Hybrid Interaction-Aware model for Surrounding vehicle Behaviour Prediction using Bi-LSTM for Autonomous Driving

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Abstract

Intelligent decision-making is critical in any Advanced Driver Assistance Systems (ADAS). Recognizing the behavior of surrounding human-driven vehicles is vital for improving driving efficiency and safety in a mixed driving scenario where the autonomous vehicle interacts with the human-driven vehicle. This paper proposes a hybrid interaction-aware model for predicting lane change and turning behaviors of surrounding vehicles in a mixed driving scenario. Unlike the existing behavior prediction models, which use handcrafted features for predicDtion, the proposed model uses Bi-LSTM with attention to predict the behavior in different driving scenarios in mixed traffic and an interaction-aware module to optimize prediction results. The proposed method is trained and validated using real-world trajectory dataset. Simu[*]lation is performed with MATLAB Simulink to validate the proposed model. It has been demonstrated that the proposed work gains better inference and prediction results in diverse traffic scenarios from the proposed prediction method for surrounding vehicles.

Keywords: Behavior prediction, Autonomous driving, Bi-LSTM, Lane change behavior

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1 Introduction

Autonomous vehicles are placed as a critical player in the future automotive industry. Many research communities are currently focused on developing the technology that will be employed in autonomous vehicles. The current state of art technologies and the natural driving data sources provide a vast potential for developing more robust autonomous systems. Autonomous vehicles are the solutions to many challenges that are existing in the transportation field [1]. They combine modern communication and network technologies and involve functions for perceiving the environment and decision making. These vehicles promise to deliver a safe, comfortable, and energy-efficient driving experience [2]. Motion planning in autonomous driving is the process of choosing the sequence of steps to take in order to arrive at the desired destination. The vehicle to travel between the source and the destination avoiding the obstacles and following the road structure uses sensor data fusion. The vehicle perceives its environment, collects the data through the sensors and the perception system builds meaningful descriptions of the environment. This information is used to make meaningful decisions in the autonomous vehicles' motion planning in a dynamic traffic environment.

Autonomous vehicles must recognize and foresee the future behaviour of nearby vehicles to avoid collisions and increase efficiency. But understanding the behaviour of the surrounding vehicle is complex in an environment where autonomous and human driven vehicles co-exist. To address the problem of anticipating the surrounding vehicle behaviour, several studies have been proposed by researchers [3]. The sensors attached to the autonomous vehicle captures the parameters such as location, velocity, acceleration etc. from the surrounding agents and process them to accurately predict the surrounding vehicle’s behaviour. Figure. 1 shows the current mixed driving scenario.

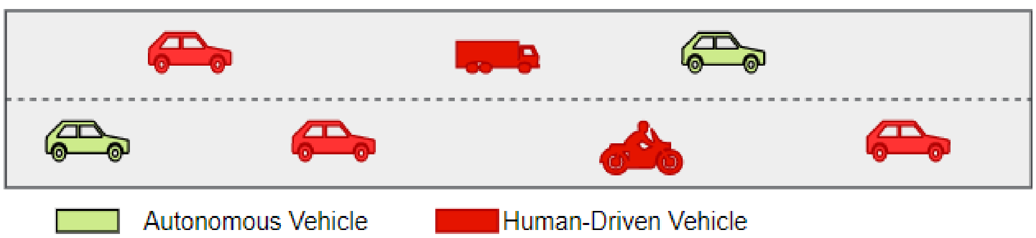


Figure 1: Mixed Driving Environment

In any traffic scenario, the most common driving behavior is a lane change. Millions of accidents occur each year globally, mostly due to improper lane changes. So understanding the behavior of nearby vehicles is very decisive for the autonomous vehicle for safe navigation. But due to the complexity in human driving behavior understanding, lane change and turning behavior intention inference and prediction have become vital in a mixed traffic environment [4]. Considering this, the proposed work suggests a Bi-LSTM with attention to accurately predict the behavior of the surrounding human-driven vehicles in different traffic scenarios. Figure. 2 presents the lane changing behavior of a vehicle in a straight highway. Figure. 3 shows the turning behavior of a vehicle in an intersection.

The rest of the paper is structured as follows: Section 2 discusses the overview of the current state of art methods. Section 3 gives the proposed method. Section 4 presents results of evaluation of the suggested scheme. Finally, Section 5 concludes the paper.

