Learning lane change trajectories from on-road driving data

Conference Paper · June 2012

DOI: 10.1109/IVS.2012.6232190

4 authors, including:

Wen Yao
Peking University

Huijing Zhao
Peking University

Franck Davoine
Université de Technologie de Compiègne

2012 Intelligent Vehicles Symposium
Alcalá de Henares, Spain, June 3-7, 2012

Learning Lane Change Trajectories From On-road Driving Data

Wen Yao, Huijing Zhao, Franck Davoine, Hongbin Zha

Abstract— **Lane change is one of the most principle driving behaviors on structure roads. It frequently happens in daily driving. A key issue in lane change technique is trajectory planning, where a set of trajectories describing possible vehicle motions are generated by applying a parametric function, and by uniformly sampling the end states in configuration space; the trajectories are then examined to find an optimal one for execution. However, such a trajectory set has poor efficiency due to the large sample number. Many trajectories in this set seldom happen in real human driving behaviors. In this research, lane change trajectories are collected from real driving data of different drivers. Their statistics are analyzed, through which, a simplified trajectory set is generated. Experiment results show that the trajectory set has much less number of samples but can still guarantee to cover usual lane change behaviors of human being.**

I. INTRODUCTION

A. Motivation

An advanced intelligent vehicle is usually equipped with three modules: perception, decision and execution .*Perception module* finds the host vehicle's pose (i.e. location and orientation), and monitors road and other traffic participants at its local surroundings using sensors such as GPS/IMU, camera, LiDAR, radar and so on. Based on such information, *decision module* aware driving situation through risk assessment, prediction etc., makes a "good" decision for maneuver. *Execution module* converts the decision to either messages for driving assistant or control commands for autonomous driving. In this research, we focus on the trajectory planning for lane change behavior, which is a key issue in decision module.

Lane keeping (or car following) and lane change are two principal driving behaviors on structure roads, which happen frequently in daily driving. Comparing with lane keeping or car following, which is well studied [1][2] with many mature techniques being applied in commercial products, lane change is more complicated. A key issue in lane change technique is trajectory planning. A trajectory is planned, which satisfies the host vehicle's non-holonomic constrains, and then optimized considering the indices such as safety, time and comfort, and more importantly, is in line with human driving behaviors. There have been many researches on lane change trajectory planning [3][4][5], a classic framework contains the following steps: 1) sampling the host vehicle's future states (e.g. in 2 seconds) and constructing a set of end state candidates; 2) a set of trajectories (trajectory set) that describing possible vehicle motion paths are generated by applying a parametric function to an initial state with each end state candidate; 3) examining the trajectories to find an optimal one for execution, according to an objective function on the indices such as safety, time and comfort. A key issue here is how to sample the candidate states so that it can cover various cases in daily lane change behavior. A common solution is to sample the configuration space of future states using uniform lattice. Though all the trajectories in the uniformly sampled space are guaranteed to be feasible for vehicle's maneuver, many of them are seldom used by human being in real driving situation. These trajectories rise computation cost and degrade efficiency of the planner.

Inspired by human lane change behaviors, this work propose a method to simplify the above traditional trajectory set through learning from the real driving data of different drivers, where a trajectory set that representing the usual lane change behaviors is generated, so that online computation can be conducted with more focus and efficiency. This research is described as a function in the driving behavior learning module, which is an offline procedure to generate models for online inference and planning.

B. Related Work

From the 2007 DARPA Urban Chanllenge competition for intelligent vehicles in simplified urban scenarios, to the on-road driving experiment of Google driveless vehicle, driving behavior research in urban scenario becomes more and more active. Lane change behavior is one of the most important part of daily urban driving. There are a lot of research work on this topic. Authors of [3] constructs a roadmap for highway lane change in traffic simulation application. Authors in [4] develop an optimal trajectory generation method for dynamic highway scenarios which is able to plan for safe lane change and overtaking behaviors. State lattice is used for trajectory generation in dynamic on-road driving scenarios in [5]. These algorithms select an optimal solution from a set of trajectories which are safe and feasible for intelligent vehicles. Human drivers' characteristics are seldom considered in these work.

