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An Ensemble Model for Lane Change Intention Inference for Autonomous Driving

Syama R
Department of Computer Science and Engineering
National Institute of Technology, Trichy
Tamil Nadu, India
{Assistant Professor, Department of Computer Science and Engineering, SCT College of Engineering, Pappanamcode}
syama.nitt@gmail.com

Dr. C Mala
Department of Computer Science and Engineering
National Institute of Technology, Trichy
Tamil Nadu, India
mala@nitt.edu

***Abstract* - Advanced Driver Assistance System (ADAS) requires an accurate and timely recognition and prediction of the lane change intention of the driver for decision making. Traditional intention models are based on mathematical, logical and machine learning which struggle to adequately represent the entire lane change process. Here, a novel ensemble model is proposed for identifying the lane change intention of human-driven vehicle before the trajectory begins by analyzing the various factors in discretionary lane change of vehicles in hybrid traffic scenarios where the autonomous and human-driven vehicles coexists. The proposed ensemble model combines the Support Vector Machines (SVM) and Random Forest (RF) to precisely identify the lane change behavior. The model is evaluated using the benchmarked dataset NGSIM which includes naturalistic highway driving data consisting of different lane change scenarios. The ensemble model is compared with other models and shows an average accuracy of 96% for different lane change maneuvers.**

Index Terms - Intention Inference, Autonomous Driving, Ensemble Model.

I. INTRODUCTION

The vehicles that sense their surroundings and move without human interventions are referred to as autonomous vehicles. The primary motivation for the development of autonomous vehicles is the need for safe, energy-efficient, sustainable, and comfortable transportation services. In the existing mixed scenario, the autonomous vehicles must share the roads with the human-driven vehicles. Thus there is a need for accurately estimating the intention or future movement of the surrounding vehicles for safe and efficient operation [1]. The automation can be implemented by several processing steps such as sensing, prediction and planning. The prediction step defines the actual decision-making process in autonomous vehicles. It requires the understanding of the intention of the various agents in the traffic environment [2].

The decision-making process of autonomous vehicles becomes more intricate when they operate in a mixed driving environment where they co-operate with the human driven vehicles also. In order to determine the movements, the autonomous vehicles must clearly observe the environment and anticipate the decisions of the human driver in the real world. Fig. 1 shows the lane change process in a mixed traffic environment.

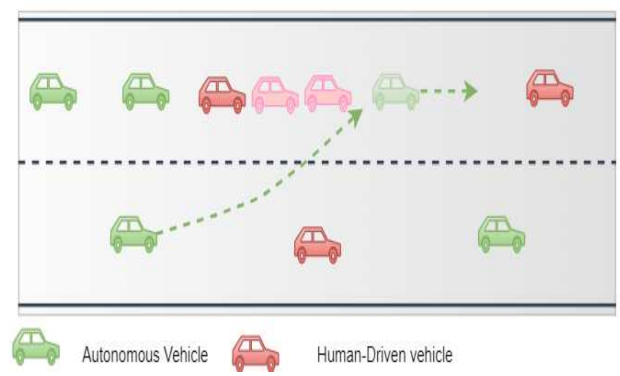

Fig. 1. Lane change in a straight highway

The lane change behaviour is the most common and is the most studied driving behaviour since a large number of accidents occurred in highways are due to the improper lane changes [3]. In a straight highway, the driver changes the lane for offering better traffic conditions like to obtain a desired speed, avoid the traffic, to avoid some vehicles etc. As soon as the driver decides to move to the adjacent lane, he checks whether the conditions are satisfactory to change the lane. If the driving conditions are not satisfactory, it decides to stay in the same lane. For these driving behaviours to be accurately predicted, the dynamic interactions among the drivers should be properly modelled.

