Vehicle Trajectory Prediction using Deep Learning Technique for Intelligent Transportation System

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***Abstract*—This paper proposes a prediction of vehicle trajectory by using deep learning algorithm in the intelligent transportation system. The trajectory of a vehicle is adjusted based on the predicted trajectory of neighbouring vehicles. To achieve vehicle trajectory accurately, a deep learning technique such as a deep neural network (DNN) algorithm is proposed and compared with long short term memory (LSTM) algorithm. The performance of the proposed algorithms is verified by using next-generation simulation (NGSIM I-80) vehicle trajectories dataset. Simulation results showed that the DNN algorithm outperformed the LSTM algorithm in terms of root mean square error (RMSE) values of predicted vehicle trajectories and achieved the lowest computing time.**

***Index Terms*—Vehicle trajectory, deep learning technique, DNN, intelligent transportation system**

I. INTRODUCTION

The emerging of intelligent transportation system technology has been rapidly developed primarily in the advance vehicle control system. In order to achieve the vehicle control system safely, the prediction of the vehicle trajectory shall be considered. The main objective of the vehicle trajectory prediction is to adjust the vehicle driving situation based on the acquired information related to future motion and velocity of the neighbouring vehicles.

Several studies have been conducted to predict the trajectory of vehicle, such as based on probabilistic with Gaussian mixture models as proposed in [1]. Their proposed method is evaluated with the dataset of [2] that consist of 69 real word trajectories. However, the probabilistic method when encountered with a huge amount of trajectories data, might be suffered to cope up the future trajectory prediction.

Since the trajectory of a vehicle in the next-generation simulation (NGSIM I-80) dataset that used in this paper have a big amount of raw data, the deep learning is appropriate technique to comply with the issue as mentioned above. The deep learning algorithm can learn the patterns by using stacked machine learning approaches and capable to solve complex problems such as trajectory prediction [3], channel modulation classification [4] and even in spectrum sensing [5].

This paper utilized a deep learning technique to predict a vehicle trajectory in the intelligent transportation system and the main contributions are consist of:

- The proposed DNN algorithm is compared with LSTM algorithm to predict the vehicle trajectory for the intelligent transport system.
- To evaluate the proposed algorithms, the root mean square error (RMSE) values and computing time are considered.

II. PROPOSED SYSTEM

A. NGSIM I-80 Dataset

The NGSIM vehicle trajectories dataset [6], which has been provided by the US department of transportation federal highway is used for the simulation in this paper. NGSIM I-80 dataset comprises of several areas in US and trajectories of more than 7000 individual vehicles in the real traffic that recorded over 45 minutes with a sampling frequency at 10 Hz.

The huge amount of trajectories raw data in the dataset is filtered into 600 data, and scale it into a range between 0 and 1 before being processed as an input in the deep learning algorithms. Since there are lot of parameters in the NGSIM I-80 dataset, the velocity and time were choosen to interpret the trajectory of vehicle.

B. Deep Learning Algorithms

In this paper, two kinds of deep learning algorithms which are the DNN and LSTM were observed to predict the trajectory of a vehicle in the intelligent transport system. The detailed configuration of each architecture is provided in Table I for DNN and in Table II for LSTM algorithm. The input of the system is historical data from NGSIM I-80 dataset, which has been pre-processed and divided into 70% for training data and 30% for testing data. Then it feeds into DNN and LSTM algorithms respectively to predict the vehicle's future trajectory. The block diagram of predicted vehicle trajectory process using DNN algorithm is shown in Fig.1.

