# Prediction of Following Vehicle Trajectory Considering Operation Characteristics of a Human Driver

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*Abstract*— **In this paper, we propose a novel method to predict the trajectory of a following vehicle, based on the operation characteristics of a driver. If a lead vehicle suddenly decelerates to avoid colliding with interrupting vehicles, it may lead to an accident with the following vehicle. To prevent such accidents, it would be beneficial to predict the future positions of surrounding vehicles. Previous studies have proposed similar prediction methods; however, these studies have not considered the operation characteristics of drivers, even though the prediction performance largely depends on these characteristics. In this research, we assumed a driving scene wherein a human driver follows an autonomous vehicle. The proposed method is implemented in the autonomous vehicle. Consequently, the method is able to predict the trajectory of the following vehicle operated by a human driver. The contribution of this paper is to estimate the operation characteristics of the following driver and to apply the estimated result to obtain the trajectory prediction. It is demonstrated that the proposed method shows high prediction accuracy as compared to the previous methods.**

## I. INTRODUCTION

According to the conducted survey, over 90% of car accidents have been caused by human errors [1]. To solve this problem, autonomous driving and advanced driver-assistance systems (ADAS) have been introduced as solutions that could substitute or help human drivers. However, the coexistence between human drivers and autonomous vehicles needs to be considered as a critical issue as it is impossible to substitute human drivers all at once. In the environment where people and automated machines coexist, understanding the operation characteristics of human drivers is significantly important to establish safe autonomous driving. A previous study reported that the adaptive cruise control can effectively maintain a safe distance from the preceding vehicle; however, it can occasionally cause a collision with the following vehicle [2]. If the lead vehicle suddenly decelerates to avoid colliding with interrupting vehicles, it may lead to an accident with the following vehicle as shown in Fig. 1. Humans require a certain amount of time to react to sudden events such as deceleration of the preceding vehicle. Therefore, autonomous vehicles should consider these characteristics of human drivers and adjust the distance for safety, when a human driver follows.

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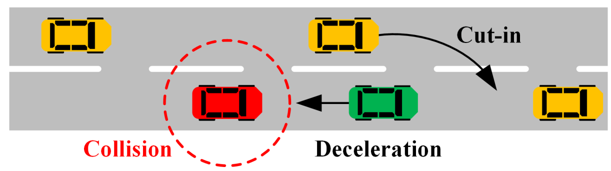



Fig. 1. Collision with the following vehicle: if the lead vehicle suddenly decelerates to avoid collisions with interrupting vehicles, it may lead to an accident with the following vehicle.

There are two requirements to realize safe autonomous driving. The first one is anticipation of future actions of surrounding vehicles. If it is possible to anticipate maneuvers of surrounding vehicles based on the sequence of their past movements, the autonomous vehicle will be able to generate a safe path to avoid possible collisions with them. Various studies have been conducted to achieve this requirement [3], [4], [5]. However, these methods require specific parameters to obtain a large impact on the performance although they can be employed to anticipate future actions. The values of parameters were statistically determined based on training data. However, the constant value cannot handle the individual differences nevertheless each driver may have different characteristics. Consequently, it may lead to deterioration of the accuracy of anticipation. For instance, the reaction time of each driver largely varies depending on various factors such as age, driving experience, gender, etc. [6]. Previous methods proposed in [3], [4], [5] do not consider the individual differences, and it may deteriorate the overall performance of a prediction method.

The second requirement is estimation of the operation characteristics to overcome the above limitation. Our approach implies estimating the operation characteristics of surrounding traffic participants and applying the result to anticipate their future actions. In [7], a method to estimate the operation characteristics of the host driver was proposed based on the extended Kalman filter. This method employs twelve parameters to model the characteristics of a driver. Filev et al. considered a driver as the second order system [8], and two parameters to represent the operation characteristics were estimated. However, above two papers did not discuss how to use the estimated results for the trajectory prediction. Otherwise, it should be noted that Zhu et al. proposed

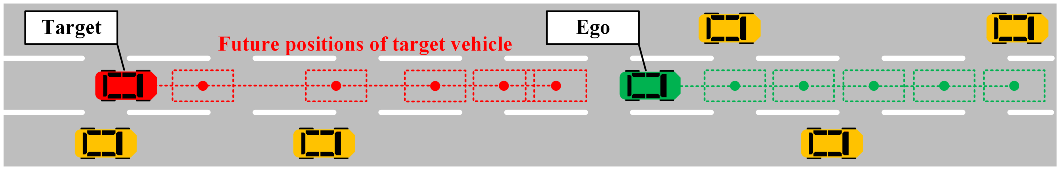



Fig. 2. Problem definition: the green vehicle represents the *ego* vehicle, and the red one is the *target* vehicle. The *ego* vehicle has measurement devices used to estimate the distance and speed of the *target* vehicle. The proposed method is implemented onto the *ego* vehicle.

a method to predict a trajectory of the following vehicle using a deep learning framework [9]. It was demonstrated that the method achieves great accuracy based on their real experiments. However, the data-driven approach has the limitation that the performance largely depends on the chosen training data. If the real conditions differ significantly from that of the training data, the performance of the approach may deteriorate.

