Trajectory Prediction of Surrounding Vehicles Considering Individual Driving Characteristics

Hanwool Woo [1)] Yonghoon Ji [1)] Yusuke Tamura [1)] Yasuhide Kuroda [2)] Takashi Sugano [2)] Yasunori Yamamoto [2)]

Atsushi Yamashita [1)] Hajime Asama [1)]

1) Department of Precision Engineering, The University of Tokyo

7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan (E-mail: woo@robot.t.u-tokyo.ac.jp)

2) Mazda Motor Corporation

2-5 Moriyacho, Kanagawa-ku, Yokohama 221-0022, Japan

3-1 Shinchi, Akigun Fuchucho, Hiroshima 730-8670, Japan

We propose a method to predict trajectories of surrounding vehicles considering individual driving characteristics. Trajectory prediction of surrounding vehicles is attracting a lot of attention now, and it is expected to apply to advanced driver assistance systems. However, previous methods perform the trajectory prediction based on common driving patterns even though each driver shows a different driving characteristic. The proposed method focuses on the following behavior behind the preceding vehicle and estimates a driving characteristic of each driver using machine learning techniques. Based on the estimation result, the proposed method adjusts the prediction model and appropriately generates a trajectory. As the result, the performance of trajectory prediction can be dramatically improved.

KEY WORDS: **Safety,** Accident avoidance/Collision prediction, Intelligent/Computer application [C1]

1. Introduction

According to a survey by the Japan Metropolitan Police Department, over 90 % of car crashes are caused by human mistakes [(1)]. Recently, autonomous driving technologies and advanced driver assistance systems have attracted considerable attention as solutions for preventing car crashes. The implementation of intelligent technologies to assist drivers in recognizing situations around their own vehicles can be expected to decrease the accident rates. Car crashes often occur when traffic participants attempt to change lanes as shown in Fig. 1. If the safety support system of ego-vehicle can predict lane-changing trajectories of surrounding vehicles; accident rates can be significantly decreased.

There are many previous studies about the trajectory prediction. Wolf and Burdick proposed a method for an autonomous vehicle by applying the potential field method [(2)]. However, this method can only be used to calculate self-trajectory, as the desired velocity needs to be known in order to calculate the potential energy. Therefore, their method is not suitable for the trajectory prediction of surrounding vehicles. Houenou et al. proposed a method based on a motion model and a maneuver recognition model [(3)]. Kasper et al. also used a method to predict a lane-changing maneuver by the regression analysis [(4)]. However, these methods do not consider adjacent vehicles when they generate a trajectory. Furthermore, previous methods perform the prediction based on common driving patterns even though each driver shows a different driving characteristic. Generally, drivers have different driving characteristics influenced by several

Fig. 1 Lane change of surrounding vehicle: the target of trajectory prediction is a surrounding vehicle driving near the ego vehicle containing the measurement devices. The proposed method predicts the trajectory of the lane-changing vehicle indicated by the red rectangle in the figure.

conditions such as personality, driving environment, and experiences [(5)(6)]. According to a previous research [(7)], driving characteristics were found to affect driving patterns in unique ways even if the drivers were under similar conditions, thus limiting the performance of prediction systems.

In order to solve this issue, it is necessary to determine driving characteristics of surrounding drivers and adjust the trajectory prediction model according to their characteristics. Quintero et al. employed an approach to classifying a driver as exhibiting either an aggressive or moderate driving characteristic [(8)]. This method analyzes the changes in the longitudinal and lateral positions by using the throttle, brake, and steering as features. Aljaafreh et al. defined driving characteristics and categorized them into below normal, normal, aggressive, and very aggressive [(9)]. They proposed a method

to estimate the characteristic based on acceleration patterns. The acceleration and deceleration in the longitudinal and lateral directions were used as features. However, these features cannot be measured from within the ego vehicle. Therefore, it is impossible to estimate the driving characteristics of surrounding drivers using these factors.