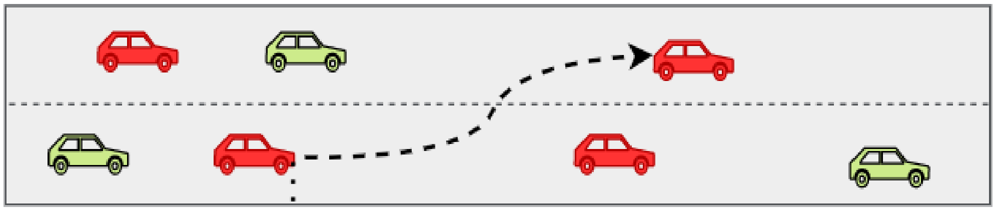


Figure 2: Lane Change Scenario in a straight highway

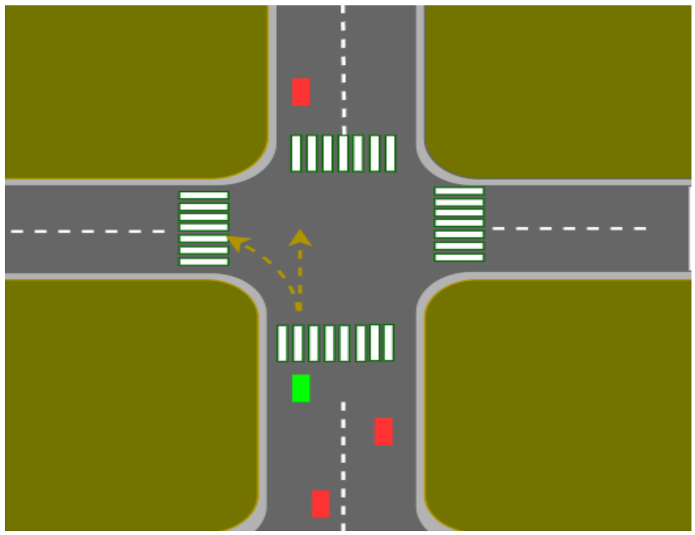


Figure 3: Turning Behaviour in highways

2 Related Works

The extant literature covers a wide range of study aspects in predicting lane change behaviour in autonomous driving. There are different categories of prediction models for a lane change. The most common approaches are based on mathematical and machine learning approaches. One of the mathematical approaches for behaviour prediction is proposed in [5]. A fuzzy and LSTM based prediction approach are presented in [6]. The authors suggested a path planning method which ensures safety of autonomous vehicles. The proposed method is trained and validated using the NGSIM dataset. Baumann et.al introduced an improved cognitive model to characterize the behaviour of drivers in the autonomous driving environments and showed the correlation between the cognitive behaviour of the driver and the movements of the driver [7]. These studies may not consider the surrounding vehicles' behaviour in the real traffic scenarios. Furthermore, these studies obtained a prediction accuracy of 85% to 90%. In order to increase the system's accuracy, researchers have suggested machine learning based models. The authors proposed a Support Vector Machine (SVM) model to identify the lane change behaviors [8]. SVM with Bayesian filtering was adopted in [9]. Several methods have suggested for lane change behaviour prediction using neural networks. A trajectory prediction method using reinforcement learning and graph neural network is proposed in [10]. To increase the potential accuracy of prediction, the authors designed a hybrid neural network using deep learning models in [11]. The system considers the vehicle kinematics data and driver

behaviour Ontology and HMM based approaches are used in [12] for predicting the behavior of vehicles. This work also implements the driver model to give more realistic behaviors. An integrated approach of SVM and ANN is suggested by the authors in [13] for autonomous vehicle decision-making. This model obtained an improved accuracy compared to the simple models. Numerous methods have been presented for behavior prediction in a mixed scenario. The authors propose a highway lane-change prediction method using a double layer structure which uses SVM and HMM/GMM[14]. The binary classification of the trajectory as lane change and lane keep is performed by SVM and then uses HMM/GMM for lane change classification into left and right.
The major contributions can be listed as follows:

- To build a hybrid model for surrounding vehicle lane change and turning inference and behavior prediction using Bi-LSTM with an attention mechanism.
- To estimate the lateral and longitudinal parameters for improving the prediction accuracy.
- To predict the final behaviour considering the interaction aware mechanism to generate an optimal behavior.

