Neural Network Based Lane Change Trajectory Prediction in Autonomous Vehicles

Ranjeet Singh Tomar* and Shekhar Verma

Indian Institute of Information Technology-Allahabad
Deoghat, Jhalwa, Allahabad – 211012, India
Tel.: +91-9532876120; +91-9450965336
{rs63,sverma}@iiita.ac.in

Abstract. During a lane change, vehicle collision warning systems detect the likelihood of collision and time to collision to warn vehicles of an imminent collision. In autonomous systems, a vehicle utilizes data obtained by its own sensors to predict future state of traffic. The data from on board sensors are limited by line of sight, measurement noise and motion parameters of the vehicle which affect the accuracy of prediction. Alternatively, in cooperative driving, vehicles transmit their parameters continuously. This is also beset by communication delays and message loss. To avoid these limitations, a vehicle should estimate its future state and broadcast it to others vehicles in the neighborhood. This necessitates vehicles to predict their future trajectories based entirely on its past. Since, low cost global positioning systems are becoming an integral part of vehicles; a vehicle knows its own position. This can be utilized by the vehicle for prediction of its future trajectory. In this paper, the effectiveness of lane change trajectory prediction on the basis of past positions is studied. The lane change trajectory of a vehicle is modeled as a time series and back propagation neural network is trained using real field data and its efficacy for short range and long range prediction is benchmarked. Simulation results using NGSIM data indicate that future lane change trajectory cannot be predicted with sufficient accuracy. The most important reason seemed to be the influence of other neighboring vehicles on the trajectory on the lane changing vehicle in addition to noise and complex dependence of future on the past values. The results also indicate that a vehicle changes its motion parameters during the entire lane change process. This confirms the active intervention of the driver in adjusting the trajectory on the basis of his assessment of the future state of its surrounding vehicles and entails the consideration of the state of surrounding vehicle for accurate prediction.

Keywords: Artificial Neural Network (ANN), Lane Change process, Autonomous Vehicle, Vehicle Trajectory and Driver Behavior.

1 Introduction

The nature of traffic on the road is influenced by the density of vehicles, behavior of vehicles, the nature of the drivers and other interventions like lane change. The non

* Corresponding author.

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uniform traffic distribution, limitation of drivers and their driving behavior along with the need for lane change, traffic merging and braking etc. are potential source of collisions on the road. A lane change process may cause transient disturbance in vehicular traffic in its immediate neighborhood which may be detrimental to safety. An unsafe lane change may result in a collision. Vehicles need to be equipped to detect an impending collision and take action like warning the driver or passing control to an autonomous auto-pilot to avoid a collision. To predict a possible collision, a vehicle may have the information about itself and its neighbors in the current and intended lanes. To obtain this information, sensors like global positioning system, radar, camera and other acoustic sensors may be employed on the vehicle to measure data like relative position, speed, and acceleration etc. of itself and neighboring vehicles. This information is processed onboard the vehicle in real time to estimate the likelihood of a collision. In the lane change scenario, the information is processed to detect a possible lane change and determination of lane change trajectory. The estimated trajectory is then used in conjunction with the estimated trajectories of neighboring vehicles to estimate a probable collision and time to collision. An appropriate decision like warning or taking over from the driver depending on the probability and time to collision may be taken. However, such an autonomous collision warning system uses information measured by the onboard sensors and its ability is limited by the limitations of the sensing capability of these sensors. Onboard sensors can only sense the information of immediate neighbors and are blinded by surrounding vehicles, other obstacles and their own placement on the vehicle. Further, the sensed data is conditioned by the relative vehicle-vehicle coordination frame and corrupted by noise associated with the sensing process. Alternatively, vehicles in a neighborhood can cooperate among themselves to obtain the required information. Cooperative systems like adaptive cruise control [1], [2], cooperative intersection safety systems [3], [4], [5] cooperative forward CWS [6], [7], and cooperative CWS [8] based on OBU-OBU and RSU-OBU-RSU information exchange have been proposed. In cooperative driving, sensors onboard a vehicle continuously monitors different parameters like position, speed, acceleration, yaw etc. The vehicles share their current state and parameters along with information obtained from their neighbors. Every vehicle is equipped with sensors which the vehicles moving on the road form a travelling path a-b-c-d-e-f-g shown in Fig 1. A vehicle has dynamic information of 'self', immediate and non immediate neighboring vehicles. It is thus able to look beyond its surrounding vehicles, other obstacles and is not limited by the placement of onboard sensors. Moreover, the information is not conditioned by the relative motion framework between vehicles and environment noise. Thus, a vehicle can plan its lane change and other maneuvers according to the nature of traffic in its extended neighborhood, intersections, traffic lights and messages from other vehicles in the VANET. Both autonomous and cooperative driving has its own merits and limitations. Autonomous driving is limited by the sensing capabilities of its sensors and do not messages containing information or subjective assessments from other vehicles. However, cooperative driving suffers from some fundamental drawback. One, if some vehicles on the road are not a part of the VANET, then they do not exist for other vehicles. The portions of the road occupied by such vehicles are unmapped and treated as empty spaces by other vehicles. The degree of penetration of VANET must be high before it can be utilized for exchange of critical information.

Second, all members of the VANET must be honest. All messages must be authenticated and their integrity preserved before being accepted. Security provisioning in VANETs is still an open issue. Moreover, the security overhead must be small enough not to cause unacceptable delays that may render the messages obsolete for usage for time critical maneuvers. Three, the accuracy, reliability and timeliness of sensed information must be ensured. Finally, reliability of data and communication delay over the shared wireless medium in a highly mobile environment must be within acceptable limits. Till these issues are addressed, autonomous and cooperative driving systems must coexist and work in combination for a viable collision warning system [9].

In a lane change maneuver, the trajectories affected vehicles need to be estimated for determining the feasibility of lane change, forecasting the possibility of collision when the lane change starts and generation of warning to the drivers if required. In an autonomous driving system, a vehicle must do a long range prediction its own trajectory and the trajectory of its surrounding vehicles to determine the feasibility of lane change. This should be followed by short term and long term prediction for warning the driver and determination of time to collision [10]. Even in a cooperative driving system, communication of the entire predicted trajectory by vehicles may save time for collision estimation by a vehicle planning a lane change maneuver. However, it is known that the during the lane change maneuver, the behavior of surrounding vehicles affects the behavior of the lane changing vehicle and this influence is mutual. This mutual influence of trajectories on one another may preclude the possibility of accurate prediction of trajectories and the correct estimation of the likelihood of collision. In this study, the viability of prediction of lane change trajectory using only the past position values of a vehicle's path using artificial neural network is studied. Since the position of a vehicle is sensed at regular discrete intervals of time, a vehicle's trajectory can be considered as a time series and trajectory prediction becomes time series prediction. The future values of this time series is forecast using a finite window of past values and both short range and long range prediction using neural network is considered [11].

The rest of the paper is organized as follows. Section 2 describes lane change maneuver and the problem of trajectory prediction. In section 3, neural network based time series prediction is described and section 4 describes neural network modeling with simulation results in section 5. The paper is concluded in section 6.

