Prediction of Lane Change Trajectories through Neural Network

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Abstract

Lane changing process is an essential maneuver, however, the process is responsible for large number of collisions and traffic instability. In this work, the effectiveness of neural network for prediction of future lane change trajectory based only on the past vehicle path is presented. Existing lane change models and lane change process do not consider the uncertainties and perceptions in the human behavior that are involved in lane changing. A neural network may learn and incorporate these uncertainties to predict the lane changing trajectory in the near future more accurately. A multilayer perceptron (MLP) has been employed to train itself from existing NGSIM field data and predict the future path of a lane changing vehicle. The impact and effectiveness of the proposed technique is demonstrated. Prediction results show that an MLP is able to give the future path accurately only for discrete patches of the trajectory and not over the complete trajectory. The results confirm to the observation that a vehicle trajectory has immediate influence from its neighborhood whose information is imperative for trajectory prediction.

Keywords- Neural networks, lane change process, vehicle trajectory, driver behavior.

1. Introduction

The growth of automobile traffic in highways become very fast. Due to the advances in technology, automobiles are available at cheaper prices leading to increase in the rate of traffic at a much greater speed as compared to the addition of road capacity of the highways. Lane change is a necessary phenomenon but inappropriate lane change is [1] the source of accidents and traffic instability due to lack of forewarning and traffic management problems [2].

A driver plans his journey from the source to his final destination and estimates the time required to reach its final destination. Accordingly, he starts his journey from the source to reach the final destination as per time assigned. On the expressway, the normal driver may face different traffic states like congestion, traffic signal and slow ahead vehicles with his non lane changing attitudes, which may affect his original travel time estimation [3]. To keep his estimation, the behavior of the driver may change from normal to aggressive. He may ignore the safety rules and minimum gap with the preceding vehicle, change lanes aggressively fast. He may also be prone to driver errors on the highways. When a driver looses patience during lane change, then his behavior may change to a more aggressive behavior. The aggressive behavior of the driver is characterized by increased speed, reduced time gap, and rapid acceleration and deceleration on the highways. This aggressive behavior also increases driver indiscretion and risk taking nature. The change in behavior coupled with the lack of the awareness of the global scenario of the traffic state for spatial temporal anticipation and reduced maneuvering time may result in collision when the front or side ahead vehicle brakes during lane changing on the highways. Absolute errors in the decision-making time, typically caused by driver at the time of lane change failure to accurately and within time frame interpret information about other vehicles in the close proximity, have often resulted in serious accidents and congestion on the highways [4].

The lane changing process is one of the most critical actions that a driver performs at the time of travelling on the highways. Drivers perform some action and reaction during driving on the highways according to his destination or time dependent events. This reaction is perceived by the following vehicle and this continues. The perception-reaction time constitute the propagation delay. In critical cases, propagation delay may not leave sufficient maneuvering time to avoid collisions if inter-vehicles spacing is not adequate [5], [6]. Errors in the lane changing decision-making process, typically done by driver failure to most accurately and timely interpret the information about other travelling vehicles in the close proximity; have often resulted in serious accidents. In order to suppress such errors, or at least minimize their impact

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on the other vehicles, and increase the level of safety of the travelling vehicles, the vehicles of the future time would have to incorporate a solution that will allow accurate consideration of all aspects of a lane-changing maneuver [7]. A number of real-time issues would be needed to be considered like calculating properties of the other vehicles like velocities, acceleration, deceleration, position; determining when the lane-change maneuver should start; and predicting optimal and safe trajectories, and minimum safety distance between the vehicles. All these necessitate the prediction of an impending lane change and the future lane change trajectory to be traversed by a vehicle. The positions of other vehicles in the neighborhood require communication between the vehicles. Since the vehicular ad hoc network (VANET) standard is not yet in place and at present there is no inter vehicle communication, prediction of a vehicle future path from only its past trajectory is required. In the present work, the efficacy of neural network for prediction of lane change trajectory solely on the past path of a vehicle is evaluated and predicted.

The rest of the paper is organized as given. Section 2 describes the neural network based trajectory prediction; in section 3, the experimental simulation setup and results are discussed. The paper concludes with the section 4.