3 Proposed Method

This work aims to detect and predict the behaviours of surrounding vehicles in a mixed traffic domain in which the autonomous and human-driven vehicles share the road. Here, a behaviour prediction method based on Bi-LSTM with attention is proposed here to infer and foresee the behaviour of the surrounding vehicles in different highway scenarios. In the current driving scenario, the behaviour prediction which infers the behaviour intention becomes complex since the autonomous vehicles have to co-operate with the human driven vehicles where the understanding the human driver behaviour is complex.

The behaviour prediction must be employed to predict the behaviour of the vehicle accurately. The decision always depends on the current interaction among the vehicles on the road; therefore, the interaction among the vehicles on the road, therefore the interaction among vehicles must be properly modeled. Thus an interactive behavior predictor must be introduced so as to minimize the false positives and improve accuracy.

Thus, a Bi-LSTM with an attention-based model is proposed here for interaction-aware behaviour prediction of lane change behaviour for autonomous vehicles. The structure of the proposed model is given in Figure 4. The proposed architecture consists of intention recognition, behaviour prediction and the interaction aware prediction modules. The intention recognition module uses a Bi-LSTM model for inferring the behaviour of the human driven vehicle. The module collects the ego vehicle states such as velocity, lateral and longitudinal positions and the environment states which include the target vehicle states and lane data. These collected data are fed to the Bi-LSTM model with attention to generate the intention probability of the diverse intentions. The behaviour prediction block predicts the behavior of the target vehicle using the environment states and the intention inference. This module estimates the maximum yaw rate and the behaviour of the vehicle. Then the optimal behaviour is estimated using the intention inference and the predicted behaviour.

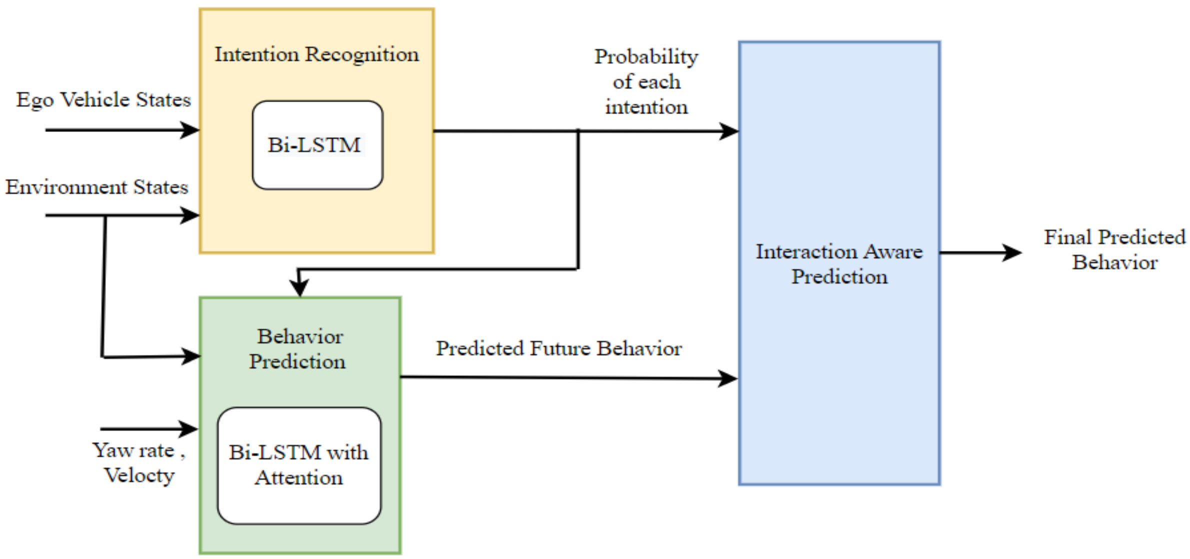


Figure 4: Overall structure of the proposed behaviour prediction system

The vanishing gradient problem in RNN can be solved using LSTM which is having 3 gates and a memory cell. The cell state is the key to LSTM. It is calculated as:

$$S = \frac{h_{t-1}}{x_t} \quad (1)$$

$$f_t = \sigma(W_f \,.\, S + bias_f) \quad (2)$$

$$i_t = \sigma(W_i \,.\, S + bias_i) \quad (3)$$

$$o_t = \sigma(W_o \,.\, S + bias_o) \quad (4)$$

$$k_t = f_t * k_{t-1} + i_t * \tanh(w_k).S + bias_k \quad (5)$$

$$h_t = o_t * \tanh(k_t) \quad (6)$$

where S indicates the cell state, h_t represents the hidden state, f ,i, and o are the forget gate, the input gate and the output gate respectively. W_f, W_i , W_o and W_k denotes the weight matrices, $bias_f$, $bias_i$ and $bias_o$ are the bias of LSTM cells used for training. σ represents the sigmoid function and * is the elementary multiplication.