There is also a lot of research work which focuses on human driver. Differential GPS data is used to detect drivers' lane change behavior in [6]. Steering model are built from lane change behavior analysis in [7][8]. But these work usually starts from an assumed model instead of from human drivers' lane change data. Researchers in [9][10][11] compare different drivers at high level but do not focus

This work is partially supported by the NSFC-ANR Grants (No.61161130528), and the NSFC Grants (No.60975061, No.90920304).

W. Yao, H. Zhao, and H. Zha are with the State Key Lab of Machine Perception (MOE), Peking University, Beijing China. yao.wen@pku.edu.cn

F. Davoine is with CNRS, LIAMA Sino French Laboratory, Beijing, China.

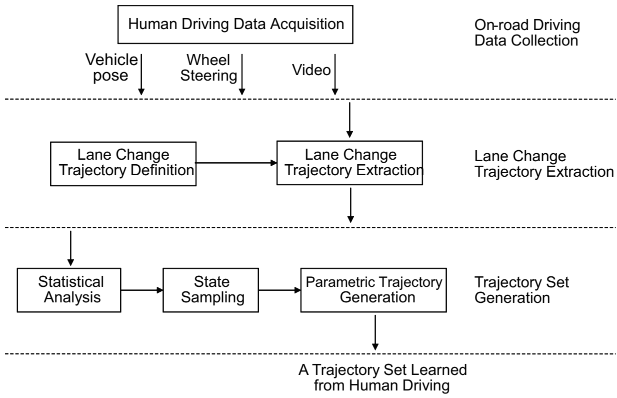


Fig. 1. Research Flow

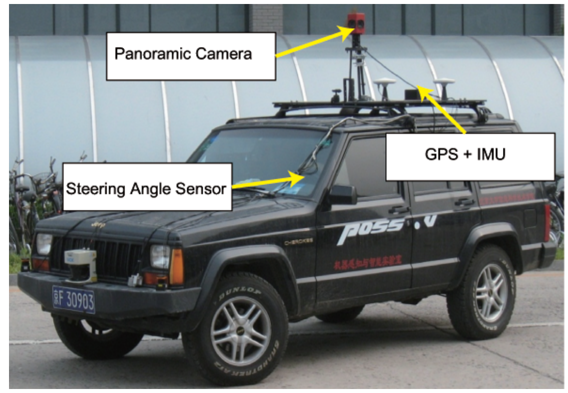


Fig. 2. Sensor setting on our data collection platform: POSS-V

on detailed trajectory features. A multi model cognitive framework is proposed in [12] to analyze the motivation and decision of human drivers. Perception data from vision system is used to give behavior suggestion in [13] when host vehicle is close to traffic signals. And work in [14] fuses the information both from vehicle and driver to detect and predict the state of human drivers.

Previous work on driver behavior analysis and lane change motion planning are separated from each other. In our work, real human driving behaviors are brought into existing lane change behavior planning framework. We analyze the real data of human drivers in urban scenario (city ring road for example) and improve lane change planning benefiting from the human drivers' preference which is hard to be formulated in motion planning problem.

C. Paper Overview

Unlike existing approaches, this paper develops a trajectory set of lane change behaviors, which is a subset of traditional ones, and is generated through learning from the real driving data of different drivers. Main contributions of this paper are 1) a method of extracting lane change trajectories from the real driving data is proposed; 2) a lane change trajectory set is developed, which is a subset of traditional parametric ones, and represents usual human driving behavior. The research flow is outlined in Fig.1.There are three main modules as described below:

1) Driving data collection: a vehicle platform is developed to collect real driving data. It uses GPS to record the vehicle's trajectory, IMU to record steering wheel angle, and video data for examination;

2) Lane change trajectories extraction: the GPS point sequence is segmented to extract those points belonging to a lane change by examining steering wheel angle and video data with human intervention.

3) Trajectory set generation: the real lane change trajectories are studied to find their major statistical distributions. They are used to locate the most usual human driving trajectories, and reject the seldom used ones to reduce the size of uniform latticed trajectory set.

The rest of this paper is organized as follows. Section 2 introduces the experimental platform for human driving data collection and the experimental settings. Section 3 studies data features and gives description to the method of lane change trajectory extraction. The statistics of real lane change trajectories are analyzed, and a trajectory set simplification method is proposed in section 4, followed by conclusion and future work in section 5.

