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Artificial Intelligence for Vehicle Behavior Anticipation: Hybrid Approach Based on Maneuver Classification and Trajectory Prediction

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ABSTRACT Innovative technologies and naturalistic driving data sources provide a great potential to develop reliable autonomous driving systems. Understanding the behaviors of surrounding vehicles is essential for improving safety and mobility of autonomous vehicles. Onboard sensors like Radar, Lidar and Camera are able to track surrounding vehicles motion and to get different features like position, velocity and yaw. This paper proposes a hybrid approach to integrate maneuver classification using neural networks and trajectory prediction using Long Short-term Memory (LSTM) networks to get the future positions of adjacent vehicles. In this study we use the Next Generation Simulation (NGSIM) public dataset that provides a real driving data. The proposed approach is validated experimentally using VEDECOM demonstrator data. The results demonstrate that the proposed approach is able to predict driver intention to change lanes on average 2.2 seconds in advance. The Root Mean Square (RMS) errors of lateral and longitudinal positions are 0.30 m and 3.1 m respectively. The results demonstrate a high performance compared to various existing methods.

INDEX TERMS Artificial intelligence, autonomous vehicle, intention prediction, LSTM, maneuver classification, neural networks, trajectory prediction.

I. INTRODUCTION

The technologies used in intelligent transport systems, especially in autonomous vehicles, are today at the heart of the research and innovation activities of many research teams. Perception, sensor data fusion, motion planning and control are the main technical challenges to ensure secure and safe autonomous driving. Motion planning in dynamic environments is a very active research domain found in many applications. In the context of autonomous driving, it refers to the process of deciding on a sequence of actions to reach a specified goal. Motion planning uses sensors data fusion such as the location of obstacles, road signs and marking to

bring the vehicle from start location to a goal location while avoiding obstacles and respecting road structure.

An autonomous vehicle deployed in complex traffic needs to have the ability to predict the future motion of surrounding vehicles (Fig. 1). Sensors reaction and data fusion time constitute the processing delay in the autonomous system. In critical cases, processing delay may not leave enough time to avoid collision. However, motion planning needs to know in advance how the traffic participants that share the same environment will move. In order to anticipate the motion of vehicles and increase the level of safety, many solutions are proposed to predict the intention of target vehicles. To address this issue, many studies have attempted to incorporate different models to identify vehicle future motion. These models are classified into three main classes [1]–[4]:

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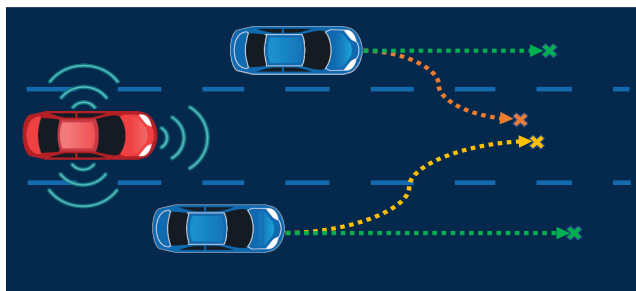


FIGURE 1. Representation of the driving scene: Maneuver classification and trajectory prediction from an autonomous vehicle.

physics-based motion models, maneuver-based motion models, and interaction-aware motion models.

With the development of Artificial Intelligence (AI), intelligent driving technology has made a great progress. Deep Learning and AI are the main technologies behind many breakthroughs in autonomous driving. Therefore, intention prediction begin to migrate from classic models to AI based models.

In the state of art, two principle approaches based on AI are used to anticipate the motion of the vehicle: maneuver classification and trajectory prediction.

A. MANEUVER CLASSIFICATION

Maneuver classification or situation recognition are two terms used to address the problem of understanding the driver's behavior. In the intelligent vehicle community, many works on this topic have been devoted in recent years. Regardless, a full understanding of traffic scenes remains challenging. Lane Change (LC) is a maneuver that allows drivers to enter a lane that suits their requirements and comfort.

LC is a succession of critical actions that needs constant attention and correct assessment, which makes it one of the most common causes of accidents on highway [2]. The turning lights cannot be used as an indicator of lane change because 48.35% of drivers fail to comply with appropriate turn signal usage when executing a lane change maneuver [5]. If safety support system can anticipate actually lane change before other vehicles cross the lane marking, accidents rates can be significantly decreased. Lane change prediction problems are mainly treated as classification problems [3], [4], [6]–[9]. This maneuver can be classified into three main classes: Left Lane Change (LLC), Right Lane Change (RLC) and Lane Keeping (LK). For the detection of lane change performed by other drivers, perception sensors data should be used as features. The properly selected features determine the detection performance [8]–[11].

This problem is addressed in the literature from different points of view, most of them are based on probabilistic methods. Bayesian Networks Approach proposed to recognize driving maneuvers on highways and the experiments are performed on real world vision data [6]. The authors of [3] used Hidden Markov Models (HMM) for situation modeling

and recognition. A maneuver is defined as a distribution over sequences of states, the HMM try to identify each one of these states. The approach was evaluated on real data for highway driving in many situations, it was able to recognize and track multiple situation instances. However, we note that the most recent works use machine learning based approaches: Support Vector Machine (SVM) [4], [7], [8] and Random Forests [9]. This type of models relied on vehicle dynamic data as input to detect driver's intention of lane changing and finally a multiclass probabilistic output would be given as results.

