

# CAEV- Deep Learning-Based Hybrid Model for the Behavior Prediction of Surrounding Vehicles Over Long-time Periods

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## Original Article

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## Title page

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## ORIGINAL ARTICLE

# Deep Learning-Based Hybrid Model for the Behavior Prediction of Surrounding Vehicles Over Long-time Periods

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**Abstract:** Autonomous vehicles need to have the ability to predict the future behavior of surrounding vehicles, which helps with proper trajectory planning and tracking. Many behavior prediction methods have limited application because they have a very limited prediction horizon. This paper proposes a deep learning-based hybrid model for behavior prediction over long-time periods, including maneuver recognition and a behavior prediction module. In the previous module, the CNN extracts the social characteristics of the target vehicle and LSTM outputs the maneuver probability vector and forms a contextual feature vector with the social features. In the lateral module, LSTM and Attention are based on the contextual feature vector to capture multi-time step information in the behavior time window to complete the prediction of the target vehicle behavior. Real-car collection and open-source vehicle trajectory datasets were used for training and testing. The results show that the proposed algorithm could predict vehicle behavior with an accuracy of 89.73% and an average prediction time of 2.032 s, which has a high engineering application value.

**Keywords:** Autonomous vehicles • Behavior prediction • Deep learning • Long-time periods • Hybrid model

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## 1. Introduction

Autonomous vehicles (AVs) have received extensive research interest in recent years because they can enhance road safety, ease road congestion, decrease fuel consumption, and free human drivers [1-2]. Developments in the field will increase in both quality and importance with time [3]. However, how the AV can predict the behavior of nearby road-users is a tricky and considerable issue in the increasingly complex and highly uncertain traffic environment [4]. The approach proposed here could improve the ability of AVs to understand the traffic environment and help with proper trajectory planning [5] and tracking [6].

One part of this problem is to predict the behavior of pedestrians, which is well-studied in computer vision literature [7-9]. There are also several review papers on pedestrian behavior prediction [10]. Another part of the problem is the prediction of the other vehicles' future behavior on the road [11]. Both parts are similar but different. For example, vehicle trajectories have certain similarities in the same typical behaviors. Furthermore, roads for vehicles have a clear lane structure and movement direction. In this paper, we focus on vehicle behavior prediction because there are more difficulties due to the higher randomness and mobility of these road-users, especially over long-time periods.

Earlier researchers focused on rule-based methods for vehicle behavior prediction. These methods tended to use

some rules to judge future vehicle behavior. Houenou et al. [12] predicted behaviors, such as lane keeping (LK) and lane changing (LC), based on a handcrafted model that evaluates the similarity between the vehicle trajectory and the lane centerline. Lefèvre et al. used Time to Line Crossing (TTC) to predict by rule matching whether the vehicle will depart from the current lane or not [13]. These methods can generate good results in the specific driving environment. However, they require lots of prior knowledge to select model parameters and thresholds, which is difficult to apply for long-range prediction.

Traditional machine learning-based methods are an effective remedy to eliminate the engineers' burden. This is because the behavior prediction model can be learned directly by drivers' behavior labels using supervised learning techniques and no hand-crafted rules are needed. Mandalia et al. [14] used a support vector machine (SVM) to classify LC behavior, which can reflect the inter-class differences of samples of different behavior categories well; however, this type of method ignores the asymptotic characteristics of time series and cannot reflect the coherence property of a vehicle state sequence. Dynamic Bayesian networks (DBN) are widely used in perceptual prediction problems. Agamennoni et al. [15] proposed a motion Bayesian motion prediction model, but their application in AVs is limited due to the high computational cost. Li et al. [16] separately established hidden Markov models (HMMs) for each behavior while Deng et al. [17] proposed a driving behavior prediction method based on an improved HMM, which uses a genetic algorithm to construct a pre-filter for optimizing the data feature input of the prediction algorithm. However, these methods assume that the state of each time step of the vehicle is only related to the previous time step without using contextual information, and the effect of long-time prediction is not good.

Different from rule-based and traditional machine learning-based methods, deep learning-based methods have received increasing attention in recent years, and they superiority in highly complex and non-linear scenarios. Recurrent neural network (RNN) architecture has been widely used in the field of time series data analysis. However, it is difficult to train these networks to learn long sequences in practice due to gradient vanishing or exploding [18]. Long short-term memory (LSTM) model is

a variant of RNN by adding a cell structure to the network, which can solve this problem. However, in the previous vehicle behavior LSTM prediction algorithms [19-21], the last or the average state value in the hidden layer is usually used as a high-level expression basis for vehicle behavior prediction. The difference in the contribution of features to the prediction results leads to the loss of some information during data transmission of the hidden layer unit. Even though they have good performance over a short-time period, this makes the accuracy of the vehicle behavior prediction algorithm over long-time periods unable to meet ideal requirements.

To make wise decisions, the planning module of AVs needs to reason about long-term future outcomes, which requires predicting future behaviors within three to five seconds [22]. A shortcoming of the aforementioned works is that they do not consider the impact of the vehicle's current maneuver on the future behavior trend, which contributes to low accuracy in long-term prediction. This limits the application of these algorithms because there is inadequate time and space for planning. The current maneuver of the vehicle is important prior knowledge to characterize the vehicle's future behavior over long-time periods. Nachiket et al. [23] proposed a trajectory prediction framework based on the double-layer model that first recognizes the maneuvering modes of vehicles on the highway and then uses them as a basis to predict their future multi-step positions, which significantly reduces the mean square error between the predicted trajectory and the real trajectory.

Inspired by this, the proposed method uses a deep learning-based hybrid model for the behavior prediction of surrounding vehicles over long-time periods. The current maneuver of the vehicle is considered to be a low-level expression of the vehicle's future behavior. The probability vector output from the maneuver recognition module is combined with the vehicle's social features to construct a contextual feature vector. An attention mechanism is also integrated to select key information in the entire vehicle contextual feature sequence, which has performed well in vision and translation tasks [24-25].

The main contributions of this paper can be summarized as follows:

- (1) The neighborhood traffic information of the target vehicle is considered, the correlation between the traffic

subjects is realized, and the social characteristics of the target vehicle are input into the convolutional neural network (CNN) to extract valid information and output the current maneuver probability vector of the target vehicle.

(2) The current maneuver of the predicted vehicle is considered, a prediction algorithm model with LSTM network as the main body is built, and an attention mechanism is introduced to improve the prediction accuracy of the algorithm.

(3) The vehicle natural trajectory data collected from real vehicles and the high D dataset are used to generate the training and test sample sets, and the performance of the proposed method was verified.