II. ON-ROAD DRIVING DATA ACQUISITION

In order to collect real human driving data in urban street scenarios. We develop our data collection platform POSS-V (PKU Omni Smart Sensing - Vehicle) as shown in Fig.2. Different sensors provide different types of data:

1) GPS/IMU integrated system: Records position data of the host vehicle with time stamps as (x, y, z, yaw, t) with 10Hz frequency. Lane change trajectory key points can be extracted from this data if we know the exact beginning and end time of a single behavior;

2) Steering angle sensor: A small inertial measurement unit fixed on the steering wheel. It records the steering wheel operation of human driver with time stamps which have been synchronized with GPS. Steering angle data can be used to check the accurate start and end of each lane change operation;

3) Panoramic Camera: Records video information around our host vehicle. The recoded images can be used to visually check each lane change trajectory segmented from GPS position data;

4) Coarse start/end time of each lane change trajectory is recorded manually which helps to quickly extract the lane change behavior.

The experiments are carried on the 3^{rd} and 4^{th} ring roads of Beijing, China. They are the two main urban ring roads of Beijing. The environment is open with available GPS signal during most of the time. Some detailed information about our ring road experiment is shown in Table I

To avoid too much redundant data in traffic jam which is very common during rush hours in Beijing, we choose to start experiments at about 14:00 when there is seldom traffic jam but still a lot of cars on road to interact with our data collection platform. Drivers of our platform are required to change lanes or take over other vehicles when it is possible.

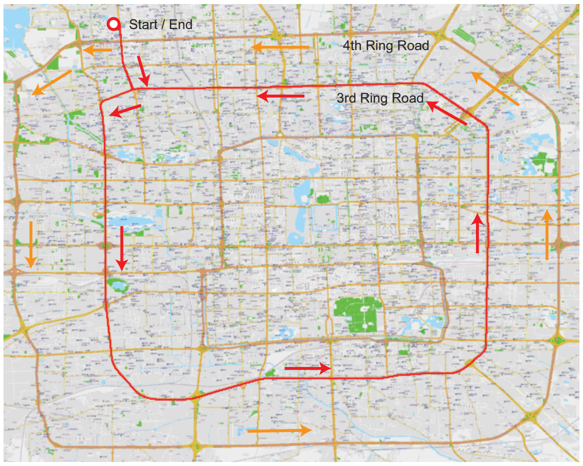


Fig. 3. Experiment on Beijing's 3rd (red) and 4th ring road driving in counter-clockwise direction.

TABLE I

EXPERIMENT PARAMETERS

	Ring Road 3	Ring Road 4
Distance(km)	48.3	85.3
Design Speed(km/h)	80	80
Experiment Rounds	1	6
Lane Change Trajectories	27	474
Drivers	1	5

The GPS position data from a typical round on ring road 3 is shown in red in Fig.3.

III. LANE CHANGE TRAJECTORY EXTRACTION

Considering the high volume data from perception module, the first step is to extract lane change trajectories from GPS points. In this work, we focus on the lane change behaviors happened on straight lanes. One reason for this is that according to the driving habits of most drivers, lane change behaviors are much more probable to be executed on straight road rather than curve road; another reason is that with the trajectory generation algorithm introduced in [4] (which will be recalled in section 3), the states of vehicle are defined in a moving frame as a two dimension coordinate (longitudinal, lateral) with respect to a center line which can be the road shape. So the method we present here almost remains the same for lane change trajectories on curve road. In current work, moving obstacles are not considered since we focus on the generation of a candidate trajectory set which learns from off-line collected data. But it is sure to be important to analysis the interaction between other traffic participants and our host vehicle in future work.

A. Lane Change Behavior Definition

The GPS/IMU integrated system records GPS points sequence representing the trajectory shape of our host vehicle with time stamps. A typical lane change trajectory is shown in Fig.4.

