

Direction Convolutional LSTM Network: Prediction Network for Drivers' Lane-Changing Behaviours

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Abstract—Recent research on the prediction of driver's lane-changing behaviour requires vehicle surrounding information, as it is believed that driver's decision on lane changing is made consciously based on those information. However, current research has shown that the usage of such surrounding information leads to high false alarm rate of lane-changing predict system [1]. Therefore this paper contributes to developing a lane-changing prediction method which uses vehicle state information only. From the perspective of the observer's daily experience, this paper selects vehicle's lateral trajectory and the spectrum of its lateral trajectory as input to predict drivers' lane-changing intention. A Direction Convolutional LSTM (DCLSTM) network has been developed to predict drivers' lane-changing behaviours. Recent pure LSTM methods proposed by researchers provide high accuracy when predicting the generation of drivers' lane-changing intentions, but they have relatively low accuracy in predicting drivers' lane-changing direction. DCLSTM retains pure LSTM network's high accuracy in the prediction of drivers' lane-changing intentions, while its prediction of drivers' lane-changing directions is also accurate. All the training and testing data are extracted from the NGSIM dataset.

I. INTRODUCTION

With the development of autonomous driving technologies and Advanced driver-assistance systems(ADAS), drivers' driving experience has been greatly improved. ADAS could enhance the overall performance of vehicle control and safety on roads. By minimizing the driver-made mistake, ADAS performs well in lane centering, lane change assistance and traction control system [2]. However, it still can't replace human drivers' role in many scenarios, especially when estimating the intention of surrendering vehicles' lane-changing is necessary.

In platoon control of autonomous vehicles, many researchers hold negative opinions on their usage in urban environment. This is because human drivers' frequently cut in influences the controllability of autonomous vehicle platoons [3]. One potential way out of this situation is to predict human driver's lane-changing behaviour and then control platoon vehicles to reject such cut in. Such a prediction system can also significantly enhance existing ADAS, especially when drivers

TABLE I
FEATURES

Regular features
• longitudinal distance between an observed vehicle vs. host vehicle
• longitudinal relative speed between an observed vehicle vs. host vehicle
• longitudinal deceleration required for an observed vehicle to avoid a collision with the host vehicle
• time to a longitudinal collision between an observed vehicle vs. host vehicle
• timegap between an observed vehicle vs. host vehicle
• lateral velocity of host vehicle
• lateral distance between the center of an observed vehicle and its left lane marking
• lateral distance between the center of an observed vehicle and its right lane marking
• distance between the center of an observed vehicle and the center-line of assigned lane
• time to cross the right lane marking of assigned lane for an observed vehicle
• time to cross the left lane marking of assigned lane for an observed vehicle
• required acceleration which is needed to stay in the current lane
• angle of an observed vehicle relative to the direction of its lane
• lateral speed of an observed vehicle relative to its lane
• number of lanes on the right side of an observed vehicle
• number of lanes on the left side of an observed vehicle
• type of left lane marking
• type of right lane marking
• curvature of the road
• distance to the next approach to the highway
• distance to the next exit of the highway
• speedlimit of the current highway section

intend to make a lane change, or there is a vehicle around aiming to make a lane change. Correct and sufficient surrounding information is of vital importance to all human drivers, and also can alert and reduce reckless driving behaviours.

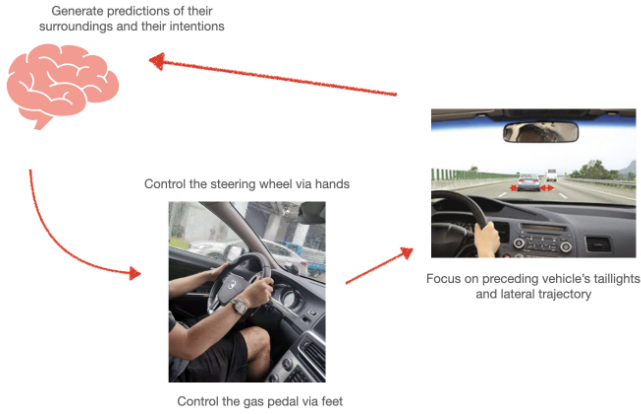


Fig. 1. Drivers' detailed close-loop behaviour.