The remainder of this paper is organized as follows: Section 2 proposes the deep learning-based hybrid method for behavior prediction over long-time periods. Section 3 introduces the dataset, data processing methods, and experimental details. Section 4 discusses the training results for each prediction task. Section 5 concludes this paper.

## 2. Methodology

As is shown in Fig.1, the framework of the proposed method consists of the maneuver recognition module and the behavior prediction module. In the maneuver recognition module, the long-term and short-term memory network outputs the maneuverable probability vector, which forms a context feature vector with social features. In the behavior prediction module, to complete the prediction of the target vehicle behavior, LSTM and the Attention mechanism capture the multi-time-step information in the behavior time window based on the context feature vector.

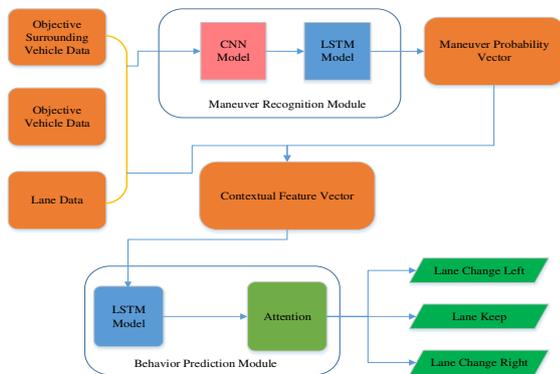


Figure 1 Framework of the proposed method

### 2.1. Social Characteristics

For an autonomous driving system or a human driver, the generation mechanism of the vehicle behavior starts from the intention demand and the expected benefit, which must be influenced by interaction with other surrounding vehicles. Additional information is needed to reduce future uncertainty. For the model to better understand this interaction, the resulting probability distribution of the maneuver recognition and behavior prediction will depend on the trajectory history of the target vehicle and the surrounding vehicles. Therefore, the characteristic data of the algorithm includes the information of the identified vehicle itself and its environment. The vehicle social features can be expressed as

$$\mathcal{O} = \{\mathfrak{R}, \mathcal{H}, \mathcal{M}\}, \quad (1)$$

where  $\mathfrak{R}$  is the status information of the target vehicle itself,  $\mathcal{H}$  is the information of its surrounding vehicles, and  $\mathcal{M}$  is road information.

For current intelligent cars, there are two ways to obtain information about surrounding traffic vehicles: on-board sensors and connected cars. The technology of a connected car can indeed bring very valuable priori information to behavior prediction, such as sending the driver's intention or the decision result of the driving system or even the future driving trajectory directly to other vehicles. However, under the current traffic environment, most cars are not equipped with connected car technology. Considering the robustness and safety of data transmission, the V2V communication network today needs to be further improved to have a beneficial effect on traffic. Thus, the characteristic information of surrounding vehicles should be obtained by the main vehicle by only relying on the on-board sensor. As shown in Fig.2, the red car is the target vehicle and the white vehicles are the neighborhood vehicles of the target vehicle.

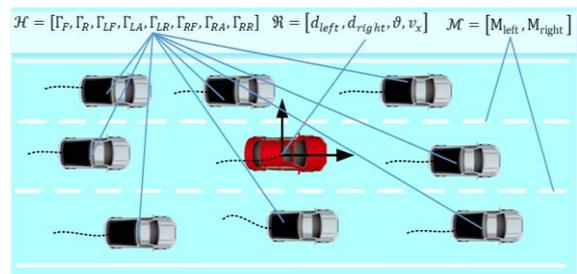


Figure 2 Social characteristics of vehicle behavior

The status information of the target vehicle is defined as

$$\mathfrak{R} = [d_{left}, d_{right}, \vartheta, v_x], \quad (2)$$

where  $d_{left}, d_{right}$  is respectively the lateral distance between the target vehicle and the left and right lane lines,  $\vartheta$  is the heading angle of the target vehicle, and  $v_x$  is the lateral speed of the target vehicle.

In this experiment, we considered the eight vehicles around the vehicle to be the objective vehicle's interaction objects. The vehicle collections concerned are defined as

$$\mathcal{H} = [\Gamma_F, \Gamma_R, \Gamma_{LF}, \Gamma_{LA}, \Gamma_{LR}, \Gamma_{RF}, \Gamma_{RA}, \Gamma_{RR}], \quad (3)$$

where  $\Gamma_F, \Gamma_R, \Gamma_{LF}, \Gamma_{LA}, \Gamma_{LR}, \Gamma_{RF}, \Gamma_{RA}, \Gamma_{RR}$  respectively

For road information,

$$\mathcal{M} = [M_{left}, M_{right}], \quad (5)$$

where  $M_{left}$  is the auxiliary label of the left lane;  $M_{left} = 1$  when there is a lane on the left side, otherwise,  $M_{left} = 0$ ;  $M_{right}$  is the auxiliary label of the right lane; and  $M_{right} = 1$  when there is a lane on the left side, otherwise,  $M_{right} = 0$ .

## 2.2. Maneuver Recognition Module

The maneuver recognition module focuses on the lateral movement of the vehicle, which are lane change left (LCL), lane change right (LCR), and LK. The social feature vector of the target vehicle is taken as input, which is extracted through the dynamic sliding time window method. The convolution operation and pooling process are designed to increase the depth of the social feature information of the target vehicle and reduce the feature dimension. The LSTM layer is input for learning. Finally, the vehicle's current maneuver probability vector is obtained through the SoftMax function.

The original social features consisting of observable historical state information of the surrounding target vehicles are  $\mathbf{O} = [O_1, \dots, O_{T-1}, O_T]$ , where  $T$  represents the size of the dynamic sliding window. To perform higher-level and more abstract processing on raw data, CNN models use local connections and weight sharing, which can effectively extract internal features in the data automatically. According to the characteristics of the social characteristics of the target vehicle, a CNN framework consisting of two convolutional layers, 1 pooling layer, and 1 flatten layer was constructed. The convolutional layer was designed as a one-dimensional convolution (Conv1D), and the ReLU activation function was selected for activation. Convolutional layer 1 and convolutional layer 2 both had 64 convolution kernels of size 3.

$$C_1 = f(X \otimes W_1 + b_1) = ReLU(X \otimes W_1 + b_1)$$

indicate the front, rear, left-front, left-adjacent, left-rear, right-front, right-adjacent, and right-rear vehicle of the identified vehicle.

$$\Gamma = (\Delta x_i, \Delta y_i, \Delta v_i) \quad (4)$$

Here,  $\Delta x_i$  is the lateral relative distance between the  $i$  position vehicle and target vehicle,  $\Delta y_i$  is the longitudinal relative distance between the  $i$  position vehicle and target vehicle, and  $\Delta v_i$  is the relative longitudinal speed between the  $i$  position and the target vehicle.

$$(6)$$

$$C_2 = f(X \otimes W_2 + b_2) = ReLU(X \otimes W_2 + b_2) \quad (7)$$

Here,  $C_1, C_2$  are the outputs of convolutional layer 1 and convolutional layer 2,  $W_1, W_2$  are weight matrices,  $b_1, b_2$  are deviations, and  $\otimes$  is the convolutional operation.