A typical lane change trajectory on straight road approximately satisfies the following requirements:

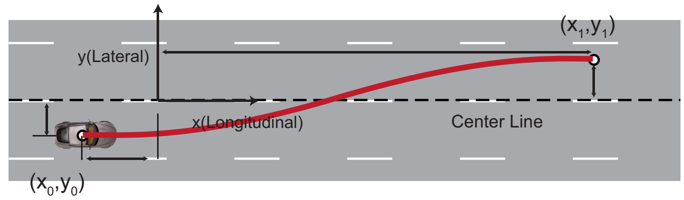


Fig. 4. A typical lane change trajectory

1) The yaw angles are the same at both ends of a lane change trajectory:

$$yaw = \frac{dy_0}{dx_0} = \frac{dy_1}{dx_1} = 0 \tag{1}$$

2) The curvature at both ends of a lane change trajectory is zero, which means the steering angle is zero at the beginning and the end of a lane change behavior:

$$k = \frac{d^2y_0}{dx_0{}^2} = \frac{d^2y_1}{dx_1{}^2} = 0 \tag{2}$$

3) Normal lane change behavior should change just one lane in a single operation and the host vehicle should not cross the border of lane when it is not in lane change operation. Let D_v be the width of our host vehicle, D_{lane} represent lane width, it satisfies:

$$D_v < |y_1 - y_0| < 2D_{lane} - D_v \tag{3}$$

As a result of limited sensor precision and complicated human maneuvers, practical lane change behaviors of human driver do not strictly satisfy these constrains. In the following 2 section, we introduce our data acquisition approach to extract lane change trajectories approaching to above definition from GPS point sequences .

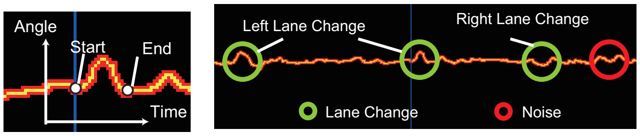
B. Data Processing

One problem here is that, though GPS/IMU can return the yaw angle of the host vehicle, it is not always accurate enough. In addition, the GPS receiver records position point data at a frequency of 10Hz. When the host vehicle is running at 80km/h on ring road, the recorded points are rather coarse. So we need to do some interpolation between recorded GPS points. In order to easily get the yaw angle and curvature at any point along a lane change trajectory and guarantee the continuity of trajectory and curvature at each GPS point, we use cubic spline to connect each pair of GPS points.

Given time points $\{t_i\}_{i=0\sim n}$ and GPS points $\{P_i\}_{i=0\sim n}$, using cubic spline to represent $P_i(t)$ on $[t_i, t_{i+1}]$,

$$P_i(t) = [P_i, P_{i+1}, R_i, R_{i+1}] \cdot M_H \cdot \begin{bmatrix} 1 \\ \frac{t-t_i}{\Delta t_i} \\ (\frac{t-t_i}{\Delta t_i})^2 \\ (\frac{t-t_i}{\Delta t_i})^3 \end{bmatrix} \tag{4}$$

where $\frac{t-t_i}{\Delta t_i} \in [0, 1]$, $\Delta t_i = t_{i+1} - t_i$, $R_i (i = 0, 1, \cdots, n)$ is



(a) Start and end of a lane change in steering angle curve

(b) Left/right lane change and noise

Fig. 5. Lane change behaviors in steering angle data

the tangent vector at $P(t)_{t=t_i}$,

$$M_H = \begin{bmatrix} 1 & 0 & -3 & 2 \\ 0 & 0 & 3 & -2 \\ 0 & 1 & -2 & 1 \\ 0 & 0 & -1 & 1 \end{bmatrix}$$

let $P(t)$ to be C^2, we constrain

$$P_i''(t)|_{t=t_{i+1}^-} = P_{i+1}''(t)|_{t=t_{i+1}^+}$$

with boundary conditions

$$P_i''(t)|_{t=t_0} = R_0'$$
$$P_n''(t)|_{t=t_n} = R_n'$$

we get $n+1$ equations to solve the yaw angle and curvature at each GPS point $P(t)$ along a continous trajectory.

C. Lane Change Trajectory Extraction

To extract the lane change trajectory segments is the foundation of analyzing and learning lane change behaviors. The key problem to extract such trajectories is to find the exact start and end time of a lane change behavior. Since the accuracy of GPS positioning is limited, it is hard to directly find lane change trajectories according to Eqs.(1) and (2).

In order to solve this problem, we record the steering angle with a small IMU set on the steering wheel. A normal lane change trajectory will result in a small wave on the steering angle curve as shown in Fig.5(a).