Artificial Neural Networks (ANN) have also been considered to identify the driver's intention for lane change [10]–[12]. ANN try to learn the pattern of human reasoning, learning and cognitive capabilities of driving using the factors influencing the driver' lane-changing decisions. In recent years, and based on their success in other domains, more advanced methods utilizing Recurrent Neural Networks (RNN) [14], deep learning [15]–[17], and reinforcement learning have arisen as well [18]. Convolutional Neural Networks (CNN) are also used for LC detection using image prediction [19], [20]. Learning based approaches require high-quality motion datasets containing interactive real-world driving scenarios for training and testing. A short overview of used datasets will be given in the following sections.

B. TRAJECTORY PREDICTION

Vehicle trajectory prediction represents a significant body of research in autonomous vehicles field. Kinematic and dynamic motion models are well studied for motion predictions [1]. The common approach consists of prediction vehicle trajectories by propagating its state over time. It uses assumptions of underlying physical system and by assuming that one or more state variables like speed acceleration and heading are constants for a period of time [1], [21], or by using techniques such as Kalman Filter (KF) [22]. However, these approaches are limited to simple patterns of vehicle motion. Moreover, while this approach performs well for short-term predictions, its performance degrades for longer prediction horizons [1].

Many other techniques have already been explored to overcome these limitations, such as maneuver-based models, to predict the vehicle trajectory at a higher level. This model can be combined with prediction techniques to estimate the next position of the vehicle. An LSTM model that outputs the multi-modal distribution over future motion is portrayed in [23]. This model generates future trajectories of surrounding vehicles by learning a model that assigns probabilities to six maneuver classes. A model based on driving behavior estimation and classification using Hidden Markov Models is exhibited in [24]. The trajectory prediction method generates different statistical trajectories based on the classification results. Dynamic Bayesian Network based filter is proposed in [25] to simultaneously estimate the current position, the type of the situation as well as the anticipated

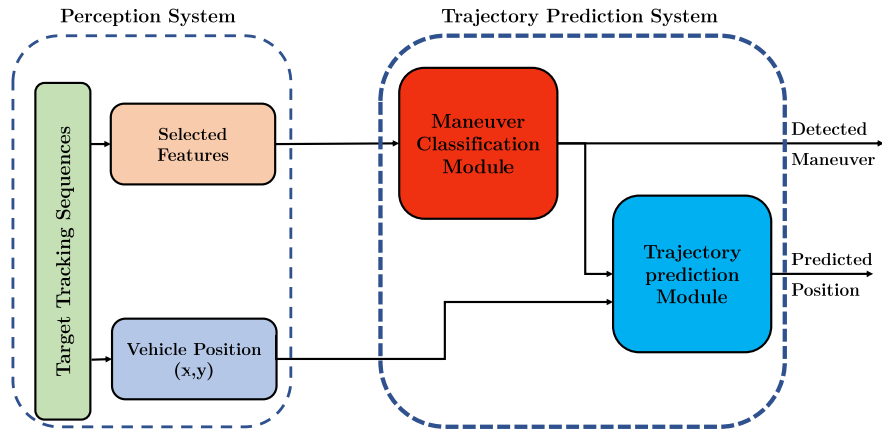


FIGURE 2. System overview: Integration of Maneuver classification and trajectory prediction based approach.

trajectory of traffic participants. Some methods integrate motion models combining to ensure more accuracy in both long-term, and short-term prediction. For example, physics- and maneuver-based models were combined [26]. The probability of trajectory prediction of each model was interacted, mixed, combined, and updated to predict the long-term vehicle trajectory using an interactive multiple model trajectory prediction.

In recent works, researchers focused on machine-learned prediction models. One line of research follows the recent success of recurrent neural networks, namely: Long Short-Term Memory (LSTM) [27]. LSTM networks have successfully been proven to perform well with long sequence applications [28]. The memory cells enable the networks to improve prediction feasibility by combining its memories and the inputs. In the main time, the forget gate defines the information from the old state that can remain in the network. LSTM-based approaches are able to predict vehicle position in horizons up to two seconds. In [29], authors proposed an LSTM-based approach that predicts the location of vehicles in an occupancy grid at intervals of 0.5 s, 1 s and 2 s in the future. In [30], an LSTM encoder-decoder framework is applied to predict future trajectory sequence of surrounding vehicles in real time. They proposed a Deep Neural Networks (DNN) architecture based on LSTM to obtain the lateral acceleration and longitudinal velocity 10 s in the future. Prediction accuracy is in the order of 70 cm for the lateral position and lower than $3m.s^{-1}$ for the longitudinal velocity. This approach did not perform well in LC situations. In addition, a prediction horizon of 10 s is not always accurate because human behavior is not predictable for more than 5 s, especially in a highway environment.

The contribution of this paper could be summarized as follows:

- Learn a hybrid model of vehicle trajectory prediction that is based on ANN maneuver classification and LSTM trajectory prediction.
- It was a bright idea to evaluate NGSIM trained model with on-board sensors data. This could provide a valid

reference while selecting proper dataset for trajectory prediction.

The remainder of this paper is divided into the following sections. A system overview is introduced in Section II. Section III describes the driving behavior representation and the features selection. Section IV details the specific implementation of the proposed approaches and presents the experimental results to prove the effectiveness of the proposed approach. Finally, Section V concludes the paper with an outlook and a discussion of future work directions.