To overcome the above limitations, we propose a novel method to predict trajectories of surrounding vehicles considering individual driving characteristics. Most of previous methods need to determine values of parameters in the trajectory prediction, and they use machine learning techniques so that the performance is maximized. However, this approach has a problem that individual differences cannot be considered. To solve this problem, the proposed method estimates the driving characteristic of the target driver and adjusts parameters of the trajectory prediction method. Our previous work was proposed to appropriately determine the driving characteristic of the target vehicle which follows the preceding vehicle [10]. Only measurable information regarding the ego vehicle is used, thus, it is possible to estimate the driving characteristics of surrounding drivers. The proposed method uses a potential field method toward to the longitudinal direction and a sinusoidal model in the lateral direction. The potential field method is generally used for path planning in robotics [11][12]. This method sets a goal to generate an attractive potential energy and obstacles to generating a repulsive potential energy. By setting the environment, it can generate both paths to keep the current lane or change a lane [13]. However, parameters have constant values in previous methods, as the result, the performance of trajectory prediction may degrade depending on conditions. The proposed method adjusts the values of parameters based on the result of driving characteristic estimation to improve the prediction performance.

The remainder of this paper is organized as follows. Section 2 presents the problem setting and the overview of the proposed method. Section 3 describes the trajectory prediction method. Section 4 explains the experiments using a driving simulator and presents the evaluation results. Finally, Section 5 presents the conclusions and future work.

2. Overview

2.1 Problem setting

In this study, the scene is modified to obtain a straight two-lane infinite highway, which has only one side as shown in Fig. 2. The ego vehicle, indicated using green color, houses measurement devices such as a GPS and laser scanners and predicts a trajectory of the target vehicle which is the red one. The ego vehicle also estimates the driving characteristic of the target vehicle. The proposed method

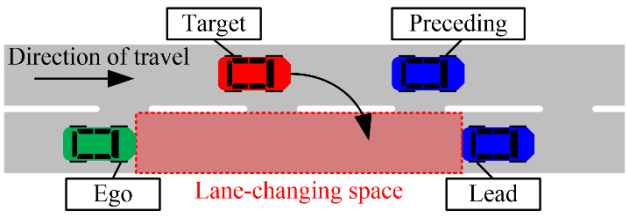

Fig. 2 Problem setting: the proposed method focuses on a situation when the target vehicle cuts in the front space of the ego vehicle since it is the main factor of accidents.

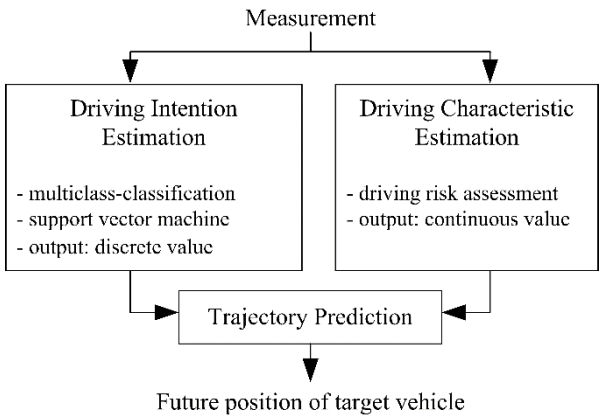

Fig. 3 Overview of proposed method

focuses on a situation wherein the target follows the preceding vehicle, the driving characteristic is estimated at each time step. The revision to previous studies shows a prevalence of driving characteristic estimation using either two or three levels. One of the motivation to estimate the driving characteristic is to detect *aggressive* drivers in surrounding vehicles. As these drivers show a risky driving pattern (e.g., improper position, inconsistent or excessive acceleration), it is strongly required to react to their behavior as soon as possible. In this study, the driving characteristic is categorized into two levels: *moderate* and *aggressive*, as observed in a previous study [7]. The driving characteristic of the target is derived.

Based on the estimated characteristic, a lane-changing trajectory of the target is predicted until two seconds in the future. The proposed method focuses on a situation when the target vehicle cuts in the front space of the ego vehicle since it is the main factor of accidents. Therefore, the proposed method is mainly designed to predict the lane-changing trajectory, of course, it can be used to the lane-keeping situation. The construction and evaluation of the proposed method are conducted with respect to lane-changing situations.

