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A Human-like Trajectory Planning Method by Learning from Naturalistic Driving Data

Xu He, Donghao Xu, Huijing Zhao, Mathieu Moze, François Aioun, Franck Guillemard

***Abstract*— Trajectory planning has generally been framed as finding the lowest cost one from a set of trajectory candidates, where the cost function has been hand-crafted with carefully tuned parameters by experts. Such methods have technological feasibility of achieving vehicle autonomy, while the resultant behaviors could be much different with those of human drivers. This research proposes a human-like trajectory planning method by learning from naturalistic driving data. A cost function is formulated by incorporating not only the components on comfort, efficiency and safety, but also lane incentive by referring to a human driver's lane change decisions. Coefficients of the cost components are learnt by correlating the probability of a trajectory being selected with its distance (i.e. similarity) to the human driven one at the same driving situation. A data set is developed by using the naturalistic data of human drivers on the motorways in Beijing, containing samples of lane changes to the left and right lanes, and car followings. Experiments are conducted on three aspects: 1) lane change trajectory planning to a given target lane; 2) lane change trajectory planning with simultaneous decision of a target lane; and 3) trajectory planning with simultaneous decision of maneuver. Promising results are presented.**

I. INTRODUCTION

A. Motivation

In the last few decades, there are tremendous development and progress in Advanced Driving Assistant Systems (ADAS) and autonomous vehicles [1]. Advanced intelligent vehicles have great potential to improve the performance and safety of the transportation system and free people from the tasks of driving. While an autonomous driving system needs not only to keep safety, but also follow human drivers behavior, so as to let the passengers of a driverless car feel comfortable and convinced, and other traffic participants of the road keep their usual way in risk prediction and decision making. It is thus important to develop trajectory planning methods that achieve human-like autonomous driving.

The trajectory planner for on-road autonomous driving [2][3][4][5]usually takes the following steps: 1) Given an initial state of the vehicle, sample a set of end points; 2) Generate trajectories by linking the initial state to each end point with consideration to the vehicles kinematic and dynamic constraints; 3) Evaluate the trajectories by a cost function, and select the optimal one for the vehicle to execute. Trajectory optimization [6][7] has also been conducted to minimize the cost of an initial estimate. However finding a proper cost function to evaluate candidate trajectories is highly non-trivial. Cost functions are carefully designed by incorporating the terms on efficiency, comfort and safety, while tuning parameters usually require significant amount of hand-engineering by experts, more importantly the resultant behaviors may be much different with those of human drivers. Such trajectory planning methods have technological feasibility of achieving vehicle autonomy with optimality on efficiency, safety and comfort, while humanization has been ignored.

Inspired by the recent efforts on naturalistic driving data collection and analysis [8][9][10][11] and the promising progress on learning-based approaches [19][20], this research proposes a trajectory planning method by learning from naturalistic data aiming at human-like autonomous driving on crowded highway scenes.

B. Related Work

Trajectory planning has been address with different scopes as the major part of motion planning research. [2][3] decomposed planning into mission planning, behavior executive and motion planning, while in [6][14], motion planning has a much broader meaning, consisting of global, behavioral and local planning. In those work, trajectory planning plays significant role in motion planning. This research addresses on the trajectory planning problem of generating a kinematical and dynamically feasible path and velocity profile for the autonomous vehicle to travel, while planning global path on road network and traffic rules is not concerned.

Hierarchical architecture has been widely used [2][3][6][15] to decompose the workload of planning for long-term and complex driving tasks, no matter how the scope of trajectory planning is defined. For example in [2], hierarchical layers deal with the tasks at mission, behavior and trajectory levels, where mission planning returns an optimal route to the destination, behavior executive makes tactical decisions on such as car following or lane changing, trajectory planning generates a desired trajectory concerning the vehicles kinematic and dynamic constraints, and output for control modules execution. Such hierarchical architecture has a shortcoming on that the higher-level decision making module usually does not have enough detailed information, and the lower-level layer does not have authority to reevaluate the decision [3]. For example, the behavior executive make a decision of lane changing, whereas the trajectory planner may fail to find a feasible trajectory to fulfill the lane changing mission. To solve this problem, [3] integrated behavioral decision

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Contact: H.Zhao, zhaohj@cis.pku.edu.cn.

and trajectory planning into one layer by using a prediction engine. After sampling candidate strategies that contain both longitudinal and lateral movements, the prediction engine forward-simulates each candidate to get trajectories of the subject as well as environmental vehicles. These candidates are finally evaluated by a cost function, and the best one is forwarded to the corresponding ACC or lateral controllers for execution.

Trajectory planning has generally been framed as finding the lowest cost one from a set of trajectory candidates [2][3][4][5][7][16]. A cost function encodes a systems preference, therefore has significant impact on the robots performance. However designing a proper cost function could be highly non-trivial, which is usually hand crafted [3][7], needs to balance the contributions (e.g. weights) of many components that could potentially be correlated or even contradictory, and it is even harder to design a correct setting to generalize enough to various conditions. Furthermore, an autonomous vehicle needs not only fulfill its mission (e.g. achieving a destination efficiently and safely), but also follow human drivers behavior. Hence designing a cost function that encodes human drivers preference in decision making and operation is of great importance.