II. SYSTEM OVERVIEW

This work aims at developing a framework for trajectory prediction based on Artificial Neural Network (ANN) and deep LSTM Recurrent Neural Networks from an autonomous vehicle (Fig. 2). We propose a new hybrid model that combines maneuver-based approach and trajectory prediction. We focus on LC intention prediction for the case of highway traffic. The target vehicle is considered as an independent agent, so that the interaction with other vehicles is not taken into account. Lane change event occurs when the vehicle trajectory segment and the lane marking intersect. Through our previous work [33], the results demonstrate that the driver's intention for lane change can be detected more accurately by using ANN-based models. ANN uses driving sequences as input to classify maneuvers. We define the classification task as the recognition of three maneuver classes: left lane change, right lane change and lane keeping. LSTM trajectory prediction module takes the output of classification with a sequence of past locations of the target vehicle to giving the future locations of this vehicle at that time instant.

The system is subdivided into two main parts: maneuver classification and trajectory prediction, as shown in Fig. 2. In the maneuver classification part, the current driving maneuver of the target vehicle is estimated via Artificial Neural Networks. For this purpose, an ANN is fed with measured vehicle features, which are supposed to be available from perception system that uses on-board vehicle sensors

data. The prediction part takes classification results with the history locations to predict the new position of the vehicle. Therefore, if we knew the accurate maneuver performed by the driver, the prediction model would generate the trajectory that overlays with the performed maneuver.

A. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a system inspired by the functioning of biological neurons configured to perform specific tasks such as: pattern recognition, signal processing, learning by example, memorization and generalization. An ANN is organized in layers (Fig. 3), each of these layers comports several neurons, each of these neurons, that represents an autonomous processing unit, is connected to the totality or certain neurons of the preceding layer. It is a supervised learning algorithm that learns a function by training on a dataset.

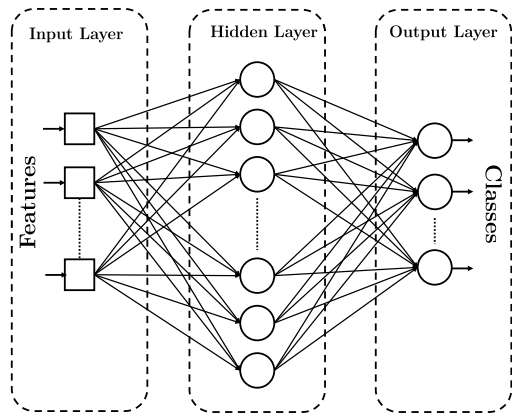


FIGURE 3. Artificial Neural Network.

Given a set of features and a target, an ANN is able to learn a non-linear approximator for either classification or regression. It is a complicated, non-linear, dynamic system in which the neurons are connected in some topological structure. The multilayer feed forward network (MLF) is the most commonly used network. The ANN approach performs well in many pattern-classification applications [34], [35]. The number of processing elements in the input layer corresponds to the number of features obtained in the maneuver dataset. The output nodes represent the maneuver classes.

B. LONG SHORT-TERM MEMORY

Long Short-Term Memory networks (LSTM) are an extension for recurrent neural networks, which makes it easier to remember past data in memory (Fig. 4). Therefore, it is well suited for learning important experiences that have very long delays between the two sequences. The units of an LSTM are used as building units for the layers of an RNN, which is then often called an LSTM network. LSTMs allow RNNs to remember their inputs over a long period of time. This is

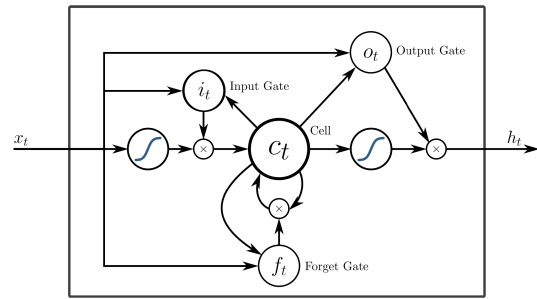
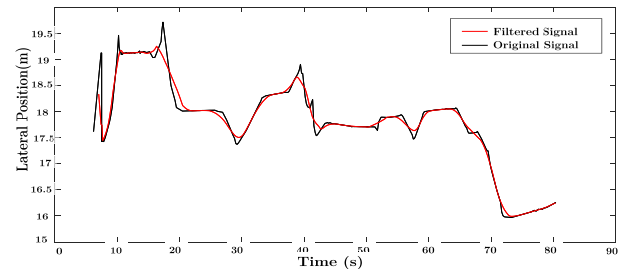
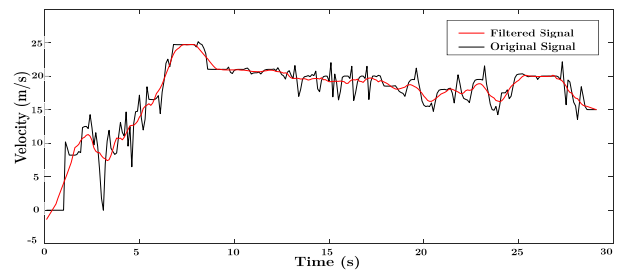


FIGURE 4. Long Short-term memory cell.



(a) Vehicle lateral position.



(b) Vehicle velocity.

FIGURE 5. Input data smoothing using Savitzky-Golay filter in red filtered signal, in black original signal.

because LSTMs hold their information in a memory, which is very similar to a computer's memory because the LSTM can read, write and delete information from its memory [27]. The equations for the forward pass of an LSTM unit with a forget gate are presented below:

$$i_t = \sigma(x_t U^i + h_{t-1} W^i + b_i) \quad (1)$$

$$f_t = \sigma(x_t U^f + h_{t-1} W^f + b_f) \quad (2)$$

$$o_t = \sigma(x_t U^o + h_{t-1} W^o + b_o) \quad (3)$$

$$q_t = \tanh(x_t U^q + h_{t-1} W^q + b_q) \quad (4)$$

$$p_t = f_t * p_{t-1} + i_t * q_t \quad (5)$$

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

$x_t \in \mathbb{R}^d$ represents the input x at position t .