2 Lane Change Maneuver and Problem Formulation

Lane change is a frequent action undertaken by vehicles on the road and usually results in a definite gain to the vehicle in terms of driving comfort or reduced time to travel. Lane change can be defined [12] as an intentional and significant shift in the lateral position of a vehicle from one lane to another (Fig.1). Continual change in lateral positions within a lane or an unintentional foray into an adjacent lane by a meandering vehicle does not constitute a lane change. It could be a deliberate voluntary action, a mandatory procedure in a merging/splitting section of the road or an act forced by a slower leading vehicle or a faster following vehicle. The process itself is risky and is performed voluntarily only when the gain offsets the risk.

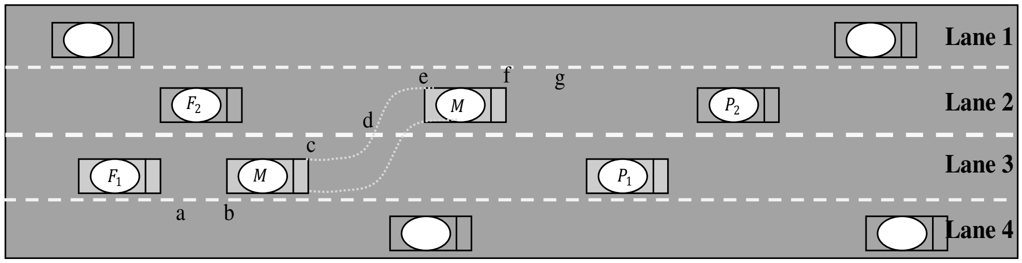

Fig. 1. Lane change maneuver

The lane change process can be viewed as a series of multiple distinct phases: Planning phase, Preparation phase, Crossover phase and the Adjustment phase. Whenever the driver intending a lane change finds a sufficient gap between vehicles in the target lane, the planning phase of lane change commences. The planning phase is devoid of any physical intervention. In this phase, a driver assesses the feasibility of lane change and also estimates the benefit of a lane change vis-a-vis the risk involved in the process [13]. This assessment is subjective and depends on the nature of the driver, his assessment of the behavior of drivers in his target lane, the relative position and speed estimates and its predicted speed and longitudinal and lateral acceleration/deceleration required for a safe lane change in addition to the gain to be derived from lane change [14]. If the driver decides to change the lane, the preparation phase starts. In this phase, the driver continues in his trajectory in the initial lane but accelerates or decelerates relative to the projected position of the vehicles in the destination lane just after its entry into the lane. After this adjustment, the vehicle accelerates laterally to shift in the chosen destination lane. The crossover phase is characterized by significant initial acceleration and then a deceleration after the vehicle has crossed over to the destination lane. This lateral acceleration should be less than the comfortable acceleration threshold and the lateral speed is greater than zero and less than the maximum permissible lateral speed. The longitudinal speed is usually assumed to be constant. However, actual lane change data shows that the speed varies during the crossover phase. Around 80% of the drivers accelerate/decelerate during the crossover phase. Of this 60% accelerate while others decelerate to achieve safety in the target lane [15]. The longitudinal acceleration should be less than the 2g and deceleration less than 0.8g as already assessed in the planning phase. This ensures a smooth curvature of the vehicle trajectory and allows safe braking in the event of lane change abortion. In the last phase, the vehicle accelerates/decelerates to adjust its speed and to maintain a safe gap in accordance with the state of its leading vehicle. Thus, the lane change process can be characterized by variable speeds with constant acceleration and deceleration in both longitudinal and lateral directions.

Lane change maneuver is a major source of accidents on the road. Different studies have reported that more than 10% of the road accidents are lane change collisions and also results in cascading accidents in both the original and target lanes [16]. Even when the collision is avoided by emergent action by lane changing vehicle or other vehicles, an incorrect lane change process induces severe turbulence in the traffic and discomfort to the driver that propagates over a long distance. More than 75% of the lane change collisions are associated with recognition error in the planning phase

[17]. It has been found that the main cause is the failure to assess the feasibility of lane change in the planning phase. If the trajectories of the vehicles affected by lane change can be predicted, the chances of a possible collision can be estimated with sufficient accuracy. Appropriate long range warning messages can be issued to the driver for a corrective or preventive action. Interestingly, around 78% of these accidents occur at low speeds (6-7 ms^{-1}). This indicates that wrong decisions in the previous phases are not corrected in the later stages. Moreover, almost 95% of the accidents are lateral collisions that occur during the crossover phase in the middle of actual lane changing. Lateral collisions at low speeds in the cross over phase indicate short range prediction of vehicles trajectories can help in avoiding the collision. Very few rear end collisions take place in the adjustment phase. This takes place only when the vehicle in its new lane is not able to decelerate. The leading vehicle is not aware of this and collision can be avoided only when there is a communication between the vehicles.

A collision during lane change is indicated by an intersection of the trajectories of the lane changing vehicle with either the following or leading vehicles in the original or target lane in spatial-temporal domain. This requires the knowledge of the trajectories of vehicles involved in the process with absolute position values [18]. The aim of this work is to study the feasibility of accurate trajectory prediction of a lane changing vehicle in an autonomous driving system to achieve satisfactory estimation of safety of the maneuver. The autonomous system uses only in-vehicle sensors to find the past position values without any measurement or inter-vehicle communication of the relative states of other vehicles. A long range trajectory prediction helps in determination of the feasibility of lane change. An early warning message to the driver can prevent a collision. When the lane change process is underway, short range prediction of future positions of the vehicle can accurately predict the chance of collision and time to collision. Warning to the drivers or automatic cruise control system can abort the process and avoid an imminent collision. Abortion of lane change due to correct or incorrect prediction can lead to turbulence in the traffic while prediction of safe lane change when there is an impending collision can be disastrous. Thus, an in-vehicle positioning module with position sensors is the key element in autonomous driving system [19]. The positioning module should give reliable and accurate position coordinates of a vehicle's location. A typical vehicle has 3-12 m length and 1-3 m width. For lanes with 3-5 meter width, the minimum separation between LC vehicle and other neighboring vehicles can be very small. This requires precise position measurement with low error variance (0.2-0.5 meter) to avoid false collision predictions. A differential global positioning system with an error variance of 0.2-0.5 m is a feasible choice for position measurement. The speed of vehicles on highways ranges from low speed (~10 ms^{-1}) to high speed (~20 ms^{-1}) with an acceleration of (± 2 ms^{-1}). The distance traversed by a vehicle in 0.1s is about 0.1-0.2 m which is discernible. Hence, the car coordinates should be sampled at this rate.

3 ANN Based Vehicle Trajectory Prediction

The dimensions of a typical vehicle are 3m X 8m with its position specified by the midpoint of its front bumper. The motion profile (speed, acceleration) and position measurements corrupted by noise. A fast and reliable coarse estimation of longitudinal positions with relatively precise estimation of lateral positions of a lane changing vehicle is required. A low order estimator is needed which can predict the future values with only the imprecise past positions of the vehicle given at regular time intervals. Since we consider only a low order estimator, other inputs like driver behavior, state of other vehicles and car state like steering angle etc. have not been incorporated. The accuracy of prediction may improve with these additional inputs; however, only rough estimates are required and our aim is to study the practicability of short range and long range trajectory prediction only from the past values of the trajectory. The future coordinates of a vehicle can be estimated form current and past values and the future states can be predicted from the one step future estimate and the other past values. No underlying model or statistics of the states or driver characteristics is considered.

