Model-based trajectory prediction approach using an improved dynamic window approach and an interactive behaviour model

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***Abstract*—The capacity of predicting trajectories of surrounding vehicles for autonomous vehicles is significant as it would improve safety and smoothness. We propose a novel approach which combined an improved dynamic window approach (IDWA) and an interactive behaviour model for vehicle trajectory prediction. The advantages of this approach are its adaptive ability to different scenarios and its high accuracy. Firstly, an improved approach is proposed to take into account the Ackermann steering constraint and thus the approach would be adaptive to predict vehicle trajectories in different scenarios. Secondly, to improve the accuracy of predicted results, an interactive behaviour model of vehicles is constructed. The proposed approach was tested on a real road dataset NGSIM I-80 (I) and an experimental platform PreScan. The results show that our proposed approach performs better than the baseline approach of the constant velocity model approach in NGSIM I-80 (I) and has an excellently adaptive ability in different scenarios validated in PreScan.**

***Index Terms*—vehicle trajectory prediction, improved DWA, Ackermann steering constraint, interactive behaviour model**

I. Introduction

TO guarantee the safety and smoothness of autonomous driving, it is significant to predict the future trajectories of surrounding vehicles in dynamic and uncertain environments. Trajectory prediction of surrounding vehicles has become a hot research issue in autonomous driving field.

The approaches of trajectory prediction for surrounding vehicles can be roughly divided into two classes. One is a data-based prediction approach, and the other is a model-based prediction approach. The data-based prediction approach uses the historical driving data and environmental data to acquire implicit relationships and further predicted future trajectories. The approach needs to train different models to predict vehicle trajectories in different kinds of scenarios. Common data-based prediction approaches include Gaussian Process (GP) model [1], Gaussian Mixture Model (GMM) [2], Dynamic Bayesian Network (DBN) [3], Recurrent Neural Network (RNN) [4], [5], Gated Recurrent Unit (GRU) [6]. All of these methods need a great amount of data to train the model and the trained model cannot adapt to other different scenarios.

The model-based prediction approach constructs the prediction model using expert knowledge to predict vehicle trajectories without learning from data. The most common model-based methods are based on a constant velocity model (CVP), a constant acceleration model or a constant yaw rate model. To improve the prediction accuracy, a prediction method combined these three kinematic models has been proposed [7]. Similarly, Liebner et al. propose an intelligent driver model (IDM) using a variety of motion models [8]. Besides, a method based on a prototype trajectory set is also presented [9]. This method uses the collected driving data and ongoing historical driving trajectories to predict. In order to deal with the uncertainty caused by complex traffic changes in the actual situation, Vasquez et al. use a Gaussian Process based trajectory template [10], [11]. Schlechtriemen et al. use the Gaussian Mixture Regression (GMR) trajectory template [12], [13], which can not only deal with the uncertainty, but also reduce the parameters of the trajectory prototype set. These prototype trajectory set based method can be only trained for a specific scene, and thus it is difficult to extend to other traffic scenarios. Therefore, it is necessary to propose an approach which has an excellently adaptive ability with high prediction accuracy.

The dynamic window approach (DWA) is a classic motion planning method and is widely used in the robotic planning problem [14], [15]. In this paper, we propose a novel model-

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based trajectory prediction approach for surrounding vehicles. In order to predict vehicle trajectories accurately, the proposed approach is based on DWA and combined with vehicle interactive behaviour models. From the experimental analysis, it can be seen that our approach can predict vehicle trajectories more accurately with wide environmental adaptability than CVP. Moreover, our approach does not need a large amount of data to learn the prediction model when comparied with data-based approaches.

The rest of this paper is structured as follows. Section II introduces an improved DWA method for trajectory prediction. It also models the interaction behaviour between the target vehicle and its surrounding vehicles, and designs the cost function of different interactions. Experimental results in different scenarios (i.e., a real-traffic highway scenario and a simulational urban crossroad scenario) are included in section III. Finally, the concluding remarks are given in section IV.