2.2 Overview of proposed method

To overcome the limitation of the previous methods, the proposed method adjusts the trajectory prediction model based on the individual driving characteristics. Figure 3 shows the schematic of the proposed method. It comprises the three parts: driving characteristic estimation,

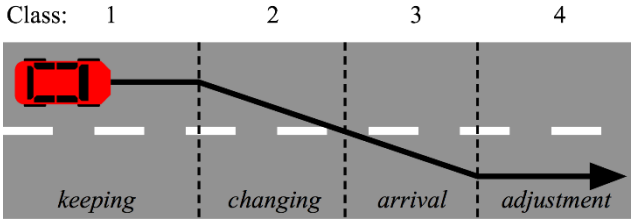

Fig. 4 Driving intentions: the proposed method defines that drivers have four intentions when they change lanes: *keeping*, *changing*, *arrival*, and *adjustment*.

driving intention estimation, and trajectory prediction. Inputs of the method are the positions of the ego vehicle and surrounding vehicles. The position of the ego vehicle can be measured by a GPS and that of surrounding vehicles can be acquired by laser scanners. Using this information, the features are extracted for the driving characteristic estimation and the driving intention estimation.

First, the driving characteristic estimation is performed using three information: relative velocity, relative distance, and repulsive potential energy. These relative numbers are calculated between the target vehicle and the preceding vehicle. The proposed method considers the driving risk, which is defined as the possibility of colliding with the preceding vehicle. The repulsive potential energy is used to evaluate the driving risk by using the dynamic potential field method. Details of this method are explained in our previous paper [10].

Second, the proposed method defines that drivers have four intentions when they change lanes: *keeping*, *changing*, *arrival*, and *adjustment* as shown in Fig. 4. Each driving intention is defined as a class, and the proposed method treats the driving intention estimation as a multiclass problem by the SVM (support vector machine). The method is based on the lateral movement of the target vehicle. Details of this method are explained in our previous papers [13][14]. The output of this part is the intention at the current time.

Third, the results of above two parts are used for the trajectory prediction. The proposed method uses the potential field method, and the estimated driving characteristic of the target vehicle is used to adjust the parameters. The values of parameters determine acceleration and deceleration tendency of the driver, and they largely affect the performance. The trajectory prediction adopts the result of driving intention estimation to identify the strategies that drivers may execute while driving. Generally, drivers execute different strategies with different driving intentions. When drivers have intentions such as *keeping* and *adjustment*, they aim at the front of the current lane and pay more attention to the vehicle in the same lane than vehicles in the other lanes. They may attempt to remain at the center of the lane. On the other hand, when drivers have intentions such as *changing* and *arrival*, they aim at the front of the next lane and must consider adjacent vehicles on not only the current lane but also the next lane. Therefore, in addition to the strategy, drivers must consider

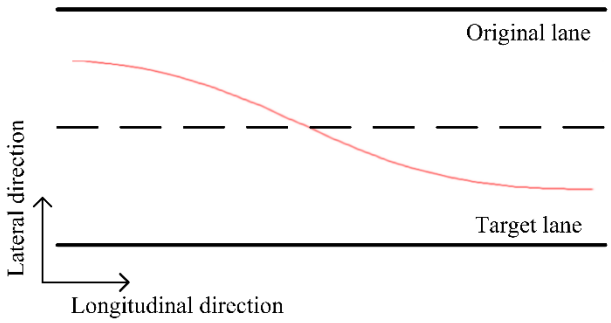

Fig. 5 Sinusoidal model for lane-changing trajectory.

surrounding vehicles while driving. The proposed method changes the strategy according to the estimated intention. The detail of this method is discussed specifically in Section 3.

3. Trajectory prediction

The proposed method predicts a trajectory according to the estimated driving intention of the target driver. First, when the driving intention is *keeping* and *adjustment*, the goal is set to the front of the current lane. The proposed method sets the goal to the center of the current lane. The surrounding vehicles generate the repulsive potential energy, and it makes the target keep a gap between front and back. However, the driver is not concerned with the vehicles in the next lane.

