2018 21st International Conference on Intelligent Transportation Systems (ITSC)
Maui, Hawaii, USA, November 4-7, 2018

Human-Like Maneuver Decision Using LSTM-CRF Model for On-Road Self-Driving

Xiao Wang†, Jinqiang Wu†, Yanlei Gu‡, Hongbin Sun†*, Linhai Xu†, Shunsuke Kamijo‡, Nanning Zheng†
†Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, China.
‡Institute of Industrial Science, The University of Tokyo, Japan.
*E-mail: hsun@mail.xjtu.edu.cn

***Abstract*—In the near future, self-driving vehicles will be frequently tested in urban traffic, and will definitely coexist with human-driving vehicles. To harmoniously share traffic resources, self-driving vehicles need to respect behavioral customs of human drivers. Taking on-road driving for example, self-driving vehicles are supposed to behave in a human-like way to decide when to keep the lane and when to change the lane. This point, however, has not been well addressed in current on-road maneuver decision methods. In this paper, a human-like maneuver decision method based on Long Short Term Memory (LSTM) neural network and Conditional Random Field (CRF) model is proposed for on-road self-driving. Different from previous works, this paper considers the maneuver decision problem as a sequence labeling problem. Its input is a time-series vector which describes a period of neighboring traffic history, and its output is a one-hot vector indicates the suitable maneuver. The proposed model is trained on the NGSIM public dataset, which contains millions of driving maneuvers collected from thousands of human drivers. Simulations with manipulated conditions reveal human-like reasoning for maneuver decision inside the proposed model. Comparative experiments further demonstrate a better human-like performance achieved by the proposed method than that of previous methods.**

I. Introduction

On-road driving maneuvers mainly include lane keeping and lane changing behaviours, which are believed to have major impacts on public traffic. For on-road self-driving, maneuver decision is to choose a reasonable behavior according to the given neighboring traffic. A good maneuver decision module is thus important for self-driving vehicles, as well as traffic safety and efficiency. Maneuver decision for on-road self-driving had been well considered in literatures. As reviewed by Paden et al. [1], current maneuver decision methods make great efforts on predicting trajectories of other traffic users, and quite a few approaches followed to improve the prediction performance [2]–[4]. However, they overlooked the fact that human drivers have their own disciplines for maneuver decision. More specifically, human drivers have been accommodated to lots of behavioral customs which dedicate to cooperate with other drivers. If self-driving vehicles behave egocentrically regardless of these behavioral customs, contradictions between human and machine are inevitable and dangerous. Therefore, maneuver decision calls for a human-like manner.

In fact, maneuver decision in a human-like manner is not only needed, but also critical. As it is said, self-driving vehicles are on their way from research prototypes to one of on-road transportation. During the progress of this technology, self-driving vehicles will inevitably coexist with human-driving vehicles. In order to harmoniously share traffic resources, self-driving vehicles have to learn behavioral customs from human drivers and behave in a human-like way. Taking the on-road driving for example, self-driving vehicles need to act as a human driver to decide when to follow the lane, when to prepare for lane changing, and when to shift to the left or right lane. This point was first considered in the field of traffic engineering, where considerable attention had been paid to model and understand lane changing behaviors of human drivers [5]. Not until recently, approaches for human-like on-road maneuver decision have appeared for self-driving vehicles. These studies tried to learn driver behaviors either from human driving datasets [6]–[8] or computer simulations [9]–[11]. Though lots of results had been made, those learning models they adopted limited their human-like performance. Furthermore, those neighboring traffic situations they considered are often too idealistic to capture what human drivers really face to. For human drivers usually face to dynamic and versatile traffic situations, where even the size of a neighboring vehicle will affect their maneuver decisions.