For any driving system, whether it's a human driver or an autonomous system, the environment always determines the vehicle behaviour. The change of lane and turning behaviour is always influenced by the behaviour of the surrounding vehicles. In order to cope with this uncertainty, the proposed work incorporates an interaction-aware module, to better model the behaviour of the surrounding vehicles. Thus the proposed work makes use of the trajectory history of the vehicles under consideration. Thus the system takes the surrounding environment states, lane information and ego vehicle states as input. The autonomous vehicles obtain the environment states from the on-board sensor data and from the other connected autonomous vehicles. But under the existing traffic scenarios, the on-board sensor data acts as a critical element in providing the major part of the information for the system. The input X to the method can be given as:

$$X = \{A_s , E_s, R_s\} \quad (7)$$

where A_s denotes the Autonomous vehicle states, , E_s denotes the surrounding vehicle states and R_s denotes the lane information. The autonomous vehicle information includes the lateral and longitudinal distances between the vehicles and lanes, velocity and steering angle of the vehicles and R_s denotes the lane information. In this work, eight surrounding vehicles are considered as interacting vehicles with the ego vehicles. E_s includes the lateral and longitudinal positions and velocity of the eight interacting vehicles. The information about the eight adjacent vehicles is sufficient enough to model the interactions of the ego vehicle.

The intention recognition module considers the lateral position to infer the behaviour of the vehicle. The ego vehicle states and environment states are given as input to the system and the output from the system identifies lane change and lane keep behavior. This output can be used to classify the behaviour of the surrounding vehicles into lane keep, left or right lanes in a straight highway and left and right turns and straight move at intersections. The system makes sure that it completely avoids the multiple lane changes, false lane changes and false turnings. A Bi-LSTM-based model is used for estimating the probability of each intention of the vehicles. In this proposed approach, Bi-LSTM is used which consists of two independent LSTM to transfer the information in forward and backward direction and then merges the information. At each time period, the forward LSTM calculates the hidden vector $f_{h(t)}$ based on m previous vector $f_{h(t-1)}$ and input x_t. The backward LSTM computes the hidden vector $b_{h(t)}$ based on the previous vector $b_{h(t-1)}$ and input x_t. These hidden vectors are merged together to form the final hidden vector. This structure helps to learn the long-term interactions and improves the prediction accuracy. The Softmax function can be used to generate the intention probability for each behavior.

The behavior of the surrounding vehicles depends on the present state of the vehicle and also the history information. But not all the data has an equal contribution to the prediction module. An attention mechanism extracts the most critical information from the provided information. In the attention layer, a Multi-layer perceptron is used to get a new hidden vector. Then a weight value for each input feature is calculated from the new hidden vector p_t from $h_t$and context vector c_t. c_t gives a high dimensional representation for getting the importance of different parameters and this is randomly initialized and learned during the process of learning. The weighted mean of the hidden vector is calculated using the softmax function. The function calculates the similarity between p_t and c_t.The following equations can be used.

$$p_t = \tanh(W_t \ \ h_t + bias_t) \tag{8}$$

The Softmax classifier takes the vectors and classifies them into 3 lane change behaviour classes such as lane changes to left, right and lane keep. The interaction aware module is attached to enhance the safety of the vehicle. It considers the interaction of the autonomous vehicle with other vehicles in the scene. Here, the collision probabilities of each vehicle to the autonomous vehicle are considered to enhance the accuracy. Here, the system takes a group of eight surrounding vehicles and consider their interaction within the autonomous vehicles. These eight vehicles can be autonomous vehicles or human driven. These data are collected from the onboard sensors. The assumption is that these eight vehicles are the closest vehicles that can affect the behaviour of the autonomous vehicles and all the other interactions are neglected. Whenever a vehicle wants to change the lane, it must first consider the interaction with these adjacent vehicles and check for the collision-free gap between the vehicles in the neighboring lanes. The vehicle reduces its speed gradually, turns the steering angle and then decides whether to change lane or not based on the collision index. At intersections, the vehicle starts to decelerate, then based on the collision index it starts to increase the speed and travels away from the intersection. The intention recognition and behavior prediction modules obtain the probability of each intention and predict future behavior. The false predictions obtained from the intention recognition module must be eliminated. The input data collected from the other modules are used for the false prediction elimination.

