Long-Term Prediction of Vehicle Trajectory Based on a Deep Neural Network

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***Abstract*— Accurate prediction of the future locations of the host vehicle as well as that of the surrounding objects is one of the key challenges in improving road traffic safety. The traditional approach for this task has been using physics-based motion models such as kinematic and dynamic models, the result of which is not reliable for long-term prediction. In this paper, we present simulation results demonstrating the effectiveness of employing a deep neural network (DNN) for vehicle trajectory prediction. The DNN is trained to output the trajectory of the vehicle for the following few seconds.**

***Keywords*— Trajectory prediction, vehicle navigation, deep neural network, intelligent vehicles.**

I. Introduction

The development of automated driving technologies has been a very active subject of research, and this is believed to result in a significant improvement of road safety and efficiency. One of the critical factors in the development of automotive safety applications is an accurate prediction of the future states of the vehicle on the road. Traditionally, the study of trajectory prediction has been concentrated in the field of robotics; however, it now has become one of the key technologies in automated driving.

Previous research on vehicle trajectory prediction has mainly employed physics-based and maneuver-based motion models [1]. Physics-based motion models, such as kinematic and dynamic models, treat vehicles as objects governed by the laws of physics and primarily use control inputs and vehicle states [2], [3]. This prediction method is fairly accurate for short-term trajectory prediction but unreliable for long-term trajectory prediction (more than one second). This is because any motion change due to a particular vehicle maneuver is not taken into account. To address this problem, maneuver-based motion models taking consideration of driver intentions have been introduced [4]–[6]. Examples of maneuver-based motion models include the following: Growing Hidden Markov Model (GHMM), which was used to predict the trajectory to a predefined target point [7]; and utilization of vehicle-to-vehicle (V2V) communications for collecting path history information from vehicles ahead [8]. However, such maneuver-based approach can suffer from heavy computation load due to generating a very large number of prototype trajectories; moreover, further difficulties can arise when adapting to different road layouts as previously trained motion models may not suffice.

In this paper, in order to make more reliable prediction of the vehicle trajectory, we propose a deep neural network (DNN) model that takes as input vehicle velocity, acceleration, yaw rate, steering, and road curvature. Employing a DNN-based prediction method allows us to avoid the need for both designing a system model with complex equations and obtaining accurate noise statistics. In addition, our approach can easily be extended to predicting vehicle trajectory in a wide range of driving scenarios by expanding on the current simulation scenario.

The rest of this paper is organized as follows. In Section II, we introduce a DNN model and propose our method for vehicle trajectory prediction. Simulation scenarios and experiment results are presented in Section III, and the paper is concluded in Section IV.

II. Proposed Approach

This section describes how a DNN is employed for vehicle trajectory prediction. When a DNN is used for trajectory prediction, various driving conditions and driving patterns can be trained. In the offline phase, a training process takes place that involves calculating appropriate weights using both input and desired data. To enhance the accuracy of the DNN-based vehicle trajectory prediction, various driving scenarios including a variety of road curvature should be trained offline.

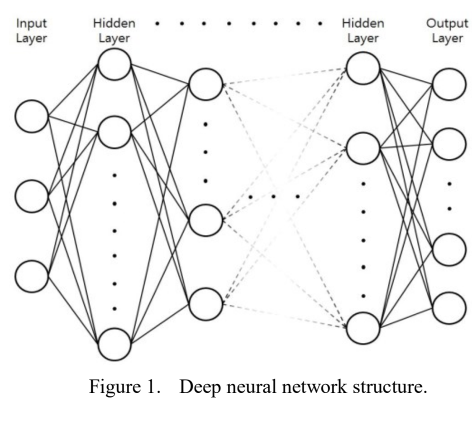

Figure 1. Deep neural network structure.

A. Structure of a Deep Neural Network

A DNN structure is shown in Figure 1. Data entered into the input layer eventually reach the output layer through multiple hidden layers. When values are transferred from one layer to the next layer, they are multiplied by weights. Each layer is composed of several nodes. An activation function is used when a node in a hidden layer transfers the inputted value to the next layer. Sigmoid and hyperbolic tangent functions have been often used for the activation function; however, this may result in vanishing problems since errors do not propagate properly to the input layer when there are many hidden layers. This hinders successful training of the network. This problem can be resolved by replacing the activation function with a function called a rectified linear unit (ReLU), which outputs the same value as the input value when it is greater than zero; otherwise, the function outputs zero. However, a ReLU function is not suitable for use in this study because the final outputs of our DNN model include expected future lateral movements, which can be negative. Instead, we employ a Leaky ReLU for the activation function, which is slightly different from the original ReLU. A Leaky ReLU is defined as follows:

$$f(x) = \begin{cases} kx & x \leq 0 \\ x & x > 0. \end{cases} \quad (1)$$

If the input value for the Leaky ReLU function is greater than zero, the output value is same as the input value. If the input value of the Leaky ReLU function is less than or equal to zero, the output value is the input value multiplied by a fixed constant k.

B. Cost Function

The cost function takes as input desired values and output values to calculate the cost. The following cost function is used in this work:

$$C = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2, \quad (2)$$

where m is the number of data set for training, i is the index of data set, $\hat{y}_i$ is the output value from the DNN, and y_i is the desired value. The sum of the squared difference between the output value and desired value is divided by $2m$ to determine the cost.