To get rid of the aforementioned deficiencies, a new method aiming at human-like maneuver decision for on-road self-driving is proposed. At first, the maneuver decision problem is considered as a sequential labeling problem. The reason comes from the common sense that most drivers deliberatively made maneuver decisions based on several steps of observation, just as an observation sequence labeling process. Besides, maneuver sequences of human drivers have strong regularities: the behavior of preparing a lane changing will always happen after lane keeping maneuvers, and lane changing maneuvers will always be followed by lane keeping behaviors. Thus, it will be beneficial to model the observation and decision sequences jointly, instead of generating each decision independently. Based on these assumptions, the maneuver decision problem is redefined. Its input is devised as a time-series vector, which comprehensively represents the context of a short-term history of neighboring traffic. Its output is a one-hot vector, of which each bit indicates a possible maneuver choice. Then, the state-of-the-art model for sequential labeling, named LSTM-CRF, is deployed to solve the above problem. This model is constructed by two

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layers of LSTM and one layer of CRF, and is trained by the public NGSIM dataset [12]. However, as this dataset is heavily unbalanced due to the dominance of lane keeping maneuvers, end-to-end training will not work. A combination of two LSTM-CRF sub-models is proposed to mitigate this issue. One is dedicated to distinguish whether the current traffic situation is ordinary or salient, while the other one only gives maneuver decisions in salient traffic situations.

Simulations with manipulated conditions illustrate the proposed maneuver decision method does carry out a reasoning procedure which is similarly conducted by human drivers. By comparing the outputs from the proposed method and the ground truth collected from human drivers, how human-like the method is can be numerically evaluated. Experiments show the proposed approach achieved an averaged F_1-score of 98.9% for all maneuvers inside the NGSIM dataset. Compared with previous works, our method improves the human-like performance by up to 34.9%, with only 14ms of computation for each decision step. Note that this is much shorter than average human reaction time, which is usually more than 200ms. Further discussions on treating wrong maneuver decisions reveal the practicable potential of the proposed method for real-world self-driving applications.

II. Related Work

Maneuver decision for on-road self-driving has been extensively studied [1]. Gap acceptance model, and its variants, have been profoundly adopted in maneuver decision problems [13]–[15]. These hand-coded models are capable of giving feasible maneuver decisions, nevertheless, their decisions are given in a robotic way, which will not easily understood and accepted by human drivers.

As the main character of on-road driving maneuvers, lane changing behavior had been well studied in the field of traffic engineering [5]. It is assumed that lane changing can be classified as either mandatory or discretionary. Mandatory lane changing happens when a human driver shifts lane for a specific destination, such as merging into a left-turn lane before an intersection. Discretionary lane changing happens when a human driver shifts lane initiatively for better driving conditions. While mandatory lane changing tends to be passive and objective, discretionary lane changing is more subjective, contains lots of behavioral customs of human drivers. Thus, lane changing behavior is generally referred to as discretionary lane changing behavior among studies.

Plenty of models had been proposed to learn lane changing behavior from human driving datasets. Machine learning models, such as Support Vector Machine (SVM) [6]–[8], Neural Network (NN) [16], or Decision Trees (DT) [17], had been applied for this task. However, inside human driving datasets, many samples are controversial, some are even contradictive. Besides, the occurrence of lane keeping samples is usually an order of magnitude more than that of lane changing samples. Thus, human-like performance of these models is often limited, especially when dealing with the entire datasets, not only with those easily picked samples. Other studies also tried to learn driver customs from simulations [9]–[11]. Nevertheless, the traffic scenarios they simulated are prone to be much more simplified than what a human driver normally faces to, which make them vulnerable for real-world applications. Recently, Wang et al. [18] proposed a deep neural network based on-road car-following model. Their work inspired us to build on-road maneuver decision model based on deep learning techniques, which is good at finding intricate features and relations inside datasets.

Studies about driving behavior detection and prediction also inspired us. Woo et al. [19] proposed a lane change detection method. They adopted the horizontal distance of lane shifting as a remarkable feature for lane changing events. This feature is also considered in the proposed method. Schlechtriemen et al. [20] proposed a Mixture of Experts approach to predict possible behavior of the ego vehicle. They derived promising features about the ego vehicle, but ignored the individual state of each surrounding vehicle, which is also essential for maneuver prediction. Altché et al. [3] proposed a method using LSTM neural network to predict trajectories of surrounding vehicles. Their model is promising, however, their predictions are heavily influenced by noisy training samples. Patel et al. [4] proposed RNN-based model to predict lane changes of surrounding vehicles. Their results illustrate that a short history of surrounding traffic is beneficial for prediction performance. This factor is also considered in this paper.

