基于驾驶行为动态模型的生成车道转换路径方法

ABSTRACT Modeling driving behavior and emulating driver control strategy is one of essential parts for risk assessment and auxiliary control in the driver assistance system and vehicle active safety system. In this paper, we propose a dynamic lane-change model which reflects the driver control strategy of adjusting longitude and lateral acceleration. The proposed model is intuitive and can clearly describe the habit and randomness of the lane-change behavior with limit parameters. Especially, by using the proposed model and method driver can choose the different driving scenes, such as slow or sudden, to generate different lane-change trajectories. Compared with the conventional polynomial lane-change path planning, the dynamic model can generate the feasible lane-change trajectories and show the good performance of approximating the real lane-change trajectories.

KEYWORDS Lane-Change Trajectories; Dynamic Model; Driving Behavior; Human Behavior Learnin

1 Introduction

Driving a vehicle is a process of dynamic information exchange among the driver, vehicle state and the driving environment. The driver generates the vehicle trajectories through detecting and recognizing the obstacle on the road and then drives the vehicle along the planned trajectories. The driver maneuvers and driving tasks are updated timely when the driving environment and the vehicle state are changing over time\(^\text{[1]}\)[\(^\text{[2]}\)]. Therefore, the kernel of modeling driving behavior is emulating the driver control strategy and characterizes the driving style feasibly and efficiently for different driving tasks\(^\text{[3]}\)[\(^\text{[4]}\)].

While emulating the human control strategy and characterizing the driving style is difficult problem to solve. A lot of methods and models have been proposed in a wide variety of fields from the vehicle control to intelligent transportation system. Most driver models use the conventional approach which been extensive studied in other fields such as stochastic switched autoregressive exogenous\(^\text{[5]}\)[\(^\text{[6]}\)], The cerebellar model articulation controller (CMAC)\(^\text{[7]}\)[\(^\text{[8]}\)], Hidden Markov model (HMM)\(^\text{[9]}\)[\(^\text{[10]}\)[\(^\text{[11]}\)], neural network\(^\text{[12]}\)[\(^\text{[13]}\)], fuzzy system\(^\text{[13]}\)[\(^\text{[14]}\)[\(^\text{[15]}\)], Bayesian network\(^\text{[16]}\)[\(^\text{[17]}\)[\(^\text{[18]}\)], gauss mixture model\(^\text{[13]}\)[\(^\text{[13]}\)], support vector machine\(^\text{[19]}\)[\(^\text{[20]}\)]. However, these methods are too complicate to clarify the physical meaning clearly and the training process is usually time-consuming and off-line. In\(^\text{[21]}\)\(^\text{[22]}\)\(^\text{[23]}\), the various dynamic model of car-following of driver behavior are studied and the linear and non-linear property of the models are analyzed. In\(^\text{[24]}\), Treiber proposed the MOBIL lane-change model to derive lane-changing rules based on the longitude accelerations of the vehicles on the target and current lane. The model only studies longitude acceleration and ignore the lateral acceleration. In\(^\text{[25]}\)\(^\text{[26]}\)\(^\text{[27]}\), the lane-change path is generated by the 5-order polynomial. The lateral acceleration is 3-order polynomial which guarantees the smoothness of lane-change path. Although this method can plan the optimal lane-change path based on constrains on lateral jerk, the
generated path is obvious a single path when the initial and final state are fixed.

In this paper, we propose a dynamic lane-change model which reflects the driver control strategy of adjusting longitudinal and lateral acceleration. Our aim is that the model can clearly describe the habit and randomness of the lane-change driving behavior with limited parameters. Finally, we applied the model in different scenes and plan the safe path by generating the trajectories and detecting the collision. The rest of this paper is organized as follows: Section 2 introduces proposed method and the framework. Section 3 presents the experiment set-up and results. The discussion and the conclusion are given in Section 4.

## 2 Modeling Driving Behavior and Planning the Trajectories

The driving model of our study is concentrated on modeling the lane-change driving behavior of adjusting the longitude and lateral acceleration generating the trajectories and planning the safe path for the lane-change driving task. These correspond to a portion of strategic level and tactical level. Figure 1 shows the process and architecture of our system.

In Figure 1, the driver activates the lane-change module by the human-machine interface (HMI). For example, the driver can trigger the lane-change module by pressing the corresponded button.

### A. Data Collection

The first step of modeling driving behavior is collecting the measurable data of driver, vehicle and driving environment. Though the different types of sensors have different sample rates and accuracy, the data should be collected at a fixed sample rate and accuracy. We usually select the lower samples rate and accuracy in consideration of the performance and requirement of the approach. We use the linear-interpolating method to resample the data.