The most common closed-loop of human driving behaviour is shown in TABLE 1. Drivers use their steering wheels to correct errors that happen on the road. In the meantime they press and release the gas pedal slightly using their feet to maintain a steady speed. Their eyes focused on preceding vehicle's taillights and its drifting inside its lane, and also feedback this information to their minds. Subsequently, their minds generate predictions of their surroundings and their own behaviours next, which will trigger subsequent steering and gas pedal pushing actions.

In the past, researchers extracted features directly from various lane-changing scenarios [4]. Table II summarizes regular features currently used by researchers. Compared with human-made prediction on real road, those features are extremely redundant. Some of the selected features have limited contributions to human-made prediction. Therefore by imitating human's lane-changing prediction method, current existing methods can reduce their reliance on redundant information and hardware costs on processors, sensors, etc. This paper constructs a Direction Convolutional LSTM (DCLSTM) network, and selects vehicle's lateral trajectory and the spectrum of its lateral trajectory as input based on human drivers' daily experiences. This is the first time that the spectrum of its lateral trajectory has been considered as an input feature of drivers' lane-changing prediction. Comparative experiment with some baseline methods has been conducted using NGSIM dataset. From the result it can be concluded that this DCLSTM network is simple in structure, precise in prediction, and does not require surrounding information. It also has significant advantages over previous LSTM methods in the prediction of drivers' lane-changing directions, while retaining high precision in the prediction of drivers' lane-changing intentions.

II. MOTIVATION

During the past decades, researchers have developed many vehicle-following [5] and lane-changing dynamic models [6]. With those models, it is possible to establish the dynamic model of driving. Assume driving automaton $G = (Q, \Sigma, \delta, q_0, Q_m)$ (Figure 2), where $Q = \{0, 1\}$ represents

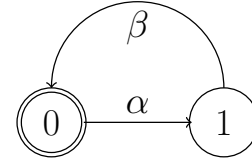


Fig. 2. Driving automaton.

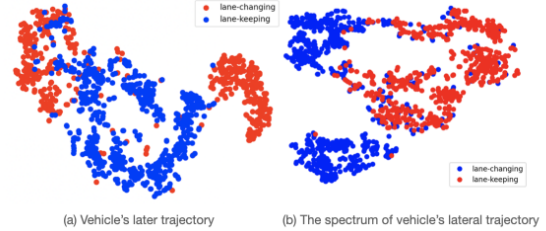


Fig. 3. 2D Dimensionality Reduction Result Using t-SNE.

two states, vehicle-following and lane-changing, respectively. $\Sigma = \{\alpha, \beta\}$ is the set of events, denoting a driver's intentions of making a lane change (α) or maintaining the current lane (β), respectively, and δ is the transition function. $\delta(0, \alpha) = 1$ means that event α triggers state Q change to 1 from 0. $\delta(1, \beta) = 0$ means that event β triggers state Q change to 0 from 1. State 0 is both the initial state and marker state, the latter denotes that, in any circumstances, a driver always wants to go back to the vehicle-following mode, meaning that a lane-changing mode is always temporary.

However, this automaton is not sufficient to imitate drivers' driving behaviours. It still lacks a mapping $f(X) \rightarrow \Sigma$, where X is driving-related information. As mentioned in previous section, this paper adopts vehicle's lateral trajectory and the spectrum of its lateral trajectory as X . The relationship between X and Σ is shown in Figure 3. Utilizing t-distributed Stochastic Neighbor Embedding(t-SNE) method [7], input features of lane-keeping and lane-changing have been reduced to 2-dimension. From Figure 3 it can be concluded that using vehicle's later trajectory and the spectrum of its lateral trajectory to establish mapping f is possible.

Recently, researchers have developed many methods to predict drivers' lane-change intention and vehicles' trajectory. For example, people have been exploring rule-based algorithms [8] [9] and Knowledge-representation algorithms [10], and most of them only pay attention to various machine-learning based methods. Generally speaking, machine-learning based methods are trying to identify a mathematical model for corresponding problems: given vehicle-related features as input, and its driver's lane-changing intention as output, the methods attempt to generate a function that may be sufficiently close to a real one, if the latter exists, as reflected in given input/output data.