2. Neural Networks and Prediction

Lane change trajectory of a vehicle is determined by the driver's behavior. A driver may be conservative or aggressive; cautious or rash and it may travel at a low or high speed. The driver may pay scant or careful attention to his neighborhood and may or may not incorporate his observations in the lane change behavior [8]. The paths have large subjective influences which make neural networks an attractive candidate for prediction of the future trajectory based on the lane change trajectories of different drivers [9]. Neural network is a more adaptable and acceptable system that can learn relationships via repeated presentation of data available and is capable of generalizing the new, previously unseen data. Some neural networks are guided or supervised, in that a human being determines what the neural network should learn from the data available. In this time, we give the neural network a set of input values and corresponding desired output values, and the neural network tries to learn the input-output parameter relationship process by adapting its free parameters.

To model the lane change real data we used a very simple MLP with single input. Perhaps the results of the simulation could have been improved by using the more inputs, including more lags of the inputs that were used, or by using some form of time lagged or leaded recurrent network. The time delay in form of time lagged recurrent networks included in the neural network. This technique shows the test process to evaluate the performance of the proposed neural network and trained to perform regression and correlation. This neural network develops a very simple model for predicting the lane change in advance. We can use this network model as an initial point for creating own more complex lane change model. The inputs to the network model consist of the relative velocity of the vehicles who involved in the lane change and travel in the passing lane, acceleration / deceleration, safety distance in time between the vehicles, and current states of the vehicles in which vehicles are travel (collision, near collision, absolute safe and safe) on the highways. The desired output is the prediction of the next states during the lane change on the highways. A simple MLP has been used to model this real data. Since this a real lane changing application, the true value of this network model can only be determined by applying the model to a lane change strategies and computing the safety profits over several time spans.

3. Training & Prediction

3.1 Test Setup

Data based on individual vehicle trajectories were collected and have been made available under the Next Generation Simulation (NGSIM) project, a national effort aiming to develop improved algorithms and real datasets for calibration and validation of real traffic simulation models. The Next Generation Simulation (NGSIM) data provide a unique dynamic opportunity to investigate driver behavior, driver behavior modeling, better understand traffic dynamics and formulate improved models. The Next Generation Simulation (NGSIM) freeway research database consists of the vehicle trajectories on two test sites. The I-80 (BHL) test section is a 0.40 mile (640 m) 6-lane system freeway weaving test section with a HOV lane. Processed real data include 45 minutes of the vehicle trajectories in transition (4:00-4:15 pm) and congestion phase (5:00-5:30 pm). The US101 site test section is a 0.3 mile (500 m) weaving test section with the five lane system. Processed real data include 45 minutes of the vehicle trajectories in transition (7:50-8:05 am) and congestion phase (8:05-8:35 am) [10].

For the ANN simulation, highway traffic data of about 2100 ft is taken which is the distance traveled across the road by typical vehicle in 80 seconds. The highest velocity of vehicle is 75 ft/s, the slowest velocity is 21 ft/s and the average velocity is 42 ft/s on the highways. The vehicle acceleration/deceleration is in the range of ± 11.2 ft/s^2. We consider the 50 vehicles moving on the highway that are also involved in the lane change. 1000 epochs, minimum weight delta = 0.001, initial weights = 0.3, learning rate = 0.3, network momentum = 0.6 and sigmoid function have been used in neural network training of vehicle trajectories. A single input, single output based multilayer perceptron (MLP) network with one (single) hidden layer is used for training, testing and prediction of the vehicle trajectories.

The simulation gives the epoch at which the data training and cross validation mean-squared errors (MSEs) are minimum. When the mean square error is approaches zero and cross validation MSEs follow the mean square errors, the learning simulation is acceptable (Fig. 1). The mean square error is 0.012 and cross validation mean square error is 0.022 that are near zero for the purpose of trajectory learning. The learning curve between MSEs and cross validation MSEs is shown in the Fig. 1.

