Trajectory Prediction of Surrounding Vehicles Using LSTM Network

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We propose a method to predict trajectories of surrounding vehicles using a long short-term memory (LSTM) network. Trajectory prediction of surrounding vehicles is attracting a lot of attention now, and it is expected to apply to advanced driver-assistance systems (ADAS). Although many prediction methods using a deep learning framework have been proposed, most of them only focus on the subject vehicle even though surrounding vehicles largely affect the driving pattern of the subject. To solve this problem, the proposed method takes account into the relationship between the subject and surrounding vehicles using the LSTM network. It is demonstrated that the proposed method successfully achieves the goal of the trajectory prediction.

KEY WORDS: **Safety,** Accident avoidance/Collision prediction, Intelligent/Computer application [C1]

1. Introduction

According to a survey by the Japan Metropolitan Police Department, over 90 % of car crashes are caused by human mistakes [(1)]. Recently, autonomous driving technologies and ADAS have attracted considerable attention as solutions for preventing car accidents. The implementation of intelligent technologies to assist drivers in recognizing situations around their own vehicles can be expected to decrease the accident rates. It was reported that a lane change, as shown in Fig. 1, is the main factor of car crashes [(2)]. In the real world, there are drivers with an aggressive driving style, who may perform a risky lane change even when safety is not ensured. To prevent this type of dangerous situation, the prediction of future actions of the surrounding traffic participant is strongly required. If the safety support system of ego vehicle can predict lane-changing trajectories of surrounding vehicles; accident rates can be significantly decreased.

There are many previous studies about the trajectory prediction. Wolf and Burdick proposed a method for an autonomous vehicle by applying the potential method [(3)]. However, this method can only be used to calculate self-trajectory, as the desired velocity needs to be known in order to calculate the potential energy. Therefore, their method is not suitable for the trajectory prediction of surrounding vehicles. Houenou et al. proposed a method based on a motion model and a maneuver recognition model [(4)]. Kasper et al. also used a method to predict a lane-changing maneuver by the regression analysis [(5)]. However, these methods do not consider adjacent vehicles when they generate a trajectory.

Our research group have developed methods to predict lane-changing trajectories of surrounding vehicles [(6)(7)]. These methods apply a sinusoidal model and a potential field method to generate the trajectory. However, the models require parameter tunning to achieve good performance in the trajectory prediction. As the result, the models should be repeatedly tunned according to driving conditions, and it leads to consume tremendous time and effort. To solve this problem, a deep learning framework can be the one of solutions in order to achieve a generalization capability.

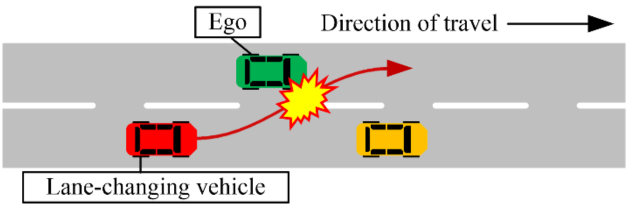

Fig. 1 Lane change of surrounding vehicle: a surrounding vehicle near the ego vehicle performs a lane change.

The LSTM is a type of network in the recurrent neural network (RNN) and is capable of learning long-term dependencies. Generally, the RNN has a problem called as the vanishing gradient problem. It is caused by long-term dependencies, and the LSTM is able to deal with the problem through a forget gate. Kim et al. applied the LSTM to the trajectory prediction of other vehicles [(8)]. Their method constructs one LSTM network with respect to each vehicle. However, it only focuses on the subject vehicle and does not consider the relationship with surrounding traffic participants. As the result, there is a possibility that the prediction performance is degraded under heavy traffic scenes.