Drivers' intension prediction is a discrete prediction problem, which is usually solved by classification strategies. In the past, researchers have explored Support Vector Machine(SVM)

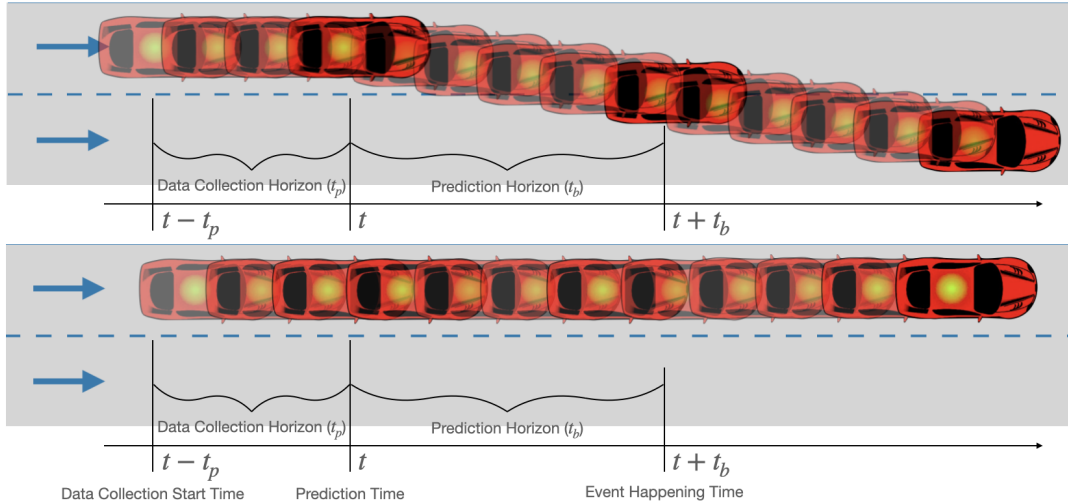


Fig. 4. Lane-changing prediction.

[11], Bayesian Classifier [12], Hidden Markov Model(HMM) [13], and MLP [14]. Currently, researchers have turned to develop LSTM [15] network or CNN for better prediction results.

A. Alahi et al [16] used LSTM to predict pedestrians' future trajectories based on past trajectories and surrounding agents. S. Sh et al [17] transferred this idea of implementing LSTM to predict human trajectory into the prediction of drivers' lane-changing behavior and achieved significant performance using the NGSIM dataset. O. Sheel et al [4] proposed drivers' attention mechanism of each lane with three LSTMs to predict lane-change maneuvers. They use the NGSIM dataset as well as the Fleet data dataset. In addition, there are many other LSTM structures have been proposed to contribute on vehicles' future trajectory prediction [18] [19]. However, pure LSTM structures only provide high accuracy when predicting drivers' lane-changing intentions. Their prediction accuracy of drivers' lane-changing directions is relatively low.

CNN is powerful in image classification, thus the utilization of CNN in drivers' lane-changing prediction still mainly relies on image processing. Like D. Fernandez-Llorca et al [20] studied Two-Stream Convolutional Networks and Spatiotemporal Multiplier Networks approaches using The PREVENTION dataset, they input a serial image frame of vehicle on road to predict its lane-change decision. Others like O D. Candid et al [21] established several CNNs to extract features for vehicles lane-changing classification using the HighD dataset. They then implement k-NN algorithm to process the classification. This paper base on CNN's high accuracy in lane-changing direction classification, embedded a parallel CNN layer into LSTM network to construct a DCLSTM network. This network retains pure LSTM network's high accuracy in the prediction of drivers' lane-changing intentions, while its prediction of drivers' lane-changing directions is also accurate.

III. PROBLEM STATEMENT

This lane-changing prediction problem could be formulated as a classification problem. In a nutshell, it is to create a mapping from input features to the happening of its driver's lane-changing behaviour, that is, to determine whether the event α is happening. The input features should be observable or measurable by sensors installed on autonomous vehicles. As shown in Figure 4, each feature's data collected contain time-serial information of t_p length in time domain ended t_b seconds before corresponding vehicle changed its lane.

This paper defines the lane-changing prediction as $f : X \rightarrow Y$. The input $X = \{x_1, x_2, \dots, x_n\}$ is selected historical time-serial information set of target vehicle. n is the number of input features. Each element of X , $x_i = \{x_{iT} | T \in [t - t_p, t]\}$ represents one vector and it is t_p length in time domain. t_b is the length of Prediction Horizon in time domain. In this paper, $t_b = 2$ seconds and this problem is named as a lane-changing prediction problem. The output $Y = \{-1, 0, 1\}$, where 0 represent no lane-changing, $-1, 1$ represent lane-changing to left lane and right lane respectively.