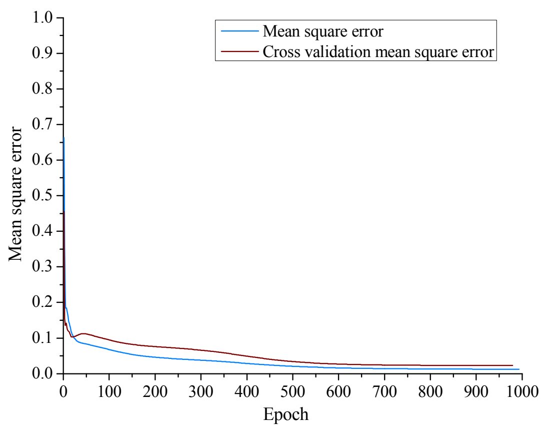

Fig.1 Learning curve for prediction of trajectory

3.2 Results and Discussion

Fig. 2a shows the learning curves for actual and predicted trajectories in the longitudinal direction at high speed of the vehicle. The prediction in the initial phase considers the distance between 1000 ft-2100 ft along the road and the velocity of the monitored vehicle being more than 50 ft/s. In initial phase, the prediction of the trajectory of the vehicle against the actual trajectory gives large prediction error because of the small number of previous samples for simulation and the random nature of the learning process in the sample interval of 1 to 10. As soon as the velocity increases and the sufficient number of previous samples become available, the prediction becomes more accurate. This is shown in the Fig. 2a in the sample interval of 10 to 40 (1200 ft to 1380 ft). In the sample interval 41-75 (1385- 1550 ft.), there is a large prediction error. After sample 75 (> 1550 ft.), samples are dropped due to high speed resulting is large deviation from actual trajectory.

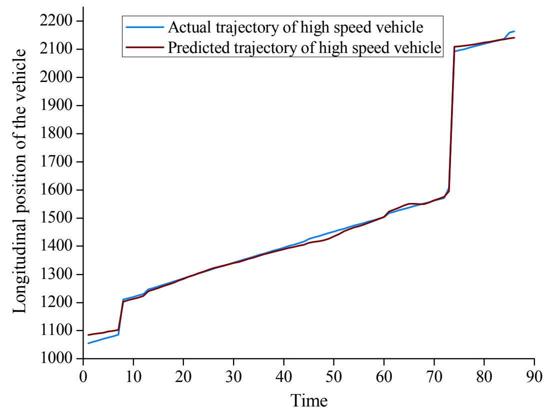

Fig.2a Predicted trajectory at high speed of vehicle in longitudinal direction

Fig. 2b shows the vehicle performing the lane change at the higher speed with the velocity of 52 .57 ft /s and the lateral position between 24 ft-25 ft. Fig. 2b shows the learning curves for both the actual trajectory of the vehicle and predicted vehicle trajectory on the highways in the lateral direction at high speed of the vehicle. The predictions in the initial phase consider the distance between 20 ft-30 ft across the road and longitudinal velocity of the monitored vehicle being more than 50 ft/s. The prediction of the trajectory has large error because of the small number of previous samples and the random nature of the learning process in the sample interval of 1 to 20 (28.5 ft - 29.5 ft). As soon as the velocity increases and the sufficient number of previous samples become available, prediction becomes more accurate in the sample interval 20 to 45 (22.5 ft - 28.5 ft). In the sample interval of 45 to 75 (21 ft - 22.5 ft) at high speed, prediction of the vehicle trajectory has large error. After the sample interval 75 (20 ft - 21 ft), more samples have been dropped because of the high speed of the vehicle, resulting in poor prediction of the trajectory.

Fig. 2c shows the learning curves for both the actual trajectory of the vehicle and predicted vehicle trajectory on the highways in the longitudinal direction at low speed of the vehicle. The predictions in the initial phase consider the distance between 290 ft -675 ft along the road and the velocity of the monitored vehicle is less than 26 ft/s on the highways. In initial phase, the prediction of the trajectory of the vehicle against the actual trajectory is large because of the small number of previous samples for the simulation and the random nature of the learning process in the sample interval of 1 to 20 (290 ft - 360 ft).