Vehicles change their speed during the lane change process. The change in speed starts with discretionary variation during the preparation phase where speed is adjusted according to the speed of vehicles in the target lane. This is followed by constant acceleration/deceleration in both the longitudinal and lateral directions in the crossover phase. Finally, the vehicle adjusts itself in the target lane by appropriate change in speed. It was observed from the NGSIM lane change data that the vehicle trajectories can be divided into sections corresponding to distinct longitudinal speeds. This has been utilized to improve the accuracy of prediction. The trajectory is divided into three low, medium and high speed sections. The windows of past positions were separately considered for each of the distinct sections. The sequence of position coordinates at discrete time intervals is a time series corresponding to a vehicle's trajectory. The x-coordinate is the longitudinal position and the y-coordinate is the lateral position of a vehicle. Change in x-coordinate indicates the motion of the vehicle in the lane while an appreciable change in the y-coordinates indicates lane change. The basic idea of the trajectory forecasting is based on the observation that different phases of the lane change process can be characterized by different speeds of the vehicle. Thus, the complete lane change trajectory can be decomposed into subsections of low and high speed. A sliding window of the past spatial positions in each of the sections can be utilized for both near future position predictions and long term sub trajectory prediction. Both the low speed and high speed sub trajectory predictions can be concatenated for forecasting the entire lane change trajectory.

Time series is a data sequence ordered in time. The aim of prediction is to determine the future data points from the past finite data set of a finite time series. The prediction is based on the assumption that the future of a time series is based on its past. Short range prediction assumes that the system has a finite memory and this memory can be used to predict the immediate future. Long range prediction assumes the existence of underlying principle or law governing the behavior of the system. This knowledge can be imbibed for forecasting the future behavior of a system. For a deterministic system, the underlying equations can be solved to characterize the future behavior of the system else the parameters of the underlying probability distribution function may be estimated for modeling the time series. The model can be used for describing the future behavior of the system. Linear models like autoregressive (AR) and autoregressive moving average (ARMA) have been utilized to predict the future behavior of many systems. However, these statistical models fail to describe the behavior of nonlinear dynamic systems or wide band spectra systems that require very high order linear model. Nonlinear techniques like artificial neural networks can be for characterization and prediction of such systems. A neural network can be trained from existing instances of a time series and can then predict the behavior of an unknown instance of the series. The structure of the neural network is governed by the complexity of the time series.

The back propagation (BP) network is an established ANN that has been used extensively and has exhibited the ability to model nonlinear functions. The BP network is simple and is able to extract underlying patterns from time series data. It uses supervised learning in which learning is stopped when the mean square error becomes less than a threshold. The structure of the BP network in terms of the number of inputs and hidden layers is governed by the complexity of the time series.

4 Neural Network Modeling

Artificial neural networks can model complex relationships between inputs and outputs or to find patterns in data. They offer a potential alternative to other methods like hidden markov model (HMM) based techniques [20] or other prediction algorithms [21] for prediction of future trajectories of vehicles moving on the road. This work uses a neural network, to determine the future positions or trajectories of lane change vehicles. The training is done offline for two reasons. One, the computation load is reduced and two, there is slim advantage of online training as the amount of data to characterize lane change trajectory for an individual driver may not be sufficient. Two approaches are considered. The first, approach uses a prediction type of neural network with hidden layers and back propagation learning algorithm to model lane change process and predict the trajectory of lane change vehicles. A series of consecutive positions of vehicles at regular time intervals, describe the start of lane change process and changes in the trajectories over time, are input to the neural network. This is used for predicting the future positions of the vehicle. The second approach concentrates specifically on lane changing and makes use of a learning classification type of neural network. The input to the neural network consists of same time-space position points. The neural network classifies the input data by determining the trajectory of vehicle. In our problem, the back propagation neural network with one, two and five hidden layers is selected. The input layer has eight inputs and the output layer has one output. The details are as follows:

Inputs:

i. The longitudinal positions of the lane change vehicle.
ii. The lateral positions of the lane change vehicle.
iii. The velocity of monitored vehicle.
iv. The acceleration / deceleration of monitored vehicle.
v. The longitudinal positions of the following vehicle in destination lane.
vi. The lateral positions of the following vehicle in destination lane.
vii. The velocity of following vehicle in destination lane.
viii. The acceleration / deceleration of following vehicle in destination lane.

Outputs:

i. The longitudinal positions change of the lane change vehicle.
ii. The lateral positions change of the lane change vehicle.

The optimal construction of BP ANN is a four step process as described below (Fig.2):

Step 1: Input and Output

The inputs to the system are the position, velocity and acceleration / deceleration of the lane change vehicle with future position values as output.

Step 2: Neural Network Creation

The neural network based model creates an interconnection between the processing elements (PEs) in the form of weighted matrix populated by the time series of the input parameters. In this recurrent network, some of the connections may be absent, but there are feedback connections. An input presented to a recurrent network at time t will affect the networks output for future time steps greater than t. Therefore, a recurrent network needs to be operated over time.

Step 3: Training and Testing

The training and testing set is used to test the performance of the network. Once the network is trained the weights are frozen, the testing set is fed into the network and the network output is compared with the desired output. The weights are changed based on their previous value and a correction terms and rules. Once the rule is selected, correction should be applied to the weights, as per the learning rate. If the learning rate is too small, then learning takes a long time. If it is set too high, then the adaptation diverges and the weights are unusable. For the momentum component there are two parameters to be selected: the step size and the momentum. We determine the best values for these parameters and for optimized modeling require that the network be trained multiple times in order to produce the lowest error. This model terminates the training based on mean squared error. The minimum function terminates when the MSE drops below the specified Threshold. Cross validation monitors the error on an independent set of data and stops training when this error begins to increase. We use the threshold value for this model is 0.0001.

Step 4: Production and Errors

The most important factors for the evaluation of a neural network is the production and the testing error. Training error must be extremely low. If the training error is low 0.0001, the production of the desired output efficiently approaches to the realistic values. Testing error actually evaluates the neural network performance and the better production of the real data.