III. Proposed Human-Like Maneuver Decision Method

A. Problem Definition

The symbolic definition of maneuver decision problem for on-road self-driving will be given in this section. Without loss of generality, the neighboring traffic around the ego self-driving vehicle can be modeled as Figure 1. The traffic lane, on which the ego vehicle is driving, is regarded as the center lane. According to that, left and right lane are also considered to fully cover the neighboring traffic. For each lane, two vehicles are observed. One is in front of the ego vehicle, another is at its behind. In total, features from these six observed vehicles are collected to describe the current neighboring traffic. In order to be practicable, all the devised features can be easily detected by vehicular sensors. For each vehicle i (Left-Front, Left-Behind, Front, Back, Right-Front, Right-Behind) at each time step t (every 0.1 seconds), the following five features are extracted.

1) Its distance $d_{i,t}$ apart from the ego vehicle. This distance is truncated in the range of [-50m, 50m].
2) Its absolute speed $v_{i,t}$, measured in meter per second (m/s).
3) The horizontal shifting distance $h_{i,t}$ from center of its driving lane, measured in meter.
4) The angle difference $a_{i,t}$ between its moving direction and its driving lane, measured in radian.
5) Its 2-dimensional size s_i in the aerial view, measured in meter^2.

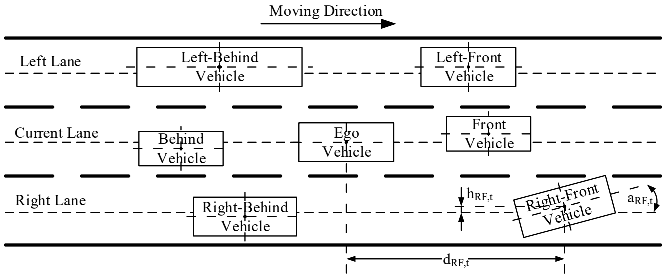

Fig. 1. The abstracted model for the neighboring traffic around the ego vehicle during on-road self-driving.

Furthermore, the absolute speed $v_{ego,t}$ and size s_{ego} of the ego vehicle are also added as two crucial features. These features are devised according to the following reasons: The relative distance $d_{i,t}$ can effectively reveal spacial distributions of neighboring traffic. The absolute speed of ego $v_{ego,t}$ and surrounding vehicles $v_{i,t}$ not only describe the relative difference of speeds, but also depict the moving condition of the entire neighboring traffic. Note that acceleration information is not included, as this information will be carried by the changes of the absolute speed at each time step. The horizontal shifting distance $h_{i,t}$ and angle difference $a_{i,t}$ are two sensitive indicators for driving intentions of the observed vehicle. The 2-dimensional size s_i of each vehicle is also considered, this is because vehicles with different size will have different driving inclinations. If there is no vehicle at a specific position, a virtual vehicle will be placed. This virtual vehicle is designed as with the maximum relative distance from the ego vehicle, the same speed as $v_{ego,t}$, zero horizontal shifting distance, zero angle difference and zero 2-dimensional size.

For each surrounding vehicle, its feature $f_{i,t}$ is defined as:

$$f_{i,t} = [d_{i,t}, v_{i,t}, h_{i,t}, a_{i,t}, s_i] \tag{1}$$

Based on the abstracted model shown in Figure 1, the context vector c_t of neighboring traffic at time step t is defined as:

$$\begin{aligned} c_t = [&f_{LF,t}, f_{LB,t}, f_{F,t}, f_{B,t}, \\ &f_{RF,t}, f_{RB,t}, v_{ego,t}, s_{ego}] \end{aligned} \tag{2}$$

For on-road self-driving, a one-hot vector m_t is used to describe the available maneuvers at each time step. Finally, the maneuver decision for on-road self-driving is symbolic defined in the form of a sequence labeling problem as following.

$$m_t = Model(\bigcup_{i=t-t_h}^{t} c_i) \tag{3}$$

Its input is a time-series vector consisted of context vector c_i over a time window of t_h. Its output is the decided maneuver for the current time step t. If the model can tune its parameters according to human driving experiences, human-like maneuver decision can be achieved. In this paper, deep learning techniques are applied to solve this problem.