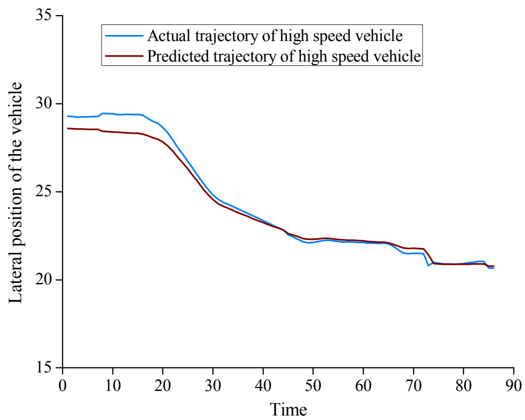

Fig.2b Predicted trajectory at high speed of vehicle in lateral direction

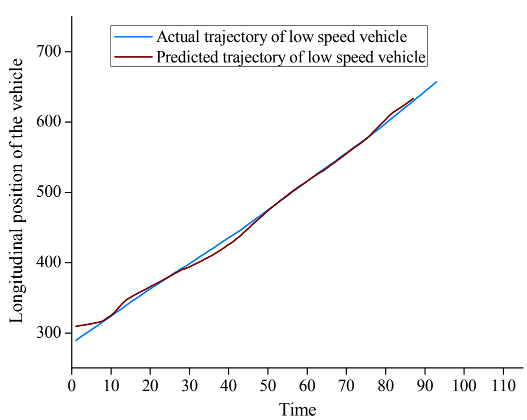

Fig.2c Predicted trajectory at low speed of vehicle in longitudinal direction

As soon as the velocity increases and the sufficient number of previous sample become available, the prediction nears the actual data in sample interval 20 to 30 (360 ft - 390 ft). The sample interval of 31 to 50 (390 ft - 475 ft) has large error because the distance travelled by the vehicle is very less which is not sufficient to fix the future path of the vehicle. In the sample interval of 51 to 75 (475 ft - 590 ft) at the low speed, the predicted trajectory is nearer to the actual trajectory. After the sample interval 75 (590 ft - 675 ft) the more samples are in close proximity because of the low speed of the vehicle, resulting in higher prediction error.

Fig. 2d shows the vehicle at the lower speed less than 26 ft/s. Fig.2.d shows the learning curves for both the actual trajectory of the vehicle and predicted vehicle trajectory in the lateral direction with this low speed. The predictions in the initial phase are for 28 ft - 32 ft across the road and the velocity of the monitored vehicle less than 26 ft / sec. on the highways. In initial phase the prediction of the trajectory of the vehicle has large error in the prediction because of the small number of previous samples for the simulation and the random nature of the learning process in the sample interval of 1 to 20 (28.5 ft - 29.5 ft). As soon as the velocity increases and the sufficient number of previous samples become available, the prediction becomes more accurate in the sample interval of 20 to 40 (20.8 ft - 30.7 ft). For the sample interval of 40 to 50 (30.7 ft - 31.1 ft), the low speed dependent prediction of the vehicle trajectory has more error in the prediction. In the sample interval 50 to 80 (30 ft-31.1 ft), more samples are available at low speed of the vehicle, so the prediction is accurate. After the sample interval 80 (30.2 ft - 31.5 ft), samples are close to each other and some of the sample leave from the simulation because of the low speed of the vehicle, so the prediction of the trajectory of the vehicle becomes large error.

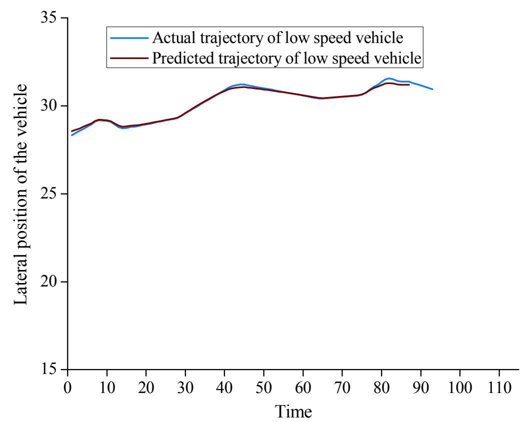

Fig.2d Predicted trajectory at low speed of vehicle in lateral direction

It is clear from the experiment that neural network is able to train itself and predict the future positions of a lane changing vehicle in certain discrete sections of the path only and not over the complete lane change path. Since, the lane changing feasibility, planning and execution by a vehicle are all influenced by its neighborhood state; their influence must be considered for the construction of a vehicle's future trajectory. It is also observed that the prediction is not consistent for different vehicles which indicate that online learning may be more useful in prediction of future states of a vehicle.

4. Conclusion

A lane change involves a significant lateral shift in the position of a vehicle. The process may result in a gain for the individual vehicle but may cause significant traffic instability. It is also a major cause of collisions and subsequent loss of lives. Prediction of lane change and lane change trajectory can impact the influence of this process. Since, the overall process is impacted by a multitude of factors like driver's behavior, a vehicle's neighborhood and its past path, the accurate prediction of its future is difficult and wrong predictions may be harmful for everyone. Neural network based prediction presented in this work shows that it is able to give accurate prediction for some parts of the path but the deviation is significant for certain sections at both low and high speeds. This indicates that the prediction process should be customized for individual vehicles and must be cooperative and not autonomous.

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