As only few previous studies focused on both the operation characteristics and trajectory prediction, we propose a novel method to predict future positions of the following vehicle. The proposed method estimates the operation characteristics of the following driver and applies the estimated characteristics to the trajectory prediction. General Motors (GM) model is used to model the behavior of the following driver in the proposed method [10], as it is widely used among available car-following models. The following driver is stimulated by the distance and relative speed with respect to the preceding vehicle, consequently, the driver determines its acceleration as a response. The model has three parameters to represent the operation characteristics. Several studies reported the optimized values of the parameters using real traffic datasets [11], [12], [13]. However, the values vary depending across the papers, as all datasets were recorded at different locations. Therefore, the constant values of the parameters cannot be adjusted according to the changes in the driving conditions. To address this limitation, our approach aims to estimate the real-time values of the parameters, using the Levenberg–Marquardt algorithm [14], [15]. This approach takes into account the changes in the driving conditions, unlike the previous methods based on pre-determined values. Moreover, the proposed method estimates the reaction time of the following driver in real time. The previous methods used the fixed reaction time of 1 s, although the performance of the trajectory prediction largely depends on the reaction time [9]. In this paper, the three parameters of the GM model and the reaction time are defined as the operation characteristic variables. The proposed method performs the optimization of the four considered variables and applies the result to the trajectory prediction at each time step. Owing to this approach, the trajectory prediction can be robust with respect to the changes in driving conditions.

## II. Overview

### A. Problem definition

This paper assumes the driving condition in which human drivers and autonomous vehicles coexist. Figure 2 represents

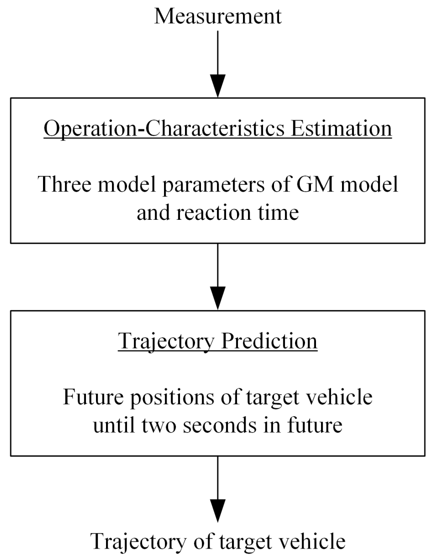



Fig. 3. Schematic of the proposed method: the proposed method consists of two parts: operation characteristic variable estimation and the trajectory prediction. The inputs sourced to the method are the position and speed of the two vehicles, and the output is the longitudinal position of the *target* until two seconds in the future.

the driving scene assumed in this paper. The human driver follows the autonomous vehicle, which has embedded measurement devices such as a GPS tracker and laser scanners used to estimate movements of the following vehicle. The sensing range is assumed to be within 120 m, and the distance and relative speed between the two vehicles can be estimated. The proposed method is implemented in the autonomous vehicle in order to predict future positions of the following vehicle and estimate the operation characteristics of the driver. In this paper, the autonomous vehicle is defined as *ego*, and the following vehicle is defined as *target*. The *ego* vehicle is indicated using green color, and the *target* vehicle is depicted using red color.

### B. Overview of proposed method

Figure 3 shows the schematic of the proposed method. It comprises of two parts: estimation of the operational characteristics and the trajectory prediction. Inputs of the method are the position and speed of the two vehicles: *ego* and *target*. The position of the *ego* can be acquired through the GPS tracker, and the speed can be measured using a controller area network (CAN) bus. The position and speed of the *target* can be measured by laser scanners. Using this information, four operation characteristic variables are estimated: three parameters of the GM model and the reaction time. The estimation results are used as the input to the trajectory prediction module. The values of the considered variables determine the acceleration and deceleration tendency of the following driver, and they significantly affect the prediction accuracy. The proposed method uses the GM model to calculate acceleration and deceleration of the *target*. Based on the calculated acceleration, a trajectory of the *target* is predicted until two seconds in the future.

This paper focuses on the situation when a vehicle follows the preceding vehicle while keeping the current lane. Therefore, the proposed method is designed to predict the lane-keeping trajectory. The method to predict the lane-changing trajectory is explained in our previous papers [16], [17]. Moreover, only the longitudinal position of the *target* is predicted while the lateral position of the vehicle is assumed as the center of the current lane. As a result, the output of the proposed method is the longitudinal position of the *target* until two seconds in the future.