IV. SOLUTION

Recent research has shown that pure LSTM structures is able to provide high accuracy when predicting drivers' lane-changing intentions. However, the prediction accuracy of drivers' lane-changing directions made by pure LSTM network is still relatively low. In this section, we proposes a DCLSTM network by embedding a parallel Direction Convolutional Neural Network layer into a pure LSTM network.

A. Direction Convolutional Neural Network

This paper adopts a Direction Convolutional Neural Network (DCNN) to predict lane-changing direction [22]. We first reconstruct the lateral trajectory into 28×28 matrices, then feed them into the CNN classifier. The network structure and

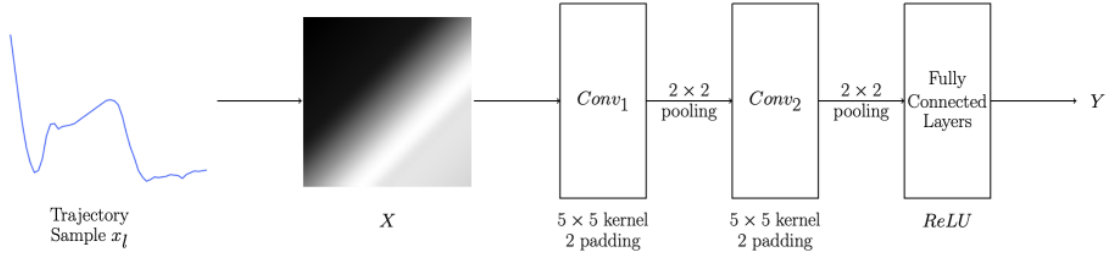


Fig. 5. DCNN structure.

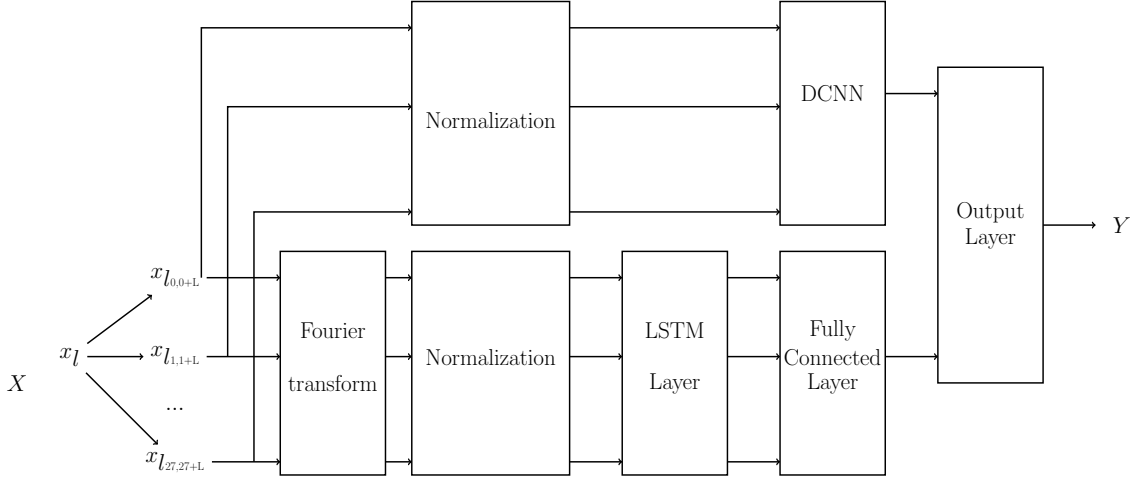


Fig. 6. DCLSTM network.

a sample input $x_l = \{x_{lt} | t \in [0, 54]\}$ is shown in Figure 5. This DCNN is defined as $f_{DCNN} : X \rightarrow Y$.

$$X = \begin{bmatrix} x_{l0} & x_{l1} & \cdots & x_{l27} \\ x_{l11} & x_{l12} & \cdots & x_{l28} \\ \vdots & \vdots & \ddots & \vdots \\ x_{l27} & x_{l28} & \cdots & x_{l54} \end{bmatrix},$$