C. Backpropagation

For cost minimization, a gradient descent algorithm is used to update the weight. The derivative of the cost function with respect to the weight is found and then multiplied by the learning rate α to update the weight W as shown in (3).

$$W = W - \alpha \frac{\partial C}{\partial W} \quad (3)$$

D. Proposed Method for Trajectory Prediction

The input layer data for the DNN contain vehicle state information, such as vehicle velocity, acceleration, yaw rate, steering, and road curvature. In the output layer, six nodes are present, each corresponding to the predicted longitudinal and lateral movements at the following 1, 2, and 3 seconds. A linear activation function is employed in the output layer, considering that the final outputs of our model can be positive or negative. The desired values consist of the change of the vehicle positions along the longitudinal and lateral directions during appropriate time steps.

III. Experiments

To verify the performance of the trajectory prediction based on the DNN, we constructed a simulation environment using PreScan and MATLAB/Simulink. We obtained the necessary data set for learning and validation from the vehicle driving simulation. Vehicle state information collected from the simulation experiment is shown in Table I.

TABLE I. Vehicle State Information

Information	Description	Unit
Velocity	Absolute velocity of the object	m/s
Acceleration	Absolute acceleration of the object	m/s^2
Yaw rate	Angle velocity (change in heading per second)	degree/s
Steering	Steering wheel angle	degree
Curvature	Curvature of the lane markers	m^{-1}

A. Simulation Description

For the purpose of obtaining the training data, we designed a simulation testbed with roads of various curvatures as shown in Figure 2. The test vehicle was equally driven in clockwise and counterclockwise directions, and the total driving distance during the entire simulation experiment was 46 km. The vehicle speed ranged from 50 km/h to 100 km/h, and the average speed was about 75 km/h for the entire course of the simulation. Vehicle state data (ground truth) were collected every 0.01 second. A total of 22 million data sets were obtained and used as input data for training the DNN.

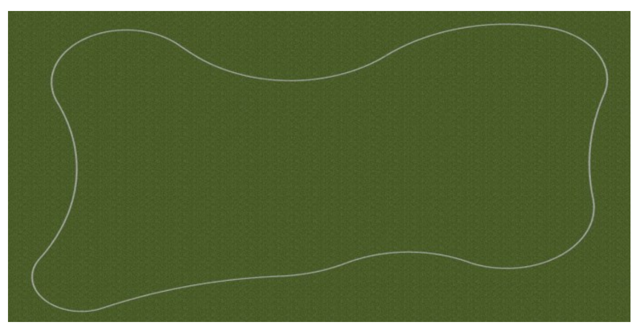

Figure 2. Simulation driving scenario for training data collection.

B. Trajectory Prediction Results

In order to evaluate the reliability of the proposed vehicle trajectory prediction method, the mean absolute error and standard deviation of the errors were calculated for each prediction term, ranging from 1 to 3 seconds. We used 75% of the simulation data for training, 20% for validation, and the remaining 5% for testing. The data set for testing were

TABLE II. TRAJECTORY PREDICTION RELIABILITY

		Prediction 1 sec	Prediction 2 sec	Prediction 3 sec
Scenario 1 (low curvature)	MAE (m)	0.001	0.005	0.018
	STD (m)	2×10^{-6}	5×10^{-5}	3×10^{-4}
Scenario 2 (high curvature)	MAE (m)	0.018	0.099	0.317
	STD (m)	0.001	0.020	0.169

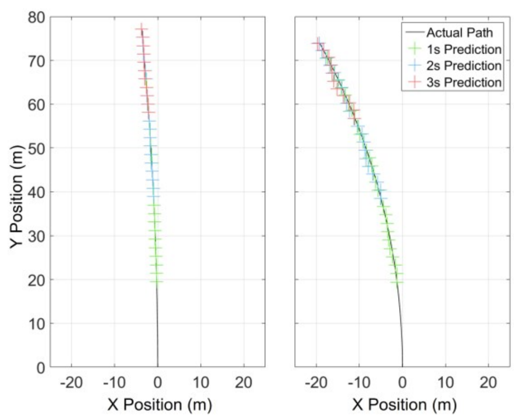

Figure 3. Vehicle trajectory prediction results compared with the actual vehicle position.

collected in separate simulation driving scenarios consisting of two curved roads. The vehicle speed in the testing scenarios was set to 70 km/h.

Table II presents the mean absolute error (MAE) and standard deviation for the trajectory prediction results. This result suggests promising avenues for employing the DNN-based vehicle trajectory prediction for the purpose of risk assessment and driving assistance. Figure 3 shows the actual vehicle trajectory as well as the prediction results for two different testing scenarios. The plots correspond to the vehicle positions from 0 to 4 seconds during the simulation. The x- and y-axis in the figure correspond to the global coordinate axes in the simulation environment, not the axes of the vehicle coordinate system.

IV. CONCLUSION

This work presents a novel method for vehicle trajectory prediction, utilizing a DNN and vehicle status information. The simulation results from this study confirm the feasibility of DNN-based long-term trajectory prediction for vehicles driving on roads with varying curvature. In future work, we plan to carry out an extension of this work to trajectory prediction of other vehicles in the surrounding environment, as well as to the development of collision detection and warning algorithms.

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