Research on Multi-objective Trajectory Prediction Algorithm Based on Driving Intent Classification

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Abstract. The trajectory prediction of the multi-object vehicle ahead plays a huge role in improving the vehicle’s driving safety and improving the planning and traffic efficiency of the vehicle. However, due to the uncertainty of the driving intention of the multi-object vehicle and the uncertainty of the vehicle dynamics, its trajectory prediction faces a huge challenge. First, the fuzzy C-means (FCM) method is used for multi-object trajectories. After offline training is carried out using the relevant information of the vehicle trajectory, the driving intention can be automatically fuzzy classification. Secondly, the long short-term memory (LSTM) method uses the history and current trajectory information of multi-object vehicles ahead to predict the future trajectory under different driving intentions. Then, according to the fuzzy classification results of the driving intention, the predicted trajectories are merged, and the trajectory prediction of the multi-objective vehicle ahead in the next 1s is realized through an iterative method. Finally, use real vehicle data for experimental verification. The results show that 92.1% of the lateral distance prediction error in the tenth step is less than 0.13m. The maximum distance prediction error is 0.54m. In the longitudinal distance, the prediction error of 94.5% is less than 0.6m. The maximum distance prediction error is 1.0m.

Keywords. Trajectory prediction; multi-objective, driving intent classification.

1. Introduction
The vehicle’s trajectory in front is the key factor affecting the fuel economy, driving safety, and traffic efficiency of the vehicle. For example, in the scene of lane change, overtaking, and so on. the driving trajectory of the vehicle in front has a significant impact on the future planning of the vehicle. However, the sensing equipment used for the track detection of the vehicle in front of the vehicle is usually limited, which leads to significant uncertainty in the vehicle’s dynamic characteristics in the track prediction. There is also uncertainty about the driving intentions of the car ahead. At the same time, there is more than one traffic participant in front of the vehicle, so multi-objective trajectory prediction is also a complex problem. Therefore, in the case of multi-objective driving intention and dynamic characteristics of the leading vehicle with uncertainties, and limited data sources, the trajectory prediction of the leading vehicle is faced with challenges.

At present, there are several approaches to solve vehicle trajectory prediction: model-based parameter method: this method assumes that the vehicle’s behavior is entirely dependent on the physical constraints of the vehicle and predicts the future trajectory through vehicle kinematics or vehicle dynamics. Brannstrom [1] proposed a bicycle model is adopted to represent the vehicle dynamics model, and the future trajectory is predicted according to the vehicle’s current state. Xiao [2], proposed a trajectory prediction method based on the constant yaw angular velocity and acceleration motion model and a trajectory prediction method based on maneuver identification is proposed. Trajectory prediction
algorithm based on waveform processing: Kalman filter algorithm as the representative, Kalman filter uses sensor fusion, information fusion to improve the system’s accuracy. By measuring the output with random noise, the optimal system state is estimated. Liu et al. [3] estimated the vehicle state based on the minimum model error criterion and the extended Kalman filter. However, the above two methods are difficult to obtain accurate parameter models in the case of limited acquisition of previous vehicle data, fail to consider the influence in the multi-objective environment and predict the future driving intention of the object, and fail to make full use of historical information, so it is difficult to achieve good results.

Machine learning-based trajectory prediction algorithm: by analyzing the historical trajectory data to extract features, using regression method to predict the future position, such as the support vector machine to estimate the future trajectory of out-of-control ships, to prevent the collision. Rehder et al. [4] introduced the concept of short-term goals and decomposed the problem into target distribution estimation and target-oriented programming, and the target was defined as the mixture of Gaussian latent variables. The above methods do not consider the driver’s driving intention and only predict the trajectory for a single target.

In addition, it is difficult to observe the target driving intention through the sensor directly. At present, domestic and foreign scholars mostly use machine learning to recognize and predict lane-changing driving intention. Kumar et al. [5] combine SVM with a Bayesian filter to predict driving intention. Liu et al. [6] used a parallel Bayesian network to identify drivers’ lane-changing behaviors, reducing the time spent and error rate. However, most of the above methods divide lane changing operation into lane changing and lane-keeping. Some studies classify lane changing as emergency lane changing, but the classification accuracy is low, and the process of lane changing cannot be accurately described.