To retain more data fluctuation information, the pooling layer selects one-dimensional maximum pooling (MaxPooling1D) as follows:

$$P_3 = \max(C_2) + b_3, \quad (8)$$

where  $P_3$  is the output of the pooling layer, the function  $\max$  represents the pooling operation, and  $b_3$  is the offset. After processing the convolutional layer and the pooling layer, the original data is mapped to the feature space of the hidden layer. The flatten layer is built to extract the feature vectors after pooling. The output length of the feature output layer is  $l$ , which can be expressed as  $\mathbf{H}_C = [h_{c1}, h_{c2}, \dots, h_{cl}]$ . The traditional LSTM network is a one-way transmission from left to right. It can only obtain the information above and cannot pass the following information to the upper layer. However, the input of the current moment of vehicle maneuver depends not only on the previous trajectory frame but also on the subsequent track frame. Therefore, a bidirectional LSTM network is used. The number of unidirectional LSTM network units is 128. The combination of the two units fully considers the timing information before and after the trajectory frame.  $\overrightarrow{\mathbf{h}}^t$  is the positive hidden layer output,  $\overleftarrow{\mathbf{h}}^t$  is the reverse hidden layer output, and then the output layer of the network is  $\widetilde{\mathbf{h}}_t = \overrightarrow{\mathbf{h}}^t \oplus \overleftarrow{\mathbf{h}}^t$ . Therefore, the model can learn the past and future state data of the vehicle at the same time. The algorithm output is between 0 and 1 to obtain the probability of each of the maneuvering categories. The selected activation function of the output dense layer is the SoftMax function, and the maneuvering category

probability vector  $\mathbf{m}_t = (P_{m_1}, P_{m_2}, P_{m_3})$ .

### 2.3. Behavior Prediction Module

The prediction module also targets the future lateral behavior of the vehicle. It should be noted that the lateral behavior here was not the same as the maneuver because they were marked differently. The output category probability vector  $\mathbf{m}_t$  of the maneuver recognition module and the vehicle social feature vector  $\mathbf{O}_t$  form a context feature vector  $\mathbf{Con}_t = (\mathbf{m}_t, \mathbf{O}_t)$ , which are used as input of the prediction module. Two layers of LSTM loop bodies are used in the vehicle behavior prediction module. The numbers of units in the first and second layer were both 128, and the dropout ratio between the two layers was 0.2.

Attention is a model that simulates the attention of the human brain. It draws on the human brain's attention to things at a specific time to focus on a specific place and reduces or even ignores attention to other parts. For the problem of sequence analysis, the attention mechanism allows the model to know which part of the data is important during the training process by assigning different weights to the sequence features so that the model pays high attention to this information and improves the accuracy of the model, without adding computing and storage costs. Therefore, to improve the recognition effect, the attention mechanism is introduced into the LSTM model to effectively highlight the factors that affect the behavior of surrounding vehicles. The attention structure is shown in Fig.3, where  $x_t (t \in [1, n])$  represents the input of the LSTM network,  $h_t (t \in [1, n])$  is the hidden layer output obtained by LSTM for each input,  $\alpha_t (t \in [1, n])$  is the attention probability distribution value of the Attention mechanism to the output of the hidden layer of LSTM, and  $y$  is LSTM network output with the attention mechanism.

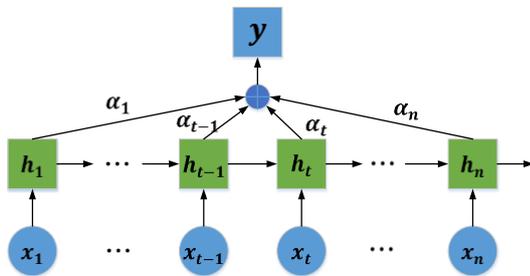


Figure 3 Attention mechanism structure

The output matrix  $\mathbf{H} = [h_1, h_2, \dots, h_l]$  is used as the input of the attention layer. At each moment, the output of

the network layer  $h_i$  as a proportion of the attention of the vehicle behavior is expressed by the score function  $Score$ . The larger the score, the more  $h_i$  on the vehicle behavior and the greater the contribution weight of the representation. The function  $Score$  is

$$Score(\bar{\mathbf{h}}, h_i) = \mathbf{w}^T \tanh(\mathbf{W}\bar{\mathbf{h}} + \mathbf{U}h_i + b), \quad (9)$$

where  $\mathbf{w}, \mathbf{W}, \mathbf{U}$  are weight matrices,  $b$  is the offset amount,  $\tanh$  is the nonlinear activation function, and  $\bar{\mathbf{h}}$  can be regarded as the behavioral representation vector of the vehicle state information one level higher.  $\bar{\mathbf{h}}$  is a randomly initialized training process and then updated step-by-step as a parameter.

Then, the score function  $score$  of each time step is normalized, and the attention probability distribution matrix  $\mathbf{A} = [\alpha_1, \alpha_2, \dots, \alpha_T]$  of each input distribution is obtained as follows:

$$\alpha_i = \frac{\exp[score(\bar{\mathbf{h}}, h_i)]}{\sum_{j=1}^T \exp[score(\bar{\mathbf{h}}, h_j)]}, \quad \sum_{i=1}^T \alpha_i = 1. \quad (10)$$

The output of the attention layer at time  $t$  is

$$\mathbf{v}_t = \sum_{i=1}^T \alpha_i h_i. \quad (11)$$

The attention layer is followed by a fully-connected layer with several units of 20, and the SoftMax function is used to obtain the vehicle behavior prediction probability vector.

$$\mathbf{y}_t = \text{softmax}(\mathbf{W}_v \mathbf{v}_t + b_v), \quad (12)$$

where  $\mathbf{W}_v$  is the weight for the connection, and  $b_v$  is the offset. Finally, the maximum probability is taken as the prediction result of the vehicle behavior as follows:

