (which refers to the Prediction Model) represents the prediction model we proposed.

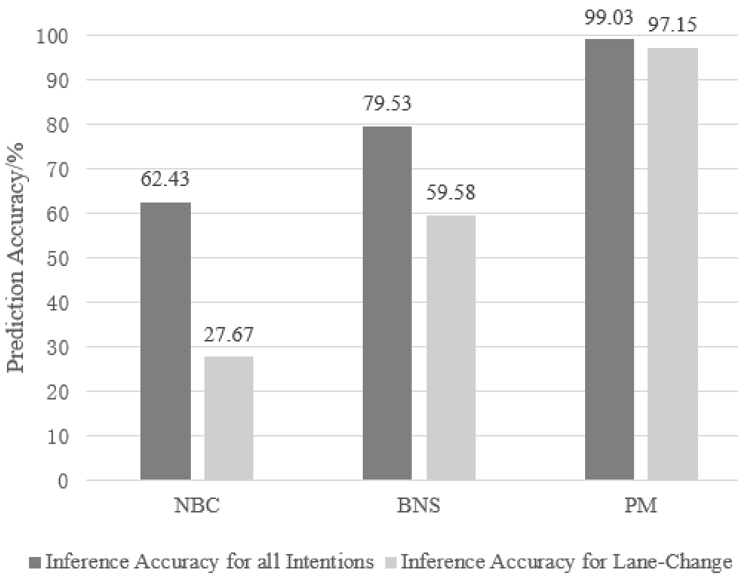

Figure 3: Intention reasoning results for I-80 data set.

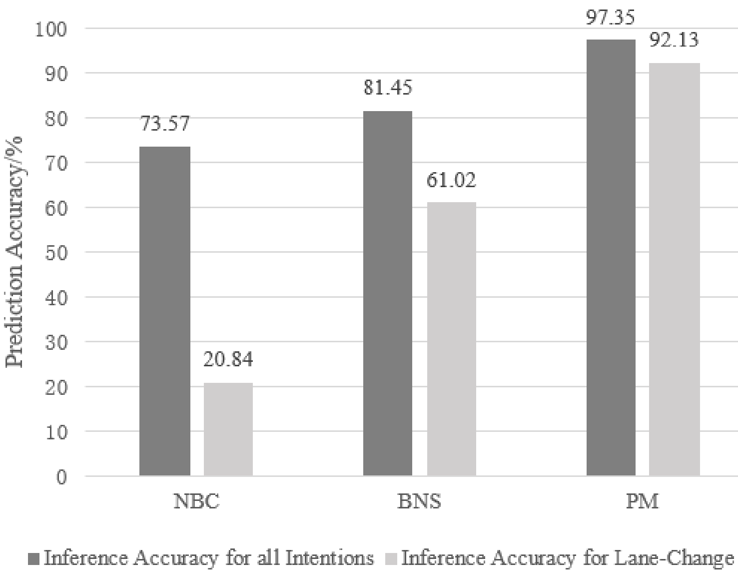

Figure 4: Intention reasoning results for US101 data set.

It can be seen from the Figure 3 that the inference accuracy for all intentions of the naive Bayes classifier NBC is relatively average, while the inference accuracy for all intentions of the proposed prediction model is higher. Compared with the naive Bayes classifier, the Bayesian model with the discretized relative motion status and road structure characteristic value as parent nodes can improve the accuracy of prediction. Also, compared with BNS that uses continuous variable parent nodes, the Chi-Merge algorithm used for discretization improves the inference accuracy.

From the perspective of the inference accuracy for lane-change intention, the inference accuracy of the Naive Bayes classifier is very low, which is less than 30% in the NGSIM data set, indicating that its reasoning ability for vehicle lane-change is poor. Combined with the inference accuracy for all intentions, we can infer that the NBC model has a higher inference accuracy for straight samples, thus keeping the inference accuracy at an average level. The control model BNS's inference accuracy for lane-change has improved compared to the control model NBC, but it only remains at 50%-60%. The prediction model PM using discrete variables improves the inference accuracy of lane-change and maintains a high accuracy of 94%-97%, indicating that the proposed model can perform good inference and identification of the vehicle's lane-change behavior intention.