$Y = \{-1, 1\}$, where $-1, 1$ represent lane-changing to left lane and right lane respectively. Every convolution layer is followed up with *ReLU* activation function and a max-pooling layer. The first convolution layer $Conv_1$ takes in a channel of dimension 1. Its kernel size is chosen to be 5×5 with stride of 1. The output of $Conv_1$ is set to 16 channels. Input X is padded with a padding size of 2 so that the output dimension of $Conv_1$ should be $16 \times 28 \times 28$. Then after *ReLU* activation and a max-pooling layer with kernel size of 2, the output dimension becomes $16 \times 14 \times 14$. Sequentially, the second convolution layer $Conv_2$ takes in a channel of dimension 16. Its output channel size is set to be 32. The kernel size for $Conv_2$ is again 5×5 with stride of 1 and the padding size of $Conv_2$ remains the same as $Conv_1$. The output dimension of $Conv_2$ will be $32 \times 14 \times 14$. $Conv_2$ is followed up with *ReLU* activation and a max-pooling layer with kernel size of 2. Hence the input dimension of the Fully Connected Layers is $32 \times 7 \times 7$ which is equal to 1568. In later section, this

CNN structure would be embedded into the aforementioned DCLSTM network designed by this paper to make drivers' lane-changing prediction.

B. Direction Convolutional LSTM Network

We now design a DCLSTM structure which implements vehicle's lateral trajectory and the spectrum of its lateral trajectory to solve lane-changing prediction problem. This DCLSTM network is defined as $f_{DCLSTM} : X \rightarrow Y$, $X = \{x_l\}$, $Y = \{-1, 0, 1\}$

As shown in figure 6, the input trajectory x_l would be first cut into $L = 27$ length sequential segments $x_{l_{m,m+L}} = \{x_{lj} | j \in [m, m+L]\}$, $i \in [0, 27]$, then go through Fourier transform process to generate spectrum data. Only the real part of Fourier transform result is required,

$$Ft(x_{l_{m,m+L}})_k = \Re(\sum_{n=0}^L x_{ln} \cdot e^{-\frac{i2\pi}{L+1}kn}).$$

After a normalization process, the whole data would be fed into a LSTM network which contains a LSTM Layer and a followed up Fully Connected Layer. The hidden dimension for this LSTM Layer is 128. Synchronously, the input trajectory x_l would be reconstructed into aforementioned 28×28 matrices and its normalization result would be fed into the DCNN. The output of DCNN and LSTM network would be fed into a output layer for Y .

V. EXPERIMENT

We carry out experiments with the Federal Highway Administration’s Next Generation Simulation(NGSIM) dataset. The NGSIM dataset is one of the largest open source datasets which provide vehicle trajectory data [23]. It is also the most commonly used dataset in numerous vehicle trajectory studies. This dataset recorded the position, velocity, acceleration, vehicle type, front vehicle, following vehicle and lane information of passing vehicles on U.S. Highway 101 and I-80 Freeway. The sampling frequency is 10Hz, which means the time interval between two consecutive data points is 0.1 seconds. The dataset was split into a train dataset and a test dataset. The train dataset contains 66% of the whole samples. The test dataset was again split into a validation dataset and a test dataset, each of them contains 17% of the whole sample trajectories. In total, 401 times left lane-changing, 438 times right lane-changing and 847 times lane-keeping have been extracted from the NGSIM dataset.

In this section, some baseline methods have been evaluated together with DCLSTM. As shown in TABLE II, these baseline methods are LSTM [15], Surrounding Aware LSTM (SALSTM) [17] and extended LSTM with attention (LSTM-A) [4]. DCLSTM only require vehicle features. LSTM, SALSTM and LSTM-A additionally require different surrounding information. The network structure of each method is shown in TABLE III.

In Table IV, their performance has been evaluated. Combined with their network structure, it can be analyzed that the increase of pure LSTM network size would not lead to better prediction results. The increase of input data dimension can significantly improve LSTM network’s performance on the prediction of drivers’ lane-changing directions and the length of prediction horizon, but also bring bad influence on the prediction of drivers’ lane-changing intentions. DCLSTM network performs the best in the prediction of drivers’ lane-changing directions and it does not required surrounding information. By monitoring the spectrum of vehicle’s lateral trajectory instead of its surrounding information, DCLSTM’s prediction of drivers’ lane-changing intentions remains precise. From this result it can be concluded that surrounding information is not necessary in the prediction of drivers’ lane-changing directions, while it indeed contributes to the prediction of drivers’ lane-changing intentions. DCLSTM network contains more parameters compared with pure LSTM networks, but it significantly reduces the number of input features, which means that fewer sensors would be required. Less number of input feature also means that the DCLSTM network has a higher potential for improvement compared with pure LSTM networks.