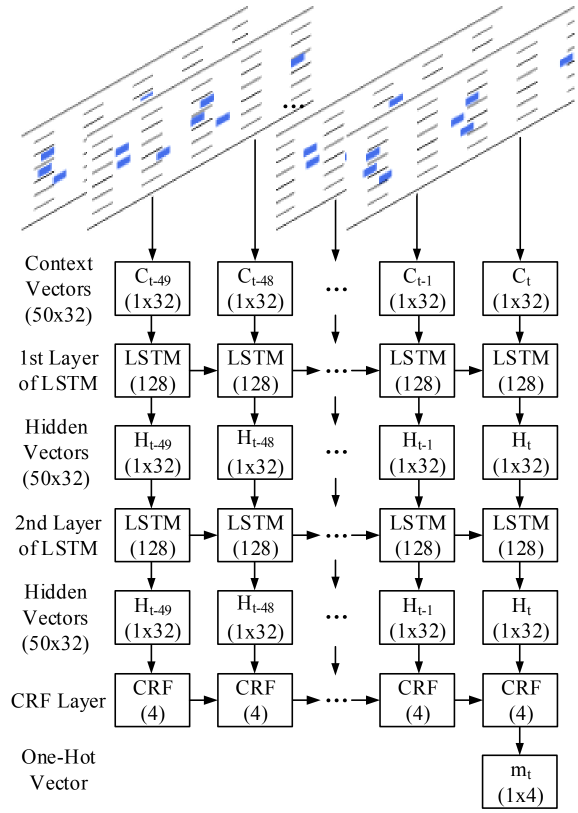

Fig. 2. The architecture of proposed maneuver decision model. Its input is a set of 50 context vectors, with 5 seconds in total and 0.1 second resolution. Its output is a one-hot vector represents the suitable maneuver candidate.

TABLE I
PERFORMANCE OF DIFFERENT LSTM NETWORKS FOR NGSIM DATASET.

LSTM Structure	Test Accuracy
64	75%
128	82%
64-64	95%
128-128	98%
64-64-64	95%
128-128-128	98%

B. LSTM-CRF Model

LSTM was first proposed by Hochreiter et al. [21] as a variant of recurrent neural network (RNN). It mitigated the gradient vanishing or exploring problem by introducing a memory managing procedure. CRF [22], as a probabilistic graph model, is able to simultaneously estimate the joint distribution of feature sequences and label sequences, and outputs the label sequence with the maximum conditional probability. Recently, Ma et al. [23] proposed a model that combined LSTM, CNN and CRF to solve sequence labeling problem, and achieved state-of-the-art performance on several popular NLP datasets. Considering the difference between NLP and maneuver decision, the combination of LSTM and CRF are deployed in this work. The reason for this combination comes from the difference between sequence labeling and maneuver decision. Labels can be independent to each other, however decisions are related. For example, the

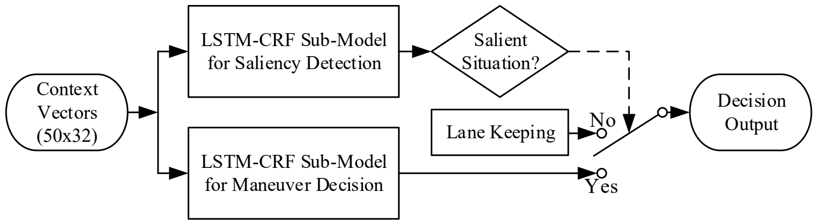

Fig. 3. The overall architecture of proposed human-like maneuver decision method. Two LSTM-CRF sub-models are combined in this method. One sub-model is to distinguish whether the current neighboring traffic situation is ordinary or salient. The other one is to make maneuver decision under salient traffic situations.