The start and end time can be located at the beginning and the end of the steering angle curve. But another problem is that in real driving conditions, human drivers are used to fine adjusting steering wheel frequently to keep the vehicle on its path. These maneuvers bring in noise into steering angle information as shown in Fig.5(b). In addition, since a skilled human driver usually turns the steering wheel slightly to make a gentle lane change at high speed, it is difficult to distinguish lane change behavior from these slight tuning operation only with some naive steering angle amplitude threshold. In our experiment, we manually record coarse time of every lane change behavior as a rough result and then use steering angle data to refine the time accuracy as shown above. We also use synchronized video images from panoramic camera as background truth to check if the extracted lane change trajectories are correct.

When we obtain the human driver lane change trajectories, we translate and rotate these trajectories to the same origin with same start orientation. For different drivers, we can obtain a trajectory set for each of them during his experiment as shown in Fig.6.

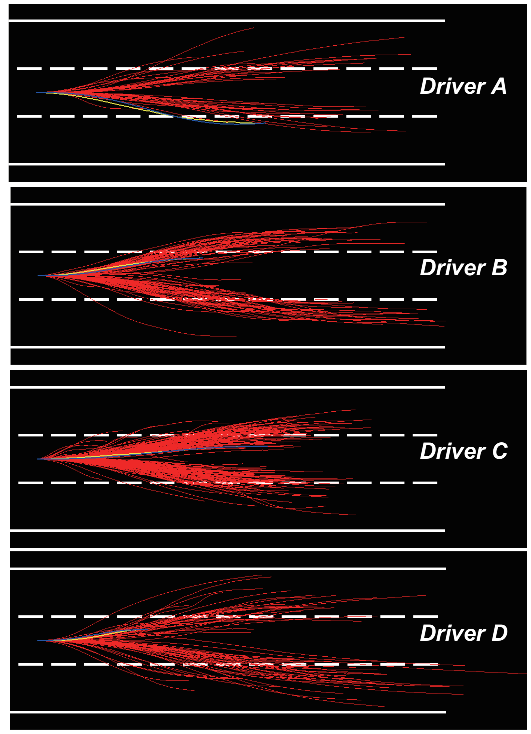


Fig. 6. Lane change trajectories of different drivers

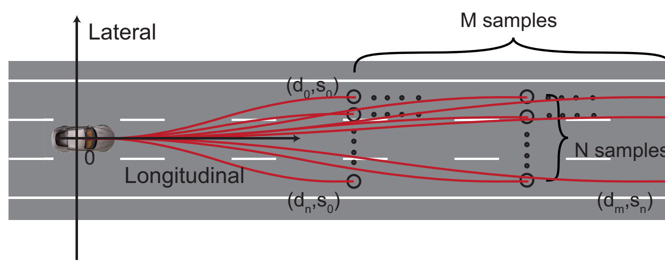


Fig. 7. Uniformly sampled end states in longitudinal and lateral direction

IV. TRAJECTORY SET GENERATION

A. Parametric Trajectory Generation Approach

A trajectory generation method is presented in [4] for motion planning in street scenario. It can quickly generate feasible trajectories which are easy to be followed for intelligent vehicles. As shown in Fig.4, a two-dimension frame is constructed along the road center line. We can construct uniform lattices with $M \cdot N$ end states nearby as shown in Fig.7. By connecting each of them with the initial state of a lane change with non-holonomic constrained curves, we obtain $M \cdot N$ candidate lane change trajectories. Given initial state of host vehicle,

$$\begin{cases} D_{lat} = 0 \\ D_{long} = 0 \\ V_{lat} = 0 \\ A_{lat} = 0 \end{cases} \quad (5)$$

D_{lat} is the lateral offset from center line. D_{long} is the longitudinal distance traveled along the center line. V_{lat} and

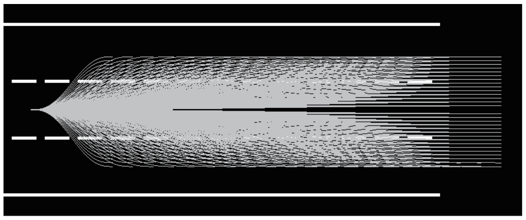


Fig. 8. Uniformly latticed trajectory set(30*20=600 trajectories)