VI. CONCLUSION

In this paper, a DCLSTM network has been designed for drivers’ lane-changing prediction. Compared with pure LSTM networks, DCLSTM network is much more precise in the prediction of drivers’ lane-changing directions, while retaining simple structure and high accuracy in the prediction of drivers’

TABLE II
INPUT FEATURES

Method	Selected input features
SALSTM	<ul style="list-style-type: none"> • Vehicle’s acceleration x_a • Vehicle’s steering angle with respect to the lane x_θ • Vehicle’s lateral trajectory x_l • The existence of left lane x_{El} • The existence of right lane x_{Er} • Longitudinal distance between ego vehicle and left-front vehicle x_1 • Longitudinal distance between ego vehicle and front vehicle x_2 • Longitudinal distance between ego vehicle and right-front vehicle x_3 • Longitudinal distance between ego vehicle and left-rear vehicle x_4 • Longitudinal distance between ego vehicle and rear vehicle x_5 • Longitudinal distance between ego vehicle and right-rear vehicle x_6
LSTM-A, LSTM	<ul style="list-style-type: none"> • Vehicle’s lateral trajectory x_l • Vehicle’s lateral velocity v_l • Vehicle’s lateral acceleration a_l • Vehicle’s steering angle with respect to the lane x_θ • Estimated time to longitudinally travel from the front-center of ego vehicle to the back-center of left-front vehicle t_1 • Estimated time to longitudinally travel from the front-center of ego vehicle to the back-center of front vehicle t_2 • Estimated time to longitudinally travel from the front-center of ego vehicle to the back-center of right-front vehicle t_3 • Estimated time to longitudinally travel from the front-center of left-rear vehicle to the back-center of ego vehicle t_4 • Estimated time to longitudinally travel from the front-center of rear vehicle to the back-center of ego vehicle t_5 • Estimated time to longitudinally travel from the front-center of right-rear vehicle to the back-center of ego vehicle t_6 • Distance to the nearest on-ramp x_{on} • Distance to the nearest off-ramp x_{off} • One hot encoding of the lane identifier id
DCLSTM	<ul style="list-style-type: none"> • Vehicle’s lateral trajectory x_l • The spectrum of vehicle’s lateral trajectory $Ft(x_l)$

lane-changing intentions. Surrounding information has been evaluated as unnecessary in the prediction of drivers’ lane-changing directions. A new important feature, the spectrum of vehicle’s lateral trajectory has been discovered by this paper. The usage of DCLSTM can reduce the quantity requirement of surrounding information related sensors, and reduce the hardware cost accordingly. In real/simulated traffic scenarios,

TABLE III
NETWORK STRUCTURE.

Method	LSTM	Hidden	Total	Input Data
	Cell	Dimension	Parameters	Dimension
SALSTM	1	128	99715	64
LSTM-A	3	128	208009	14
LSTM	1	128	74115	14
DCLSTM	1	128	101476	28

TABLE IV
PERFORMANCE

Method	t_b	Prediction Accuracy		
		Left Changing	Right Changing	Lane Keeping
SALSTM	2	87.4%	85.84%	85.33%
LSTM-A	1	78.4%	66.2%	95.1%
LSTM	1	77.2%	63.4%	95.8%
DCLSTM	2	91.3%	94.1%	90.7%

to implement this DCLSTM network, users should collect their vehicles' lateral information as well as surrounding vehicles' lateral information through installed Lidar or camera units. To predict users own lane-changing behaviours, only need to feed their vehicles' lateral information into DCLSTM network. To predict surrounding vehicles' lane-changing, users should first group their samples according to different collection scenarios, then go through their training processes with respective DCLSTM networks. In the future, combined with surrounding information, this research would be implemented into vehicles' trajectory prediction. Some simulators would also be established to collect data information of drivers' driving behaviours for further studies.

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