To conclude, the control models NBC and BNS have weak reasoning and identification capabilities for vehicle lane-change intentions. And the prediction model as proposed using discretized relative motion states of vehicles and road structure characteristic values as parent nodes, can maintain a high accuracy of lane-change intention reasoning. It also shows strong intention reasoning and identification capabilities, and has certain robustness to dynamic traffic scenarios and specific road structures.

3.3. Intention Inference Results for Specified Behaviors Based on Lane Divisions

In this study, we mainly focus on vehicle behavior prediction in special structural scenarios including ramps and merges. Therefore, we conduct a comparative analysis of the effects of road structure characteristic values. We chose the prediction model PM proposed in this study as the experimental model, and the prediction model without road structure characteristic values as the control model (Prediction Model without Road Characteristic, PM_nrc). As shown in Figure 5, we specify the comparison objects to the vehicles driving in different lanes, distinguish the lanes adjacent to or connected to structures such as ramps and merges from the main roads, and infer the vehicle intention results in each lane respectively. It can be seen that when the driver enters the distribution lane from the transition lane, he observes the relative motion of the surrounding vehicles while maintaining observation of the exit ramp position, and check the relative distance between his own vehicle and the exit ramp. In the same way, when the driver drives from the distribution lane to the transition lane, he will observe the surrounding vehicles and the entrance and exit ramps at the same time. These lane-change behaviors are driven by specific driving routes and must be performed, so we call them forced lane-changing behaviors[16-18]. Correspondingly, unforced lane changing behavior is also called free lane changing behavior.

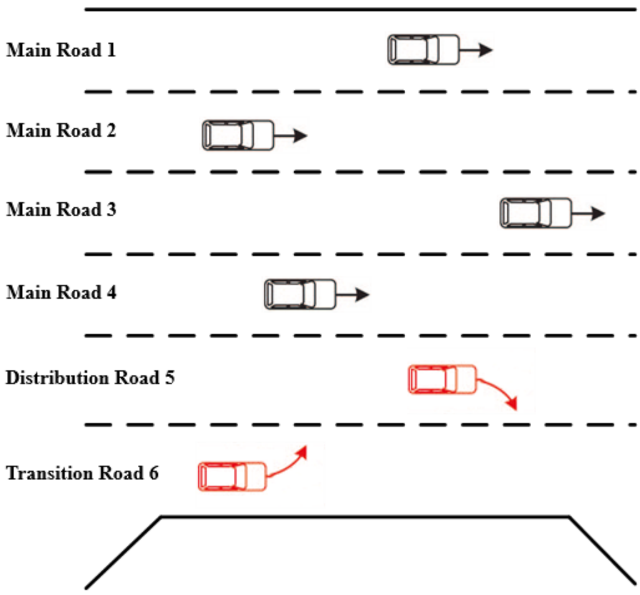

Figure 5: Lane divisions and corresponding vehicle behavior of I-80 and US101 data set.