Machine learning methods have been used to learn cost functions or parameter settings from the data of human demonstration. Research efforts are also addressed for autonomous driving applications. The problem of learning driving style from expert demonstration is formulated using inverse reinforcement learning (IRL) [21], and adapted to learn a cost function of path planning for an application of parking lot navigation [22]. The method is then extended to maximum entropy formulation [23], and exploited to compute trajectories that mimic the driving styles of demonstrators for autonomous driving on highways [24]. Model-based approaches are also studied. [19] predicted lane change trajectories by interpolating the K-nearest instances of human drivers. [17][20] learnt parameters of longitudinal driving models. [18] fit speed and path model parameters for traffic-free planning.

C. Overview of the research

This research proposes a trajectory planning method by learning from naturalistic data aiming at human-like autonomous driving on crowded highway scenes. At a certain driving condition, a set of trajectory samples is first generated containing both longitudinal and lateral movements, a desired one is then selected with a cost function, which is designed with not only the factors such as the efficiency, comfort and safety as an existing autonomous driving system does [3][7], but also concerns lane incentive referring to a human driver's lane change decision [25]. A method is developed to learn cost coefficients by correlating the probability of a trajectory being selected with its distance (i.e. similarity) to the human driven one at the same driving situation. In the authors early works, a system of on-road vehicle trajectory collection [26] is developed together with methods of lane change extraction and analysis [27]. Based on these work, a data set is developed using human driver's data on the motorways in Beijing, containing samples of lane changes to the left and right lanes, and car followings. Experiments are conducted on three aspects to seek answers whether the learnt planner could propose autonomously a trajectory that is close to that of human driven one at the following prepositions: 1) when a target lane is decided (i.e. lane change trajectory planning to a target lane); 2) when lane change maneuver has been decided, while it could be made either to the left or the right lane (i.e. lane change trajectory planning with simultaneous decision of the target lane); and 3) subsequent maneuver on either left/right lane change or car following has not been decided (i.e. trajectory planning with simultaneous decision of maneuver). Performance of the proposed method is demonstrated by the experimental results.

This paper is structured as follows. An extensive review of the literature works on driving behavior modeling, trajectory planning and learning from data is given in section I. The proposed method framework and details are described in section II and section III, respectively. Experimental results using on-road driving data is presented in section IV, followed by conclusion and future works in section V.

II. Problem Formulation

At a certain driving situation $\mathcal{S}$, a traditional trajectory planning method will first generate a set of synthesized trajectories $\{T_1, T_2, ..., T_n\}$, then select an optimal one for the autonomous driving system's execution, e.g. $T_{opt} : opt = \arg\min_j f(T_j)$, based on a cost function f. However, the cost function has been hand crafted to balance the contributions of different components, and the selected trajectory may not follow human driver's behavior. As illustrated in Fig. 1, this research exploits the same work flow, but learns a cost function f that has preference to the trajectories T_j that are similar with the human driven ones.

In this work, a human driven sample $\mathscr{H}^i = (\mathcal{S}^i, T^i_{GT})$ consists of a $\mathcal{S}^i$, describing the driving situation at time t_s and a given human driven trajectory T^i_{GT} from t_s to t_e, where t_e is the real terminal time for lane changes, and given by fixed duration $\tau = t_e - t_s$ for car followings. Lane change is defined like [27] as the segment that ego vehicle heads towards the road direction at the start time t_s and end time t_e, meanwhile the ego has a lateral shift of approximately a lane width during the period. Let $T^i = \{T^i_1, T^i_2, ..., T^i_{n_i}\}$ be a set of trajectories that is generated at the driving situation $\mathcal{S}^i$ by tessellating a predicted range of terminal states. Here, T^i serves as a proposal of all candidate motion sequences in future seconds. Let $d^i_j = d(T^i_j, T^i_{GT})$ be a measure, evaluating distance between a synthesized trajectory T^i_j and the human driven one T^i_{GT} at the driving situation.

Let f be a cost function that is formulated on the trajectory's comfort, efficiency, lane incentive and safety with a set of coefficients Ω. Considering that lower cost prompting higher probability of the trajectory being selected, we therefore convert cost to probability $p(f(T^i_j))$ with a softmax transform function p. Intuitively we would like that