$i_t \in \mathbb{R}^h$ input gate's activation vector.

$f_t \in \mathbb{R}^h$ forget gate's activation vector.

$o_t \in \mathbb{R}^h$ output gate's activation vector.

$h_t \in \mathbb{R}^h$ is the hidden state at t .

$U \in \mathbb{R}^{d \times h}$ and $W \in \mathbb{R}^{h \times h}$ are parameters.

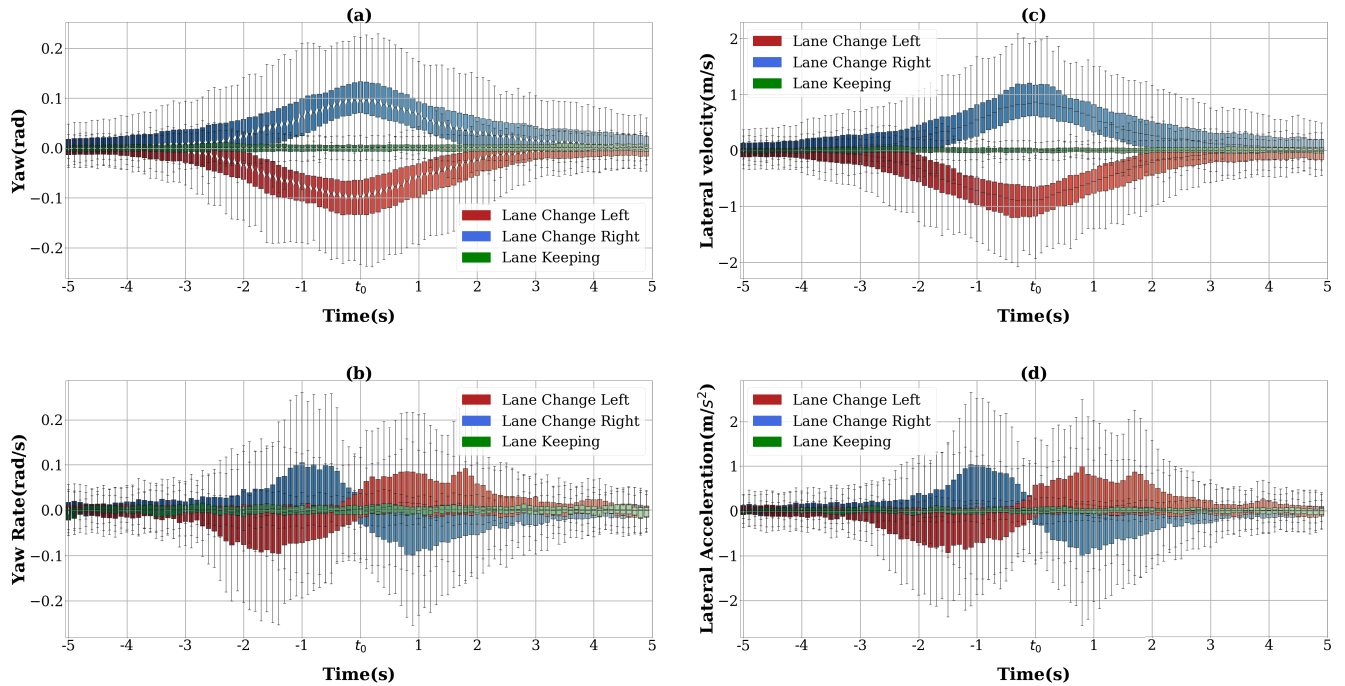


FIGURE 6. Boxplot representation of Yaw (a), Yaw angle (b), Lateral velocity (c) and Lateral acceleration (d) for the three maneuvers.

III. FEATURES SELECTION AND DRIVING BEHAVIOR REPRESENTATION

A. DATASET

All of the aforementioned research areas require interactive vehicle driving data from real-world scenarios, which is the most fundamental and indispensable asset.

Additionally in this work, the public dataset Next Generation Simulation (NGSIM) is used for training and testing. NGSIM dataset is one of the most popular dataset used in vehicle motion comprehension and prediction studies [32]. NGSIM is a program funded by the U.S Federal Highway Administration. It contains detailed vehicle trajectory information. Data is collected from 8 synchronized digital cameras mounted on top of buildings adjacent to US-101 and I-80 highways, including 600 meters of study area, with a total of 45 minutes of data are available in the full dataset captured at 10 Hz. Moreover, NGSIM is widely used for research, development, and validation of behavioral algorithms [23], [24], [31]. NGSIM contains the information related to each vehicle. For every sample, we have vehicle unique identifier, longitudinal and lateral positions, velocities and accelerations, as well as vehicle type, lane ID, and time/space headways. In our study, we have used some available features. In parallel, we have calculated other features like vehicle yaw related to the road, lateral velocity and lateral acceleration.