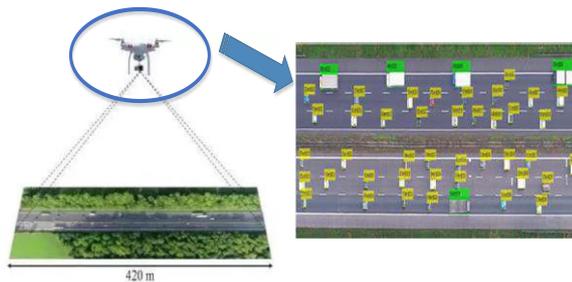
$$\hat{s} = \arg \max(\mathbf{y}_t). \quad (13)$$

## 3. Experiment

### 3.1. Dataset

The vehicle trajectory dataset used in this paper was partly derived from a new method for measuring vehicle data from an aerial perspective proposed by the Institute of Automotive Engineering of the Aachen University of Technology in Germany in 2018 [26]. This method used a series of UAV image records to extract the vehicle's characteristic information with a distance of about 420 meters on a German highway from a bird's-eye view. The bird's-eye view of the collected road sections is shown in Fig.4. The public dataset included available data for six locations, 16.5 hours, and 110,000 vehicles. The total driving distance was 45,000 kilometers. It also included 5,600 complete LC records, which could meet the

verification requirements of traffic scenarios. Compared with data collected by driving simulators in most studies, using real data for model validation makes the model more robust and practical. Compared with the classic NIGSIM trajectory dataset, the high D dataset can effectively solve the problem of false overlapping collisions and provide more complete vehicle status information, especially regarding the number of LCs of vehicles, the warning time of the preceding vehicle collision, and the ID of the surrounding vehicles, which provides a wealth of research materials for vehicle interaction prediction and saves much work in data preprocessing.



**Figure 4** Bird's-eye view of a road in the High D dataset

The high D dataset collection roads are like the highway structure in China, most of which are two-way two-lane or three-lane roads. However, to avoid overfitting the model to the high D dataset and enhance the generalization performance of the training model, another part of the original vehicle trajectory dataset used for training and verification was derived from the vehicle trajectory collected by the unmanned experimental platform under real road conditions. The data collection roads were mainly located near Jingjiang Road, Zhenjiang, Jiangsu Province. As shown in Fig.5, an ARRIZO EX electric vehicle was used as the main body of the unmanned experimental platform. It was equipped with a joint navigation system, 64-line lidar, a high-performance industrial computer, Delphi-ESR front and rear millimeter-wave radar, Minieye HD camera, and other vehicle equipment.



**Figure 5** Unmanned experimental platform based on ARRIZO

EX

The unmanned experimental platform fully combined GPS and inertial navigation technology and performed differential decomposition through RTK technology, which could reduce the occlusion impact of buildings and trees; provide accurate position and speed information; and calculate the attitude results of the host vehicle. The platform mainly obtained the position and speed information of surrounding vehicles through 64-line lidar. The radar implemented real-time data recording through the ROS system. Firstly, a trajectory\_node node needed to be created. The radar recorded data in real-time through the ROS system. This node subscribed in real-time to the topic / box\_info and / track\_info sent by the lidar sensing module Perception SDK, which contained the location center and speed of the surrounding vehicles. The data was transformed from the local coordinate system of the host vehicle to the global coordinate system of the road. This study used a road joint coordinate system like the Cartesian coordinate system. The longitudinal y-axis points to the direction of motion of the highway, and the lateral x-axis is perpendicular to it, which makes the algorithm applicable to curved roads. For the road information of the target vehicle, it is determined by the lateral position of the vehicle, the number of lanes, and the position of the lane line.

### 3.2. Data Preprocessing

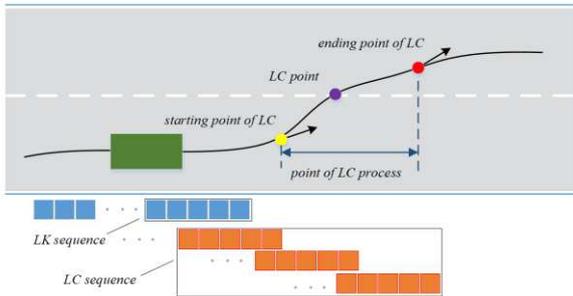
The vehicle trajectory data was obtained directly or indirectly after being collected by the UAV high-definition camera or on-board sensor. The existence of system errors and measurement errors made the traffic parameter sequence values noisier, especially the speed signal jitter. The Savitzky-Golag filter algorithm was used to pre-process the coordinates and speed of the vehicle. For this study, we mainly examined the current maneuver and future behavior of target vehicles around intelligent driving. We needed to extract the trajectory sequences of different vehicle behaviors in the dataset and made corresponding annotations.

As shown in Fig.6, the target vehicle performed a LCL behavior, and the intersection of the vehicle trajectory and the lane line is represented as a LC point. The heading angle of the vehicle relative to the lane line at each moment is

calculated as follows:

$$\vartheta_o = \arctan\left(\frac{x^{(t)} - x^{(t-2)}}{y^{(t)} - y^{(t-2)}}\right). \quad (14)$$

For the maneuver tag, to reduce the misjudgment caused by the noise error, if 3 consecutive points  $|\vartheta_o| \leq \vartheta_s$  ( $\vartheta_s$  is the threshold of the heading angle of the LC) while traversing forward from the LC point, then the first point was defined as the start point of the LC; if there are 3 consecutive points  $|\vartheta_o| \leq \vartheta_e$  ( $\vartheta_e$  is the heading angle threshold at the end of the LC) while traversing backward from the changing point, then the first point was defined as the end point of the LC. The points between the start and end points (including these two points) are defined as the LC process points. According to the experimental results, the sliding time window is selected. Here, the sequence length  $T$  was 20. If the last node of the trajectory sequence was a LC process point, then the left LC maneuver sequence and the right LC maneuver sequence were respectively determined according to the lateral position of the vehicle at the starting point of the track sequence. If the last node of the trajectory sequence was not a LC process point, then it was defined as a LK maneuver sequence.



**Figure 6** Vehicle behavior labeling logic

As the research object of the prediction module, the lateral behavior of the target vehicle was defined with three behavior categories: LCL, LCR, and LK. The observation time window was set to 2 s (20 time steps), and the predicted time domain was set to 4 s (40 time steps). The rule for marking LC was that the target vehicle crossed the lane line in the predicted time domain and started 8 s before LC. The time window slides to perform the marking process. The output of the prediction algorithm is the probability value of the three behavior categories, and then the predicted behavior is worth the maximum probability. Based on the vehicle trajectory dataset, 27,000 sample datasets were extracted. Since the straight-line driving condition occurred much more than the LC condition, the

number of LK sequences of the extracted vehicle was much larger than the LC sequence. To prevent overfitting in the training process, the number of sequences selected in each behavior sequence set was the same, where each behavior category was 9,000 and the sample set was randomly divided into a training set and a test set at a ratio of 8:2.