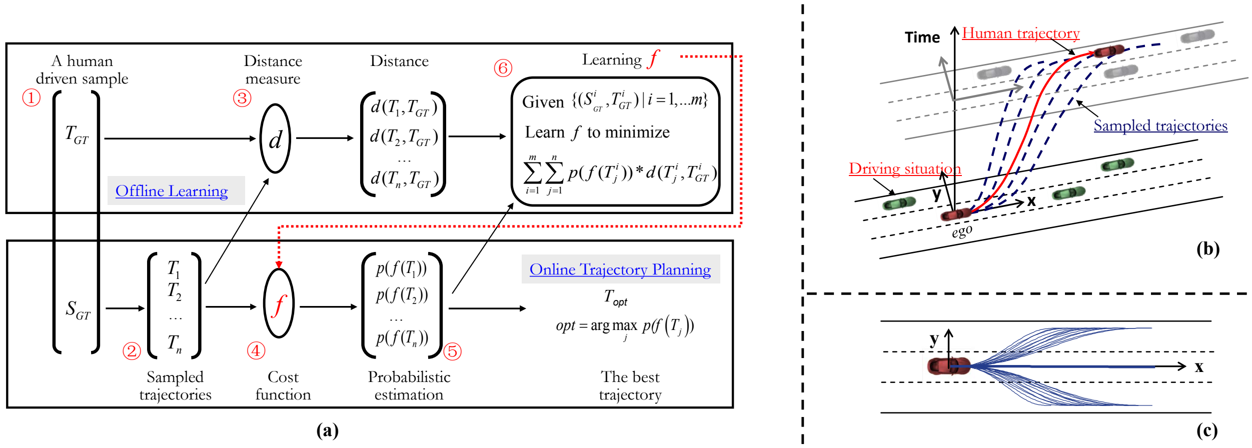

Fig. 1. (a) Proposed trajectory planning model. (b) Human driven sample. (c) Trajectory sampling method.

the more similarity (i.e. less distance) the trajectory has with the human driven one, the higher probability it has to be selected. Therefore given a set of human driven samples $\{\mathscr{H}^1, \mathscr{H}^2, ..., \mathscr{H}^m\}$, the problem is formulated as finding a cost function f (i.e. its coefficients Ω) to minimize the objective function as Eqn. 1, where n_i represents the total number of the generated trajectories corresponding to $\mathscr{H}^i$.

$$\sum_{i=1}^{m}\sum_{j=1}^{n_i} p(f(T_j^i)) * d(T_j^i, T_{GT}^i) \tag{1}$$

Below, we present details of human driven sample $\mathscr{H}^i$, trajectory set generation T^i, distance measure d_j^i, cost function formulation f, probability transform p and the learning of Ω.

III. Algorithm

A. Human Driven Sample

Each data sample is described in a Frenet frame [5] with the origin at the ego vehicle's location at the initial time. Let $p = (x, y)$ be a location at the Frenet frame, where x and y are displacements from the origin on longitudinal and lateral road directions respectively, and $\dot{p} = (\dot{x}, \dot{y})$ and $\ddot{p} = (\ddot{x}, \ddot{y})$ are velocity and acceleration vectors. A driving situation $\mathcal{S} = \{S_{ego}, S_{env}, S_{road}\}$ is described with three components, where the first two are the states of the ego and environmental vehicles at the local surrounding that are described by their location, velocity and acceleration as below,

$$S_{ego} = (p, \dot{p}, \ddot{p})_{ego} \tag{2}$$

$$S_{env} = \{(p, \dot{p}, \ddot{p})^j_{env} | j = 0, .., K\} \tag{3}$$

where $j = 0, .., K$ is the index of the environmental vehicles. In this research, the preceding and back vehicles on the left, right and current lanes are concerned. $S_{road} \in \{-1, 0, 1\}$ is about road situation, indicating that the ego vehicle is driving at the farthest left lane, a middle lane or the farthest right lane. On the other hand, a trajectory T_{GT} is a time series of trajectory points $\{P_k | t_s \leq k * \Delta t \leq t_e\}$, where $P_k = (p, \dot{p}, \ddot{p})_k$, t_s and t_e are the initial and terminal times of the trajectory, and Δt is the time interval of data sampling. In case of a lane change sample, t_e is the time when the maneuver finished and $\tau = t_e - t_s$ is the duration. At real world driving, τ is a variable. As analyzed in [27], it varies within a range of $[\tau_{min} = 6s, \tau_{max} = 10s]$. In case of car following samples, a fixed duration ($\tau = 8s$ in this research) is used.

B. Trajectory Sampling

At the beginning of certain driving situation $\mathcal{S}$, a set of trajectories $\{T_1, T_2, ..., T_n\}$ is generated by description of potential candidates about future motion sequences. In this research, the trajectory generation method [5] is used, which represents a trajectory using two quintic polynomials on longitudinal and lateral axes respectively.

$$T : \begin{cases} \mathbf{x}(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \\ \mathbf{y}(t) = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 \end{cases} \tag{4}$$

For simplicity, we set $t_s = 0$ and subsequently $t_e = \tau$. Given the value of τ and two trajectory points $P = (p, \dot{p}, \ddot{p})$ at the initial $t = 0$ and terminal times $t = \tau$, six equations can be derived for both $\mathbf{x}(t)$ and $\mathbf{y}(t)$, consequently the coefficients $\{a_0, ..., a_5\}$ and $\{b_0, ..., b_5\}$ are calculated.