B. LANE CHANGE REPRESENTATION

Our work is set to predict three types of maneuvers: Lane Change to the Right (LCR), Lane Change to the Left (LCL) and Lane Keeping (LK). Lane changes were extracted and labeled automatically following several criteria. ‘‘Lane ID’’

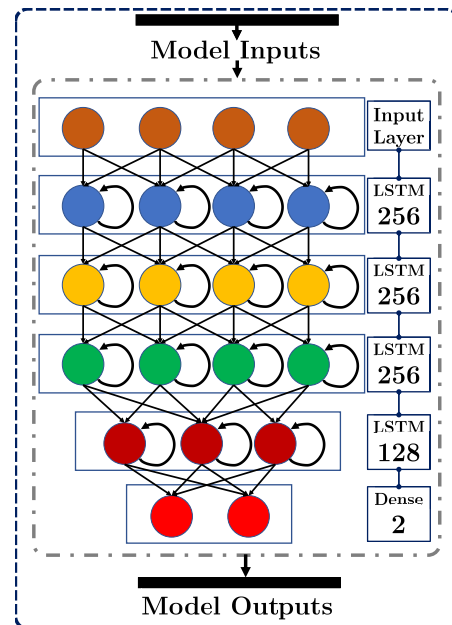


FIGURE 7. Architecture of trajectory prediction network (Training).

feature is used to extract all available lane changes in NGSIM dataset. The increasing of this feature can refer to a left lane change. Contrariwise, the decreasing refers to right lane change. Therefore, we can extract lane changes automatically and we can also label the direction of changes (right, left).

For each event we take 50 time-steps (5 s) before, and 50 time-steps (5 s) after lane crossing. So, if the instant of intersection between trajectory and lane making is considered

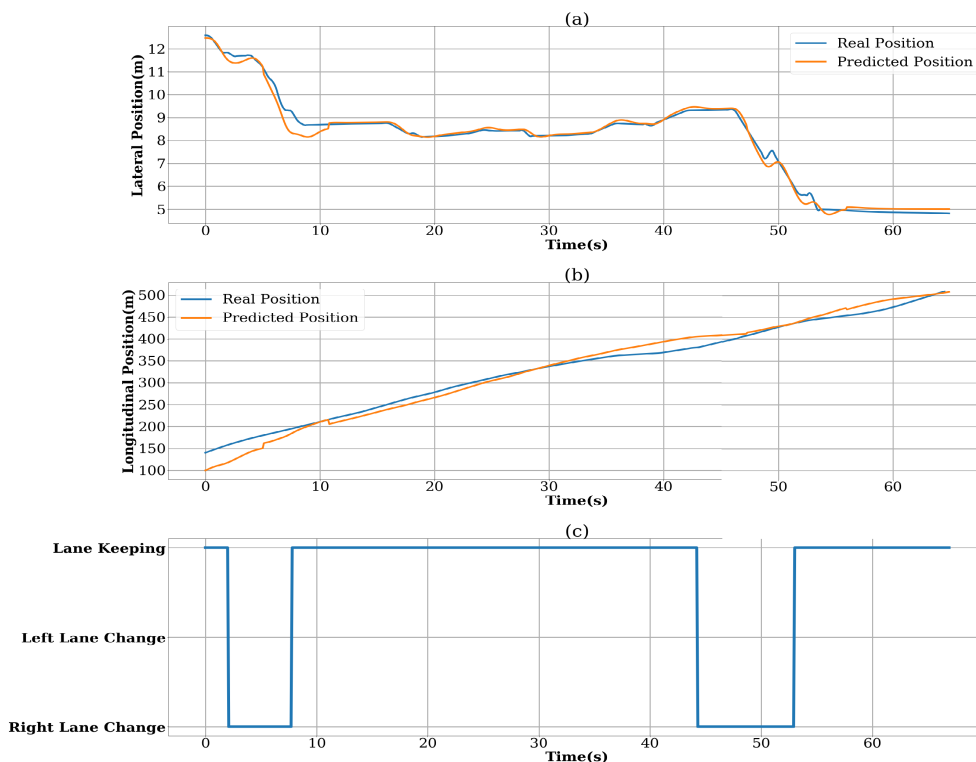


FIGURE 8. Trajectory prediction of a vehicle with two right lane changes: (a) and (b) represent predicted and real longitudinal and lateral trajectory respectively. (c) represents classification results.

as a reference time t_0 , the interval $[t_0 - 5 \text{ s}, t_0 + 5 \text{ s}]$ is the lane change trajectory segment. Based on the chosen criteria, 380 lane changes to the right, 420 lane changes to the left and more than 1000 lane keeping are extracted from NGSIM. In order to create a homogeneous dataset, we take the same number of trajectories for each class. So we take 300 trajectories of each maneuver for training and 80 trajectories for testing. Many variables must be involved in the classification. In this study, a set of 4 features are extracted from the NGSIM data. The extracted features are:

- Yaw angle w.r.t the road: yaw is the vehicle orientation heading angle related to the road. Changes in yaw can be a very important sign to detect a lane change.
- Yaw rate: yaw rate is the first derivative of the yaw. This feature used to flow the rate of changes in vehicle orientation w.r.t the road.
- Lateral velocity and acceleration: lateral dynamic is a very significant feature that gives a lot of information before the lane change event happens. Therefore, we have used local coordinates related to the road to calculate lateral acceleration and velocity.

NGSIM data have some disturbances due to measurement noise and estimation error, which may cause problems in the training step. All input data are filtered using first order Savitzky-Golay filter [37] to make them smoother (Fig. 5), and to accelerate the convergence of the loss function during training phase. It should be noted that the data were

normalized between (-2) and $(+2)$ to be used as an input for the model. After filtering and normalizing, the data are organized into time-series of different sizes. To develop and evaluate the model, the dataset was divided into training and testing datasets.