A_{lat} are the lateral velocity and acceleration components. For a sampled end state (d_0, s_0),

$$\begin{cases} D_{lat} = d_0 \\ D_{long} = s_0 \\ V_{lat} = 0 \\ A_{lat} = 0 \end{cases} \tag{6}$$

these equations mean the lane change trajectory ends at a state with a lateral offset of d_0 and longitudinal displacement of s_0 with respect to the initial state with zero final lateral velocity and acceleration. There is a unique quintic function curve connecting these two states:

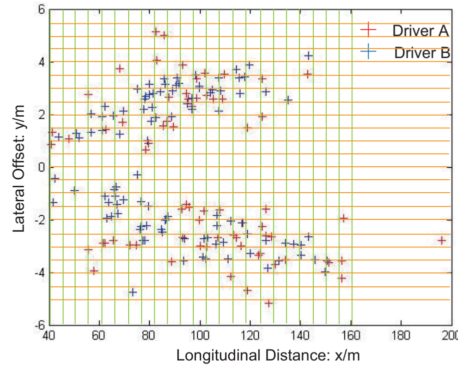
$$\begin{cases} D_{lat}(s) = a_0 + a_1 s + a_2 s^2 + a_3 s^3 + a_4 s^4 + a_5 s^5 \\ V_{lat}(s) = a_1 + 2a_2 s + 3a_3 s^2 + 4a_4 s^3 + 5a_5 s^4 \\ A_{lat}(s) = 2a_2 + 6a_3 s + 12a_4 s^2 + 20a_5 s^3 \end{cases} \tag{7}$$

With Eqs.(5)(6)(7) we obtain 6 equations to solve a_0 to a_5, so that we can get these 6 parameters which describe a quintic curve. With all the sampled end state connected to the initial state, we get a uniform latticed trajectory set as show in Fig.8. As we mentioned in section 1, in such a big trajectory set, many trajectories are seldom executed by human driver in real lane change behaviors since they are not the way human drivers change lanes. And this is the reason why we try to use human lane change trajectories described in section 3 to simplify this parametric trajectory set.

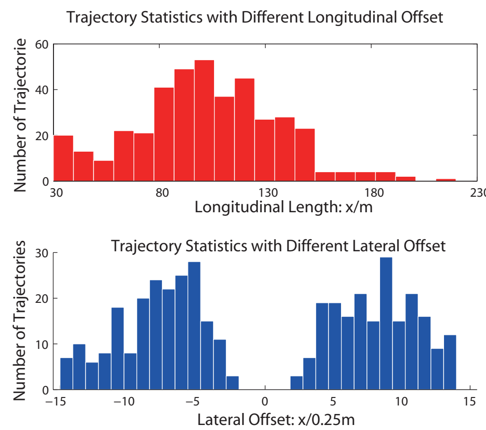
B. Learning from Human Lane Change

In order to select the trajectories which are more probably to be executed by human driver, we analyze the end states of human driver lane change trajectory data in Fig.9(a).

Fig.9(b) separately shows the distribution of end states in lateral direction and longitudinal direction. For each lateral offset sample of the lattices, we can count the number of end states with similar lateral offset (corresponding to the end states falls into the same band between two yellow line in Fig.9(a)). Assuming a simple Gaussian distribution (though not necessarily to be Gaussian), we can draw the distribution along longitudinal direction of the end states belonging to the same lateral offset sample (Fig.10(b) left), so can we do the same for the longitudinal (Fig.10(b) right). Then for each Gaussian distribution on each lateral or longitudinal sample value, we manually set a threshold T_s to find the interval $[x_a, x_b]$ which contains more than $T_s\%$ (95% for example) end states as shown in Fig.10(a). The boundary x_a, x_b of each interval for each lateral or longitudinal sample can be connected by closed loop shown in black in Fig.10(b).