Assuming that velocity on lateral axis, and acceleration on both longitudinal and lateral axes are zero at both the initial and end times, and since the trajectory point at the initial time is given by $\mathcal{S}$, which has its location at the origin of the defined Frenet frame, we have the following known conditions,

$$\begin{cases} \mathbf{x}(0) = S_{ego}.x, \dot{\mathbf{x}}(0) = S_{ego}.\dot{x}, \ddot{\mathbf{x}}(0) = 0, \ddot{\mathbf{x}}(\tau) = 0 \\ \mathbf{y}(0) = S_{ego}.y, \dot{\mathbf{y}}(0) = 0, \ddot{\mathbf{y}}(0) = 0, \dot{\mathbf{y}}(\tau) = 0, \ddot{\mathbf{y}}(\tau) = 0 \end{cases} \tag{5}$$

Highway driving has some properties that can be used in trajectory generation: lane width (D_{lane}) and speed limits (V_{max}) at a certain road are known; lateral vehicle positions at the initial and terminal time of each maneuver are usually at the middle of lanes; longitudinal displacement could vary largely with respect to different velocity at the initial time, while longitudinal speed may vary only slightly (ΔV) to keep constant and smooth driving etc. The following terminal states are tessellated.

$$\begin{cases} \mathbf{y}(\tau) \sim \{-D_{lane}, 0, D_{lane}\} \\ \dot{\mathbf{x}}(\tau) \sim [\max(S_{ego}.\dot{x} - \Delta V, 0), \min(S_{ego}.\dot{x} + \Delta V, V_{max})] \\ \tau \sim [\tau_{min}, \tau_{max}] \end{cases} \tag{6}$$

C. Distance Measure

Given a pair of synthesized trajectory T_j and human driven one T_{GT}, discretization is first conducted to convert continuous trajectories to sequences of synchronized points at an equal interval Δt.

$$T_j = \{(\mathbf{p}_j(t), \dot{\mathbf{p}}_j(t)) | t = 0, \Delta t, .., n_j \Delta t\} \tag{7}$$

$$T_{GT} = \{(p_t^{GT}, \dot{p}_t^{GT}) | t = 0, \Delta t, .., \tau = n_{GT} \Delta t\} \tag{8}$$

where $\mathbf{p}_j(t) = (\mathbf{x}_j(t), \mathbf{y}_j(t))$ and $\dot{\mathbf{p}}_j(t) = (\dot{\mathbf{x}}_j(t), \dot{\mathbf{y}}_j(t))$ are the location and velocity at the Frenet frame of the synthesized trajectory T_j at time t, while p_t^{GT} and $\dot{p}_t^{GT}$ are those of the human driven one.

Distance between each pair of synchronized trajectory points are estimated on both the location ($D_j(t) = ||\mathbf{p}_j(t) - p_t^{GT}||$) and velocity ($\dot{D}_j(t) = ||\dot{\mathbf{p}}_j(t) - \dot{p}_t^{GT}||$) components. Weighing by a parameter λ_d and taking an average of these distances during the course, a distance measure between T_j and T_{GT} is formulated as Eqn. 9, where $n_{min} = min(n_j, n_{GT})$.

$$d(T_j, T_{GT}) = \frac{\sum_{n=1}^{n_{min}} D_j(n\Delta t) + \lambda_d \dot{D}_j(n\Delta t)}{n_{min}} \tag{9}$$

D. Cost Function

This research also addresses the trajectory planning problem when the target lane has not been decided, e.g. a lane change could be made to either the left or right lane, the vehicle could perform either longitudinal driving or lane change, etc. Lane incentive [28] is incorporated in addition to the well-used components on comfort, efficiency and safety. Below, we detail the formulations on each component, followed by a summary of the total cost.

1) Comfort: High acceleration and high acceleration change ratio (i.e. jerk) could be the major reasons of uncomfort. In Frenet frame, vehicle motion is decomposed into longitudinal and lateral movements. Comfort of a trajectory is evaluated on its acceleration and jerk on two individual dimensions as formulated below.

$$\begin{cases} c^j_{lon,acc} = (\sum_{n=1}^{n_j} |\ddot{\mathbf{x}}(t_n)|)/n_j \\ c^j_{lat,acc} = (\sum_{n=1}^{n_j} |\ddot{\mathbf{y}}(t_n)|)/n_j \end{cases} \tag{10}$$

$$\begin{cases} c^j_{lon,jerk} = (\sum_{n=1}^{n_j} |\dddot{\mathbf{x}}(t_n)|)/n_j \\ c^j_{lat,jerk} = (\sum_{n=1}^{n_j} |\dddot{\mathbf{y}}(t_n)|)/n_j \end{cases} \tag{11}$$

2) Efficiency: The higher speed, the higher efficiency. Let $\bar{v}_j$ be the average speed of the trajectory, which is estimated in this research by $\bar{v}_j = (\mathbf{x}(t_{n_j}) - \mathbf{x}(0))/t_{n_j}$, efficiency is formulated as below.

$$c^j_{av} = S_{ego}.\dot{x} - \bar{v}_j \tag{12}$$

3) Lane Incentive: Lane incentive evaluates the potential of a lane being selected as the target. In this research, we do not consider the case that the vehicle must leave the current lane for its destination, which is addressed at the strategic level by path planning. A different lane is selected when the current driving condition is not satisfiable (e.g. due to a slow preceding vehicle) and the new target lane has the potential of improving driving condition. Therefore, lane incentive is evaluated on two aspects: 1) repulsion from the current lane, 2) attraction of the target lane. In case the current and the target lanes are the same, longitudinal driving is kept.

Traffic situation on each lane is crucial in lane selection. The current sensing system measures environmental vehicles location, hence their second derivative (acceleration) could be highly noisy. On the other hand, vehicles' instantaneous locations change dramatically, yielding an algorithm sensitive to estimation timing. Comparing to instantaneous locations, vehicle velocities are influential in a driver's decision making and providing more stable estimation.