Many studies have been conducted on vehicle behaviour prediction in autonomous driving systems since it is an important stage in path planning for autonomous driving in Advanced Driving Assistance Systems (ADAS). In recent years, a wide range of methods for predicting vehicle behaviour have been presented ranging from traditional approaches to deep learning methods. But most of them failed to consider the behaviour of the surrounding vehicles. They failed to accurately infer the change in the lane of the vehicle before it begins.

Thus in this paper, the lane change intentions of the surrounding human driven vehicles is identified so that the autonomous vehicle can accurately predict the lane change before it occurs. The proposed work aims on estimating the lane change in a mixed vehicle scenario where the autonomous vehicles interact with human-driven vehicles. A novel ensemble model is suggested and is compared with the existing machine learning approaches. The ensemble model outperforms the other models in each of the prediction horizons. The proposed model is validated using the benchmarked dataset, NGSIM (Next Generation SIMulation) which consists of different lane change behaviours.

The rest of the paper is organized as follows: Section II discusses the existing methods for lane change prediction. Section III presents the proposed intention detection model. Section IV addresses the evaluation results of the proposed scheme. Section V presents conclusion and future work which is followed by References.

II. Literature Review

In any traffic environment, irrespective of whether it is a vehicle driven by human or an autonomous vehicle, the response from the vehicle is based on the stimulus of the surroundings. Human-driven vehicles may have several styles of driving and same situation can be handled in dissimilar ways by distinct drivers. Driving choice may change for different passengers. Autonomous vehicles need to take decisions dynamically in the mixed scenario. It should also be adaptive to meet the requirements of different traffic scenarios. Adequate research has not been carried out on the adaptive and dynamic decision making for autonomous driving. The driving styles of the human drivers are generally decided by the behaviour of the drivers and environmental factors. [4] [5].

Traditional lane change studies concentrated on lane change warning systems. Some researchers explored the vehicle's lane change intention recognition in lane change warning systems to generate warnings when lane change occurs. The authors have presented an adaptive fuzzy neural network to predict the steering angle of the driver [4].

There are several studies on the lane change behaviour of the vehicle which mostly focused on modelling lane change behaviour and classifying the drivers based on the behaviours. A Hidden Markov Model based approach is used for modelling the lane change behaviour of different drivers in [5]. Position, speed and relative speed of the vehicle are considered to predict the driving track. [6] Proposed a vehicle lane change behaviour recognition system which uses the lateral and longitudinal position, kinematic parameters etc. to analyse the driver's lane change intention. Generally different parameters affect the lane change behaviour such as driving environment, road conditions and the driver. So it becomes more complex to model the lane change intent inference system.

A number of researches on vehicle behaviour prediction have been published. [8] Provides a study on vehicle monitoring, behaviour prediction and analysis. In order to identify and predict the surrounding agents' behaviour in the traffic environment in highway scenarios, several studies have undergone in different literatures [6]. The lane change behaviour detection and prediction studies have been classified into different categories in [7]. Physics based prediction systems are proposed in [8] while [9] concentrates on intended manoeuvre. Some others consider the interaction between different agents in the environment [10]. The basic SVMs used in [11] failed to model the spatial interactions of vehicle and trajectories.

There are only very few studies that shows the driver to make lane changes without the driver initiation. SVM-based lane change initiation method is proposed [12] and the SVM algorithm requires more research. A Random Forest model is proposed for lane change decision in [13]. The discretionary lane changes of human-driven vehicles are analyzed and based on this, the factors that affect the decision-making in actual driving situations are selected. But it failed to consider the surrounding participants. Bayesian Networks (BN) was utilized by [14] to estimate the likelihood of lane shift. A Multi-parameter lane change decision-making using SVM together with the Bayesian optimization is discussed in [15].

The existing literatures have failed to study the target vehicle's lane change behaviour in a mixed driving scenario considering the surrounding vehicle information. Limited study has been done so far to infer vehicle lane change behaviour by taking into account the influences of surrounding cars. Considering this, a novel intention decision model lane change in autonomous driving is proposed in this paper which uses an ensemble model for predicting the lane change scenarios in a straight highway in a mixed driving environment.