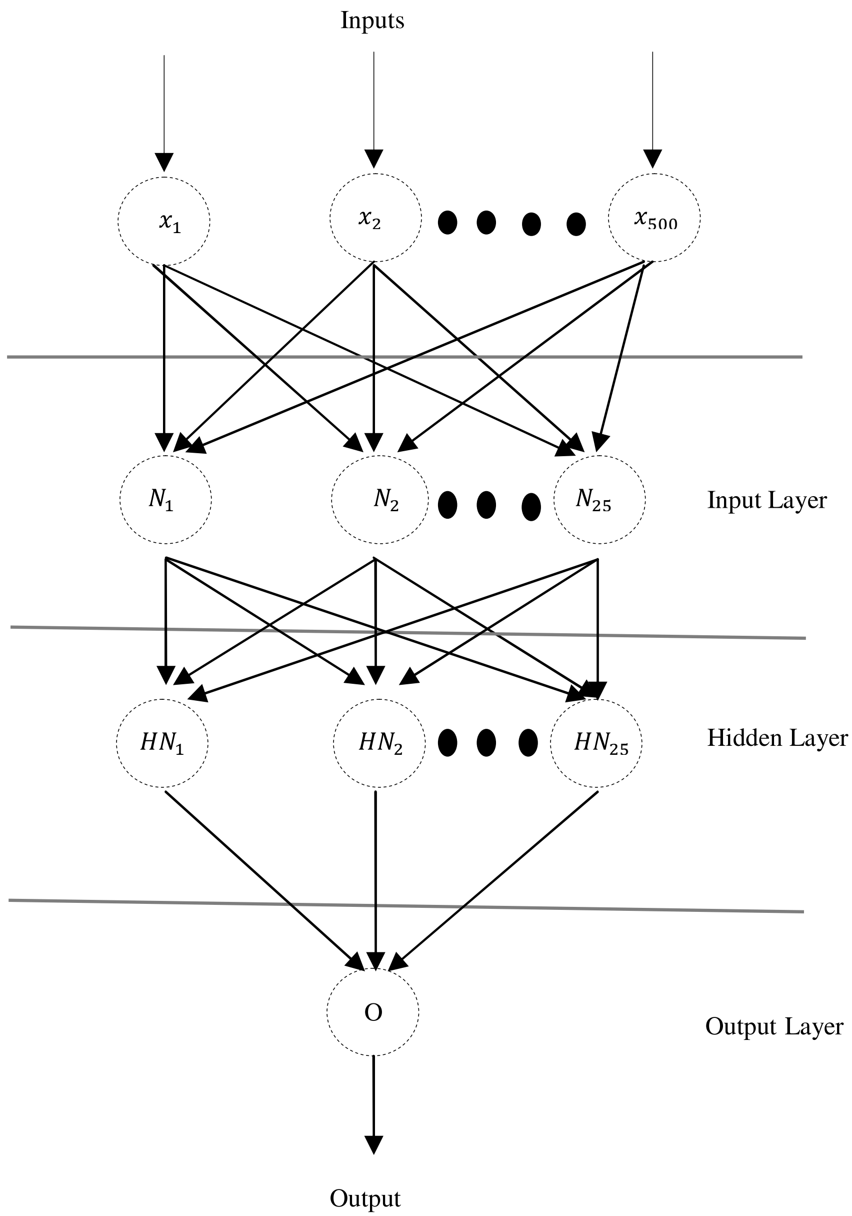

Fig. 2. Neural network modeling using one hidden layer

5 Results and Discussion

5.1 Lane Change Data

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). The NGSIM trajectory data sets contain a large number of lane change trajectories [22]. In the present study, 1000 lane change trajectories were identified and separated from other data sets. It was found that the NGSIM data sets extracted from the raw video data are noisy and have some vehicles momentarily placed in the adjacent lane incorrectly which then comes back in the original lane. It is also possible that these trajectories indicate aborted lane change processes, unintended drifts or tracking error. Since the present study focuses lane change trajectory prediction, the raw lane change data set was cleansed by considering the trajectories with significant lateral shifts signifying deliberate lane change. This was done by defining two thresholds, time threshold $\tau_t = 5s$ and space threshold τ_s. Data of vehicles meandering near lane boundaries ($\leq d_s$) for time $\geq \tau_t$ was filtered out. To examine the complete lane change trajectory, 10 s trajectories containing lane change were extracted. NGSIM data values are at 0.1s sampling intervals with a 10s data set corresponding to around 100s trajectory. The 10s trajectory data consists of time, longitudinal and lateral coordinates of the vehicle. To capture the lane change trajectory completely, 50 data values were taken from either side of the time point at which the trajectory crossed the lane boundary. By visually examining the trajectories, the start and end of the lane change were identified for each vehicle. The NGSIM data set supplies the vehicle's position by the coordinates (longitudinal and lateral positions) of the centre point of the front bumper position. It also gives the dimensions of the vehicle. We also considered the coordinates relative to the same point and a lane change is assumed to occur when the reference point crosses the threshold τ_s. The complete lane change time is impossible to assess as the planning phase duration cannot be estimated, a significant rotation of the steering wheel also requires in-vehicle sensor. However, in most of the cases, discretionary acceleration/deceleration was observed during the initial and final intervals of the 5-8 s lane change data. These are indicative of the lane change preparation stage and adjustment phase respectively. From the 5-8 s data, the mean time for complete lane change is estimated to be 5 s with a variance of 2.5 s.

5.2 ANN Test Data

For ANN modeling, highway traffic data of about 650 m which is the distance traveled across the road by typical vehicle in 80 seconds is taken. This is discretized into 500 time points. These 500 time points are used for training, testing and production. We use 200 time point for training, 150 time points for testing and 150 time points for production of the neural network model. It is observed that 1 to 100 time points, a typical monitored vehicle travelled across the road with the velocity increasing from the 7 ms^{-1} to 10 ms^{-1}. This region is treated as slow speed region for ANN modeling. From the 101 to 350 time points, the velocity increased from the 10 ms^{-1} to 16 ms^{-1}. This region is treated as medium speed region. The time point from 351 to 500, speed was more 16 ms^{-1} $\leq v \leq$ 23 ms^{-1}. The highest velocity of vehicle is 23 ms^{-1}, the slowest velocity is 7 ms^{-1} and the average velocity is 13 ms^{-1}. The vehicle acceleration/deceleration is in the range of ± 3.4 ms^{-2}. We consider 50 LC vehicles. Minimum weight delta = 0.001, initial weights = 0.3, learning rate = 0.3 and network momentum = 0.6 have been used in neural network training of vehicle trajectories. A single input, single output based multilayer perceptron (MLP) network with one, two and five hidden layers are used for training, testing and prediction of the vehicle trajectories. The number of hidden layers has been chosen (One, two and five) to determine the complexity of lane change trajectories. The simulation gives the epoch at which the data training and cross validation mean-squared errors (MSEs) are minimum. The reliability of the network model is examined by the method of cross validation that estimates the generalized error based on number of samplings. The neural network is trained with different set of data. The final training and testing error is estimated by taking the average of all the errors resulted from each time we trained the network. The number of epochs for training of the neural network was 1000. The transfer function used in every unit is the sigmoid function. When the mean square error is approaches zero and cross validation MSEs follow the mean square errors, the learning simulation is acceptable (Fig. 3). 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. We use the threshold value for this modeling is 0.0001.

During the entire lane change process, a vehicle changes its speed significantly. Fig. 4(a) shows the short term (up to ten steps – one second) prediction error for low and high speed sections of a typical vehicle in the longitudinal direction from the start of the lane change process to the adjustment phase. In the initial part of the high speed section, the prediction error is very high for neural networks regardless of the number of hidden layers. The error decreases monotonically with time. For the network with one hidden layer, the initial error is 17.9 m which decreases to almost zero but increases again with time. The prediction also swings drastically about the correct values. Similar results have been observed with networks with two and five hidden layers. However, the initial prediction errors are low but significant (two hidden layers 17.9 m, five hidden layers 10.1 m).