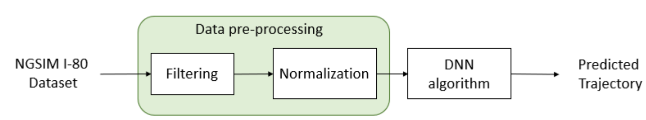
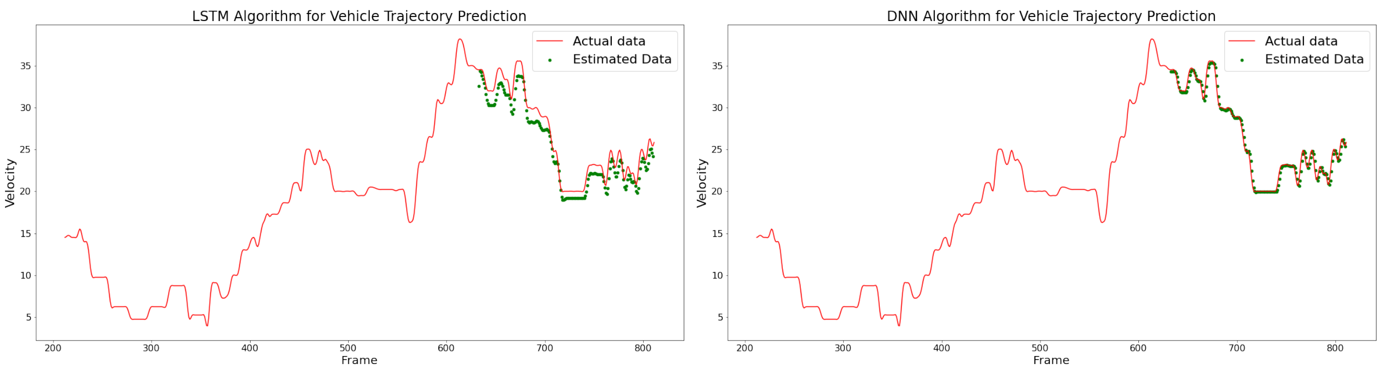


Fig. 1: Block diagram of predicted vehicle trajectory process

III. SIMULATION RESULTS

The performance of LSTM and DNN algorithms to predict the vehicle trajectory are depicted in Fig. 2. The actual data means the historical data and the true data, while estimated data is the predicted data by using DNN and LSTM algorithms. To evaluate the performance of each algorithm, the



(a) (b)

Fig. 2: The Performance of all algorithms

TABLE I: Architecture of DNN algorithm

Layer	Output Shape	Param
Dense	(1, 1, 128)	256
Flatten	(1, 128)	0
Dense	(1, 1)	129
Total params: 385		
Trainable params: 385		
Non-trainable params: 0		

TABLE II: Architecture of LSTM algorithm

Layer	Output Shape	Param
LSTM	(1, 128)	6650
Dense	(1, 1)	129
Total params: 66,689		
Trainable params: 66,689		
Non-trainable params: 0		

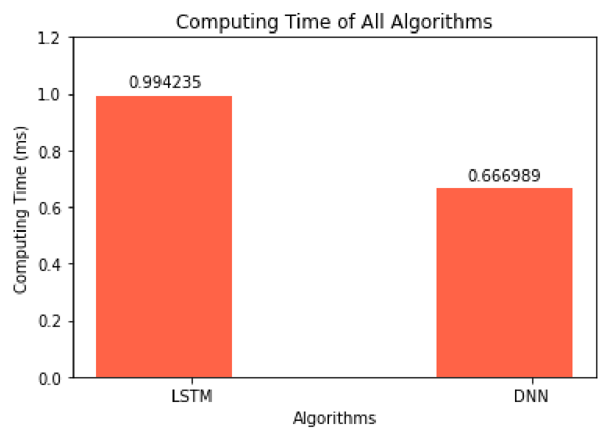


Fig. 3: Comparison of LSTM and DNN computing time

accuracy of predicted trajectory is interpreted based on RMSE values provided in Table. III. DNN algorithm achieved the lowest RMSE values in both train and test scores than the LSTM algorithm. Moreover, the computing time of DNN also outperforms the LSTM algorithm due to the total parameters of the DNN is a fewer than LSTM. The computing time of all algorithms is shown in Fig. 3.

TABLE III: NMSE (dB) comparison of CSI reconstruction algorithms

Algorithms	Loss	Train Score	Test Score
LSTM	RMSE	1.10	1.36
DNN	RMSE	0.41	0.50

IV. Conclusion

In this paper, the proposed DNN algorithm is compared with LSTM algorithm to predict the vehicle trajectory in an intelligent transportation system. The simulation results showed that the DNN algorithm was achieved better performance in terms of RMSE values and the computing time compared to the LSTM algorithm. For future work, the different deep-learning algorithms will be considered.

Acknowledgement

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