### 3.3. Implementation Details

To reduce the impact of the value span and unit of each raw data, the min-max normalization method was used to convert the raw data to between 0 and 1 as follows:

$$\tilde{x} = \frac{x - x_{min}}{x_{max} - x_{min}}, \quad (15)$$

where  $x$  is the original data,  $\tilde{x}$  is the normalized data, and  $x_{max}$  and  $x_{min}$  are the maximum and minimum values of the sample data. To facilitate the training of the model network, it was also necessary to use one-hot heat vector coding for the current maneuver and future behavior labels of the sample set of vehicles.

The maneuver recognition module selected multiple types of cross-entropy as the loss function and the expression is

$$loss = -\frac{1}{S_M} \sum_{S_M} \sum_{i=1}^3 \widehat{P}_{m_i} \log(P_{m_i}), \quad (16)$$

where  $\widehat{P}_{m_i}$  is the actual probability that a sample sequence corresponds to the current mobility category of the vehicle;  $P_{m_i}$  is the recognition probability of the current mobility category of the vehicle corresponding to a sample sequence; and  $S_M$  is each batch's sample size of the mobility identification module, which is selected as 100 in the experiment.

The behavior prediction sample was aimed at whether the target vehicle would change lanes in the future. Because of the driver's LC habits and the impact of the vehicle's LC response, some sequence samples that were far from the LC point became difficult classification samples. Therefore, a loss function of focal loss was introduced as follows:

$$loss = -\frac{1}{S_P} \sum_{S_P} \sum_{i=1}^3 \widehat{w}_i (1 - w_i)^{\text{Gamma}} \log(w_i), \quad (17)$$

where  $\widehat{w}_i$  is the actual probability of the vehicle behavior category corresponding to a sample sequence;  $w_i$  is the predicted probability of the vehicle behavior category corresponding to a sample sequence; and  $S_P$  is the sample size of each batch of the behavior prediction module, which was also selected as 100. Gamma is the sample weighting factor. When Gamma was not 1, for positive samples, a

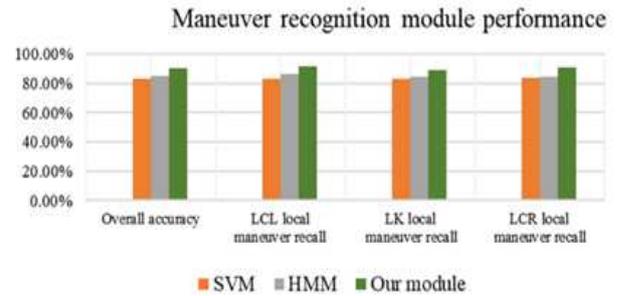
larger the prediction result probability  $w_i$  means it was definitely the simple sample, and thus a Gamma power of  $(1-w_i)$  would be small and the loss function value would become smaller. The sample with the predicted probability  $w_i$  had a relatively large loss. For negative samples, a result with a small  $w_i$  should be much smaller than the sample with a large  $w_i$ . In the training process, more attention was paid to the indistinguishable samples that are far from the LC point, and the impact of simple samples was also reduced. In the experiment, a good effect was obtained when the Gamma size was 1.2.

The algorithm used in the vehicle maneuver recognition and behavior prediction module selected the adaptive moment estimation (Adam) optimization algorithm to optimize the model parameters. Adam is a first-order optimization algorithm that can replace the traditional stochastic gradient descent process. The algorithm can back-propagate errors based on training data, iteratively update the weights of the neural network, and gradually reduce the output value of the loss function to the optimal level. The entire vehicle behavior prediction algorithm is written based on Python 3 and implemented using the Keras framework. The main parameters of the experimental platform hardware configuration were Intel Core i5-8600K 3.60 GHz, GTX 1080, DDR3 16 G of memory, and the operating system was Ubuntu Linux 16.04.

## 4. Result and Analysis

### 4.1. Vehicle Maneuver Recognition Test Results

The performance of the maneuver identification module had a significant impact on the predicted quality of the vehicle behavior. To test the performance of the maneuver identification module, if the maneuver category corresponding to the maximum value in the probability vector output by the identification module was the same as the actual tag maneuver, then it was considered to be a successful sample. In this paper, an SVM and an HMM were used as the benchmarks, and the performance of the three models in recall and overall accuracy was analyzed and compared.



**Figure 7** Performance comparison of the maneuver recognition module

As shown in Fig.7, the overall recognition rate and recall rate of each maneuver recognition of our maneuver recognition module both reached 89%, and both exceeded the other two methods, which indicates that the maneuver recognition module based on the deep learning model had good maneuver recognition ability. The recognition recall rate of left and right LC maneuvers was close, and both were above 90%, which was higher than that of the LK maneuver. A small part of the data of some LK maneuver samples had a large jitter, causing the maneuver recognition module to easily misjudge it as a LC maneuver, and thus the recall of the straight-line maneuver category was lower than the other two maneuver categories.

### 4.2. Vehicle Behavior Prediction Test Results

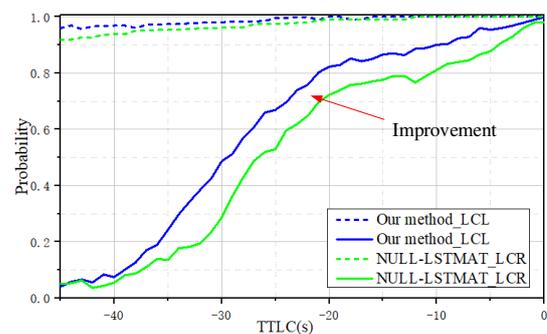
To reflect the performance of the algorithm proposed in the prediction of the behavior of unmanned surrounding vehicles, three deep learning models and the proposed method were compared through quantitative analysis. The overall accuracy, precision, recall, F1-score, and average prediction time were used as evaluation indicators. Among them, the accuracy rate is the ratio of the number of positive samples identified correctly to the number of samples identified as positive by vehicle behavior recognition, and the recall rate is the ratio of the number of positive samples identified correctly to the number of true positive samples, which is the harmonic average of precision and recall. The overall accuracy is the ratio of the number of correctly identified samples to the total number of samples. The average prediction time represents the average effective prediction range of the LC. The prediction time is usually obtained by recording the time of the first successful LC prediction. Considering the existence of sensor noise, two consecutive LCs were recorded as a successful detection of a LC, and the first recorded point was selected as the

predicted time point. The results for the vehicle behavior prediction test set are shown in Tab.1.