Based on the above problems in previous studies, we propose a method to predict a lane-changing trajectory of other traffic participants as shown in Fig. 1 by using the LSTM network while considering the relationship between the ego and surrounding vehicles. It is assumed that the ego vehicle has laser scanners, therefore, the relative position of surrounding vehicles can be

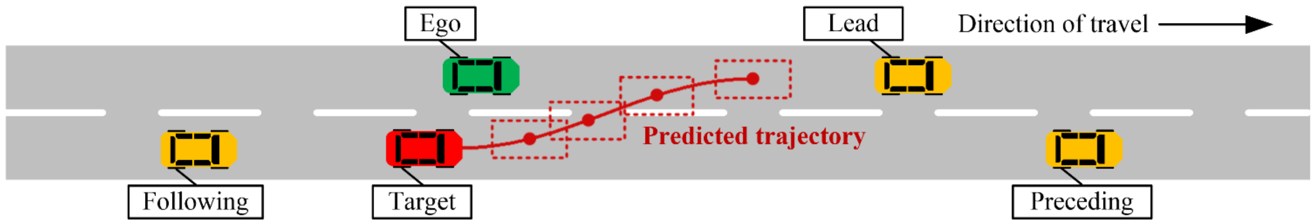

Fig. 2 Problem definition: the scene is modified to obtain an infinite and straight highway. The measurement devices such as GPS and lidars are installed in the ego vehicle, which is depicted as green color. The target of trajectory prediction is a vehicle which cuts in the front space of the ego vehicle since the situation is the main factor of an accident. The proposed method defines three surrounding vehicles of the target: *preceding*, *following*, and *lead* vehicles.

acquired. Moreover, the relative velocity is calculated by differential of the relative position. These measurements are used as the input of the LSTM network. For the proposed method, only heavy traffic scenes are used among the dataset in order to evaluate whether it is effective to consider the relationship to surrounding vehicles.

The reminder of this paper is organized as follows. Section 2 presents the problem definition in this study. Section 3 describes details about the LSTM network and how to consider the relationship with other traffic participants. Section 4 presents the performance evaluation results of the proposed method. Finally, Section 5 presents the conclusions and future work.

2. Problem definition

In this study, the scene is modified to obtain a straight and infinite highway, which has only one side, as shown in Fig. 2. The measurement devices such as GPS and lidars are installed in the ego vehicle, which is depicted as green color. The target of trajectory prediction is a vehicle which cuts in the front space of the ego vehicle since the situation is the main factor of an accident. In this paper, the target vehicle, which performs a lane change, is indicated using a red color. The ego vehicle predicts the lane-changing trajectory of the target vehicle at each time step.

The proposed method uses previously observed data for the prediction of future trajectory of the target. The coordinate of the target vehicle at time step t is denoted as (x_t^T, y_t^T). In the same way, the coordinate of the i th surrounding vehicle is represented as (x_t^i, y_t^i). The relative distance between the target and the i th surrounding vehicle is denoted as $(\Delta x_t^i, \Delta y_t^i)$, and the relative velocity is $(\Delta \dot{x}_t^i, \Delta \dot{y}_t^i)$. The proposed method defines three surrounding vehicles of the target as shown in Fig. 2: *preceding*, *following*, and *lead* vehicles. Including the ego vehicle, the proposed method takes account into these four vehicles to analyze how the relationship affects the driving pattern of the target vehicle when lane changing is performed. Details about the consideration of surrounding vehicles are described in Section 3.

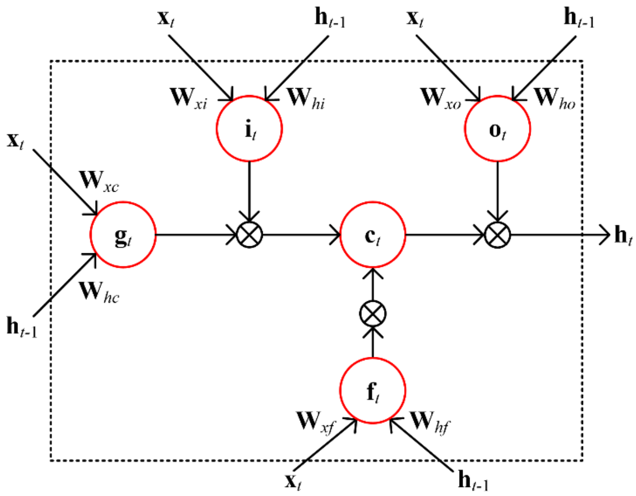

Fig. 3 Structure and data flow of LSTM network.