II. Improved DWA with Ackermann Steering Constraint

A. Overall structure of IDWA

The flowchart of the dynamic vehicle trajectory prediction approach based on the improved dynamic window method (IDWA) is shown in Fig.1. It includes four steps to get the vehicles' predicted trajectories, and they are intention prediction, IDWA, modelling interactive behaviour and using Kalman predictor. The intention prediction result [16] is used as the prior knowledge of the trajectory prediction. Therefore, the main parts of our method are in IDWA and modelling interactive behaviour, and each of them would be introduced in the following parts.

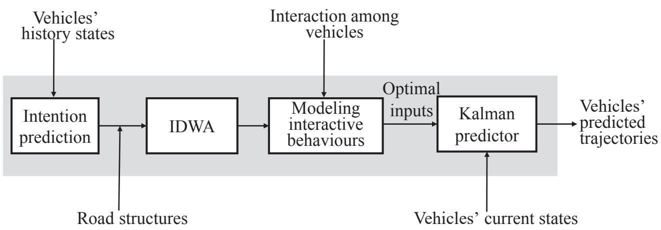


Fig. 1. Prediction Process of IDWA

B. Improved DWA based on an Ackermann Steering Constraint

Generally, the DWA method is used for the motion planning of an omnidirectional mobile robot [17]–[19], and the method should be improved to adapt to predict vehicle trajectories. Besides, the steering model of the four-wheeled vehicle satisfies the Ackerman steering constraint.

In order to take into this factor, a four-wheeled vehicle running at low speed can be approximated to a two-wheel bicycle model (shown in Fig.2). The front wheel steering angle δ, the vehicle wheelbase L_{v} and instantaneous steering radius of the rear axle R_{v} satisfy the following geometric relationship:

$$\tan(\delta) = \frac{L_{\mathrm{v}}}{R_{\mathrm{v}}} \tag{1}$$

Therefore, the angular velocity of the vehicle's steering can

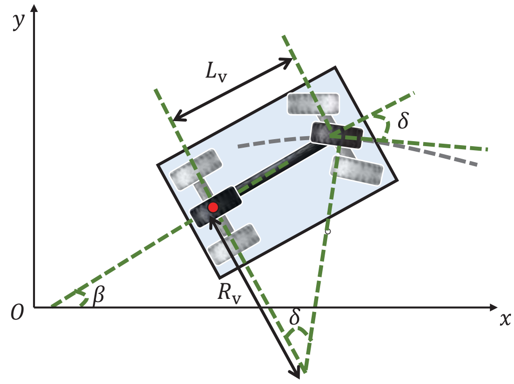


Fig. 2. Ackermann steering constraints

be approximated as

$$\dot{\beta} = \frac{v_{\mathrm{p}}}{R_{\mathrm{v}}} = \frac{v_{\mathrm{p}} * \tan(\delta)}{L_{\mathrm{v}}} \tag{2}$$

Therefore, the kinematic model of a dynamic vehicle at low speed can be modeled as Eq.(3). Unlike the traditional DWA method [14], the dynamic window V_{d} in the Eq.(3) is determined by the vehicle acceleration and the front wheel steering angular acceleration [20].

$$\begin{aligned}
\dot{x_{\mathrm{p}}} &= v_{\mathrm{p}} * \cos(\beta) \\
\dot{y_{\mathrm{p}}} &= v_{\mathrm{p}} * \sin(\beta) \\
\dot{\beta} &= \frac{v_{\mathrm{p}} * \tan(\delta)}{L_{\mathrm{v}}} \\
\dot{v_{\mathrm{p}}} &= a \\
\dot{\delta} &= \alpha
\end{aligned} \tag{3}$$

where x_{p} and y_{p} represent the vehicle position coordinate in x-axis and y-axis, respectively. v_{p} represents the velocity of the vehicle. a and α represent the vehicle acceleration and the front wheel steering angular acceleration, respectively.