To this end, repulsion from the current lane is evaluated using the signed velocity difference of the ego with its leading vehicle as formulated below. The greater the difference, the more repulsion from the current lane. And each potential target lane is evaluated individually, including the left, right and current lanes, and denoted by a subscript 'tar'.

$$c^j_{rep,tar} = S_{ego}.\dot{x} - v_{lead} \tag{13}$$

Attraction of the target lane is evaluated using the signed velocity difference of the ego with the preceding and back vehicles on the target lane as formulated below.

$$\begin{cases} c^j_{s,tar,pre} = v_{tar,pre} - S_{ego}.\dot{x} \\ c^j_{s,tar,back} = S_{ego}.\dot{x} - v_{tar,back} \end{cases} \tag{14}$$

$$\begin{cases} c^j_{e,tar,pre} = \tilde{v}_{tar,pre} - \tilde{v}_{ego} \\ c^j_{e,tar,back} = \tilde{v}_{ego} - \tilde{v}_{tar,back} \end{cases} \tag{15}$$

Evaluations are conducted at both the initial and terminal time of the maneuver, and denoted by subscripts 's' and 'e' respectively. Velocities of the preceding and back vehicles at the initial time are given in the driving situation $\mathcal{S}$, while those at the terminal time are predicted on a linear motion model. The predicted values are denoted by a superscript '$\sim$'. The greater the differences, the more attraction from the target lane.

4) Safety: Distances between the ego and environmental vehicles at each discrete time during the course of the trajectory are examined to evaluate its safety. Motion sequences of environmental vehicles are predicted on a linear motion model based on the initial states that are described in $\mathcal{S}$, and discritized to trajectory points $T_{env,q}$ at the same interval Δt.

$$T_{env,q} = \{(x_q^{env}(t_q), y_q^{env}(t_q)) | t_q = 0, \Delta t, .., n_{max} \Delta t\} \tag{16}$$

Here subscript 'q' denotes the id of an environmental vehicle, the preceding and back vehicles on the left, right and current lanes are only concerned. As longitudinal and lateral distances may contribute to different safety costs, they are estimated individually, $D^q_{x,j}(t) = (\mathbf{x}_j(t) - x^{env}_q(t))^2$ and $D^q_{y,j}(t) = (\mathbf{y}_j(t) - y^{env}_q(t))^2$, and weighed with a parameter λ_x. An average is taken on these distances to formulate safety cost as below.

$$c^j_{safe} = \{\sum_{n=1}^{n_j}\sum_{q=1}^{m_{t_n}} exp\{-(\lambda_x D^q_{x,j}(n\Delta t) + D^q_{y,j}(n\Delta t))\}\}/n_j \tag{17}$$

5) Total Cost: Summarizing all above components in a vector

$$C_j = [c^j_{lon,acc}, c^j_{lat,acc}, ..., c^j_{rep,left}, c^j_{rep,mid}, c^j_{rep,right}, c^j_{s,left,pre}, c^j_{s,mid,pre}, c^j_{s,right,pre}, ..., c^j_{safe}]$$

The total cost $f(T_j)$ of a trajectory $T_j \in T$ is formulated by weighting C_j with a set of coefficients.

$$f(T_j) = \sum_{k=1}^{K} \Omega_k \cdot (C_j)^k \tag{18}$$

where, Ω_k is a vector of coefficients weighting on each component, and K is the maximum exponential coefficient of the cost function.

E. Probability Estimation

A softmax function p is used to transform cost $f(T_j)$ to probability $p(f(T_j))$, where the lower cost is, the higher probability of a trajectory being selected.

$$p(f(T_j)) = exp\{-f(T_j)\}/\sum_{k=1}^{n_j} exp\{-f(T_k)\} \tag{19}$$

F. Learning method

Pseudo code of the learning method is described in Algorithm (1). The goal is to find a set of coefficients $\Omega = \{\Omega_1, \Omega_2, ..., \Omega_K\}$ that minimizes total distance of all trajectories combined with probability of the trajectory adopted with gradient descent methods.

Algorithm 1 Learning Method

Require: The "situation- ego trajectory" database Π
Ensure: The optimal cost function weight Ω

for each $(\mathcal{S}^i, T^i_{GT}) \in \Pi$ **do**
  Generate sampled trajectory set T^i
  for each $T^i_j \in T^i$ **do**
    Calculate the similarity measure $d(T^i_j, T^i_{GT})$
    Calculate the cost $f(T^i_j)$ using cost function
    Transform the cost to the probability $p(f(T^i_j))$
  end for
end for
solve: $\hat{\Omega} = \arg\min_{\Omega} \sum_i \sum_j p(f(T^i_j)) * d(T^i_j, T^i_{GT})$

TABLE I
DATA PROFILE.