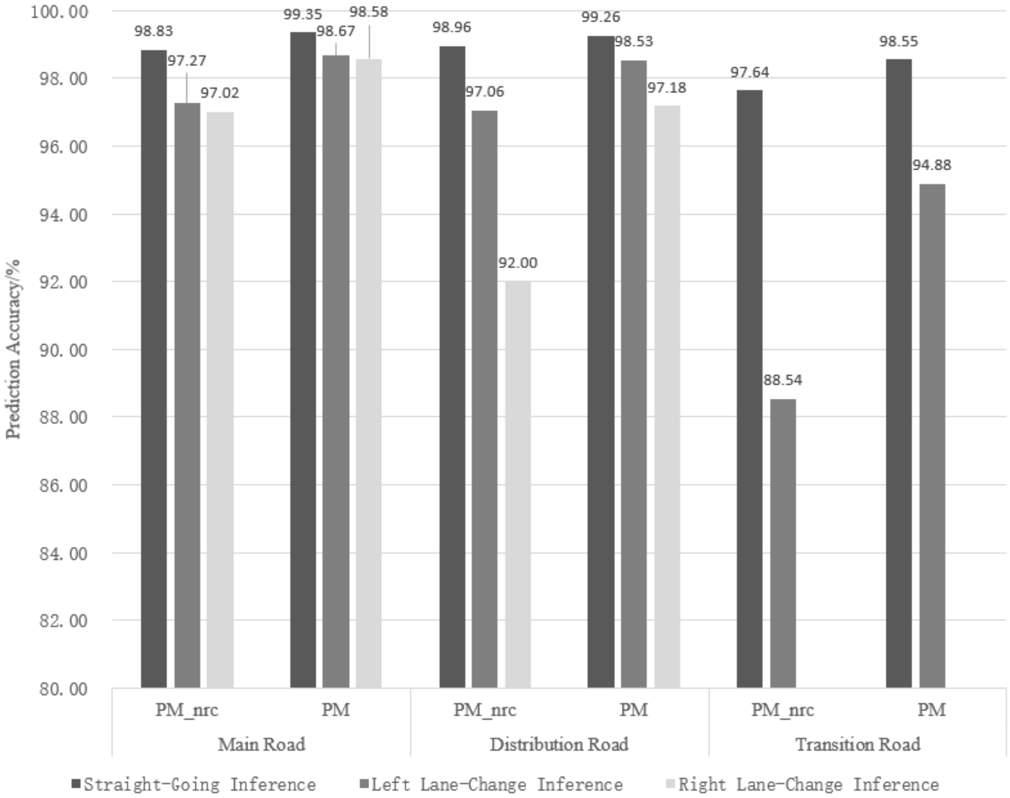

Figure 6: Intention inference results in different lanes for I-80 data set.

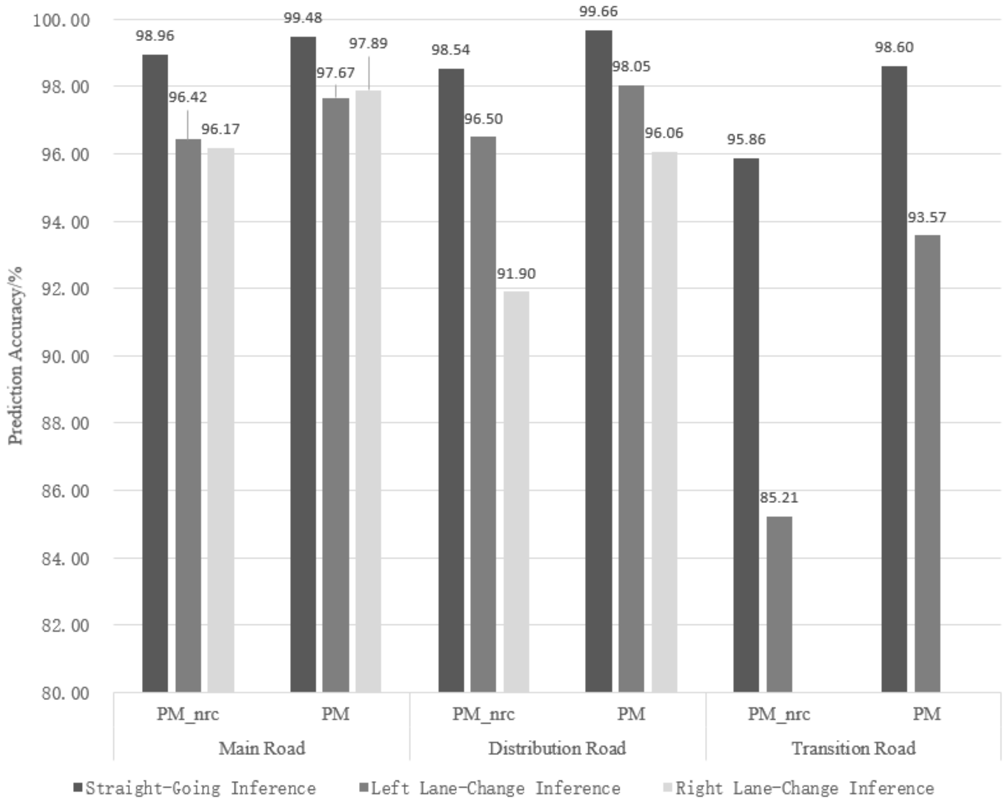

Figure 7: Intention inference results in different lanes for US101data set.