The objective of the interaction-aware prediction module is to consider the probabilities of intention and collision risk between surrounding vehicles to minimize the cost function. In this proposed approach, the cost function is calculated considering the intention probability, collision probability with target vehicle and collision probability with other nearby vehicles. In the existing studies, the collision probability with the nearby vehicles has not been considered. The collision function under various speeds is based on the Gaussian distribution. Probability of collision of ego vehicle with target vehicle while generating the trajectory x can be framed as: $P_{ix}^{ego} = \left[\sum_{n=1}^{p}\left((X_{ego}(n) - X_{i,x}\,(n))^2\right) - \left((Y_{ego}(n) - X_{i,x}\,(n))^2\right)\right]^{-1}$ (9)

where P_{ix}^{ego} denotes the probability of the collision of ego vehicle with target vehicle.

The collision probability between the different target vehicles while generating the trajectory x can be framed as:

$$P_{ijxy} = \left[\sum_{n=1}^{p}\left((X_{i,x}(n) - X_{j,l}\,(n))^2\right) - \left((Y_{i,x}(n) - Y_{j,l}\,(n))^2\right)\right]^{-1} \quad (10)$$

where i and j denotes target vehicles. The probability is calculated for the different combinations of eight surrounding vehicles. Then the cost function can be generated as:

$$Cost\ function = \sum_{i=1}^{N}[P_{ix}^{traj} + \mu_1 P_{ix}^{ego}] + \mu_2 \sum_{i=1}^{N}\sum_{j=1}^{N} P_{ijxy} \quad (11)$$

where μ_1 and μ_2 are the weight factor that can be used for the observation.

4. Results and discussions

Two scenarios are considered in this work and the validation results of the two scenarios are given.

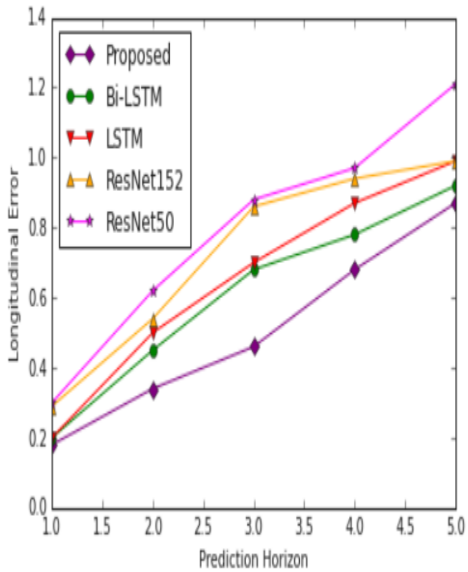
Scenario 1

In this scenario, the straight highway is considered for validating the proposed approach. The NGSIM dataset gives a complete idea of vehicle trajectory, providing the number of lane changes and surrounding vehicle information, thus reducing the pre-processing time. The proposed system is simulated using MATLAB Simulink. The Cartesian coordinate system is used in this work to extend the proposed method for curved roads. The results suggest that the proposed methodology outperforms other existing methods.

The results of evaluation metrics for the proposed approach for lane change behavior in a straight highway is compared with other models.

1. Average Displacement Error(ADE)

In this proposed lane change behavior prediction approach for the given scenario, the ADE is calculated in different prediction horizons. The system uses a 5s prediction horizon since this can model the vehicle behavior well. The error generated is compared with the error of different models and is observed that the suggested model is better than other models. The root mean square error is calculated over all the predicted trajectory positions in different prediction horizons. The longitudinal and lateral position errors are shown in Figure 5 (a) and Figure 5 (b). The proposed model improves the prediction performance in the lateral direction and the lateral error is less than the longitudinal error.