Deep neural network architecture is good at generalizing nonlinear problems between actual data and the environment [7]. Among them, Recurrent Neural Networks (RNN) have a good effect on time series data. Sc et al. [8] mainly studied the urban vehicle trajectory prediction algorithm based on the recursive neural network based on the attention model. Deo et al. [9] proposed the long short-term memory (LSTM) encoder-decoder model that uses a convolutional social pool to learn the interdependence in vehicle movement. Gupta et al. [10] predicted the future path of pedestrians by combining sequence prediction and generative adversarial network. Manh et al. [11] developed a human motion trajectory prediction system by combining scene information and human motion trajectory through LSTM. Kim et al. [12] used LSTM to analyze the temporal behavior of surrounding vehicles and predict future coordinates. Khorosroshahi et al. [13] established the activity classification framework of observed vehicles by using the LSTM model.

Aiming at the uncertainty of the multi-object vehicle’s driving intention and vehicle dynamics ahead, this paper proposes a multi-object trajectory prediction algorithm based on driving intention recognition. First, the data association algorithm is used to track multi-objects ahead; secondly, the fuzzy C-means (FCM) method is used to classify the driving intention to solve the uncertainty of the driving intention of the preceding vehicle; then, combine different Types of driving intentions, use actual measured real vehicle data to train different LSTM models, and predict the future trajectory to solve the uncertainty of vehicle dynamics. Finally, the effectiveness of the algorithm is verified by real vehicle data.

The rest of this article is organized as follows. In section II introduces the research objects and data sets of this article. Section III describes the proposed trajectory prediction model, including the algorithm principle and the trajectory prediction algorithm framework. Section IV describes the experimental results, and Section V summarizes the paper.

2. Research Object
The experimental data in this study are from the car camera and millimeter-wave radar. One camera is installed on the car’s front windshield, and the millimeter-wave radar is installed on the front of the car. We are more concerned about the current lane and adjacent lanes within the target in the trajectory prediction. On the other hand, these key targets will consume resources, single cause algorithm running
time increases. It also causes the algorithm to be unable to respond to dangerous targets promptly. Considering the above factors, it is necessary to preprocess the targets input by millimeter-wave radar and camera to delimit the region of interest and eliminate the noise points according to specific screening rules. Therefore, the region of interest is defined as 30m ahead, and the transverse distance is within the range of ±4m.

The collected track data \( V = \{V_1, V_2, \ldots, V_n\} \), where each group of data in \( V \) is the track information of one of the cars in front, including the horizontal and longitudinal coordinate information of the car in front and the horizontal and longitudinal velocity information. The data included lane keeping and lane changing conditions, and the data collection frequency was 100ms. The collected data are divided into the training set, verification set, and test set used for training, verification, and testing of the driving intention classification algorithm and prediction algorithm.

3. Multi-objective forward Vehicle Trajectory Prediction Algorithm

First, the target list sent by the radar and camera needs to be processed. In two adjacent frames, the trajectory of the previous frame is associated with the current measurement. The track is managed dynamically. By processing the radar target list, the target trajectory in the area of interest of the vehicle is obtained, thereby achieving target tracking.

Then, the data of different driving intentions are used to train the LSTM model respectively. The LSTM algorithm is adopted to predict three future trajectories under different driving intentions by taking the historical 4-step and current coordinate information as input and the future 1-step coordinate as output. Based on the trajectory information of each target, the probability of three driving intentions was identified by the FCM algorithm, and the future trajectory calculated by LSTM was fused to obtain the future coordinates under the multi-model fusion. The structure diagram of a multi-objective track prediction algorithm for the leading vehicle is shown in figure 1.