**Table 1** Vehicle behavior prediction performance results

Vehicle behavior prediction method		1DCNN	GRU	LSTM	Our method
Overall	Accuracy	84.24%	85.87%	87.67%	<b>89.73%</b>
LCL maneuver	Precision	86.09%	87.75%	89.12%	<b>91.02%</b>
	Recall	82.31%	83.28%	84.73%	<b>87.46%</b>
	F1-score	84.16%	85.46%	86.87%	<b>89.20%</b>
LK maneuver	Precision	81.92%	83.08%	85.68%	<b>87.31%</b>
	Recall	83.92%	82.43%	83.04%	<b>85.65%</b>
	F1-score	82.91%	82.75%	84.34%	<b>86.47%</b>
LCR maneuver	Precision	84.71%	86.78%	88.21%	<b>90.86%</b>
	Recall	83.85%	83.69%	83.96%	<b>86.49%</b>
	F1-score	84.28%	85.21%	86.03%	<b>88.62%</b>
Prediction time	Average time	1.737s	1.819s	1.855s	<b>2.032s</b>

According to Tab.1, the proposed method had the highest accuracy, recall, and F1 score. Compared with LSTM, our method significantly improved the recall rate in various behavior categories and achieved an overall prediction accuracy rate of 89.73%. Moreover, the proposed method introduced the attention mechanism and continuously paid attention to the feature changes at all times in the sample sequence; therefore, the sample sequence at the moment when the target vehicle reached the LC point could predict the LC behavior, resulting in the prediction of two behaviors, both the left and right LCs. The improved recall rate was significantly greater than LK behavior. Another concern is that LC behavior needs to be predicted as early as possible to give decision-making and control systems more time for execution. Considering that the actual LC duration was about 3.0 to 5.0 s, a clear LC operation occurred about 1.5 to 2.5 s before crossing the dividing line. The proposed algorithm achieved a maximum average prediction time of 2.032 s, which means that the attention model can capture LC behavior in the distant future and improve driving safety.



**Figure 8** Probability distribution of vehicle behavior prediction relative to TTLC

When the target vehicle changes lanes, how the prediction accuracy changes with time is a very important issue because, for many decision-making systems, not only the behavior categories need to be predicted but also the predicted probability distribution of each behavior category. As shown in Fig.10, the vehicle was about to complete a LC to the right. Compared with the method in this paper, the NULL-LSTMAT method in the figure did not consider the current maneuvering characteristics of the vehicle. In the figure, the abscissa is the time to reach the LC point (Time To Lane Change (TTLC)), and the ordinate is the probability distribution predicted by each behavior category. As shown, although there was not much difference between the two in the long period before the LC point, the proposed method tilted to the truth value category in the behavior

prediction probability distribution about 3 s before the LC. The current maneuvering characteristics of the target vehicle enriched the prior knowledge of the behavior prediction algorithm, which increased the probability value of LCR and decreased the probability value of LCL. This also proves that our method has a better prediction time for LCs.

## 5. Conclusion

This paper proposed a long-term prediction method for the behavior of surrounding vehicles based on the attention length and short-term memory model. The maneuver recognition module is used to calculate the probability vectors of three maneuvers and form a context feature vector with social features. In the behavior prediction module, to complete the prediction of vehicle behavior, the LSTM network and attention mechanism capture the multi-step information in the behavior time window according to the context feature vector. This method shows that a high prediction accuracy and LC prediction time can be achieved on the real-car collection and open-source vehicle trajectory datasets. The algorithm is feasible, practical, and can improve the real-time performance of subsequent decision-making systems. This work has important application in driving roles. Future research work will focus on how to ensure prediction accuracy while considering the calculation cost of the prediction algorithm.

## 6. Declaration

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### Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

### Authors' contributions

The author's contributions are as follows: Yingfeng Cai was in charge of the whole trial; Kangsheng tai and Hai Wang wrote the first manuscript; Xiaobo Chen and Qingchao Liu assisted with sampling and laboratory analyses.

### Competing interests

The authors declare no competing financial interests.