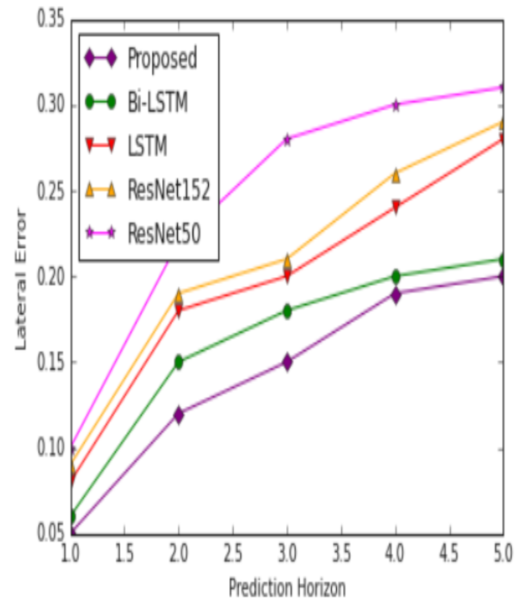
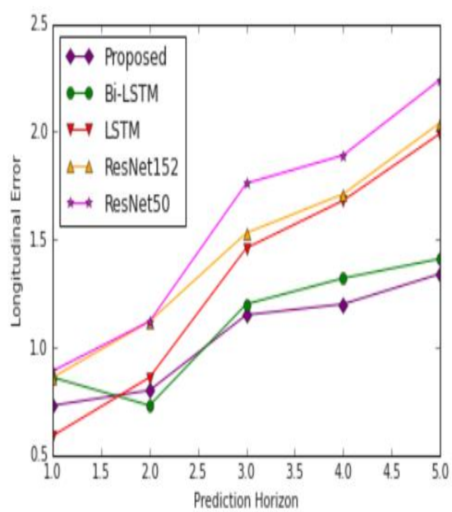


Figure 5 (a): Longitudinal Error

Figure 5 (b): Lateral Error

2. Final Displacement Error (FDE)

FDE considers the difference between the predicted and true trajectory points in the different prediction time horizons. The table shows the performance in different time horizons. The results show that the proposed model has the least errors in different prediction horizons. The distance between the predicted and actual position at different prediction horizons are given in table Table II (a) and table Table II (b). The longitudinal and lateral errors for different prediction horizons are shown in Figure 6 (a) and Figure 6 (b)



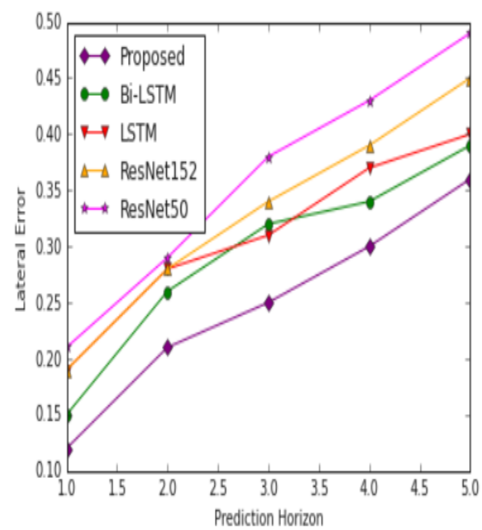


Figure 6 (a): Longitudinal Position Error

Figure 6 (b): Lateral Error

3. minADE, minFDE and Miss Rate

The Table III presents the performance of the suggested method in terms of minADE, minFDE and miss rate. The results indicate that the trajectory predicted by the model is closer to the ground truth trajectory.

Table 1 minADE, minFDE and Miss Rate of different models

Model	minADE	MinFDE	Miss Rate
Proposed	**0.803**	**1.34**	0.14
Bi-LSTM	0.92	1.875	**0.084**
LSTM	0.98	1.932	0.136
ResNet152	1.02	2.45	0.172
ResNet50	1.834	2.984	0.193

Scenario 2

The turning behaviour in the intersection is validated using the NGSIM dataset. Here, the system predicts the turning behaviour of the vehicle before the start of the behaviour. The vehicle turning behaviour includes turning to left, turning to right and moving straight. In an intersection, the turning vehicle starts to decelerate, then slowly accelerates and moves away from intersections.

Different evaluation metrics are used for analysing the prediction results of the model in a highway intersection. The different behaviours of the surrounding vehicle in an intersection such as left and right turns and straight move are examined. The results of the comparison for each metric are given below.

1. Average Displacement Error (ADE)

ADE for different prediction horizons in each model is calculated and values are given in the table, Table V. The Table V (a) shows the longitudinal error and Table V (b) shows the lateral error in different prediction horizons. Figures Figure. 7 (a) and Figure 7 (b) show the longitudinal and lateral errors respectively for different prediction horizons. The system predicts the behaviour over a prediction horizon of 5 seconds. The prediction horizon of 5s well anticipates the vehicle behaviour. From the values obtained, it is clear that the proposed hybrid approach for turning behaviour prediction outperforms the other existing models. The longitudinal error is more compared to the lateral error. Thus the proposed model improves the prediction performance mainly in lateral direction.