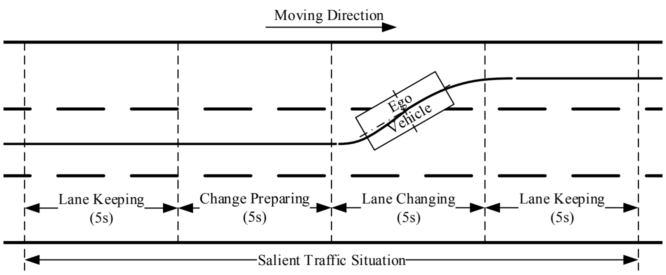

Fig. 4. Proposed four stages of lane-changing procedure inside one salient traffic situation. Other traffic situations with no lane-changing instances are regarded as ordinary ones.

decision of preparing a lane changing will always be given after lane keeping decisions, and lane changing decisions will always be followed by lane keeping decisions. LSTM can not model the relationship between decisions, thus the CRF model, which is good at addressing transitions among hidden states, is added to smooth the outputs of LSTM. Figure 2 shows the architecture of the proposed LSTM-CRF model. In the beginning, a set of context vector c_i over a time window of t_h is fed into two layers of LSTM neural network, with 128 units at each layer. Then, one layer of CRF units is deployed to output the maneuver decision. Note that the structure of the LSTM network is carefully chosen according to a comparitive experiment. In this experiment, a number of samples from the NGSIM dataset are used to evaluate the learning performance of LSTMs with different structures. Table I shows the evaluation result. The 128-128 LSTM network is chosen to achieve the best compromise between learning performance and computational consumption.

C. Proposed Method

If one can effectively train a LSTM-CRF model with human driving datasets, human-like maneuver decision can be achieved. However, it is difficult due to the unbalanced nature of human driving dataset. Lane keeping always acts as the dominance maneuver inside the dataset. Other maneuvers are, in contrary, rarely happened. This unbalancing makes it difficult to train a LSTM-CRF model end-to-end directly. Therefore, following strategies are applied to mitigate this issue.

1) Despite that human drivers will face a great variety of neighboring traffic situations, they will consider to change the lane only in some of these situations. Thus, neighboring traffic situations are first divided into ordinary and salient situations as shown in Figure 4. It is assumed that human drivers will merely follow the lane in ordinary traffic situations, and will consider other maneuvers in salient ones.
2) Similar as [19], the entire lane changing process is separated into four stages inside one salient situation, as shown in Figure 4. In the first stage, the human driver follows the lane while considering whether it is better to change a lane. In the second stage, the human driver decides to change the lane, and is looking for opportunities. In the third stage, the lane changing behavior is executed. In the final stage, the human driver adjusts the vehicle to follow the new lane. According to the statistics in [24], 5 seconds are given for each stage. The maneuver in Equation 3 is thus defined as:

$$m_t = \begin{cases} [1,0,0,0] & if\ Lane\ Keeping \\ [0,1,0,0] & if\ Change\ Preparing \\ [0,0,1,0] & if\ Left\ Changing \\ [0,0,0,1] & if\ Right\ Changing \end{cases} \tag{4}$$

3) Obviously, the task to distinguish ordinary and salient traffic situations can also be described as a sequence labeling problem. Thus, another LSTM-CRF model is applied to solve this task.

In total, the proposed human-like maneuver decision method is consisted of two LSTM-CRF sub-models, as shown in Figure 3. One is dedicated to distinguish whether the current neighboring traffic situation is ordinary or salient. The other one is to make maneuver decision merely under salient situations. During ordinary situations, only lane keeping decisions will be given.

IV. EXPERIMENT

In order to learn from human drivers, the proposed model need to be trained on naturalistic driving data. The NGSIM dataset [12] is choosen as the data source for training and testing. This dataset contains driving maneuvers and trajectories from over 5000 human drivers, collected at U.S. Highway 101 in Los Angeles, California and several other urban traffics. Because the quality of samples can not be guaranteed, cross validation is not adopted here. Instead, we picked out ideal samples for training, and used the entire dataset for performance evaluation.