To investigate the influence of different vehicle features on lane change over time, we propose a graphical boxplot representations of all extracted features (Fig. 6). Each boxplot describes 180 values of one feature in one time-step. Fig. 6 illustrates the four chosen features (lateral velocity, lateral acceleration, yaw angle and yaw rate). Each boxplot representation displays:

- Three types of maneuver (LCL, LCR, LK).
- 300 subjects for each maneuver.
- 100 time-steps (10s) starting from the 50th time-step before lane crossing and finishing at the 50th time step after lane crossing.

From boxplot representations, we choose the most relevant features that represent an important difference between the three classes. Lane changes are detected using features observation. Before LC (between 5s and 4s before lane crossing t_0), yaw (boxplot (a)), yaw rate (boxplot (b)), lateral velocity (boxplot (c)) and lateral acceleration (boxplot (d)) of the three maneuvers have roughly the same shape. From the moment -4s (4s before lane crossing), the difference between the three representations becomes significant, which clearly shows that lane changes start from 4s before the lane marking crossing. This refute the assumption cite in [36], that lane change is

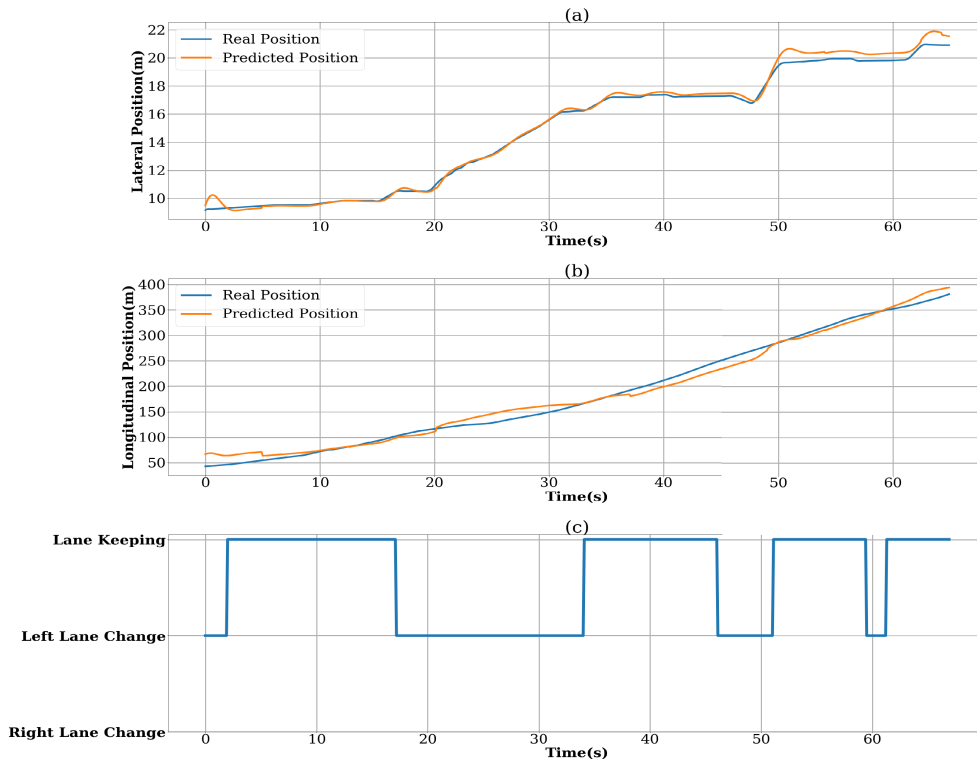


FIGURE 9. Trajectory prediction of a vehicle with three left lane changes: (a) and (b) represent predicted and real longitudinal and lateral trajectory respectively. (c) represents classification results.

labeled by a fixed period of 2s before the crossing of the lane change.

IV. MATERIALS AND METHODS

A. EXPERIMENTAL SETUP

In this part, we present the architectures of the ANN and LSTM models used in this paper. As previously mentioned, ANN is used to classify maneuvers and LSTM is used to predict the future position. The goal is to predict the longitudinal and the lateral coordinates of the vehicle trajectory using classification results and past locations sequence. In the literature, plenty of learning methods have been proposed to predict vehicle trajectory [27]–[30].

After defining the general structure of the models, the architecture of the networks will be presented. The proposed maneuver classification model is based on ANN. It is consisted of an input layer with four features, two hidden layers with a sigmoid activation function and an output layer with SoftMax activation function. Regarding trajectory prediction model, we choose a deep architecture to ensure better prediction accuracy. The proposed network architecture consists of an input layer with three features (classification result, lateral and longitudinal position), four hidden layers based on LSTM and an output layer that provides the predicted position (Fig. 7).

Once the concrete network architecture is selected, we eventually train the network using the selected features. According to previous studies [31], [38] [39] and our

experiments, the network with 4 hidden layers is chosen to achieve the best compromise between learning performance and computational consumption. The networks are trained using batches of size 500, with 4 LSTM layers of size 256 for the first 3 layers and 128 for the last layer, the output layer is a dense (fully connected) layer (Fig. 7). In this work, Keras framework [40] is implemented with the Nvidia optimized recurrent neural networks cuDNN [41] that deliver up to 6 times speedup compared to traditional DNN. The used loss functions are Categorical Cross-entropy for classification and Mean Squared Error for prediction. The used optimizer is ADAM with a decaying learning rate starting at 0.001. Furthermore, each model is trained 50 epochs. All the related models are trained on a single GPU Nvidia GeForce GTX Titan X 12 Go.