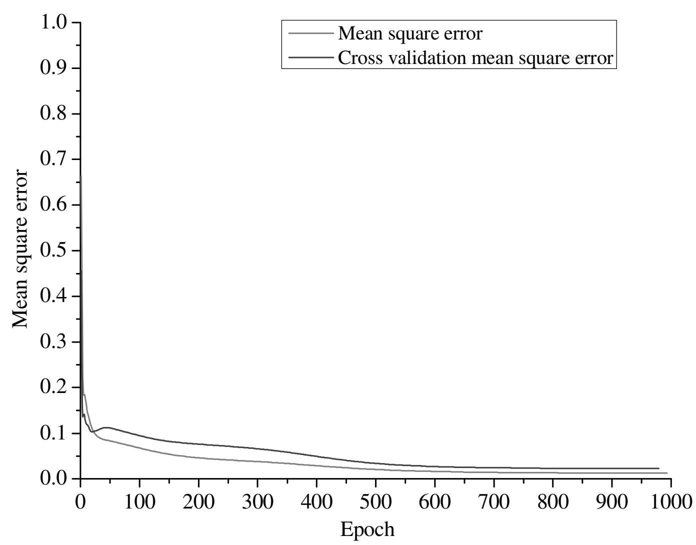

Fig. 3. Learning curve of prediction of the vehicle trajectory

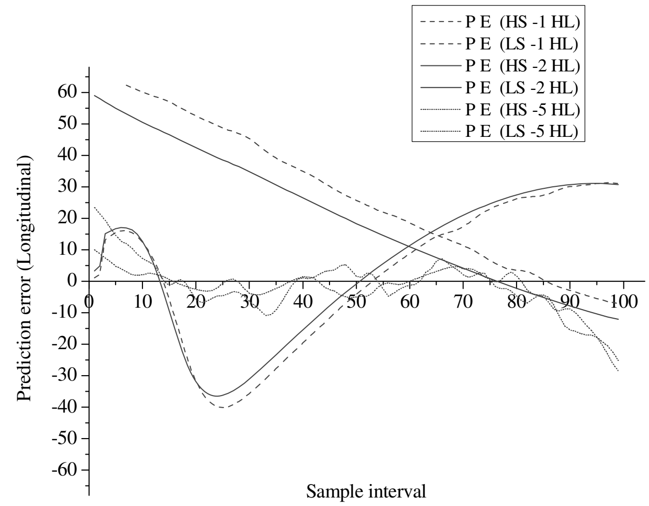

Fig. 4a. Prediction error for high Vs low speed of vehicle at 1-5 hidden layers in longitudinal direction

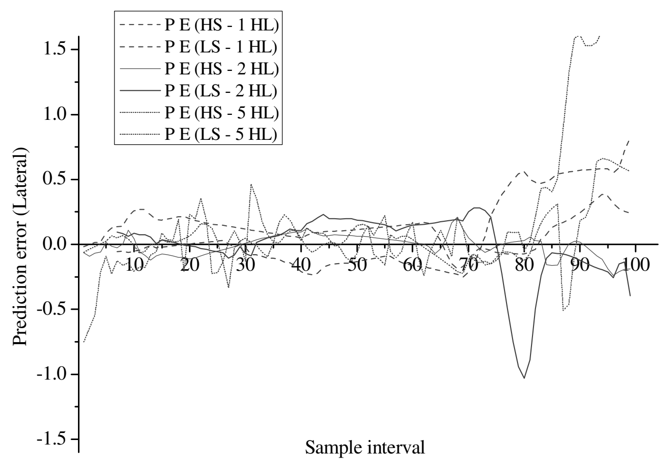

Fig. 4b. Prediction error for high Vs low speed of vehicle at 1-5 hidden layers in lateral direction

The trend is similar and the error reduces monotonically but this decrease is rapid and error swing around the correct value is lower than with one hidden layer (two hidden layers – mean error 19.0 m with variance 361.0, five hidden layers – mean error 6.4 m with variance 40.9). Initially, the number of past values available to the network for prediction is low and hence as expected, the prediction error is large. As the number of past values for prediction increase, the prediction improves. However, after the initial dip, the error increases. For the network with one hidden layer, this increase is significant, for network with two and five hidden layers, the error hovers around the mean. This signifies the complex structure of the time series. Even though the mean errors with higher number of hidden layers are lower, the error swings are significant indicating that the neural network is not able to learn the underlying pattern of the time series. It is possible that in the high speed subsection, the distance between the longitudinal positions is considerable making the prediction erroneous. The error graph in the low speed section Fig. 4(a) is quite different from the high speed section. At low speeds, the initial prediction is quite accurate. It is clear that the distance covered one time interval (0.1s) is very small making the prediction accurate (max error 18.9 m, min error 0.07 m). The error increases and then again falls in one second indicating an over estimation of the position followed by under estimation of the vehicle's future position (mean error 25.7 m with variance 660.4). This under estimation and over estimation swing increases and continues for the next 5 s (mean error 25.7 m with variance 660.4) when another swing cycle starts. The cyclical pattern is similar for two and five hidden layer networks although the amount of swing is small (mean error 22.9 m & 4.5 m with variance 524.4 & 20.3). Clearly, the network is unable to capture the longitudinal motion pattern of a vehicle at low speed during the lane change process even though the difference in position values is small in comparison to the high speed section. It can be seen that the speed of the vehicle has minor influence on accuracy of prediction. Also the structure of the network improves the prediction error profile slightly.

Fig. 4(b) shows the short range (up to ten steps – one second) prediction error curves in the lateral directions as estimated by networks with one, two and five hidden layers for both high and low speed lane change subsections. The width of a lane is 3-4 m and two vehicles in adjacent lanes may be just 2-3 m. During lane change, a lateral shift of 2-3 meters is sufficient for a vehicle to enter an adjacent lane. This requires the prediction of the lateral shift to be more accurate (less than 0.1 m) to avoid a side swipe with vehicles in target lane. When a vehicle moves at high speed (more than 16 ms^{-1}), the network under estimates the amount of lateral movement and error in the initial prediction of a lateral shift is large, especially for network with one hidden layer (0.3 m-under estimation). The prediction of network with more hidden layers is better but they also under estimate the shift (two hidden layer 0.3 m, five hidden layer 0.4 m, under estimation). Within few time samples, the networks are able to reduce the prediction error significantly. However, the average error is significant with random deviations (one hidden layer - mean 0.05 m & variance 0.003, two hidden layer- mean 0.03 m & variance 0.001, five hidden layer - mean 0.05 m & variance 0.003). The average percentage error is 30% which is very considerable for lateral shifts. The networks randomly over estimate and under estimate the lateral positions irrespective of the number of layers and the number of past values available for prediction. In contrast to longitudinal value predictions, the predictions by networks with higher layers are higher and exhibit higher variations more frequently (max over estimation error 0.1 m, max under estimation error 0.4 m) with swing observed almost every 0.4-0.5 s. It is clear that the network has not been able to learn the underlying pattern of the time series in the training phase and is not able to follow the lateral shifts during prediction in the high speed subsection of the lane change trajectory. This results in significant average error with considerable positive and negative variations. In the slow speed subsection, when the longitudinal speed of a vehicle is low, the initial prediction errors are smaller as compared to high speed section but are still significant for all the networks (one hidden layer 0.24 m, two hidden layer 0.24 m, five hidden layer 0.87 m). As expected, the shift is under estimated due to the lack of past values. The error quickly reduces monotonically in a few time samples but the network starts over estimating the lateral shifts of the vehicle. The over estimation and under estimation cycle continues over the entire slow speed section. The errors are still significant for all the networks (mean and variance for one hidden layer 0.07 m & 0.005, two hidden layer 0.05 m & 0.003, five hidden layer 0.09 m & 0.008). It can be observed that the frequency of swings is smaller with an overall decrease in the percentage error (10%) as compared to high speed section but the trends are similar. However, the amount of variation in error and its random positive and negative swings indicate that the network is not able to track the lateral movements of the vehicle with the required accuracy. Overall, irrespective of the speed of the vehicle, the errors in short range position estimation are significant with considerable random deviations. This makes such networks unacceptable for prediction of collision avoidance and emergency warning to the drivers in the midst of a lane change.