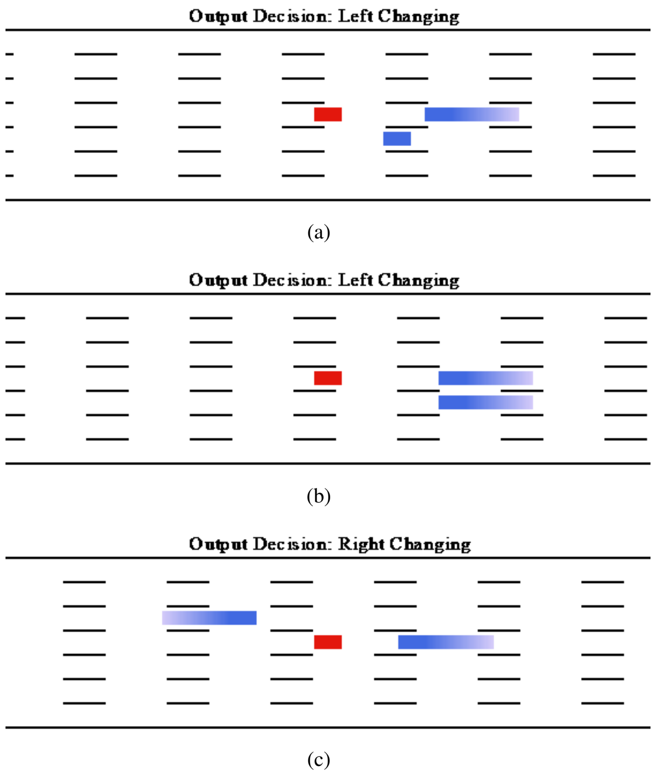

Fig. 5. Three simulations are designed to test the practical performance of proposed human-like maneuver decision model. (a) A slower front vehicle and a right-front vehicle are set. (b) A slower front vehicle and a slower right-front vehicle are set. (c) A slower front vehicle and a faster left-behind vehicle is set. In both cases, reasonable decisions are given by proposed method.

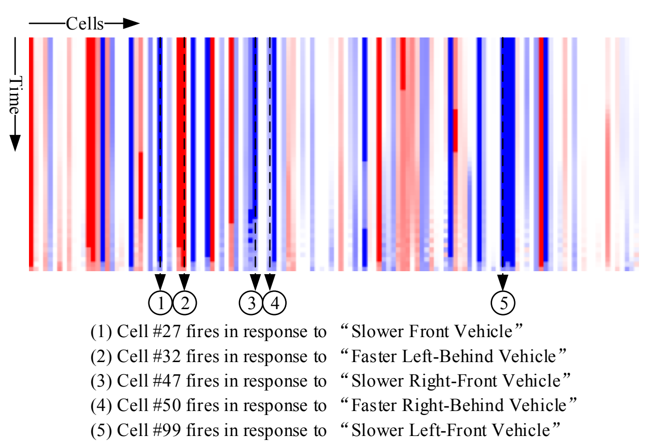

Fig. 6. Visualization of the memory cells inside the LSTM network. These cells belong to the 2nd layer LSTM of proposed maneuver decision sub-model, captured in the 3rd simulation case. Red cells are positively activated, and blue cells are negatively activated. Using control variable method, noticeable cells are found to be responsible for human-like reasoning, and are labeled on the figure.

A. Human-Like Maneuver Decision

Three simulated scenarios with manipulated conditions are designed to find out why the proposed method can make human-like maneuver decisions. In both scenarios, the ego vehicle is moving at 10 m/s, and a front vehicle with speed of 8 m/s is set to incur the lane-changing decision.