The input of IDWA is the driving intention predicted from historical behaviour data [21]. In the lateral direction, the intention includes left lane change (α_{LC}), right lane change (α_{RC}) and lane keeping (α_{KL}). In the longitudinal direction, the intention includes acceleration (a_{Acc}), deceleration (a_{Dec}) and speed maintenance (a_{O}). Therefore, taking into the intention of lateral and longitudinal direction, there are 9 kinds of specific intention for the predicted vehicle. As shown in Fig.3, the 9 kinds of vehicle intention could be expressed as the form of α, a and thus each kinds of intention can be expressed in Fig.3.

The range of a and α (shown in Fig.3) are influenced by the road structure. When the vehicle drives in straight roads, the parameters above are fixed numbers. When the vehicle drives in a bend, the parameters vary from the different parts of the bend. When it is before a bend, α satisfies Eq.(4). When it enters a bend, a satisfies Eq.(5). When it is out of a bend, the vehicle drives in a straight road and the range of α and a are the same to the straight road.

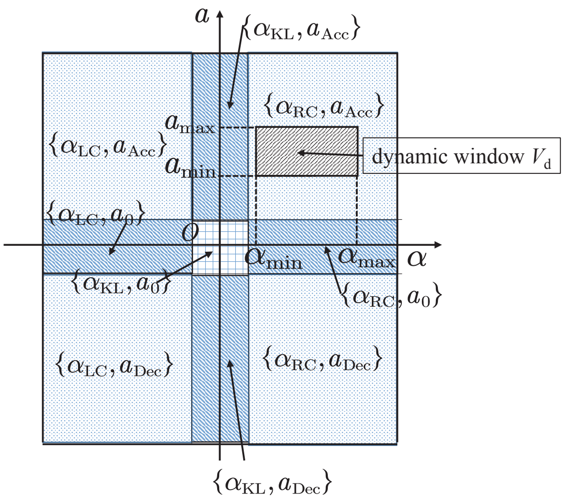


Fig. 3. The intention as the input of IDWA. There are 9 kinds of intention of the objective vehicle as the value variaties of vehicle acceleration a and vehicle angular acceleration α.

$$
\begin{aligned}
a_{\max} &= \min(\frac{v_{t\max}^2 - v_0^2}{2d_t}, a_{\mathrm{m0}}) \\
a_{\min} &= a_{\max} - a_{\mathrm{m1}}
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
\alpha_{\max} &= \min(\frac{v_0^2}{R_t}, \alpha_{\mathrm{m0}}) \\
\alpha_{\min} &= \alpha_{\max} - \alpha_{\mathrm{m1}}
\end{aligned} \tag{5}
$$

where $v_{t\max}$ indicates the allowed speed of the bend, v_0 indicates the current speed of the dynamic vehicle, a_{m0} and α_{m0} indicate acceleration limits and angular acceleration limits, respectively. d_t represents the current distance to the bend, R_t represents the radius of the bend, a_{m1} and α_{m1} represent the adjustment parameters, respectively.

C. Vehicle interactive behaviour model

As interactions among vehicles can affect traffic states, interactive behavior should be taken into account in the prediction. In order to improve the real-time performance of prediction, a two-dimensional area in the rectangular structure (named interest area) is designed, which is shown in Eq.(6).

$$
(x', y') \in \{|x' - x_{\mathrm{p}}| < d_{\mathrm{lat}}, |y' - y_{\mathrm{p}}| < d_{\mathrm{lon}}\} \tag{6}
$$

where x' and y' represent the position of other vehicles in the interest area, and d_{lat} and d_{lon} represent the lateral distance parameter and the longitudinal distance parameter, respectively.