For the applications of lane-change, we record the following data: the driving vehicle speed, longitudinal acceleration and lateral acceleration; the longitudinal distance between the driving vehicle and the leading vehicle in the current lane; the longitudinal distance between the driving vehicles and the leading vehicle in the target lane; the later position from the middle line of the current lane of driving vehicle. In the simulator, all the data are easy to be collected.

For real instrumented vehicle, the longitudinal and lateral distance, velocity and acceleration of driving vehicle can be obtained by on-board GPS and motion sensors. The gap between the driving vehicle and leading vehicle can be obtained by laser or radar sensors in figure 2. Because lateral position of other vehicles is hard to obtain, the method assumes that the vehicles in the rear of driving vehicle are always in the middle of the lane and have fixed lateral position.

### B. Dynamic Model For lane-change behavior

Modeling the driving behavior by dynamic parameter model with some measurable and limited parameters rather than non-parameter model such as artificial neural network, is easy to be implemented and efficient method. So in this study, we focus on build the driving model using the dynamic model in lane-change scenarios.

#### 1) Dynamic Model

During the process of lane change, we assume that driver control the vehicle to head for the target position by adjusting the acceleration of longitudinal and lateral timely. The adjustment process are conducted by three visual features: the longitudinal distance and relative speed between the driving vehicle and target vehicles in front of driving vehicle in the current lane, the displacement between the current lateral position and target lateral position. Therefore, the dynamic model is constructed as follow:

\[
\begin{align*}
\dot{s}(t+\tau) &= \beta_2 \dot{q}(t) + \beta_1 s(t) + \xi_2 \dot{s}(t) \\
\dot{q}(t+\tau) &= f'(x) + \xi_1 \dot{q}(t) = \dot{s}(t+\tau-1) + \xi_1 \dot{s}(t) + \xi_2 \dot{s}(t) \\
\end{align*}
\]

Where \(s, \dot{s}, \dot{q}\)’s are the relative longitude position, velocity and acceleration between the driving vehicle and leading vehicle
and leading vehicle in the current lane. \( q, dq, d^2q \) are the lateral position, velocity and acceleration. \( \beta_1 \) and \( \beta_2 \) are the threshold for lateral position. \( \tau \) is delay time of driver control. \( \beta_1, \beta_2 \) and \( \tau \) are set according to the real experiments and system. \( \theta_1, \theta_2, \theta_3, \theta_4 \) represent the regularity of driver control and \( \sigma_1, \sigma_2, \sigma_3, \sigma_4 \) are the variance of the observable data and represent the randomness of driver control. \( \Delta \bar{W} \) is the random number which is a normal distribution. 

\[
Heaviside(x) = \begin{cases} 
1, & x > 0 \\ 
0.5, & x = 0 \\ 
0, & x < 0 
\end{cases}
\]

(2)

In this model, the longitude acceleration in general depends on the gap and relative velocity between the driving vehicle and leading vehicle in the current lane. This part is the same as the car-following model. It is that the driver also presses the accelerator or brake to control the speed of the driving vehicle to keep proper space between the driving vehicle and leading vehicle. Furthermore, the item \( \Theta_3 \cdot dq \) reflects that the change of the longitude velocity also depends on the yaw rate of the vehicle during the lane-change process shown. It is given by

\[
dl_{s(n)} = V \sin(\theta(n)) - V \sin(\theta(n) - \Delta \theta) \\
= V \sin(\theta(n))(1 - \cos \Delta \theta) + V \cos(\theta(n)) \sin(\Delta \theta) \\
= dq + V \sin(\theta(n))(\Delta \theta^2/2!) + dq \Delta \theta^3/3! \\
= dq + \Delta \theta \cdot \Theta_3 \\
\]

Where the stepsize \( t(n) - t(n+1) \) is small and \( \Delta \theta \ll 1 \). \( V \) is the speed of the vehicle. \( dl_{s(n)} \) is longitude speed at time \( t(n) \). \( \theta \) is yaw angle of the driving vehicle.

For the lateral control during the lane-change process, we assume that the driver has assessed two factors. The first is whether the vehicle can drive along the target lane with current lateral velocity. The second is that whether the vehicle can keep driving along the target lane steadily. The item \( \beta_1 - q \) reflects the driver adjust the lateral acceleration to drive the vehicle smoothly into the target lane. The item Heaviside \( (q - \beta_3) \) reflect that when the vehicle cross the proper lateral position in the target lane, the driver has to adjust the lateral speed to drive the vehicle into the right lateral position. The generated lateral dynamic is as follow

\[
d^2q(t+\tau) = \Theta_3(\beta_1 - q(t)) - \Theta_3 \cdot Heaviside(q(t) - \beta_3)
\]

(4)

In the model, we do not take the vehicles in the target lane into consideration, because the collision detector module can remove the dangerous trajectories by computing the relative distance between the trajectory and the vehicles on the lanes. In addition, after the driving vehicle reach the desired position in the target lane, lane-keep model is triggered to keep the vehicle in the proper area of target lane or follow the leading vehicle in current lane.