![Figure 1. Multi-objective vehicle trajectory prediction algorithm architecture diagram.](image)

3.1. Driving Intention Classification

Under normal circumstances, the driver needs to turn on the corresponding turn signal before changing lanes. However, statistics show [14] that only 78.6% of drivers turn on their turn signals in the process of lane change, and only about 50% of drivers turn on their turn signals before a lane change. Therefore, the steering signal as a recognition feature of driving intention is not enough, and the classification of driving intention requires other characteristic parameters. By extracting corresponding characteristic
parameters, the three driving intentions of emergency lane change, normal lane change, and lane-keeping are classified. Table 1 shows the selected characteristic parameters.

Table 1. Characteristic parameter table.

| Serial number | Characteristic parameters                  |
|---------------|-------------------------------------------|
| 1             | Vehicle speed (m/s)                       |
| 2             | Horizontal relative coordinate change (m) |
| 3             | Longitudinal relative coordinate change (m) |

Firstly, the FCM was trained offline, and the characteristic data were obtained by extracting the characteristic values of the trajectory data of the 4-step history and the current moment. The extracted eigenvalues are input into the FCM algorithm. Based on the objective function, the clustering center and membership matrix are iterated continuously before the algorithm converges to maximize the similarity of feature data of the same category.

Before the objective function [15] is shown in equation (1) is satisfied, according to equations (2) and (3), the clustering center and membership function are constantly iterated to obtain the clustering center $c_1$ for an emergency lane change, the clustering center $c_2$ for normal lane change and the clustering center $c_3$ for lane keeping.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left\| x_i - c_j \right\|^{2/m-1}}$$

where $J_m$ is the objective function, $c_i$ is the cluster center of class i, and $u_{ij}$ represents the membership degree of sample $x_i$ belonging to class i. For a single sample $x_i$, the sum of the membership degrees for each category is 1.

In the actual driving of the vehicle, the eigenvalues of the current and historical 4-step sampling time are calculated. Equation (3) is used to calculate the distance between this point and each cluster center, and the corresponding membership function of this point is obtained, which is used to characterize the probability that it belongs to the cluster center.

### 3.2. Trajectory Prediction

RNN is widely used to analyze the structure of time series data. LSTM model is a variant of RNN, which can learn long-term dependent information. The main difference between LSTM and traditional cyclic neural networks is that it adds gate structures, which are forgetting gate, input gate, output gate, respectively [16]. This paper uses LSTM to understand complex vehicle dynamics models. represents the unit state of the t-th step, then is updated by equations (4)-(9).

$$f_t = \sigma (W_f h_{t-1} + U_f x_t + b_f)$$

$$i_t = \sigma (W_i h_{t-1} + U_i x_t + b_i)$$
\begin{equation}
C_i = \tanh(W_c h_{t-1} + U_c x_t + b_c)
\end{equation}

\begin{equation}
C_t = f_t \cdot C_{t-1} + i_t \cdot C_i
\end{equation}

\begin{equation}
O_t = \sigma(W_O h_{t-1} + U_O x_t + b_O)
\end{equation}

\begin{equation}
h_t = O_t \cdot \tanh(C_t)
\end{equation}

where $f_t$ represents the forget gate, $i_t$ represents the input gate, $C_i$ represents the status update, $o_t$ represents the output gate, and $h_t$ represents the final output value. $W_f, U_f, W_i, U_i, W_c, U_c, W_o, U_o$ are weight coefficients, $b_f, b_i, b_c, b_o$ are biases, and $\sigma = \frac{1}{1 + e^{-x}}$ is an activation function.

In the multi-step prediction method, there are two main categories: direct method and iterative method. The iterative method uses the prediction of each step to predict the next step until the desired step size is reached. The direct method can directly predict the $k$ step, but if $k$ changes, the model needs to be retrained. The results show that the amount of training data and calculation required by the direct method are much higher than that of the iterative method [17]. In this paper, the iterative method is adopted for vehicle trajectory prediction.

Taking the prediction of future 2-step trajectory as an example, the input data are four sets of historical trajectory information and 1 set of future trajectory information predicted in the previous step. After feature extraction of the five sets of data, driving intention is identified by the FCM algorithm, and the corresponding membership function is calculated. At the same time, five groups of data were input into the LSTM trajectory predictor. According to the membership function of driving intention, the weighted fusion of the three predicted trajectories was carried out with variable gain, and the trajectories of the vehicles ahead of 2-step in the future were finally predicted.