Lap	Date	LLC Num	RLC Num	CF Num
1	2016/10/12	9	13	29
2	2016/10/15	8	11	24
3	2016/10/17	4	-	22
4	2016/10/19	-	-	19
5	2016/10/22	12	11	15
6	2016/10/23	6	6	23
7	2016/10/24	3	2	11
8	2014/01/02	19	16	-
9	2014/01/02	7	7	-
10	2014/01/06	11	16	-
11	2014/01/06	21	24	-
12	2014/01/06	18	16	-
13	2014/01/06	17	13	-
Total		135	135	143

IV. EXPERIMENT

A. Data set

A system of on-road vehicle trajectory collection is developed in the authors early works [26], which is used in this research to collect on-road naturalistic driving data. As shown in Fig. 2, data collection is conducted on the 4th Ring Road in Beijing. It is a multi-lane motorway that is free of traffic signals, has a total distance of 65.3 km and a designed maximum speed of 80 km/h. Each data collection means one-round driving (called a "lap") on the 4th Ring Road by following traffic flow naturalistically. As listed in Tab. I, human driving samples are extracted from 13 laps of data. Lane change segments are extracted by using the method of [27], containing both left (LLC) and right lane changes (RLC). Car following (CF) ones are extracted for a fixed duration of 8s (i.e. an average duration of lane changes) when the following conditions are met simultaneously: 1) driving on straight roads and 2) keeping a distance with its front vehicle within 40m. Since driving behaviors at jammed conditions could be much different, in this research, the segments with the ego's initial speed lower than 8m/s are discarded. Fig. 3(a) shows a lane change segment, which contains both the ego and environment vehicle trajectories during the period of the lane change. With each segment, the road, ego and environmental vehicles' states at the initial time t_s are used to make $\mathcal{S}$ for driving situation, the ego vehicle's trajectory from t_s to t_e is extracted as T_{GT}, and the $\mathscr{H} = (\mathcal{S}, T_{GT})$ pair composes a human driving sample as shown in Fig. 3(b). From 13 laps of data, a set of human driving samples containing 135 left lane change (LLC), 135 right lane change (RLC) and 143 car following (CF) are developed and used in the experiments below(Tab. I).

B. Experimental Design

We seek to answer the question: whether the learnt planner could propose autonomously a trajectory that is close to that of human driven one at the following prepositions?

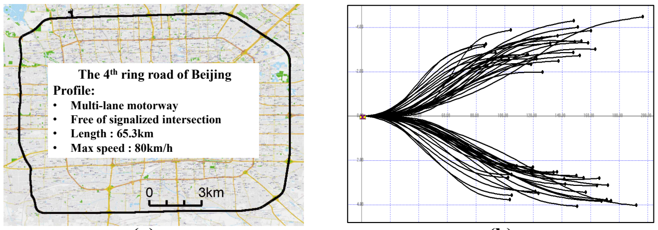

Fig. 2. Data Collection Route & Lane Changing Trajectories

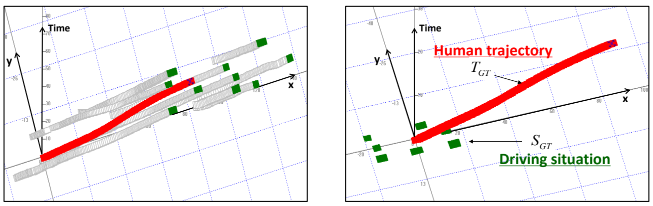

Fig. 3. Lane changing Case & Naturalistic Human Driven Sample

- $Pre.1$: a target lane has been decided;
- $Pre.2$: lane change maneuver has been decided, while it could be made to either the left or right lane;
- $Pre.3$: subsequently maneuver has not been decided, which could be left or right lane change, or car following.

The following experiments are subsequently designed.

- $Exp.1$: lane change trajectory planning to a target lane;
- $Exp.2$: lane change trajectory planning with simultaneous decision of the target lane;
- $Exp.3$: trajectory planning with simultaneous decision of maneuver.

In the first two experiments, the human driven samples of RLC and LLC are only used, while all samples are used in the third experiment. In each experiments, the samples are randomly divided into two groups as listed in Tab. II for training and testing. Experimental results are presented below.

C. Results

1) Exp.1 - Lane change trajectory planning to a target lane: For each human driven sample $\mathscr{H}^i$, the target lane is treated as a known value according to T^i_{GT}, hence a set of trajectories $\{T^i_j\}$ is synthesized to the target lane according to the driving situation $\mathcal{S}^i$. Tessellation of the terminal state is conducted on duration τ in range $[\tau_{min} = 6s, \tau_{max} = 10s]$ at resolution $1s$, and longitudinal velocity $\dot{\mathbf{x}}$ in Eqn. 6 with $\Delta V = 4m/s$ at resolution $1m/s$. A cost function f is learnt by minimizing Eqn. 1. The following measures are defined to evaluate its performance.