For parameter estimation of the model, we use the least-square estimation (LMS) to estimate the parameters. Though the optimization method is time-consuming and suboptimum, the parameters’ range can be narrowed by the empirical parameters and the vehicle performance constrains. The searching speed for fitting driving data is usually fast and even can be used in real time vehicle safety system.

2) The Max Lateral Position and Time of Arrival

In order to analyze the max lateral position and the position at the end of lane-change behavior, we simply dynamic model and concern that the relative longitude speed is zero; the delay time of the lateral control is set to zero. Furthermore, the adjustment for overshoot phenomena is ignored and the dynamic model is simplifies to

\[
d^2q = \Theta_3(\beta_1 - q), \beta_3 > 0, \beta_1 > 0
\]

(5)

When the init lateral position and lateral speed are zero, the explicit solution is

\[
d^2q = \beta_1 \theta^2 / \sqrt{3} \cos(\theta_3 \cdot t) \\
q(t) = \beta_1 - \beta_1 \cos(\theta_3 \cdot t) \\
dq = \beta_1 \sqrt{\theta^3} \sin(\theta_3 \cdot t)
\]

(6)

The max lateral position is \( 2\beta_1 \), when \( \sqrt{\theta^2} = \pi n, n=1,2,... \)

During the process of lane-change behavior, we assume that the max lateral offset can not large than 5 meter and \( \beta_1 \) should be less than 2.5, otherwise the measure for adjusting the overshooshing control should be considered. When \( \theta_3 = (\pi / 4)^n, n=1, t = 3 - 5 \) sec , the vehicle reach the max lateral offset and \( dq \) is zeros. In (6), the \( dq \) and \( d^2q \) can not be zero at the same time. Therefore the lane-change module can not keep the driving vehicle steadily driving along the target lane and it should switch to lane-keep process for keeping the driving stable.

C. The Collision Detector

In order to eliminate the generated trajectories which are too closed to the target vehicle or the barrier on the sides of road, we enclose the target vehicle or other obstacle on the lane in two or three circles, centered in \( (x_1, y_1), (x_2, y_2), (x_3, y_3) \) with radius \( R \). The more circles can be used and overlapped in order to enclose the vehicles compactly. For collision avoidance, each point \( (v_j, w_j) \) of the generated trajectories should hold the...
following equations
\[(x_i - u_j)^2 + (y_i - w_j)^2 > B^2,\]
\[\forall (x_, y_0) \in \text{Traj}, i = 1, 2, 3 \forall (v_i, v_j) \in \text{Veh}, j = 1, 2, \ldots, m\]  
(7)

For the barrier on the sides of road, we simply define the maximum lateral position M of the trajectories.
\[\text{max}(v_i) < M, \forall v_i \in \text{Traj}, j = 1, 2, \ldots, m\]  
(8)

If the points of the trajectory violate the above equations, the trajectories will cause the collision and should be removed.

3 Experiments and Results

A. Experimental Set-Up

In these experiments, a simple fixed driver simulator is used as shown in figure 3. The parameters of the simulator are as follows: The width of each lane is 3 meter and four lanes with clear weather vision. The sample rate of all the signals is 10Hz.

The test track is shown in figure 4. Two types of driver behavior are considered during the driving process: lane-keep (LK), lane-change (LC). The detail description is as follows:

1) Lane-keep: during the time of driving along all the sections shown in figure 8, the average vehicle speed is 60-120km/h and the driver is requested to drive the vehicle along one of four lanes or follows the vehicles on the lanes.

2) Lane-change: during the time of driving along the sections of A1, A2, and A3 in figure 4, two leading vehicles with the different speed are driving along the lanes. One of the target vehicles is driving slowly with the speed about 20-30 km/h. The other vehicle is the high speed vehicle with speed 80-120km/h. The high speed vehicle will start to reduce the speed sharply when the driving vehicles approach the vehicle and the desired relative speed and gap are reached. The driver is requested to change the lane in order to overtake the target vehicle or avoid the collision.

B. Experiment Results

In order to estimate the performance of proposed method, we invite 7 human to attend the experiment and collect their driving data on the designed scenarios and platform. Each driver is request to driver on every lane after the driver gets used to the simulator for a period of time. The driver marks all the time slices of lane-change behavior according to the recorded video and category the lane-change processes into two types: comfort lane-change behavior and sudden lane-change behavior. Figure 5 shows the some of samples we collected. These samples show the comfort and slow lane-change behavior last 4-6 seconds for arriving the target lane and the sudden and sharply behavior last 2.5 - 4.5 seconds. In this experiment we consider ‘arrive the target’ that the driving vehicle reach the position near the middle of target lane. The position is around the 4-4.5 meters in figure 4. For almost all the samples of lane-change behavior, when the driving vehicle arrive the target lane, the lateral velocity is not the zero and is tend to drive away form the target lane. Therefore, the driver has to adjust the vehicle to keep the vehicle driving in the target lane showed in figure 5. The phenomenon is significant in the samples of sudden and racy lane-change behavior.