Interactive behaviours in the interest area are divided into cooperative interaction and interferential interaction. If vehicle behaviours are predicted to conflict, the behaviours are defined as interferential interaction. If not, the behaviours are defined as cooperative interaction. The evaluation function considering above two kinds of interaction is designed as shown in Eq.(7).

$$
\begin{aligned}
\mathcal{TJ}^* &= \arg \min_{i=1}^{n}(K(\mathcal{TJ}_i)) \\
K(\mathcal{TJ}_i) &= \eta_1 K_1(\mathcal{TJ}_i) + \eta_2 K_2(\mathcal{TJ}_i)
\end{aligned} \tag{7}
$$

where $\mathcal{TJ}^*$ represents the trajectory with the lowest evaluation function value, n represents the number of control inputs for the sample, η_1 and η_2 represent the adjustment factor, K_1 and K_2 are evaluation factors that consider cooperative interaction and interferential interaction, respectively.

Considering cooperative interactions, collision risk is related to the distance from the predicted vehicle to other vehicles. To avoid collisions, the collision risk function is modeled as a $tanh$ function as shown in Eq.(8).

$$
K_1(\mathcal{TJ}_i) = \frac{1}{\varsigma\mu}\sum_{k=1}^{\varsigma}\sum_{j=1}^{\mu}(1 - tanh(\eta_3||P^{ij} - P^k||_2)) \tag{8}
$$

where i is the number of inputs u, μ is the number of discrete points of the analysis trajectory, and ς is the number of cooperative interactive vehicles in the interest area, η_3 indicates adjustment parameter of the $tanh$ function , P represents the vehicle position coordinates.

For interferential interactions, taking the possible collision into account, the action of selecting the shortest trajectory is penalized. The evaluation function is designed as Eq.(9).

$$
K_2(\mathcal{TJ}_i) = 1 - tanh(\eta_4 len(\mathcal{TJ}_i)) \tag{9}
$$

where $len(\mathcal{TJ}_i)$ represents the length of the track $\mathcal{TJ}_i$, and η_4 represents the tanh function adjustment parameter.

Finally, considering that it may contain some noises for the inputs of Eq.(3), the noises are assumed to obey Gaussian distribution. Then, an unscented Kalman Filter [22] is used to calculate the future states of trajectories [20].

III. Experiments and Analysis

In order to verify the effectiveness of our approach, we conducted two experiments, which are in a real-traffic dataset and a simulational environment, respectively.

A. Experiments and analysis based on NGSIM I-80 (I)

In order to verify the predictive ability of proposed IDWA, NGSIM I-80 (I), a partial open data set made by the Next Generation Simulation Program in the real road environment, was used for experiments. The experimental parameters are shown in the table I. Besides, the following evaluation metrics are used to compare IDWA and a conventional method. 1) Root Mean Square Error (RMSE), which is the Euclidean distance between the predicted trajectory and the true trajectory. 2) Mean Absolute Error (MAE), which is the mean of the absolute value of the Euclidean distance between the predicted trajectory and the true trajectory. 3) Maximum Absolute Error

(MXAE), which is the maximum value of the Euclidean distance between the predicted trajectory and the real trajectory.

$$RMSE = \sqrt{\frac{1}{T}\sum_{e=1}^{T}(x_{1,e} - x_{2,e})^2} \tag{10}$$

$$MAE = \frac{1}{T}\sum_{e=1}^{T}|\tilde{d}_e|. \tag{11}$$

$$MXAE = \max_{e\in[1,T]} |\tilde{d}_e|. \tag{12}$$

where $\tilde{d}_e = x_{1,e} - x_{2,e}$, and e is the number of frames predicting the vehicle trajectory, and T is the total number of frames predicted by the vehicle trajectory.