TABLE II
EXPERIMENT DATA

	Train Num	Test Num	$Exp.1$	$Exp.2$	$Exp.3$
CF	90	53	×	×	◯
LLC	90	45	◯	◯	◯
RLC	90	45	◯	◯	◯

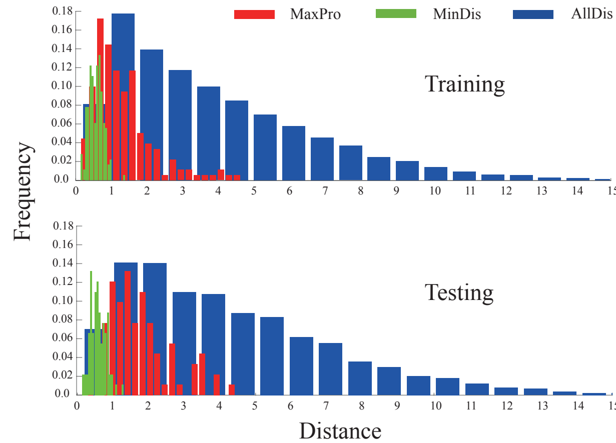

Fig. 4. Result of Exp.1 - evaluation on distance measures.

$$j^* = \arg\min_{j \in T^i} d^i_j \tag{20}$$

$$MinDis^i = d^i_{j^*} \tag{21}$$

$$r^p_i = R_p(p(f(T^i_{j^*})))/n_i \tag{22}$$

$$j^{**} = \arg\max_{j \in T^i} p(f(T^i_{j^{**}})) \tag{23}$$

$$MaxPro^i = d^i_{j^{**}} \tag{24}$$

$$r^d_i = R_d(d^i_{j^{**}})/n_i \tag{25}$$

As defined previously, d^i_j is the distance between a synthesized trajectory candidate T^i_j and the human driven one T^i_{GT}. j^* is the index of the trajectory candidate that is the closest to the human driven one in the set T^i, and $MinDis^i$ is the minimal distance. j^{**} is the index of the trajectory candidate that has the highest probability in the set T^i, and is selected using the learnt f. $MaxPro^i$ is the distance of the selected trajectory.

Histograms of $MinDis^i$ and $MaxPro^i$ are generated describing the distance profiles of the most similar trajectory with the human driven one and the selected one by using the learnt cost function, in addition with a histogram of all d^i_j, denoted by "AllDis". These histograms are plotted in Fig. 4 in green, red and blue respectively. From the results of both training and learning, it can be found that although the most similar trajectories are not selected by the learnt cost function, the selected are among the similar ones (i.e. less distance) in the set of all trajectories, demonstrating the efficiency of the learning method.

Rankings of the selected trajectories are also analyzed. Of the human driven sample i, j^* is the index of the closest trajectory, i.e. minimal distance one. The closest trajectories of all human driven samples are sorted on their probability being selected in an decreasing order, r^p_i is the ranking by n_i, where n_i is the number of trajectories in the set T^i. On

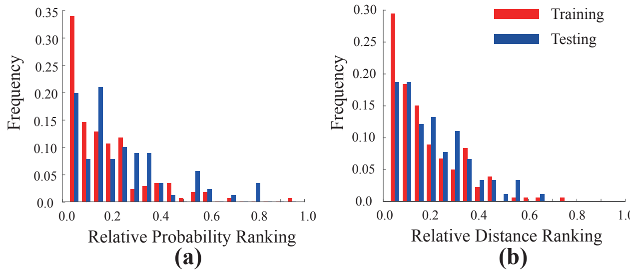

Fig. 5. Result of Exp.1 - evaluation on ranking.

TABLE III
DECISION OF THE TARGET LANE - EXP.2.
(H): HUMAN (P): PLANNED

	Training		Testing	
	LLC(H)	RLC(H)	LLC(H)	RLC(H)
LLC(P)	**81**	6	**41**	3
RLC(P)	9	**84**	4	**42**
Accuracy	90.0%	93.3%	91.1%	93.3%

the other hand, j^{**} is the index of the selected trajectory, i.e. the highest probability one. The selected trajectories of all human driven samples are sorted on their distance to the human driven one in an increasing order, r_i^d is the ranking normalized by n_i. A histogram r_i^p and r_i^d of all human driven samples is estimated and plotted in Fig. 5.a and Fig. 5.b, respectively. It can be found that most of the selected trajectories are among the top ranking ones.

2) Exp.2 - Lane change trajectory planning with simultaneous decision of the target lane: For each human driven sample, a set of trajectories is generated for lane changes to both the left and right lanes. Results are shown in Fig. 6, Fig. 7, which can be discussed and concluded in the same way with those in Exp.1.

Since this experiment is conducted with unknown target lanes, the planned trajectory suggests not only the vehicle's motion sequence in future seconds, but also the target lane,

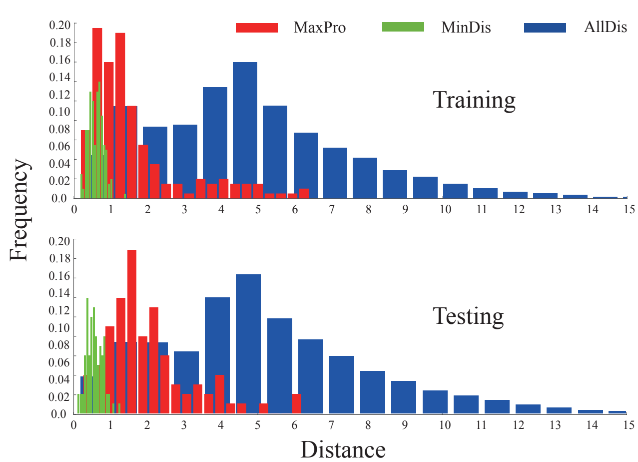

Fig. 6. Result of Exp.2 - evaluation on distance measures.