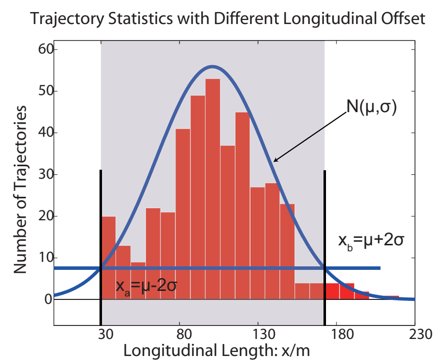


(a) End position of human lane change trajectories

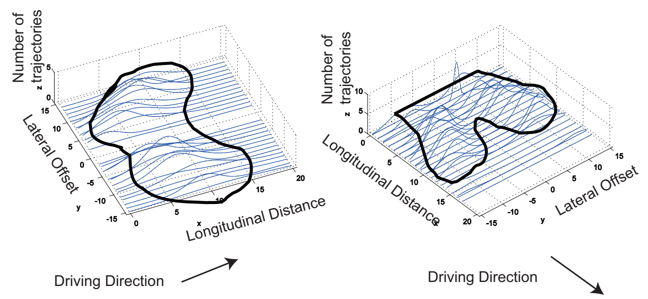


(b) The distribution of end position along lateral and longitudinal direction

Fig. 9. Then end states distribution



(a) The interval which contains more than 95% end states for each lateral offset sample



(b) The loop(black) enclosing most end states from our experiment data

Fig. 10. Extract the area where most end states locate

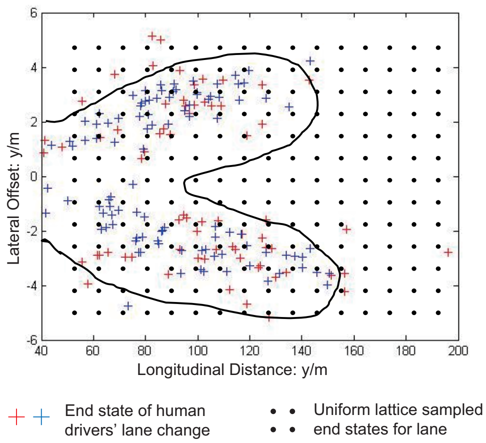


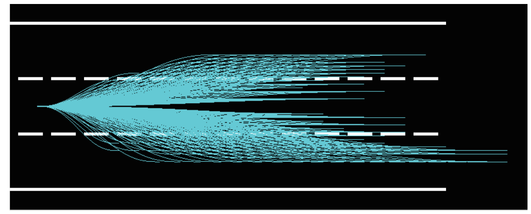
Fig. 11. The closed loop contains most human drivers' lane change end states in common lane change behaviors

These loops will enclose most human drivers' lane change end states (red and blue cross) and also contains part of the uniform lattice(black dot) as shown in Fig.11. For lateral and longitudinal samples, we can separately obtain two sets of end states S_{lat} and S_{lon}. Conservatively, we take $S = S_{lat} \bigcap S_{lon}$ to be the output states set. Set S here is the output of our application which is a smaller sub set of the uniform lattice. The result simplified trajectory set is shown in Fig.12(a).

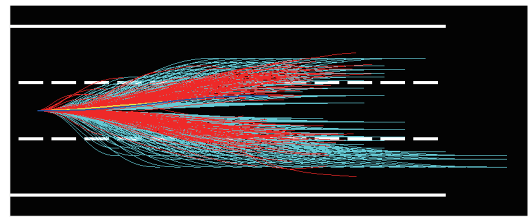
The output set has only 334 trajectories in our experiment compared with 600 trajectories in uniform latticed trajectory set in Fig.8. We also use any 6 human drivers' lane change trajectory experiment data to compute such a simplified trajectory set and check if the end states from the other one group of human driver's lane change trajectory data is included in the simplified trajectory set. As shown in Fig.12(b), the test trajectories (red trajectories) have almost all the end states included in our output trajectory set except for some abnormal lane change behaviors. Sharp break and steering or complex behaviors in urgent situations such as low speed lane change in traffic jam or aggressive lane change are not in our consideration right now. These behaviors usually result in unusual short lane change trajectories or trajectories crossing more than one lane.

V. CONCLUSIONS AND FUTURE WORKS

In this research, we present a method to develop a trajectory set of lane change behavior through learning real driving data of different drivers. We also present a method of collecting real lane change trajectories by using a vehicle platform carrying GPS, IMU and camera. The real lane change trajectories are studied to find their statistical distributions, through which a simplified trajectory set is generated. Experimental results demonstrate that although the number of trajectories is greatly reduced in comparison with traditional trajectory set, it still covers usual human lane change behaviors. This work will contribute to improve the efficiency in trajectory planning for lane change behavior.



(a) The trajectory set learnt from human driving



(b) Comparison between human driving data (red) and learnt trajectory set

Fig. 12. Result simplified trajectory set(a), comparing with the real lane change trajectories(red, b)

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