TABLE I
EXPERIMENTAL PARAMETERS BASED ON IMPROVED DWA TRAJECTORY PREDICTION METHOD

Parameter (unit)	experimental value
Angular acceleration (deg /s^2)	[-0.9,-0.2],[-0.1,0.1],[0.2,0.9]
Acceleration range (feet/s^2)	[-1.8,-1],[-1,1],[1,1.8]
Vehicle wheelbase (feet)	8.07
Concerned area threshold (feet)	length: 60, width: 18
Forecast duration (s)	2
Predition period (s)	0.1
Adjustment parameter of $tanh$	0.05

The prediction approach of CVP is a commonly used approach in the vehicle trajectory prediction field and it is used to compare with our proposed approach (IDWA). The magnitude of the results is 10^{-2} and the results are classified into two kinds and are shown in table II. As the data is collected in highway and the curvature of the road is small, it leads to that the results are similar between the two approaches. While in the situation of the lane change, the RMSE and MAE of IDWA are lower than CVP, which are reduced by 8.98% and 11.20%, respectively. The variance of IDWA also reduced by 19.65% (RMSE), 20.38% (MAE) and 9.35% (MXAE).

TABLE II
NGSIM I-80 DATABASE PREDICTION EFFECT EVALUATION VALUE COMPARISON TABLE

		CVP	IDWA
Lane Keep	RMSE	2.236 ± 4.145	2.293 ± 3.654
	MAE	1.750 ± 2.652	1.757 ± 2.285
	MXAE	4.255 ± 13.994	4.588 ± 12.843
Lane Change	RMSE	3.541 ± 1.593	3.223 ± 1.280
	MAE	2.956 ± 1.051	2.625 ± 0.837
	MXAE	6.165 ± 5.592	6.163 ± 5.069

B. Simulation based on real vehicle model

In order to verify the applicability in real vehicles of our proposed approach IDWA, the physical-based platform PreScan has been selected and several experiments have been conducted on this platform. As a T-junction is difficult for autonomous vehicles to cross, the scenarios of T-junction has been chosen and they are constructed as shown in Fig.4. In these two scenarios, from the perspective of the ego vehicle, several vehicles including the target vehicle and surrounding vehicles are driving on the road with cooperative interactions or interferential interactions. The ego vehicle applies our proposed IDWA to predict the trajectory of the target vehicle using sensors fixed on the ego vehicles to collect data of the target vehicle. The difference of Fig.4(a) and Fig.4(b) is the position of the interactive vehicle, and it would influence the results of trajectory prediction.

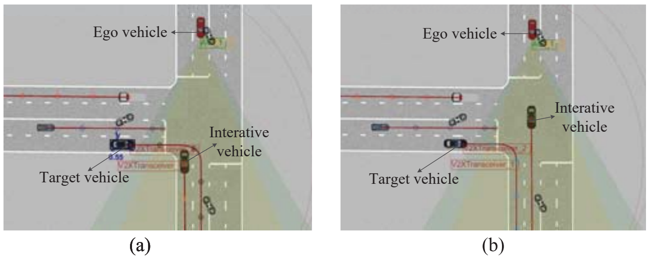


Fig. 4. Experiment scenarios in PreScan. The differences of these two scenarios are the position of surrounding vehicles of the target vehicle.