4. Results and Analysis
In order to measure the accuracy of vehicle trajectory prediction, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were selected as measurement indexes. The calculation equations are shown as (10) and (11).

\begin{equation}
RMSE(X,h) = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (h(x_i) - y_i)^2}
\end{equation}

\begin{equation}
MAE(X,h) = \frac{1}{m} \sum_{i=1}^{m} |h(x_i) - y_i|
\end{equation}

where, $m$ is the sample size, $h(x_i)$ is the predicted value, and $y_i$ is the true value.

In the multi-step prediction, the iterative method is used to predict the trajectory of the preceding vehicle. As shown in figure 2, it is the trajectory prediction map of the three vehicles ahead, respectively predicting the first step length, the fifth step length, and the tenth step length the trajectory prediction curve graph. It can be seen from the figure that the FCM-based LSTM trajectory prediction curve is closer to the real trajectory of the preceding vehicle, especially under the steering operation, the FCM-based LSTM trajectory prediction error obvious reduction. Figure 3 shows the distribution diagrams of the abscissa and ordinate prediction errors of the first, fifth, and tenth steps, respectively.
Figure 2. Multi-objective vehicle trajectory prediction map based on driving intention classification.

Figure 3. Multi-target vehicle trajectory prediction error distribution map.
As can be seen from the figure, in the first, fifth, and tenth steps of the horizontal coordinate prediction, the average error of the prediction results of the LSTM algorithm based on FCM classification is slightly lower than that of the pure LSTM algorithm. The error variance is significantly smaller than that of the pure LSTM algorithm. In the longitudinal coordinate prediction, the average error and error variance of the prediction results of the LSTM algorithm based on FCM classification in the first, fifth, and tenth steps are significantly smaller than those of the pure LSTM algorithm. The prediction error of this algorithm fluctuates slightly. The forecast result is stable.

Figure 4 shows the comparison of MAE and RMSE for different forecasting methods. It can be seen from the figure that the RMSE and MAE of the FCM-based LSTM algorithm are both smaller than the pure LSTM prediction algorithm. Taking Vehicle1 as an example, when predicting the abscissa of the 10th step, compared with the pure LSTM prediction method, the abscissa prediction error MAE is reduced by 32.92%, and the RMSE is reduced by 26.88%. The MAE of the ordinate prediction error was reduced by 61.03%, and the RMSE was reduced by 67.22%.

Figure 4. Multi-step horizontal and vertical coordinate forecast RMSE and MAE trend chart.

In the tenth step, 92.1% of the lateral distance prediction error is less than 0.13m. The maximum distance prediction error is 0.54m. In the longitudinal distance, the prediction error of 94.5% is less than 0.6m. The maximum distance prediction error is 1.0m.

5. Conclusion
In this paper, in order to solve the problem of the difficulty in predicting the trajectory of the preceding vehicle caused by the uncertainty of the driving intention and dynamic characteristics of the multi-objective preceding vehicle, a preceding vehicle speed prediction algorithm based on the combination of FCM driving intention classification and LSTM is established.

First, give full consideration to under different driving intentions for the future in front of the vehicle trajectory, the influence of by FCM algorithm, for driving intent classification, multi-object tracking information using track vehicles related information, in front of the vehicle driver’s intentions for offline training, in order to improve the classification resolution and accuracy, realize automatic recognition of vehicle driving intention;

Secondly, the LSTM model is trained with the historical and current trajectory data under different driving intents to predict the future trajectories under three different driving intents.
Thirdly, the membership function output by FCM was used as the weight of each model to carry out a variable gain weighted fusion of the three prediction trajectories, and the rolling prediction of the future 1s trajectories of the multi-objects ahead was carried out by the iterative method.

Finally, real vehicle data is used for verification. In the trajectory prediction of the future 1s, 92.1% of the lateral distance prediction errors are less than 0.13m. The maximum distance prediction error is 0.54m. In the longitudinal distance, the prediction error of 94.5% is less than 0.6m. The maximum distance prediction error is 1.0m. This shows that this method has high accuracy.

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