### Consent for publication

Not applicable

### Ethics approval and consent to participate

Not applicable

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# Figures

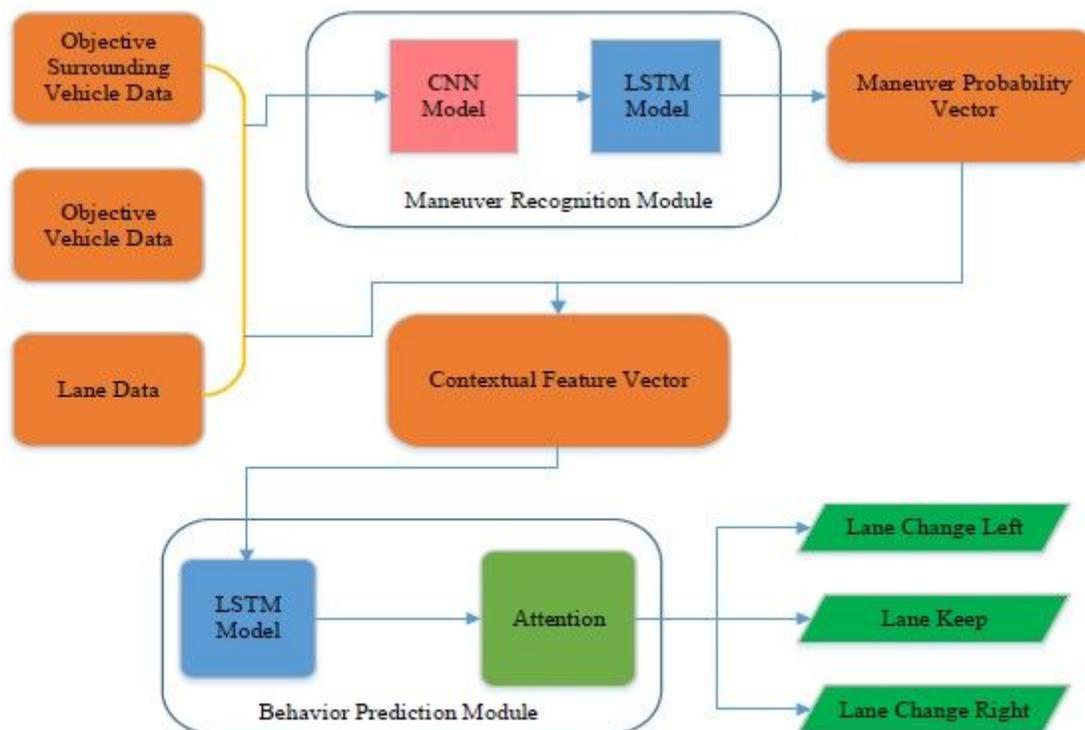


Figure 1

Framework of the proposed method

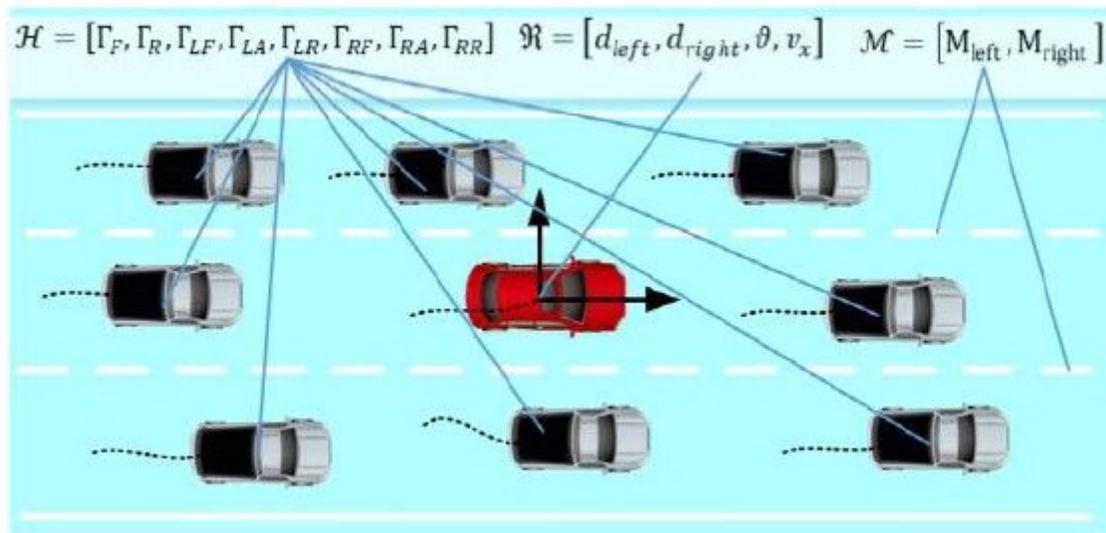


Figure 2

Social characteristics of vehicle behavior

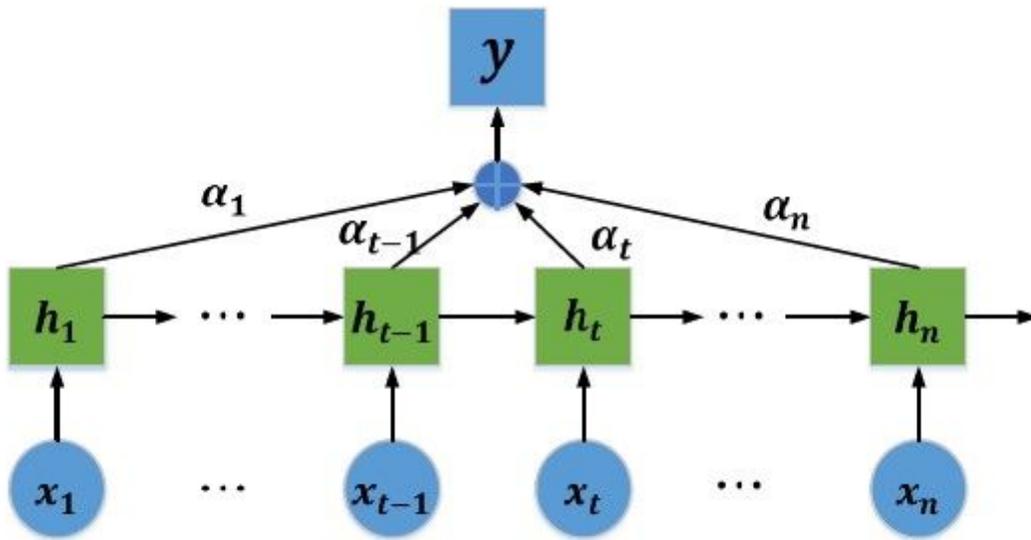


Figure 3

Attention mechanism structure

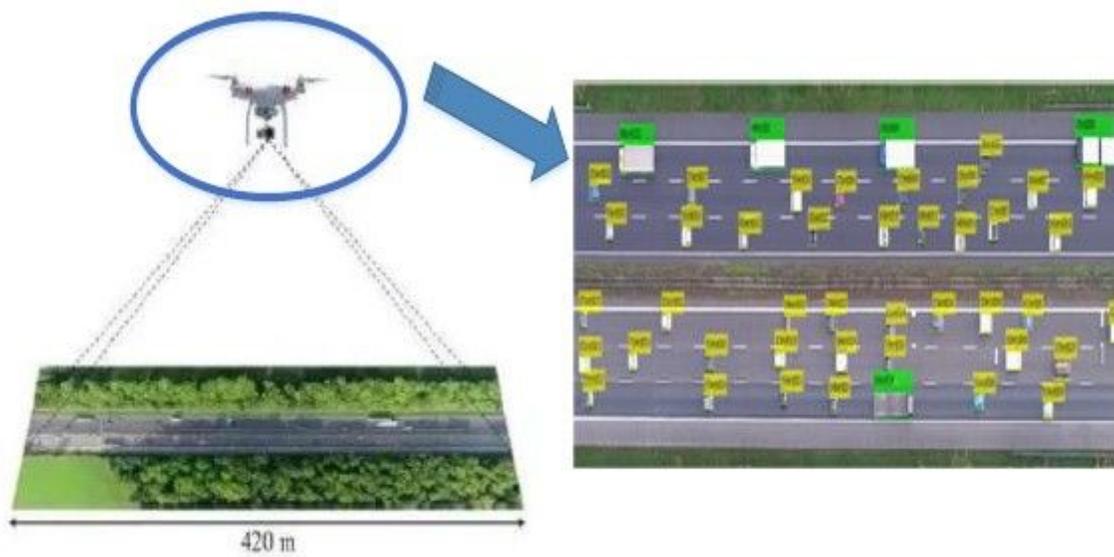