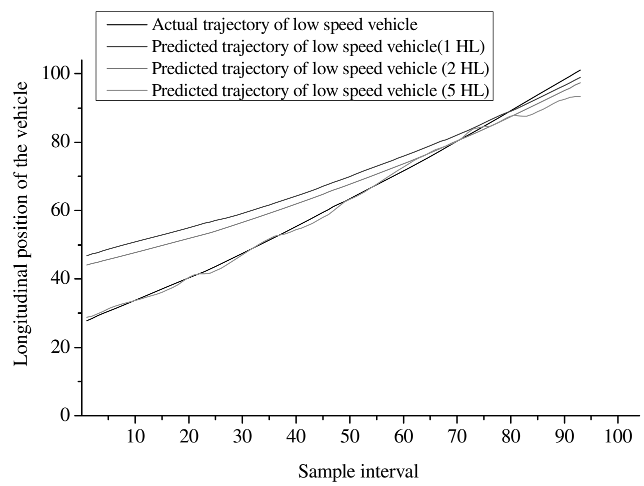

Fig. 5a. Predicted trajectory for low speed of vehicle at 1-5 hidden layers in longitudinal direction

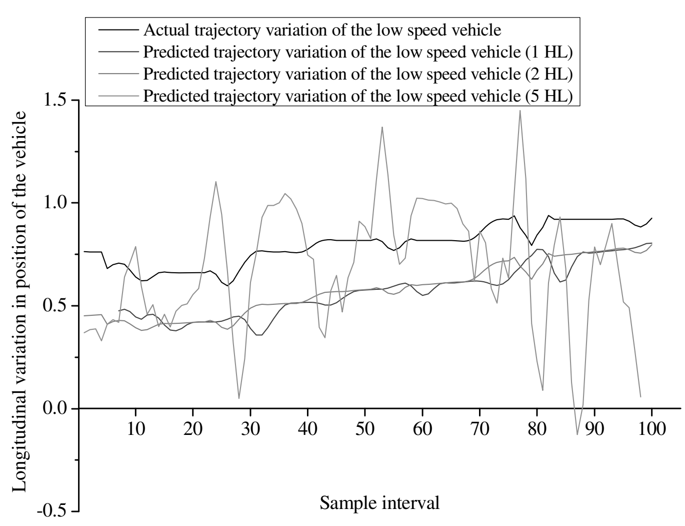

Fig. 5b. Actual Vs Predicted trajectory variation for low speed of vehicle at 1-5 hidden layers in longitudinal direction

In the second part of the simulation test, the effectiveness of neural networks for prediction of trajectory for a whole high or low speed sub section of the lane change trajectory was evaluated. Fig. 5(a) shows the curves for both the actual and predicted vehicle trajectory on the highways in the longitudinal direction for low speed sub section of lane change trajectory. The initial prediction considers the start of the low speed sub section between 84-206 m along the road and a speed of around 10 ms^{-1}. In this portion of the sub section, the prediction error is large for one and two hidden layer network (prediction error for one hidden layer 18.9 m, for two hidden layers 17.9 m) while the network with five hidden layers is able to predict the trajectory quite accurately (prediction error 7.7 m). Initially, the network does not have sufficient past values to predict the trajectory, but as the vehicle moves along the path, sufficient number of samples becomes available and the prediction becomes more accurate. As shown in Fig. 5(a), the error decreases monotonically and prediction becomes more accurate for network with one and two hidden layers. The five layer network is able to predict the trajectory quite accurately but the prediction waivers slightly under estimating and over estimating the trajectory. The prediction becomes accurate for a small time interval (80-90) and then the error again increases monotonically for all types of networks. Fig. 5(b) shows the predicted trajectory variation against actual trajectory of the low speed vehicle in longitudinal direction at various hidden layers. The average predicted trajectory variations are 1.87 m, 1.89 m and 2.24 m at one, two and five hidden layers respectively.

Fig. 5(c) shows the curves for both the actual and predicted vehicle trajectory on the highways in the longitudinal direction at high speed (> 16 ms^{-1}) sub section. The initial prediction considers the start of the high speed sub section (305 – 650 m). The prediction of the trajectory for the low speed sub section is significantly more accurate as compared to high speed sub section. All the networks are able to predict the trajectory although networks with one and two hidden layers over estimate the trajectory. As the vehicle moves, the networks are able to trace the trajectory. The prediction error for networks with one and two hidden layers decreases with time, while the five layer network continually overestimates and underestimates the trajectory. The performance of the networks seemingly improve over a period of time (70-80) but the errors increase in the later part (80-100) of the low speed subsection for all types of networks. The prediction errors are bereft of any pattern and the error variations are not dependent on the layers or the number of past values considered for long range prediction or the speed of vehicles. It is clear that network fails to estimate the longitudinal dimension of the trajectory or track it with some constant error. Fig. 5(d) shows the predicted trajectory variation with actual trajectory of the high speed vehicle in longitudinal direction at different hidden layers. The average predicted trajectory variations are 5.55 m at one hidden layer, 5.51m at two hidden layer and 4.85 m at five hidden layers respectively.

A lane change is characterized by a significant lateral shift in the position of a vehicle. To this shift from one lane to another, a vehicle first accelerates laterally to enter the adjacent lane and then decelerates to stay in its destination lane. This shift is of the order of the width of a lane (3-6 m) and sub meter accuracy is needed for lateral trajectory prediction. The predictions of the lateral dimension of the trajectory in low and high speed sub sections are shown in Fig. 5(e) and Fig. 5(g) respectively.

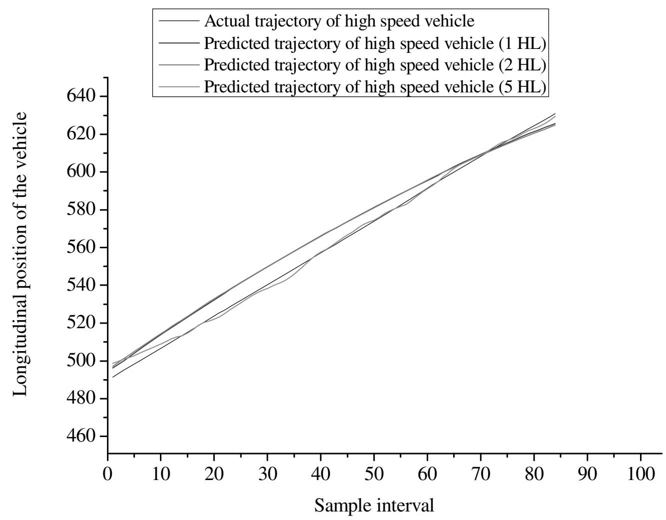

Fig. 5c. Predicted trajectory for high speed of vehicle at 1-5 hidden layers in longitudinal direction

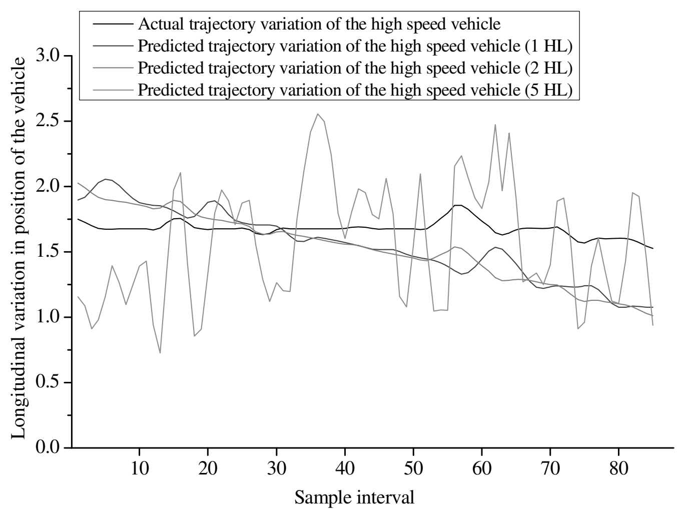

Fig. 5d. Actual Vs Predicted trajectory variation for high speed of vehicle at 1-5 hidden layers in longitudinal direction

Similarly, Fig. 5(f) and Fig. 5(h) show the predicted trajectory variation with actual trajectory of the low and high speed vehicle in lateral direction at different hidden layers. The average predicted trajectory variations in low speed are 0.030 m at one hidden layer, 0.33 m at two hidden layer and 0.004 m at five hidden layers and average predicted trajectory variations in high speed are 0.010 m, 0.011 m and 0.010 m at one, two and five hidden layers respectively.