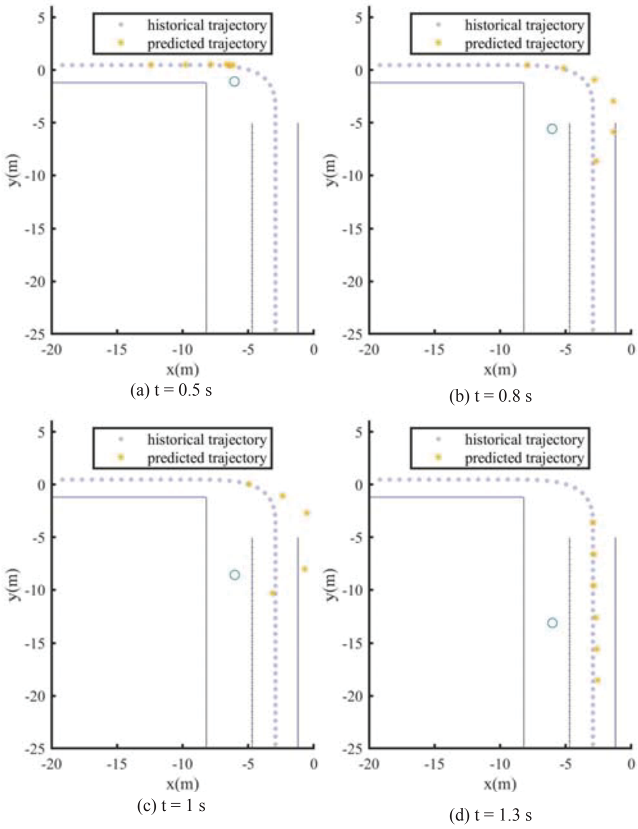
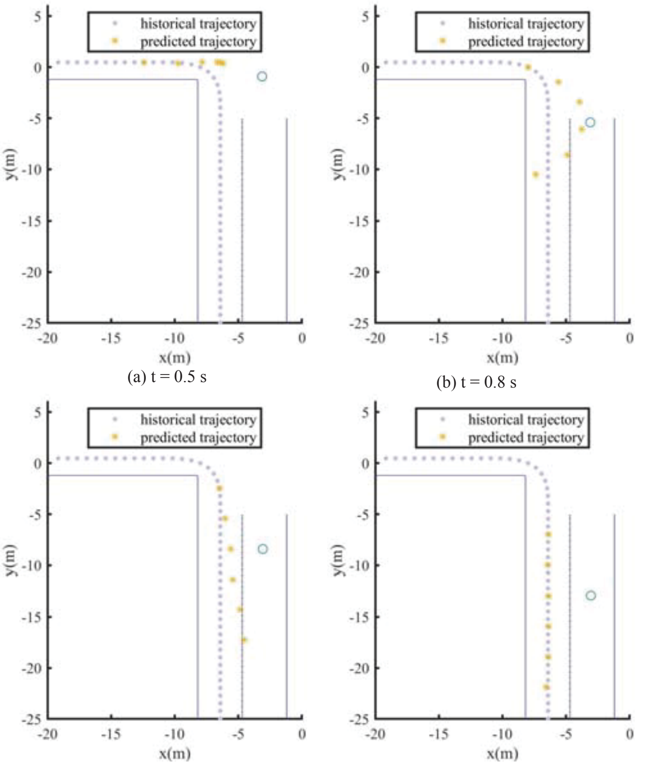


Fig. 5. The results of vehicle trajectory prediction in scenery (a) in different time step.

In these experiments, the sampling period of real vehicle trajectories is 0.05 s. The prediction duration of the target vehicle is 1.0 s, and its sampling period is 0.2 s. The results



(a) t = 0.5 s (b) t = 0.8 s (c) t = 1 s (d) t = 1.3 s

Fig. 6. The results of vehicle trajectory prediction in scenery (b) in different time step.

are shown in Fig.5 and Fig.6. When $t = 0.5$ s, the target vehicle is before the bend, and a deceleration action has been predicted. When $t = 0.8$ s and $t = 1$ s, the target vehicle is on the bend and a turning action has been predicted correctly. Besides, at $t = 1.3$ s in scenario (b), it can be seen that the predicted trajectory will be significantly offset towards the inner lane to avoid collision with the interactive vehicle in the outer lane. When $t = 1.3$ s, the target vehicle is after the bend, and we can find that the IDWA predicts the target vehicle would drive straightly, which is much correct. In general, the IDWA method can take into account the interaction between vehicles in different urban intersection scenarios and predict a more accurate trajectory.

IV. CONCLUSION

In this paper, a novel vehicle trajectory prediction approach is proposed. The advantages of this approach are its adaptive ability to different environments and its high accuracy. The proposed approach was tested on a real road data set NGSIM I-80 (I) and an experimental platform PreScan. The results show that our proposed approach IDWA performs better in prediction accuracy than baseline method CVP and has an excellently adaptive ability in different scenarios.

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