III. METHODOLOGY

A. *Intention Detection Model Used*

Lane change intention inference method is suggested using an ensemble model. In a mixed traffic scenario, the autonomous vehicles coexist with the autonomous vehicles. The vehicle whose intention is to be inferred is known as ego vehicle and the other vehicles under consideration are termed as surrounding vehicles. Lane change in the straight highway driving scenario is considered in this paper as shown in Fig. 1. The intentions of the vehicles are Lane Change to Left, Lane Change to Right and Lane Keep. The SVM and Random Forest classifiers are used as base classifiers in this proposed work. The vehicle's mobility features are extracted and are given to the base classifier models.

Various factors influence the lane change decision in a driving scenario. The lane change in the traffic environment includes a source lane and a target lane. The driver decision always depends on the surrounding vehicles' behaviour and the road characteristics. These behaviours and interactions among vehicles must be modelled properly in order to infer the lane change behaviour of vehicles accurately. SVM can classify the different lane change behaviours properly using the margin maximization. A hyperplane is calculated which can be used to maximize the margin between the elements of different classes. The kernel feature of SVM enables to project the data from the low dimensions to higher dimensions and thus convert the non-linear problem in lower dimension to a linear problem in higher dimension.

For the lane change intention inference, the following feature vectors are used.

- The Lateral and Longitudinal positions of the vehicle with respect to the lane
- Velocity
- Acceleration
- Steering angle.

These selected features well classifies the lane change intentions into the three desired categories, Lane change to Left, lane change to Right and Lane Keep. A sliding window approach can be used to define the different activities in the lane change process. The 'rbf' kernel is used by the SVM to get the probabilistic output from SVM.

The accuracy of this model is fairly good but the real world scenarios are really complex and thus the predicted accuracy may not be sufficient in all the real world conditions. So the Random Forest (RF) is applied to accurately identify the lane change intentions. The Random Forest optimum model is trained on the test set of the SVM algorithm. Random Forest method itself is an ensemble method combining bootstrap aggregating and random subspace. The generalization property in random forest can produce more robust results. A random number of decision trees are used here for prediction the lane change intention. The predicted intentions generated from SVM and RF is fed to a meta classifier based on logistic regression to enhance the result of classification. The overall process is shown in Fig. 2.

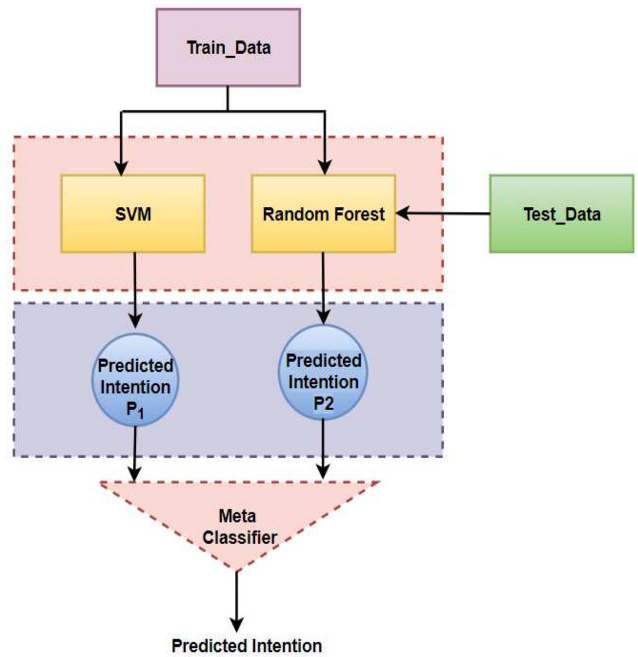

Fig. 2 Lane change intention inference process

TABLE I shows the training and testing data sample details for both lane change and lane keep scenarios.