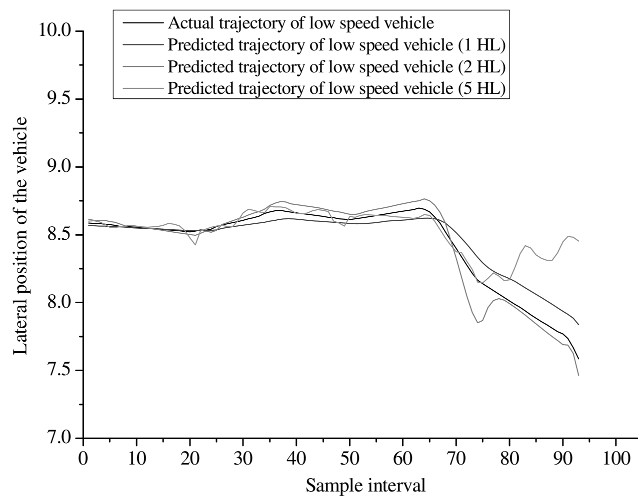

Fig. 5e. Predicted trajectory for low speed of vehicle at 1-5 hidden layers in lateral direction

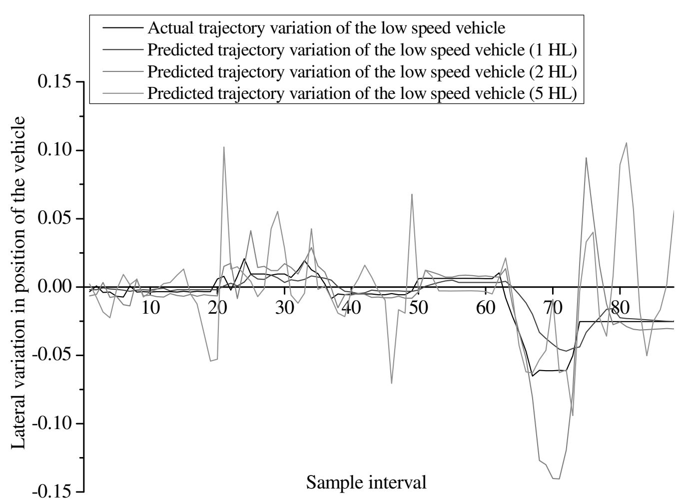

Fig. 5f. Actual Vs Predicted trajectory variation for low speed of vehicle at 1-5 hidden layers in lateral direction

In both the low and high speed sub sections, initially, the networks overestimate the trajectory. The estimation error remains invariant for a small interval for time in the preparatory phase of the lane change. However, the error becomes quite appreciable with time and random overestimation and underestimation swings in the crossover and adjustment phase of the lane change at high speeds. Since the lateral motion is characterized by change in acceleration, the networks are unable to follows this rate of change in speed resulting in the large random variations in the predicted trajectory through the low speed section of the lane change process. In the low speed sub section, the estimation error and variation in the estimation error is low during the first few time sample but the error variation starts increasing with time and in the

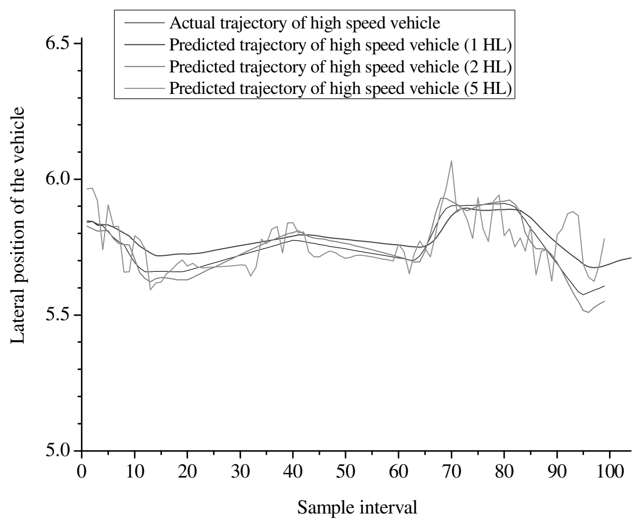

Fig. 5g. Predicted trajectory for high speed of vehicle at 1-5 hidden layers in lateral direction

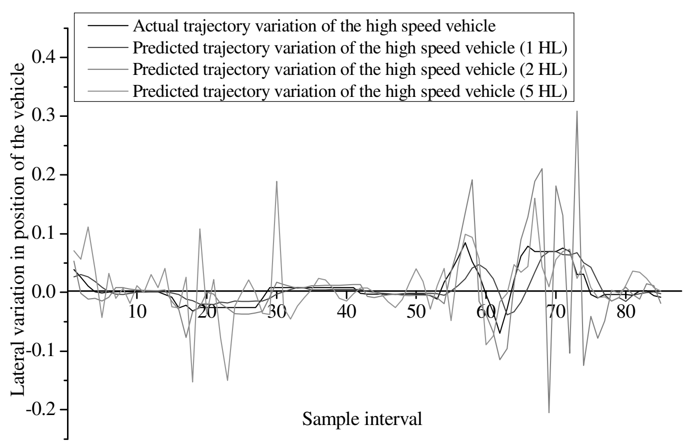

Fig. 5h. Actual Vs Predicted trajectory variation for high speed of vehicle at 1-5 hidden layers in lateral direction

latter part of the preparatory phase and during the crossover phase, the networks are not able to track the trajectory. The error and error variation becomes significantly large as the trajectory progress. Overall, networks are not able to track the trajectory in the lateral direction irrespective of the number of layers and speed of the vehicles. Moreover, the estimation further deteriorates in the crossover phase when the rate of change in lateral speed is large. It is quite possible that the driver adjusts the trajectory according to the state of its surrounding vehicles and his own assessment of safety and comfort depending on his driving behavior.

In general neural network based techniques fail to predict the near future positions as well as the long term trajectory with the required accuracy Fig. 6(a) and Fig. 6(c) in longitudinal as well as lateral direction. Fig. 6(b) and Fig. 6(d) also shows the overall predicted trajectory variation with actual trajectory of the variable speed vehicle in longitudinal and lateral direction at different hidden layers. The average overall predicted trajectory variations are 4.05 m at one hidden layer, 3.94 m at two hidden layer and 3.32 m at five hidden layers in longitudinal direction. Similarly, average overall predicted trajectory variations are 0.015 m, 0.013 m and 0.010 m at one, two and five hidden layers in lateral direction respectively.