In [30], the five-order polynomial curve is defined as
\[s(t) = a_5t^5 + a_4t^4 + a_3t^3 + a_2t^2 + a_1t + a_0\]
\[ds(t) = 5a_5t^4 + 4a_4t^3 + 3a_3t^2 + 2a_2t + a_2\]
\[d^2s(t) = 20a_5t^3 + 12a_4t^2 + 6a_3t + 2a_2\]
\[q(t) = b_5t^5 + b_4t^4 + b_3t^3 + b_2t^2 + b_1t + b_0\]
\[dq(t) = 5b_5t^4 + 4b_4t^3 + 3b_3t^2 + 2b_2t + b_1\]
\[d^2q(t) = 20b_5t^3 + 12b_4t^2 + 6b_3t^2 + 2b_2\]  
(9)
The $a_0, a_1, a_2, a_3, a_4, b_0, b_1, b_2, b_3, b_4, b_5$ are computed by the initial and final status of the vehicle.

For the comparison of dynamic model and five-order polynomial curve, we define the driving vehicle are driving along the start lane and should change lane to the destine lane for overtaking the leading vehicle with slow speed. The initial lateral position is 1 meter and the final lateral position is 4 meter. The initial accelerator and final accelerator is zero. The delay time of driver control is 1 second. Under these predefined parameters, we planned the lane-change path with two different scenes. The first is that the relative velocity between the leading vehicle and driving vehicle is 50-60 km/h. The gap between the leading vehicle and driving vehicle is about 70-83 meter. The second scene is that relative velocity is about 110-120km/s and the gap is about 120-130 m. We plan the lane-change path with the proposed method and 5-order polynomial method. Figure 6(a) (b) and Table 1 shows the 5 seconds simulated path and its statistics of the proposed model and the 5-order curve method for the first scene. Figure 6(c) (d) and Table 2 shows the 4 seconds simulated path and its statistics of the proposed model and the 5-order curve method for the second scene.

When the initial and final status of the vehicle is fixed, the five-order curve is also fixed and the variance is treated as zero. Therefore, in Table 1 and Table 2, the average length of curve is just the actual length of curve. The max and min length of curve are same as actual length.

From the Figure 6, Table 1 and Table 2, we can see that with different the arrival time of final lateral position, the 5-order curve can compute the smooth lane-change curve for both of the two scenes. However, the 5-order curve doesn’t match the real driving paths of the samples we have collected especial in the second scene. The second scene is that we think the real paths are changing sharply and the overshoot phenomenon happens frequently. Our method can also plan the safe and smooth trajectories for both two scenes. Furthermore, our method can fit the real driving paths better and model the over-shoot.

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phenomenon by analyzing the changing process of the acceleration especially for the second scene.

4 Discussion and Conclusion

The main result of this paper is modeling driver control strategy of lane-change behavior and planning the trajectories using the dynamic model. It has a high potential to estimate driving habit and lane-change trajectories while it can respond to the changes of the driving environment timely. Compared with the conventional polygonal lane-change path planning, the proposed method is intuitive and understood easily and reflects the driver control strategy and overshooting phenomena. The experiment results show that the proposed method can generate the feasible, safe and efficient trajectories. Especially, the proposed method can easily discriminate the driving habit and analyze the driver profile of lane-change behavior based on the distribution of the parameters of the proposed method. Therefore, driver can choose the driving styles, such as slow and careful, sudden and racy, to generate the lane-change trajectories and assist the lane-change process. In addition, the paper analyzes the max lateral position and its arrival time of the model and addresses the limits and solutions for the lane-change behavior. In the future, we will incorporate various driving behaviors such as lane-keep, Turiing a corner and overtake behaviors into a switch model. We will also develop and validate these models and methods in the real urban environment with multiple vehicles.

References


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徐国卿 1994年于浙江大学获得博士学位。1997年起历任同济大学副教授、教授、博士生导师、电气工程系主任、香港中文大学访问教授，香港中文大学教授。现任中国科学院香港中文大学先进集成技术研究所所长。主持或作为技术负责人承担国家863计划重大项目课题、香港创新科技基金、中科院知识创新工程重大项目等在内的30多项重要研究课题。长期从事电机与控制系统、电动汽车智能控制与系统集成技术、汽车智能安全技术的研究。获省部级科技进步奖5项。在学术期刊、重要国际会议上发表学术论文140多篇；出版专著一部；在电动汽车和智能控制领域申请（已获批和受理）国际国内专利40余项。曾被授予多项省部级荣誉称号。

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