On the other hand, when the driving intention is *changing* or *arrival*, the driver aims at the front of the next lane and may check the gap with vehicles in both lanes. The proposed method uses the sinusoidal model to generate a lane-changing trajectory in the lateral direction and the potential field method to avoid surrounding vehicles in the longitudinal direction. Details are explained as follows.

3.1 Prediction of lateral movement

For the prediction of lateral movement in lane-changing, the proposed method uses the sinusoidal model [15]. This model is able to generate a lane-changing trajectory as shown in Fig. 5, and it does not require a parameter. The acceleration in the lateral direction can be derived as

$$a_{lat}(t) = \frac{2\pi H}{t_{lat}^2} \sin \frac{2\pi}{t_{lat}} t, \tag{1}$$

where a_{lat} represents the lateral acceleration, t is the time from the beginning of lane-changing, H is the final lateral displacement, and t_{lat} is the lane-changing duration. The proposed method determines the value of H as the lane width. Furthermore, t_{lat} is calculated

using the lateral velocity at the moment when the intention is estimated as *changing*. Thus, the lateral acceleration can be calculated without any parameters.

3.2 Prediction of longitudinal movement

The proposed method predicts the longitudinal movement by using the potential field method. It defines two potential energies and generates a trajectory of the target vehicle to a goal while avoiding adjacent vehicles. The total potential energy at the position (x, y) is derived as

$$U(x, y) = U_g + U_s, \tag{2}$$

where U_g denotes the attractive potential energy from the goal, and U_s denotes the repulsive potential energy from surrounding vehicles. First, the potential energy from the goal is calculated as

$$U_g(y) = -\omega_g y, \tag{3}$$

where ω_g is the weight coefficient. The value of ω_g determines acceleration/deceleration tendency when there is no surrounding vehicle. The large value makes sudden velocity changes, and it makes a close vehicle gap between the target vehicle and the preceding vehicle. This tendency is normally considered as the behavior of *aggressive* drivers. This is one of the parameters which should be adjusted according to the driving characteristic.

On the other hand, the repulsive potential energy from surrounding vehicles is calculated as

$$U_s(y) = -\omega_s \exp\frac{(y-y_p)^2}{\sigma^2}, \tag{4}$$

where ω_s is the weight coefficient, σ is the standard deviation of a gap between the target and preceding vehicle, and y_p is the position of the preceding vehicle. The values of ω_s and σ determine how the target vehicle takes a gap from the preceding vehicle. The large value of ω_s makes enough gap between the two vehicles. σ is determined referenced by the previous study [16], and ω_s is the parameter which should be adjusted by the driving characteristic.

As explained previously, the proposed method adjusts above two parameters according to the estimated driving characteristic. Our previous work used the SVM and performed a binary classification [10]. On the other hand, the proposed method defines the repulsive potential energy from the preceding vehicle as the driving characteristic variable and uses it for the adjustment of the above two parameters. By this approach, a computation cost is significantly shortened since the classification by the SVM, which requires a high computation, is not performed. The driving characteristic variable η can be derived as

$$G(\Delta V_p) = \frac{1}{2\pi I_0\left(k(\Delta V_p)\right)} \exp\left(-k(\Delta V_p)\right), \tag{5}$$

$$H(D_p) = \frac{1}{2\pi\sigma} \exp\left(-\frac{D_p^2}{2\sigma^2}\right), \tag{6}$$

$$\eta = \varepsilon G(\Delta V_p) H(D_p), \tag{7}$$

where ΔV_p represents the relative velocity between the target and the preceding vehicle, D_p is the vehicle gap between the two vehicles, σ is the standard deviation of the vehicle gap, and ε is a coefficient. Equation (5) represents the von Mises distribution, and $I_0(\cdot)$ is the modified Bessel function of order zero. If the target driver exhibits a *moderate* driving characteristic, the driver would maintain a considerable distance from the preceding vehicle and drive safely. However, when the target driver has an *aggressive* driving characteristic, the driver closely follows the preceding vehicle with a high risk of crashing. Moreover, the driver would rapidly approach to surrounding vehicles and change a lane while accelerating. The driving characteristic variable can describe these tendencies by the value of potential energy. A large value represents an *aggressive* driving characteristic.