3. Proposed method

3.1 LSTM network

The proposed method applies the LSTM network to predict the future trajectory of the target vehicle. The LSTM is a type of the RNN and able to solve the limitations of the RNN, which are vanishing and exploding gradient problem [9], by using a forget gate. The forget gate is designed to control the information between the memory cells to store previous data.

Figure 3 shows the structure of the basic LSTM network. Let i_t is the input gating vector at the current time step t. It is represented as:

$$\mathbf{i}_t = \sigma(\mathbf{W}_{hi}\mathbf{h}_{t-1} + \mathbf{W}_{xi}\mathbf{x}_t), \tag{1}$$

where $\sigma(\cdot)$ is an activation function, $\mathbf{W}_{hi}$ and $\mathbf{W}_{xi}$ represent weight matrix for linear transformation. Furthermore, $\mathbf{h}_t$ means a output hidden state vector. The state of the memory cell $\mathbf{c}_t$ can be updated by the following equations:

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t, \tag{2}$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{hf}\mathbf{h}_{t-1} + \mathbf{W}_{xf}\mathbf{x}_t), \tag{3}$$

$$\mathbf{g}_t = \tanh(\mathbf{W}_{hc}\mathbf{h}_{t-1} + \mathbf{W}_{xc}\mathbf{x}_t), \tag{4}$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \tag{5}$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{ho}\mathbf{h}_{t-1} + \mathbf{W}_{xo}\mathbf{x}_t), \tag{6}$$

where $\mathbf{f}_t$ is the forget gate vector, $\mathbf{g}_t$ is the state update vector, and $\mathbf{h}_t$ is the hidden state vector. Moreover, $\mathbf{W}_{hf}$, $\mathbf{W}_{xf}$, $\mathbf{W}_{hc}$, $\mathbf{W}_{xc}$, $\mathbf{W}_{ho}$, and $\mathbf{W}_{xo}$ represent weight matrix. The LSTM network automatically manages the information through the memory cells, then, it updates the long-term dependencies based on the input to the memory cells.

3.2 Relationship with surrounding vehicles

The proposed method considers the four surrounding vehicles of the target vehicle including the ego vehicle. It is assumed that drivers generally pay attention to the relative distance and speed with repect to the other vehicles when they intend to change a lane. Based on this assumption, the relative amounts between the target and the four surrounding vehicles are used as the input of the proposed LSTM network. The feature vector $\mathbf{x}_t$ at time step t is defined as the following 12 features:

- lateral position of target vehicle,
- longitudinal position of target vehicle,
- lateral speed of target vehicle,
- longitudinal speed of target vehicle,
- relative distance between target and preceding vehicle,
- relative speed between target and preceding vehicle,
- relative distance between target and following vehicle,
- relative speed between target and following vehicle,
- relative distance between target and lead vehicle,
- relative speed between target and lead vehicle,
- relative distance between target and ego vehicle,
- relative speed between target and ego vehicle.

In the case that there is no corresponding vehicle, the value is zero. The input vector of the proposed LSTM network is the sequence data. Thus, the input of the network at the current time step t is defined as $\mathbf{X}_{t-\varepsilon:t} = [\mathbf{x}_{t-\varepsilon}, \mathbf{x}_{t-\varepsilon+1}, \dots, \mathbf{x}_{t-1}, \mathbf{x}_t]$ where ε represents the period of input sequence. The proposed network outputs the feature vector at the next time step $t+1$, and it is not the sequence data. The proposed method predicts the trajectory by iteratively inputting the output result to the network as the input vector at the next time step.

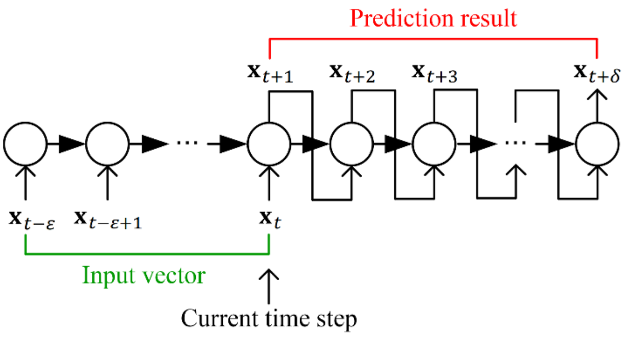

Fig. 4 Iterative approach for trajectory prediction.