TABLE I TRAINING & TESTING SAMPLES

NGSIM DATA	Lane Change	Lane Keep	Total
Train_Data	471	639	1110
Test_Data	102	173	275

B. Training and Testing Data

The benchmarked dataset, NGSIM US-101 is used for training and testing purpose which consists of realistic driving data [17]. In order to make the data suitable for training and testing and less noisy, smoothing is done on the data. The smoothing is done on the lateral and longitudinal values and the velocities and acceleration are recalculated for the smoothed lateral and longitudinal values. The lane change data is extracted from the NGSIM dataset after smoothing is done. A random sample of 1480 is extracted from the dataset in which 573 are lane change samples and remaining is lane keep samples.

IV. EVALUATION

Simulation is carried out using SIMULINK for the three lane change scenarios, Lane change to left, Lane change to Right and Lane Keep to verify the proposed model. In order to evaluate the performance, a different evaluation criterion which uses value of prediction horizon is used.

The prediction horizon is an important factor in the lane change intention inference. Generally, the lane change process can be considered as consisting of four different activities: the instant the driver of the vehicle decides for a change of lane (t1), the moment the driver checks the adjacent lanes and start to change the lane (t2), the moment the driver crosses the lane (t3) and finally the moment it completes the lane change (t4). This process is depicted in Fig. 3.

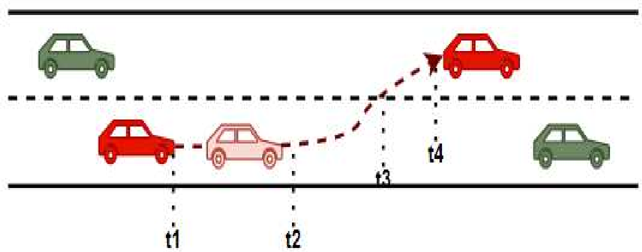

Fig. 3 Lane change process

The model proposed here is validated for different prediction horizons to accurately identify the lane change intentions of the surrounding human driven vehicle. The RMSE for the predicted intensions are as shown in Table II.

TABLE II RMSE FOR PREDICTED LANE CHANGE INTENTIONS

Model	**Prediction Horizon**			
	2s	**3s**	**4s**	**5s**
SVM	3.78	4.21	5.38	7.22
Random Forest	2.57	3.14	4.34	5.75
Proposed	2.2	2.68	3.9	4.77

When the vehicle starts to change the lane, the lateral velocity of the vehicle first reduces a bit and then suddenly increases and during the entire process it is maintained. The lateral position of the vehicle also changes to a particular direction depending on the direction. The lateral velocity of the vehicle with Vehicle_ID 43 from the NGSIM dataset is shown in Fig. 4 and Fig. 5 shows the lateral position of the vehicle with Vehicle_ID 43.

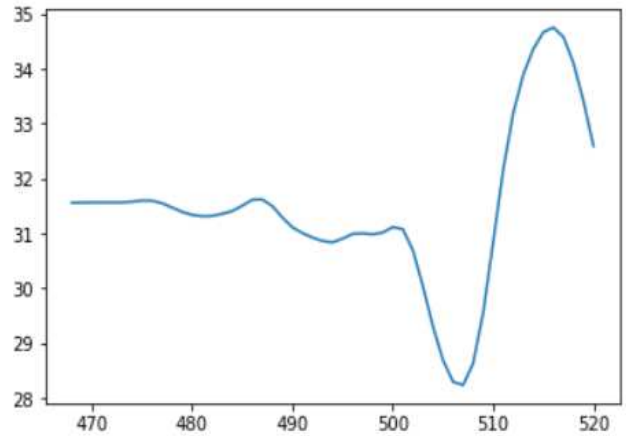

Fig. 4 The lateral velocity of the vehicle with Vehicle_ID 43.