The parameters, ω_g and ω_s, are adjusted according to the driving characteristic variable, η. The values are calculated as

$$\omega_g = \alpha_g \eta + \beta_g, \tag{8}$$

$$\omega_s = \alpha_s \eta + \beta_s, \tag{9}$$

where α_g, β_g, α_s, and β_s are coefficients. Both parameters have large values when the driving characteristic variable is large.

4. Result

4.1 Experiments

In this study, a driving simulator (DS) named as "D3 Sim (Mitsubishi Precision Co., LTD.)" was used to collect the data to develop the estimation model and the testing data for evaluation. This simulator showed visual information on display devices comprising five monitors as shown in Fig. 6. In addition, the driving seat comprises a steering, an acceleration pedal, and a brake pedal. The data were recorded at 120 Hz. A total of ten subjects of different ages

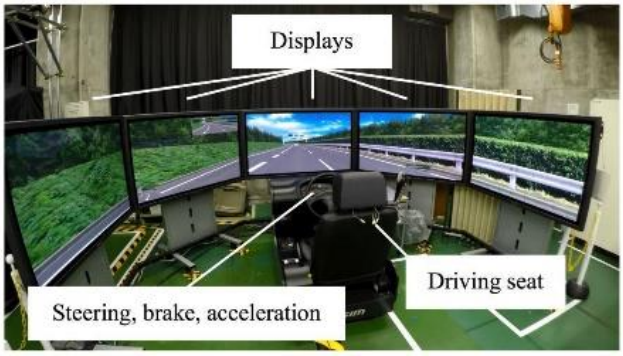

Fig. 6 Driving simulator: D3 Sim was used to acquire data for the evaluation. Display devices consist of five monitors, and a driving seat is located to the center of monitors. The driving simulator includes a steering wheel, an acceleration pedal, and a braking pedal. In addition, audio devices are also installed to make realistic environment.

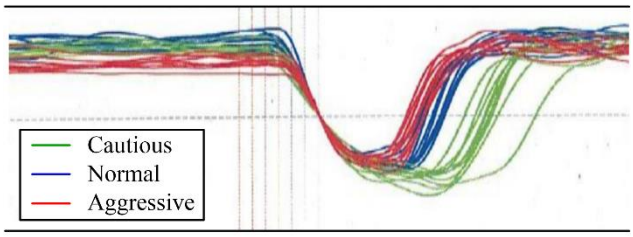

Fig. 7 Result of preliminary experiment: the driving characteristic was instructed to a subject before measurement. The subject performed to overtake the preceding vehicle. The green represents trajectories under the instruction as *cautious*, the blue is *normal*, and the red shows the result under *aggressive*. It can be confirmed that the difference of trajectories according to the driving characteristic.

participated in the experiment with different simulator/driving experiences. Their informed consent was obtained before starting the experiments.

An experimental scene was modified wherein a straight two-lane infinite highway having only one side was considered. The red car is the vehicle operated by the subjects in the experiments, the blue one is the preceding vehicle. Moreover, there is the lead vehicle, which is in a lane adjacent to that of the target vehicle. Both the preceding and lead vehicles blocked the roads of the subject vehicle while the velocities changed randomly. Thus, the subject vehicle was not allowed to overtake them. Consequently, the target was forced to follow the preceding vehicle for 60 s per one trial. Twenty trials were conducted per a subject. Totally, 200 trials were conducted in the experiments.

Furthermore, a preliminary experiment was conducted to verify differences in the driving trajectory by the driving characteristic. The driving characteristic was instructed to one subject before the measurement. The subject performed to overtake the preceding vehicle, then, return to the original lane. First, the subject drove the vehicle under no specific instruction, and the data were recorded as *normal*. Second, the subject was instructed to "drive cautiously", and