As shown in Figure 6 and Figure 7, in the road section including the ramp, the experimental model PM and the control model PM_nrc have higher inference accuracy for each intention in the main road. The control model's inference accuracy for the right lane change intention of vehicles in transition lane 5 and the left lane change intention of vehicles in distribution lane 6 is significantly lower than other lane-change intentions. Besides, the experimental model's inference accuracy for these intentions is significantly improved, indicating that the introduction of road feature values can significantly improve the model's inference accuracy for lane-change intentions corresponding to these samples. As a conclusion, the introduced feature values improve the model's inference accuracy for lane-changing intention samples, as well as the overall inference accuracy of each intention sample.

In summary, it can be seen that the introduction of road structure eigenvalues can improve the model's multi-modal identification ability of different lane changing behaviors determined by the road structure, thereby improving the model's inference accuracy for forced lane-change intentions, and thereby improving the model's ability to detect lane-change samples. The inference accuracy and the overall inference accuracy of each intention sample.

3.4. Trajectory Prediction Results

After completing the intention reasoning, the prediction model inputs the reasoning results together with other input quantities into the reasoning layer, and after processing, the final target vehicle trajectory prediction result is obtained. The root mean square error values of the trajectory prediction results of each model under different data sets are shown in Table 2 and Table 3 respectively, where PM represents the prediction model proposed in this article, and PMnm (Prediction Model without Maneuver) represents the prediction model without the intention reasoning module. The minimum error values of each group have been marked.

Table 2: The RMSE value of the trajectory prediction results for I-80 data set.

Evaluation index	Horizon/ s	Prediction Models			
		KF	LSTM	PMnm	PM(Ours)
RMSE/ m	1	0.67	0.62	0.47	**0.43**
	2	1.71	1.58	1.34	**1.12**
	3	3.02	2.80	2.30	**1.93**
	4	4.68	4.27	3.31	**2.94**
	5	6.56	6.23	4.55	**4.16**

Table 3: The RMSE value of the trajectory prediction results for US101 data set.

Evaluation index	Horizon/ s	Prediction Models			
		KF	LSTM	PMnm	PM(Ours)
RMSE/ m	1	0.79	0.74	0.54	**0.50**
	2	1.87	1.73	1.39	**1.25**
	3	3.25	3.04	2.38	**2.07**
	4	4.79	4.50	3.44	**3.21**
	5	6.67	6.38	4.68	**4.35**

The root mean square error value of the predicted trajectory represents the difference between the predicted trajectory results and the true future trajectory, reflecting the accuracy of the prediction results. Compared with the Kalman filter and the LSTM, the prediction model proposed has a lower prediction result error value, and the trajectory prediction accuracy of the model is significantly improved. Compared with the prediction model without the intention prediction module, also called PMnm, the trajectory prediction result error value of the prediction model PM with the intention prediction module is lower, indicating that the intention prediction module can improve the accuracy of the trajectory prediction results, and also verifies that multi-modal prediction can improve the accuracy of vehicle trajectory prediction.

4. Conclusion

This paper abstracts the vehicle behavior prediction problem into an uncertain reasoning problem involving multiple variables based on the human driving cognitive process model. During the research process, an intelligent connected vehicle behavior prediction model based on Bayesian network was established to predict vehicle motion behavior in highways with special road structures such as ramps and merges. The model can accurately infer the target vehicle's driving intention and predict the target vehicle's driving trajectory within the next 5 seconds. This paper uses the public NGSIM natural driving data to conduct parameter training and inference verification of the model, and compares and analyzes the inference and prediction results. It verifies that chi-square binning discretized motion states and discretized road feature values are important for predicting model performance. Improvement, and the predictive ability of the proposed model is quantified through indicators.

The current content of this study still has limitations. In the future research process, the existing work content should be improved:

(1) Multi-source feature information and its usage in an intelligent network environment still need to be studied.

In addition to motion states such as position, speed, and acceleration, the heading angle during vehicle driving is also an important motion state parameter that characterizes the vehicle's motion behavior. How to extract richer road feature information and design an appropriate reasoning structure accordingly will be the focus of future research.

(2) In actual application situations, the accuracy of results and the real-time execution of the prediction algorithm and prediction process should be considered at the same time.

In the highway scenario, the planning and control module also places high demands on the real-time performance of the prediction module. The development and verification of this study are mainly based on local offline simulation, which is different from the communication environment of intelligent connected vehicles. In subsequent research, the cost of running the prediction model should be as close as possible to the actual application environment. Real-time indicators such as time and memory usage are examined.

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