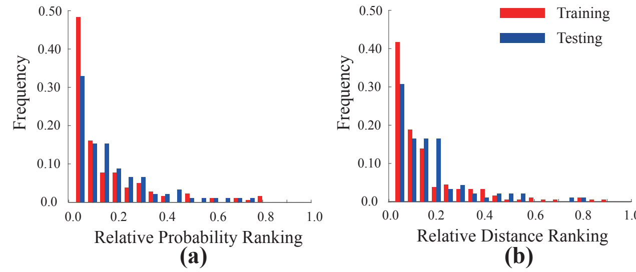

Fig. 7. Result of Exp.2 - evaluation on ranking.

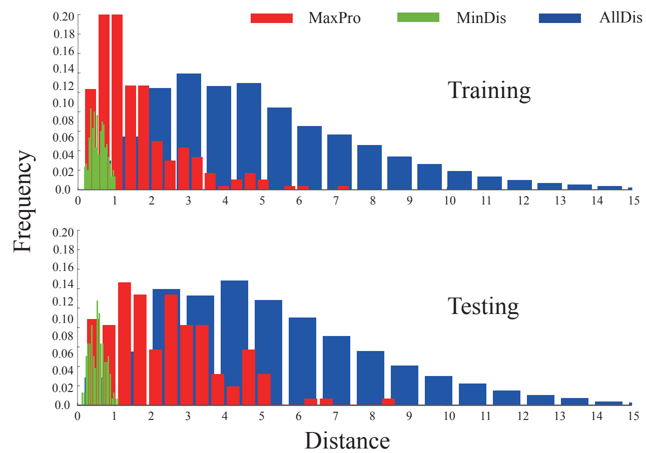

Fig. 8. Result of Exp.3 - evaluation on distance measures.

i.e. simultaneous maneuver decision of either left or right lane changes. The results are analyzed on decision making aspect as summarized in Tab. III. Treating human driver's decision as the ground truth, we evaluate the accuracy of the planned trajectories. It can be found that in the results of both testing and training, accuracy of maneuver decision of both RLC and LLC are above 90%.

3) Exp.3 - Trajectory planning with simultaneous decision of maneuver: For each human driven sample, a set of trajectories is generated containing those for changing to the left or right lanes, and keeping the current lane. Results are shown in Fig. 8 and Fig. 9 that can be discussed in the same way, while it can be found that the histograms of "Max-Pro" have less focused picks and distribute across broader range comparing with the results of previous experiments, especially in the result of testing.

The trajectory candidate of the highest probability is selected, which prompts a maneuver of LLC, RLC or CF too. The results are shown in Tab. IV. Comparing to the results of Exp.2, the accuracies are much lower. The figures prompt an underfit in training, which could be due to local minimums. This problem will be solved in future works.

V. CONCLUSIONS AND FUTURE WORKS

Aiming at human-like autonomous driving, this research proposes a trajectory planning method by learning from nat-

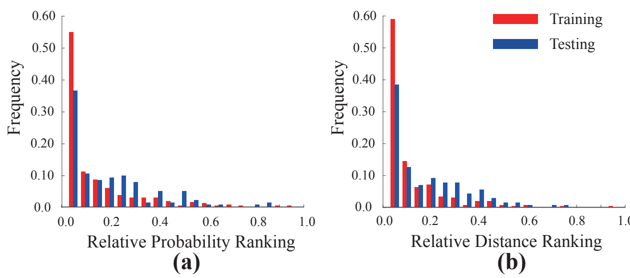

Fig. 9. Result of Exp.3 - evaluation on ranking.

TABLE IV
DECISION OF THE TARGET LANE - EXP.3.
(H): HUMAN (P): PLANNED

	Training			Testing		
	CF(H)	LLC(H)	RLC(H)	CF(H)	LLC(H)	RLC(H)
CF(P)	**77**	4	8	**34**	2	10
LLC(P)	9	**83**	3	11	**38**	2
RLC(P)	4	3	**79**	8	5	**33**
Accuracy	85.6%	92.2%	87.8%	64.2%	84.4%	73.3%

uralistic data. A cost function is formulated by incorporating not only the components on trajectory's comfort, efficiency and safety, but also lane incentive by referring to a human driver's lane change decisions. A method is developed to learn cost coefficients by correlating the probability of a trajectory being selected with its distance to the human driven one at the same driving situation. A data set is developed using the naturalistic human driving data on the motorways in Beijing, containing samples of lane changes to the left and right lanes, and car followings. Experiments have been conducted on three aspects: 1) lane change trajectory planning to a given target lane; 2) lane change trajectory planning with simultaneous decision of a target lane; and 3) trajectory planning with simultaneous decision of maneuver. Results show that the selected trajectory is among the closest to human drivers' in the set of all trajectories. In addition, the proposed method allows simultaneous trajectory planning and behavior decision. In case lane change has been decided, decision accuracy to either the left and right lane is above 90% treating human drivers' as the ground truth. However, in case either lane change or car following/longitudinal driving are candidates, the decision results are not as pleasant, which will be improved in future work.

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