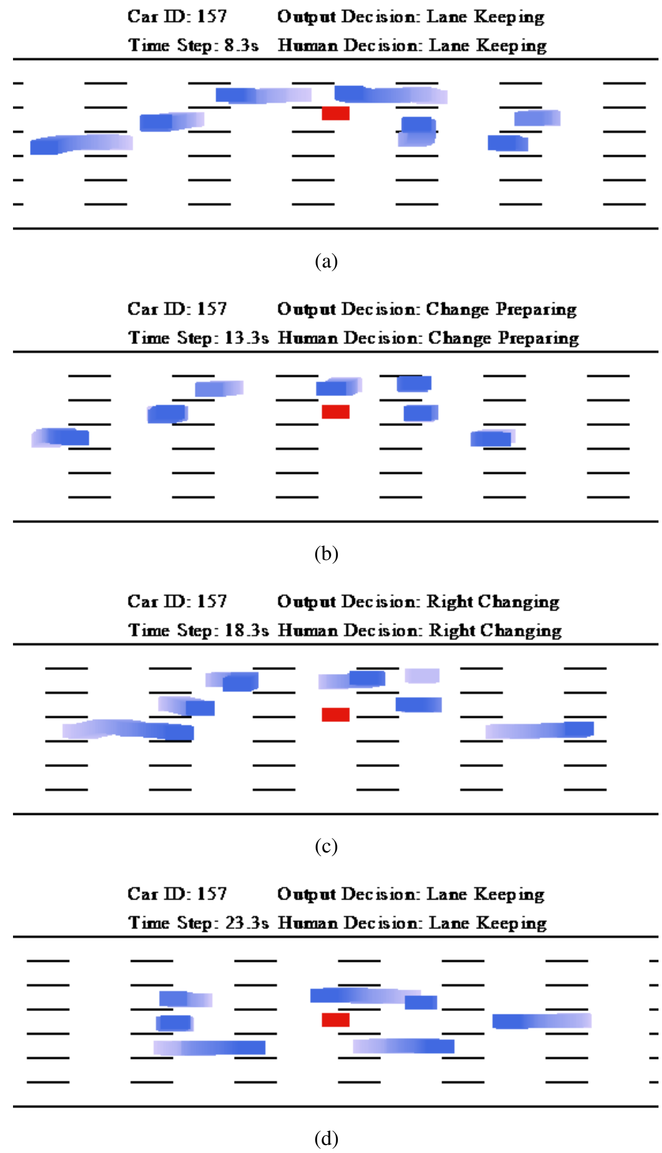

Fig. 7. One test instance for proposed human-like maneuver decision model. During the four stages of the lane-changing procedure, the proposed method gives exactly the same maneuver decision as the human driver did.

In addition, one more vehicle is set to affect the feasible changing direction, as shown in Figure 5. In the first case, a front vehicle at 10 m/s is set to block the right lane. In the second case, a front vehicle at 8 m/s is put to block the right lane. In the third case, a vehicle at 12 m/s is added at behind to block the left lane.

Note that even though these simulation scenarios are artificial, the proposed method is still able to give out human-like maneuver decisions. A closer look is token for a better understanding. Figure 6 gives the visualization of the memory cells in the trained LSTM network. These cells belong to the 2nd layer LSTM, during the 3rd simulation case. Using control variable method, noticeable cells are found and labeled on the figure. The activation of each of these cells can be easily related to a certain changing of the neighboring traffic. These relations reveal a human-like reasoning procedure

TABLE II
PERFORMANCE COMPARISON FOR MANEUVER DECISION.

Method	Lane Keeping		Change Preparing		Left Changing		Right Changing		Averaged	Time
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	F_1-Score	Consuming
SVM [7]	32.6%	58.4%	45.7%	28.5%	23.0%	11.2%	38.8%	37.4%	32.5%	0.17ms
Neural Network [16]	88.6%	80.6%	36.2%	49.6%	42.4%	57.2%	40.7%	47.1%	54.7%	0.70ms
LSTM [3]	99.5%	79.7%	39.1%	97.3%	66.5%	96.8%	61.3%	97.2%	74.6%	3.96ms
Proposed LSTM-CRF	99.9%	77.7%	42.0%	99.8%	80.1%	98.3%	78.6%	98.5%	80.6%	6.25ms

TABLE III
PERFORMANCE COMPARISON FOR RECOGNIZING ORDINARY AND SALIENT TRAFFIC SITUATION.

Method	Ordinary Situations		Salient Situations		Averaged	Time
	Precision	Recall	Precision	Recall	F_1-Score	Consuming
SVM [7]	82.3%	75.6%	34.7%	44.4%	58.9%	0.53ms
Neural Network [16]	82.1%	96.2%	68.6%	28.3%	64.3%	0.75ms
LSTM [3]	78.0%	99.4%	68.1%	40.1%	68.9%	4.01ms
Proposed LSTM-CRF	99.7%	99.6%	98.8%	99.1%	99.3%	6.25ms

TABLE IV
PERFORMANCE COMPARISON FOR HUMAN-LIKE MANEUVER DECISION WITH DIFFERENT LEARNING MODELS.