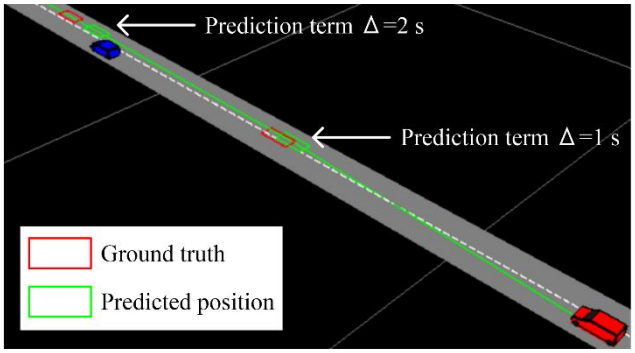

Fig. 8 Three prediction terms: the performance evaluation was performed at two prediction terms: 1 s and 2 s later. The red rectangle represents the ground truth at the terms, and the green rectangles are the predicted positions by the proposed method.

Table 1 Performance of proposed method.

Prediction term Δ	Lateral error	Longitudinal error
1 s	0.36 m	0.44 m
2 s	0.40 m	1.73 m

the data obtained were classified as *cautious*. Thereafter, the subject was instructed to "hurry", and the data were recorded as the *aggressive* driving characteristic. Twenty trials were conducted under each condition. Figure 7 shows the result. Colors depict each driving condition. The green represents the trajectory driven under the *cautious* instruction, the blue is under *normal*, and the red shows the result under the *aggressive* instruction. It is clearly shown that driving patterns largely depend on the driving characteristics, and it means that driving patterns should be different from the individual driving characteristics.

4.2 Performance evaluation

The trajectory prediction is performed until two seconds in the future. In this study, the prediction performance was evaluated at two prediction terms: 1 s and 2 s later, as shown in Fig. 8. The red rectangle represents the ground truth at each prediction term, and the green rectangle denotes the predicted position by the proposed method. The accuracy can be evaluated by the error between the ground truth and the predicted position.

Table 1 shows the evaluation result by the proposed method. First, it is confirmed that the accuracy for the case of short-term was obviously more precise than that of long-term prediction. Second, the prediction in the lateral direction was better than the longitudinal movement since the displacement in the lateral direction was smaller during lane-changing. Note that for Δ=2 s, the error in the lateral direction was under 0.5 m, and such levels seem to be enough for the purpose of avoiding car crashes. The problem to improve the

Table 2 Performance comparison.

Method	Predictino term Δ	Lateral error	Longitudinal error
Dynamics	2 s	1.02 m	7.32 m
Proposed method (w/o characteristics)	2 s	0.40 m	2.00 m
Proposed method	2 s	0.40 m	1.73 m

performance is the prediction toward to the longitudinal direction. For the velocity control of the ego vehicle to keep a safe gap with respect to surrounding vehicles, it can be considered that the prediction of longitudinal position is a more important and crucial task. Note that for Δ=2 s, the error in the longitudinal direction was 1.73 m.

In order to confirm the validity considering the driving characteristic, the performance was compared to the dynamic model and the method without the adaptation of characteristics. Table 2 shows the result of performance comparison. It is clearly confirmed that the proposed method with the adaptation of driving characteristics is able to significantly improve the prediction accuracy. Compared to the error of dynamics, that of the proposed method was dramatically decreased, especially the longitudinal error. Moreover, the accuracy in the longitudinal direction was also improved by considering the driving characteristics. From above results, it was demonstrated that the proposed method achieved the great performance in the trajectory prediction.

5. Conclusion

In this study, we proposed a novel method to predict trajectories of surrounding vehicles considering individual driving characteristics. Previous methods have the problem that performs the prediction based on common driving patterns even though each driver shows the different driving characteristic. Through comparison with previous approaches, it was confirmed that the proposed method with the adaptation of the individual characteristics can improve the accuracy of trajectory prediction. The reason for the improvement is expected to be due to the fact that acceleration/deceleration in the longitudinal direction is largely influenced by the driving characteristics. Aggressive drivers normally show inconsistent or excessive acceleration/deceleration, and that tendency should be considered to properly predict their behavior. The proposed method adapts the individual differences, while previous methods do not.

As future work, the individual differences should be considered toward not only the longitudinal direction but also the lateral direction. In this study, the proposed method uses the sinusoidal model for the lateral movement. We have continuously evaluated other approaches that are expected to improve the performance.

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