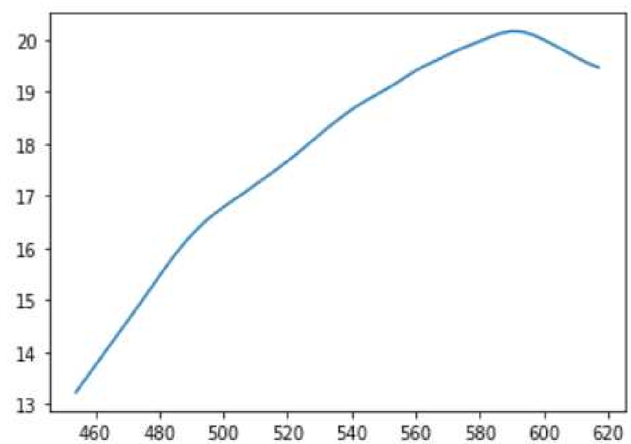

Fig. 5 The lateral position of the vehicle with Vehicle_ID 43

The intention accuracy of the proposed method is compared with the intention accuracy of SVM and Random Forest models. The Fig. 6 shows the intention accuracy of different models used in this work. From the figure it is clear that the ensemble model outperforms the other models.

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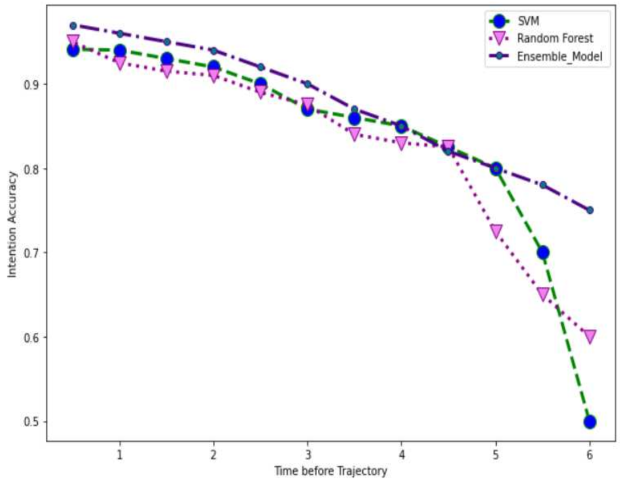

Fig. 6 Intention Accuracy for Different Models

The true positive rate (TPR) and false positive rate (FPR) are used to denote the performance of the different models. The main aim is to maximize the TPR and minimize the FPR. The precision, recall and F1 Score of the different models considered for evaluation are shown below.

TABLE II VALUES OF PRECISION, RECALL AND F1 SCORE FOR SVM

	SVM		
	Precision	**Recall**	**F1 Score**
Lane Change to Left	96.8	85.2	90.4
Lane Change to Right	80	93.8	85.8
Lane Keep	95.3	95.1	93.5

TABLE III VALUES OF PRECISION, RECALL AND F1 SCORE FOR RANDOM FOREST

	Random Forest		
	Precision	**Recall**	**F1 Score**
Lane Change to Left	95.2	92.1	93.5
Lane Change to Right	92.9	92	92.3
Lane Keep	95.8	93.1	94.1

TABLE IV VALUES OF PRECISION, RECALL AND F1 SCORE FOR ENSEMBLE MODEL

	Ensemble Model		
	Precision	**Recall**	**F1 Score**
Lane Change to Left	95.3	98.1	95.7
Lane Change to Right	95.2	92.5	93.7
Lane Keep	98.6	95.2	96.3

IV. CONCLUSION AND FUTURE SCOPE

This paper addresses the lane change intention inference problem in autonomous driving. An ensemble model for lane change intention is proposed. The proposed model is validated using the NGSIM US-101 dataset for the different lane change scenarios. The ensemble model outperforms the other models in all the three lane change scenarios. This proposed method can be used in autonomous driving for decision-making. The model can be further extended for predicting the trajectory of the vehicle and can be used for trajectory planning.

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