B. DISCUSSION AND RESULTS

This part is devoted to analyze and compare the prediction and classification results. Two cases analysis are presented to visualize and compare prediction and ground-truth measurement. This work explores the long-term (up to 1 s) prediction of future vehicle trajectories. The metric RMS error is used to evaluate the performance of models. According to the prediction, the Euclidean distance between the actual position of the vehicle and the corresponding future position is reported. The reports are classified into three categories depending on the corresponding length of the input sequence. The results achieved by maneuver detection and trajectory

TABLE 1. Models evaluation: Classification accuracy and RMSE of lateral and longitudinal position.

System Parameters			RMSE of Predicted Position (m)	
Input sequence	Prediction Horizon	Classification Accuracy	Position Prediction	
			Lateral Position	Longitudinal Position
3 s	1 s	86.19 %	0.043	0.122
	3 s		0.125	0.235
	5 s		0.235	0.264
5 s	1 s	96.65 %	0.042	0.071
	3 s		0.072	0.100
	5 s		0.126	0.142
6 s	1 s	97.49 %	0.040	0.062
	3 s		0.063	0.082
	5 s		0.092	0.112



FIGURE 10. VEDECOM demonstrator: installed sensors and intern hardware platform.

prediction algorithms are reported in Table 1. This table displays longitudinal and lateral position prediction errors as well as classification accuracy over different time horizons (1 s, 3 s and 5 s). The obtained results are summarized below.

1) MANEUVER CLASSIFICATION RESULTS

The goal here is to check if the correct maneuver is detected before the vehicle reaches the intended lane. Using neural network-based modeling, we train with time-dependent real traffic data to classify and predict the lane change. The ground truth is thus determined by analyzing vehicle Lane ID changing. As shown in Table 1, the accuracy of classification is 86.2%. It can be seen that long sequences give the best



FIGURE 11. Satory test tracks and test vehicle trajectory.

classification. For 6 s sequences, there are 97.49% correctly predicted maneuvers. The goal of classification is not only to understand the driving situation, but also to provide a supplement input for the prediction model. The validation results demonstrate the effectiveness of ANN.

2) TRAJECTORY PREDICTION RESULTS

In this experiment, 80 vehicle trajectories are used for each maneuver case to compute the mean error of the predicted position. Given the driving behavior classification results of

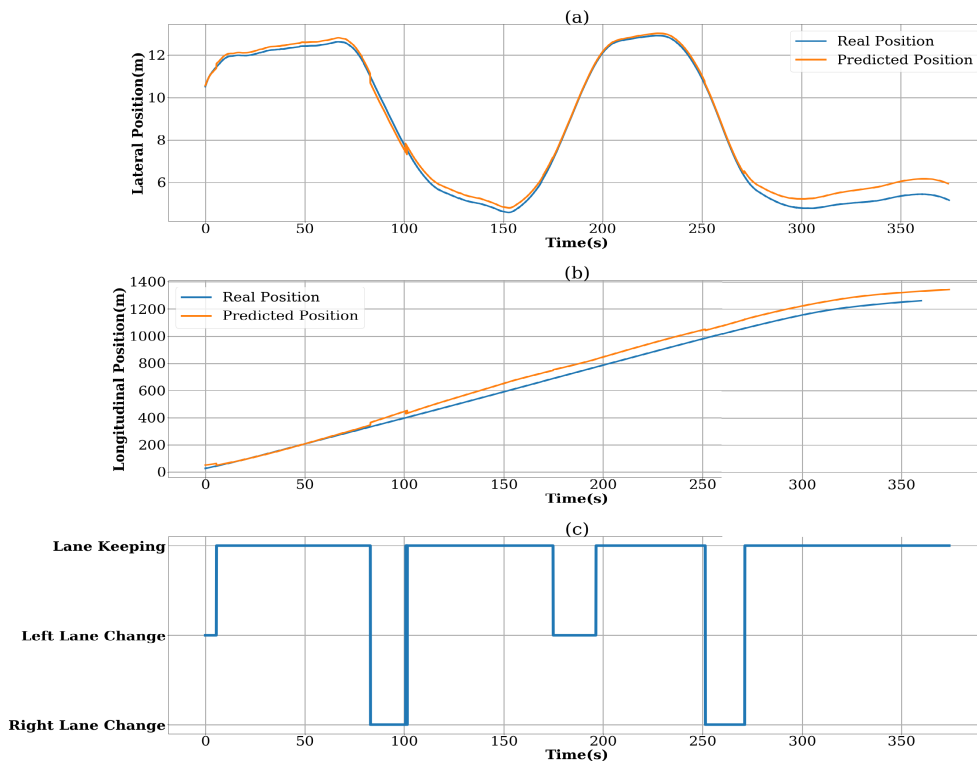


FIGURE 12. Trajectory prediction of VEDECOM demonstrator test: (a) and (b) represent predicted and real longitudinal and lateral trajectory respectively. (c) represents classification results.

a lane changing, the vehicle trajectory can be predicted accurately. One important aspect of predictors is their behaviors as a function of the prediction horizon. The interpretation of Table 1 indicates that the prediction uncertainty of the model increases largely with the increase of the prediction horizon, especially in the long-term prediction. The error for lateral and longitudinal positions is very low for short time predictions but, exponentially increases as the time horizon gets bigger. We see that the prediction accuracy for all prediction horizons increases with input sequence length. Input sequence of 6 s show a high accuracy for 5 s prediction horizon. Prediction errors are around 0.092 m for the lateral position and 0.112 m for the longitudinal position. Thus, timely historical locations acquisition is important in obtaining accurate prediction of future positions. LSTM is a complex model compared with other types of neural networks models (equations [1-6]) [28]. This complexity is a positive point that makes the model more efficient to learn complex dynamics of vehicle's motion and to predict its locations in the future during lane changes. Contrary to [31], the predicted lateral trajectory does not present an observed delayed response. Adding the maneuver information to the prediction model solve the delay limitation and enhance the prediction accuracy.