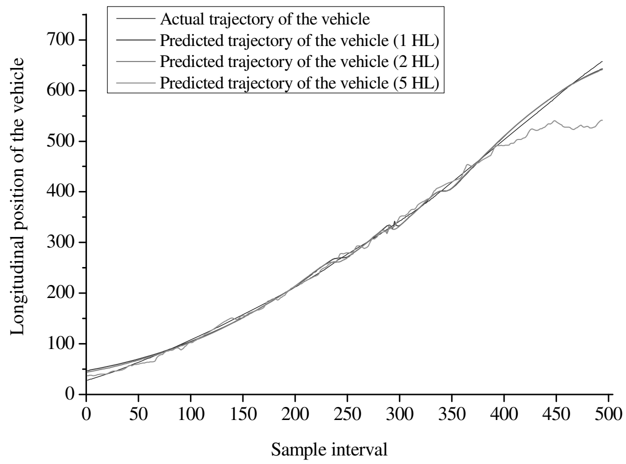

Fig. 6a. Actual Vs Predicted trajectory of vehicle at 1-5 hidden layers in longitudinal direction

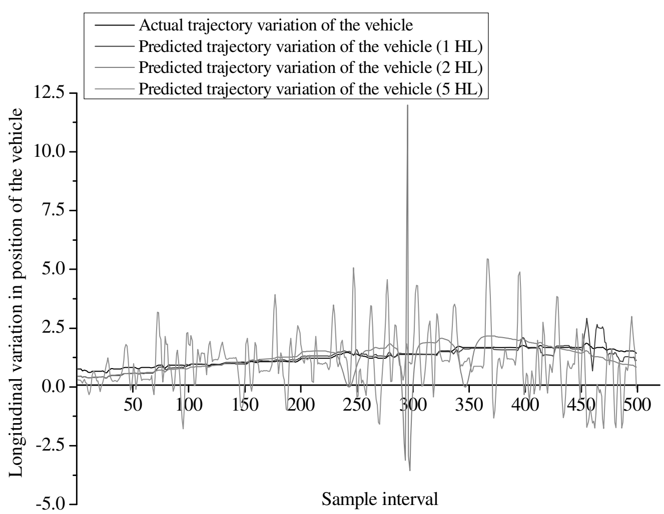

Fig. 6b. Actual Vs Predicted trajectory variation of vehicle at 1-5 hidden layers in longitudinal direction

In the lateral direction, the networks fail to follow the general trend of the trajectory and the estimation is quite random. The minor improvement in the prediction by networks with more hidden layers shows a non linear, long range dependence of future positions on the past values of a vehicle's trajectory. This confirms that planning phase in which the driver determines the viability of lane change and plans the process largely defines the overall trajectory. The errors are still present with large positive and negative variations. A neural network is not able to learn the pattern or track it. It can be surmised that the past values do not completely dictate the future positions of a vehicle's trajectory and extraneous factors like other surrounding vehicles or the driver's behavior significantly influence the trajectory of the lane changing vehicle. A trained network may collect a vehicle's lane change trajectories to improve its prediction by incorporating a driver's behavior.

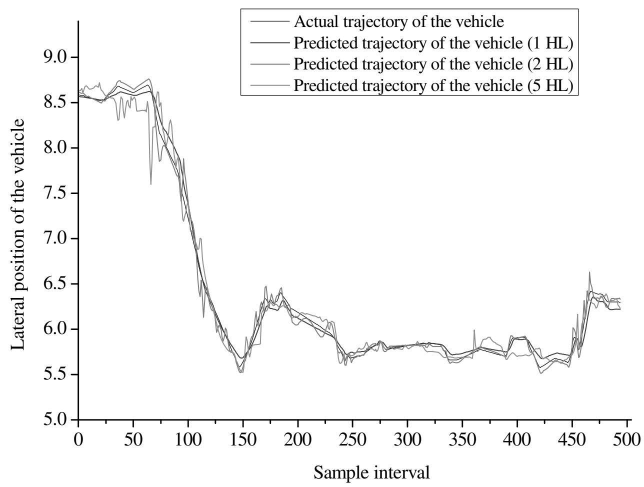

Fig. 6c. Actual Vs Predicted trajectory of vehicle at 1-5 hidden layers in lateral direction

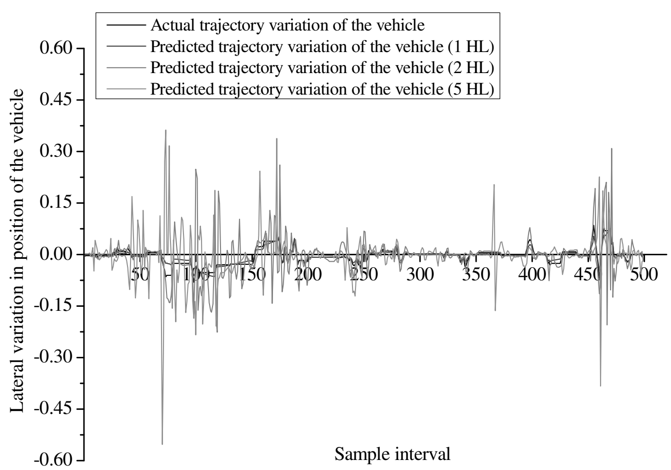

Fig. 6d. Actual Vs Predicted trajectory variation of vehicle at 1-5 hidden layers in lateral direction

6 Conclusion

The work explored the effectiveness of trajectory prediction of a vehicle during lane change using only the past coordinates of the vehicle. It was found that a neural network is unable to perform short range or long range prediction with sufficient accuracy. The network could not even trace the trajectory of the vehicle with random error in both the longitudinal or lateral directions irrespective of the stage of the lane change process, speed of the vehicle or the configuration of the network. This underscores the fact there is an active involvement of the driver who changes the trajectory of the vehicle depending on his perception of the state of neighboring traffic. This continual external influence needs to be considered for accurate prediction of the future states of a vehicle and impending collision during lane change.

The majority of the collisions during lane change on the highway are a side swipe or a rear end collision with vehicles in the target lane. The side swipe occurs between the LC vehicle and the following vehicle in the target lane while the rear end collision involves the LC vehicle and the leading vehicle in the target lane. The side swipe is combined result of the behavior of both the vehicles involved in the collision. The main reason for this behavior is the recognition error by the LC vehicle during the planning phase and the lack of sufficient deceleration from the following vehicle. This culminates into a lateral collision. The rear end collision can also be attributed to recognition error combined with a possible deceleration of the lead vehicle. The recognition error results in insufficient maneuvering time for the LC vehicle or the following vehicle in the target lane. The recognition error is a wrong estimation or a tendency of the aggressive LC driver to keep shorter time headway than required. This error can be corrected in the crossover phase if the LC vehicle is given an early warning to give sufficient maneuvering time to the drivers. However, a driver without onboard sensors is limited to line of sight information. An autonomous vehicle system is also limited by external sensed data which does not yield any information of a driver's behavior or internal state of its surrounding vehicles. It the maneuvering time can be increased by 0.5 s, a driver can correct his recognition error during the later phases and void an accident. A cooperative driving system can give that time to a driver by conveying the driving behavior of neighboring vehicle and by reducing the reaction time through early warning messages.

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