Details about the trajectory prediction are described using the output of the network in the next subsection.

3.3 Trajectory prediction

There are two approaches to predict the trajectory using the LSTM network. One is to define the output of the network as the sequece data such as $\mathbf{X}_{t+1:\delta} = [\mathbf{x}_{t+1}, \mathbf{x}_{t+2}, \cdots, \mathbf{x}_{t+\delta}]$, where δ represents the time horizon of the prediction. The other approach is to iteratively use the output result of the network as the input at the next time step as shown in Fig. 4. The proposed method applies the latter approach to predict the trajectory.

4. Results

4.1 Implementation

The proposed method was trained and tested using a real traffic dataset published by the Federal Highway Administration of the United States [10]. The dataset was collected from eastbound I-80 in the San Francisco Bay Area. The measurement area was approximately 500 m in length and consisted of six freeway lanes. The dataset consisted of measurements taken in 0.1 s increments for 15 min, a total of three times. Data from 5,678 vehicles were collected. Among them, 149 lane-changing data in heavy traffic scene were used for the training and evaluation.

The proposed method was designed to have a single layer and 256 nodes. The training was performed using the TensorFlow with a batch size of 32 for 10 epochs. The learning rate was 0.01 and Adagrad algorithm was applied as an optimizer [11].

4.2 Performance evaluation

Since the objective of this study is to predict the trajectory, the root mean square error (RMSE) was used as a performance metric. Figure 5 shows the results of trajectory prediction in a lane-changing

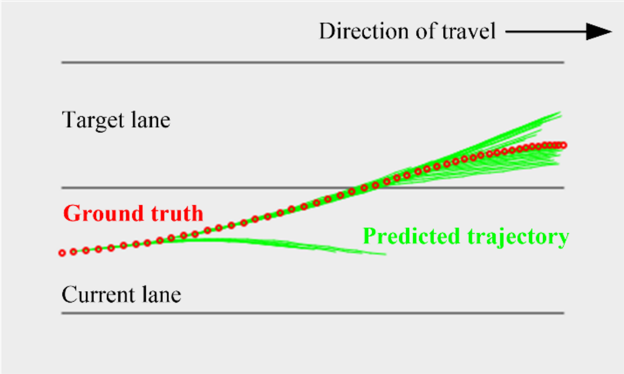

Fig. 5 One example of trajectory prediction by proposed method.

event from the test dataset. The red dot represents the ground truth, and the green line shows the predicted trajectory at each time step. The target vehicle changed the bottom lane (current lane) to the upper lane (target lane) in the figure. The time horizon of prediction δ was set as 2 s since it has been reported that the reaction time of drivers is generally 2 s in car-following behavior [12]. It was shown that the predicted trajectory is quite consistent with the ground truth. However, it is also shown that the predicted trajectory deviated from the ground truth in the initial phase. This error occurs when the LSTM network judged that the target vehicle would keep the current lane in fact the vehicle changes a lane. To improve the performance, it should be the key point to correctly judge whether the vehicle would change a lane or not.

The error in trajectory prediction by the proposed method was calculated during a lane change for the entire testing dataset. The average lateral error was 0.31 m, whereas the average longitudinal error was 3.28 m. The prediction in the lateral direction was better than the longitudinal movement because the displacement in the lateral direction was smaller during a lane change. From this evaluation, it was demonstrated that the proposed method is able to accurately predict the trajectories of the surrounding vehicles.

Conclusion

In this study, we proposed a method to predict the lane-changing trajectory of other traffic participants using the LSTM network. In particular, the proposed method focuses on the relationship with other traffic participants in which the surrounding vehicle cut-in on the front space of the ego vehicle. The proposed method applies the deep learning framework, the LSTM network, specialized in time series data analysis. It was demonstrated that the proposed method is able to successfully predict trajectories of surrounding vehicles in time horizon of 2 s.

As future work, we plan to integrate the proposed method with the lane-change prediction model in order to improve the performance. By the integration, the system can detect a lane change in the early step, as the results, it is expected to shorten the delay which occurs in the initial phase.

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