C. TWO CASES ANALYSIS

In order to evaluate our approach, we randomly selected two vehicle trajectories, including lane-changing and lane-keeping maneuvers from the NGSIM dataset. The first contains two lane changes to the right, and the second is a

succession of three left lane changes. As shown in Fig. 8 and Fig. 9, the real and the predicted positions are displayed, as well as the classification results. In this case, two parts exist, namely: the lane-changing and lane-keeping parts. The average velocity is 7.35 m/s for first vehicle and 8.03 m/s for the second vehicle. The used sequences are of 6s length and the predicting horizon is of 5 s.

The result of vehicle trajectory prediction based on LSTM and maneuver classification in the right lane-change scenario are shown in Fig. 8. Left lane change scenario is presented in Fig. 9. In both figures, we note that the classification model detected the lane changes very early before lane crossing, which give more accuracy to the predicted position. The results indicate that proposed model performs well in long-term prediction. The proposed approach can integrate the advantages of the two models (maneuver classification and trajectory prediction). In other words, classification model ensures situation recognition, and the prediction model generates the accurate trajectory that overlays with the detected situation. Moreover, the two figures (Fig. 8, Fig. 9) clearly show that a good prediction results may be obtained through the proceeding of many lane changes.

D. EXPERIMENTAL RESULTS

This part presents some results of evaluating trajectory prediction approach using lane changes real data. In our experiment, we used VEDECOM demonstrator as a test vehicle. This demonstrator is an automated vehicle based on Renault ZOE platform equipped with a long-range radar (Continental ARS 408), Lidar (Velodyne VLP-16), GPS RTK and a camera

from Mobileye (Fig. 10). We collected the test data from driving on Satory test tracks in Versailles, France (Fig. 11). During driving, the test vehicle collects the sensor measurements for lane changes scenarios with an average of 22m/s speed. We focused on the behaviors of a single driver with the hope of expanding the test to more drivers in the future.

To evaluate the trained model and proceed with prediction steps, the trajectory of the test scenario shown in Fig. 11 was set up. With this scenario, two right lane changes and one left lane changes were recorded to evaluate the prediction system described in the last section. To predict the future position reading of the test vehicle, few steps were followed. Initially, the approach detects the maneuver using lateral velocity, lateral acceleration, yaw and yaw rate. Then, it uses the detected maneuver and the past positions sequence to get the predicted trajectory. The evaluation was carried out in two steps. Firstly, we evaluate classification model to test the performance of maneuver detection. Secondly, we evaluate prediction model for 5 s horizon, then we compare the predicted and the real trajectories. The test results of position prediction and maneuvers classification are shown in Fig. 12. As presented in this figure, maneuver classification model is able to detect the lane changes accurately (recall = 1) on average 2.2 s before they occur. Additionally, it remarkably differentiates between left lane changes and right lane changes. Regarding the trajectory, the prediction results are very similar to the ground truth. The RMS errors of lateral and longitudinal positions are 0.30 m and 3.1 m respectively. The validation results demonstrate the effectiveness of the proposed hybrid model. The training using NGSIM data also proves that our model can predict the future positions of a vehicle under different driving scenarios.

V. CONCLUSION AND PERSPECTIVES

In this paper a new hybrid approach (Artificial Neural Network based maneuver classification and Long-Short term Memory Network based trajectory prediction) is proposed. The study demonstrated the ability of the proposed approach to effectively predict the vehicle position with an interesting accuracy. The role of classification model is to understand the driving scenario and provide this information to the prediction model that generates the future trajectory according to the performed maneuver. The model has been proven to achieve a low prediction error level on a large dataset of real freeway vehicle trajectories.

Using the large amount of the trajectory data extracted from NGSIM dataset, we trained the ANN to classify the three maneuvers (LCR, LCL and LK), and LSTM to learn complex dynamics of the vehicle's motion and predict its location in the future. Firstly, the classification model is trained with a maneuvers dataset that contains 6s length features sequences. Secondly, trajectory prediction model is trained with the detected maneuver with past positions sequences. The global model is able to predict vehicle trajectory using past vehicle dynamic sequences.

The approach is validated with a real data collected from VEDECOM demonstrator. We show that on a data with a high variability, our system is able to accurately anticipate the intended maneuver 2.2 seconds in advance, and predict the future trajectory with 0.30 m and 3.1 m of lateral and longitudinal position errors respectively. The results show that the proposed method provides an accurate prediction on the vehicles trajectory. This proves that our method can be a promising solution to predict the behavior of traffic participants in real road. Thus, it enhances the safety level for realizing fully autonomous driving. This work fits into the logic of many innovations that will significantly reduce the ecological impact of the transport sector and decrease the number of road accidents.

In future work, the driver behavior would be the additional information to ensure more accurate prediction. In order to strengthen the expressiveness of our findings, we will have to increase the size of our data set. In addition, this work can be extended to the prediction of vehicles trajectory in the urban driving scenes. Moreover, other vehicles or road users in the traffic will be considered, and their interacting influences could be taken into account to predict vehicle trajectories.

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