Method	Lane Keeping		Change Preparing		Left Changing		Right Changing		Averaged	Time
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	F_1-Score	Consuming
SVM [7]	29.9%	81.1%	46.2%	14.3%	28.0%	6.5%	42.8%	26.5%	27.2%	0.70ms
Neural Network [16]	81.5%	98.5%	62.7%	16.3%	68.9%	23.0%	64.6%	18.0%	44.4%	1.56ms
LSTM [3]	78.1%	99.8%	76.5%	20.8%	86.2%	46.5%	89.0%	64.9%	64.0%	10.9ms
Proposed LSTM-CRF	99.6%	99.9%	98.5%	98.0%	99.6%	98.3%	99.3%	98.1%	98.9%	14.0ms

happened inside the model, which is fundamental for the overall human-like decision performance.

B. Evaluation Results

By comparing the outputs from the proposed method and the ground truth collected from human drivers, how human-like the proposed method is can be numerically evaluated. Similar as evaluating a multi-class classifier, four prevalent criteria are used for performance evaluation: precision, recall, F_1-score and time consuming. Precision, recall and F_1-score depict the similarity between the proposed method and normal human drivers. Time consuming is to judge the practicability for self-driving applications. All the related codes are compiled and ran on a laptop with an Intel Core i7 8550U CPU and 8 gigabytes memories. LSTM and CRF model are implemented using the Keras library [25].

Samples inside salient traffic situations are firstly extracted and used to train the maneuver decision sub-model. Then, this sub-model is verified on the entire dataset. Table II illustrates the performance of the proposed LSTM-CRF and models from previous works. All the models are fairly implemented and compared. According to Table II, the proposed LSTM-CRF model achieved the best performance among all models. Nevertheless, its performance is not ideal. This is due to wrong decisions inside ordinary traffic situations. These wrong decisions impair the recall for Lane Keeping and the precision for other maneuvers.

In order to mitigate the above issue, another LSTM-CRF sub-model was adopted to recognize ordinary and salient traffic situations. The performance for this task is given by Table III. Apparently, the proposed LSTM-CRF model once more achieved much better results than other methods for this task. This is because the CRF layer can clearly distinguish long-term dependencies, and find out time-related regularizes efficiently.

Finally, the proposed human-like maneuver decision method with different learning models are implemented and compared. As shown in Figure 3, this task is a combination of saliency detection and maneuver decision. According to Table IV, this combination dose incur increases in decision precision. However, decision recall and F_1-score of previous models are heavily impaired due to their poor performance for saliency detections, as seen in Table III. In contrary, with the proposed LSTM-CRF model, the proposed method achieved an averaged F_1-score of 98.9% for all maneuvers, which is 34.9% higher than the best previous model. Note that the time consuming for each decision is only 14ms. This is much shorter than the averaged reaction time of human beings, which is often more than 200ms. Figure 7 demonstrates a test case for the proposed method, where the decided maneuvers at each time step are exactly the same as the ground truths given by the human driver. Suppose that the maneuver decision is given at each 0.1s, which is sufficient for most on-road self-driving tasks. The ego self-driving vehicle will have 86ms to update trajectories and calculate control signals. This reveals the practicable potential of the proposed method.

As the decision cannot be 100% correct, it is important to address wrong maneuver decisions safely, especially when the proposed method is applied to real-world self-driving applications. During the experiment, it is found that most wrong maneuver decisions appear as rare noises among maneuver decision sequences. It will be helpful to erase these noises by a consistency checking through time, which will cost a short decision delay as a compromise. The other way around is to check the feasibility of the decided maneuver. When a decided maneuver is given, the trajectory which the self-driving vehicle followed will be updated. During this update, wrong maneuver decisions which are dangerous can be filtered out as no feasible trajectory can be generated. Thus the safety of the entire system can be assured.

V. CONCLUSIONS

In this paper, a human-like maneuver decision model for on-road self-driving vehicles is proposed. Different from previous works, the maneuver decision problem is considered as a sequence labeling problem, and two LSTM-CRF models are combined to solve this problem. Experiments and simulations illustrate the outstanding performance and practicability of the proposed method. As this paper is to illustrate the capability of the proposed method, its time consuming will be further reduced by parallelly computation with GPU platforms. Also, traffic data from other countries will be analysed in the future work.

ACKNOWLEDGEMENTS

This research is partially supported by the National Key R&D Program of China under contract No. 2017YFC0803907, the National Natural Science Foundation of China under contract No. 61790563, and China Scholarship Council.

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