Figure 4

Bird's-eye view of a road in the High D dataset



Figure 5

Unmanned experimental platform based on ARRIZO

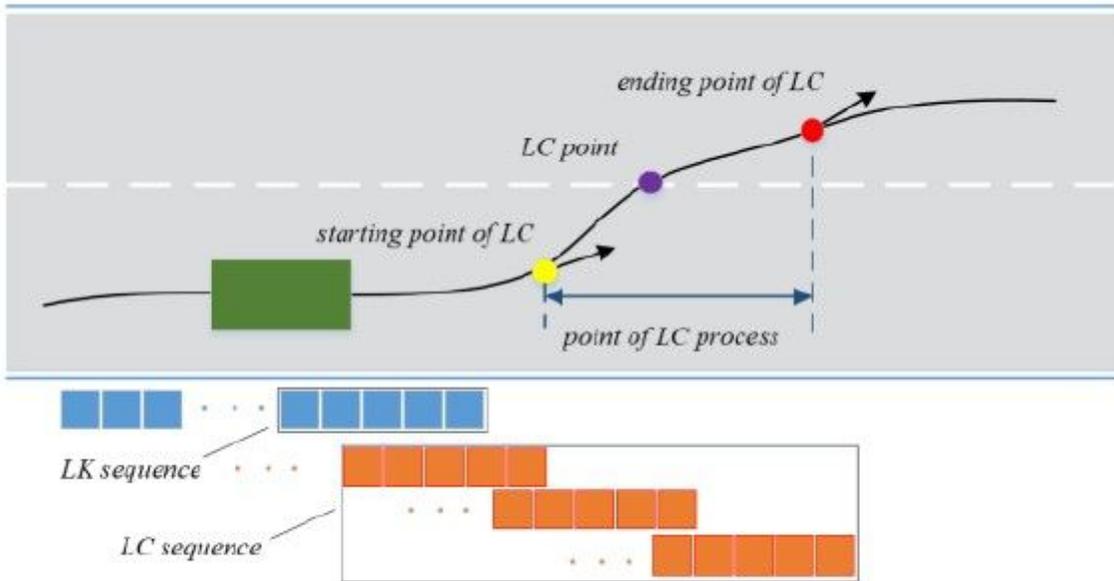


Figure 6

Vehicle behavior labeling logic

## Maneuver recognition module performance

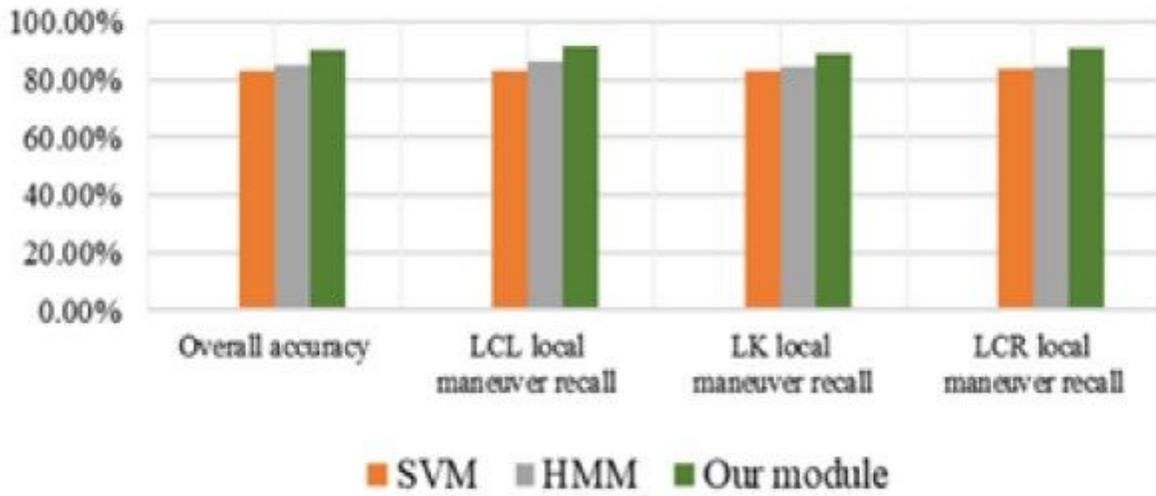


Figure 7

Performance comparison of the maneuver recognition

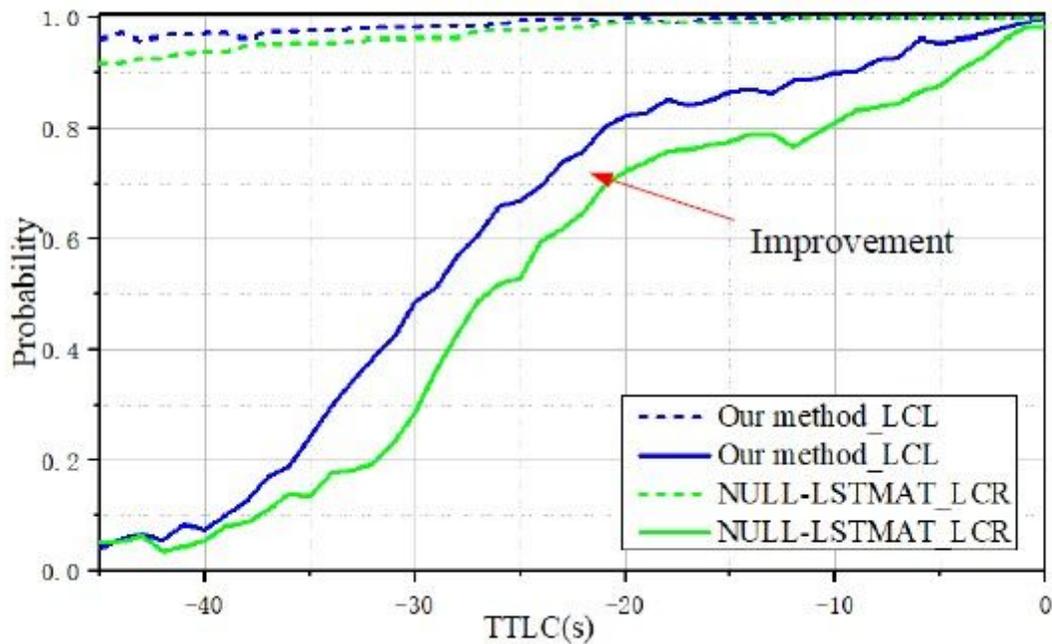


Figure 8

Probability distribution of vehicle behavior prediction relative to TTLC