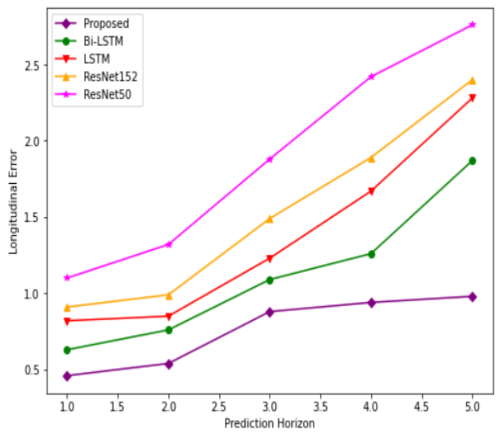


Figure. 7 (a): Longitudinal error

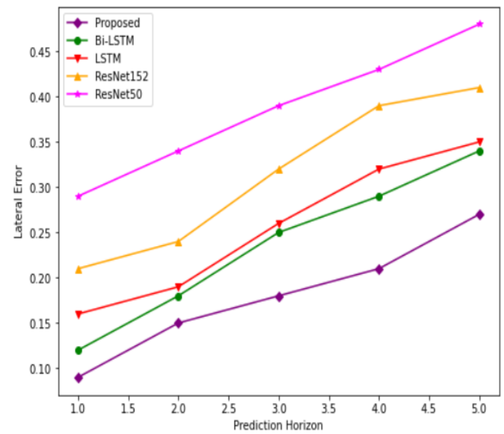


Figure 7 (b): Lateral Error

2. Final Displacement error (FDE)

The FDE of the positions of the vaehicle in longitudinal and lateral directions for different prediction horizons are given in tables Table VI (a) and Table VI (b). The system considers prediction horizons of 5s is considered in this paper since the turning behaviour can be well executed within 5s. The lateral error is less than the longitudinal error and the performance of the suggested model is increased as the lateral error is decreased. Figure 8 (a) and Figure 8(b) gives the lateral and longitudinal error in different prediction horizons.

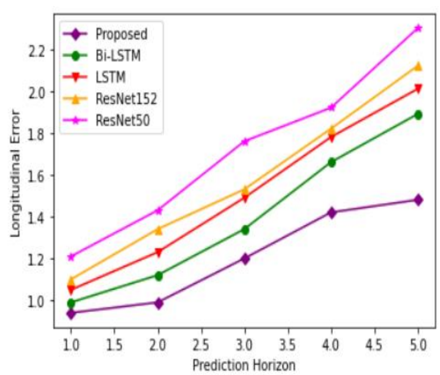


Figure 8 (a): Longitudinal error

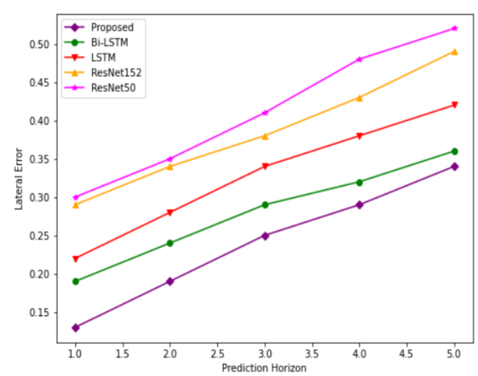


Figure 8 (b) : Lateral Error

5. Conclusion

A hybrid model for recognizing and predicting the lane change and turning behaviour of the surrounding vehicles at different traffic scenarios in a mixed driving environment is proposed using Bi-LSTM with attention. Real-world data, NGSIM dataset is used for training the system in the straight highway and intersection. The various behaviours of the surrounding vehicles are estimated and the behaviour is predicted before the trajectory begins. The proposed model works well under different traffic scenarios. This proposed method can be further extended to generate the future trajectory in different scenarios. The Bi-LSTM with attention can learn long-term dependencies which provide better performance. This can be extended from the above discussed road scenarios to more complex scenarios. The more complex datasets also can be used to validate the proposed system such as non-lane roads and unsignalized intersections in the developing countries.

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