## III. Estimation of the operation characteristics

The proposed method considers the following driver as the stimulus-response system, consequently, the acceleration or deceleration is derived from the distance and relative speed between the two vehicles: *ego* and *target*. Among various methods to model the following movement, the proposed method employs the GM model as it allows achieving good performance [18]. At any time step $t$, let the longitudinal position of the *target* vehicle be represented by $x_n^t$.

$$\hat{a}_{tgt}^t = \left[\frac{\alpha_{l,m}(v_{tgt}^t)^m}{(x_{ego}^{t-\Delta T} - x_{tgt}^{t-\Delta T})^l}\right](v_{ego}^{t-\Delta T} - v_{tgt}^{t-\Delta T}), \quad (1)$$

where $x_{ego}^t$ represents the longitudinal position of the *ego* vehicle, and $v_{ego}^t$ is its speed. Similarly, $x_{tgt}^t$ represents the longitudinal position of the *target* vehicle, and $v_{tgt}^t$ corresponds to its speed. $\alpha$, $l$, and $m$ are the model parameters to determine the operation characteristics; $\Delta T$ is the reaction time. These four variables are considered as the operation characteristic variables in this paper.

The proposed method performs the optimization of the three model parameters using the Levenberg–Marquardt algorithm [14], [15]. Although there are many iterative optimization algorithms, such as the gradient descent or the Newton method, the Levenberg–Marquardt algorithm is generally used to solve nonlinear problems. Employing the algorithm, our method estimates the optimized values at the current time based on information on the acceleration of the previous step. To perform optimization of the three model parameters, the reaction time is used at the previous step. If optimization fails, or the derived acceleration value is too large or small, the value of the previous step is used.

After optimization of the three model parameters ($\alpha$, $l$, and $m$), the estimation of the reaction time is performed. According to the previous study, the reaction time is distributed in the range between 0.92 s and 1.94 s [6]. Including the room for distribution, the proposed method identifies the optimal value of the reaction time from 0.5 s to 2.5 s in increments of 0.1 s. The value can be derived as follows:

$$\Delta T = \underset{\Delta T}{\arg\min} |a_{tgt}^{t-1} - \hat{a}_{tgt}^{t-1}(\Delta T)|, \quad (2)$$

where $a_{tgt}^{t-1}$ represents the ground truth of acceleration, and $\hat{a}_{tgt}^{t-1}$ denotes the derived value obtained using the proposed method.

Estimation of the operation characteristic variables is performed following the above process, and the optimal values are derived at each time step. However, the operation characteristics may not drastically change in a short time period. Hence, the proposed method defines a sliding window of a constant size, consequently, the values within the window are modified by a moving average.

## IV. Trajectory prediction

For the prediction of a longitudinal position of the *target*, the proposed method calculates the acceleration value using the estimated values of operation characteristic variables. Then, the position and speed of the *target* are updated as follows:

$$\hat{v}_{tgt}^{t+1} = v_{tgt}^t + \hat{a}_{tgt}^t \Delta t, \quad (3)$$

$$\hat{x}_{tgt}^{t+1} = x_{tgt}^t + \hat{v}_{tgt}^t \Delta t, \quad (4)$$

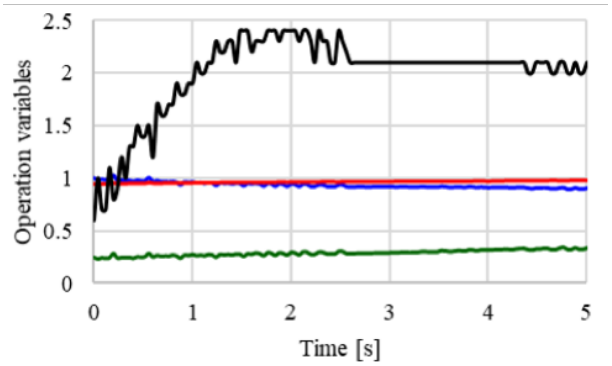
where $\hat{a}_{tgt}^t$ denotes the acceleration derived by Eq.(1). However, the *ego* vehicle is assumed to move with the constant speed until two seconds in the future, therefore, only the position is updated.

As explained previously, the proposed method predicts only the longitudinal position of the *target* vehicle. It is assumed that the *target* is placed in the center of the current lane. Moreover, prediction of a lane-changing trajectory is out of scope of this paper. The method to predict lane-changing trajectories is described in our previous studies [16], [17].

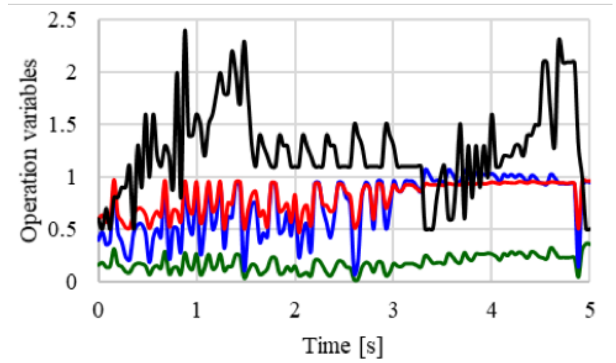
## V. Evaluation

### A. Dataset

To evaluate the effectiveness of the proposed method, real traffic data were used for analysis [19]. The traffic flow on a highway in Germany was recorded by a drone. The data were gathered at six locations, and the time series data for the sets of 110 and 500 vehicles was included. The position, speed, acceleration, size, and other parameters of each vehicle were described. A 4K camera was implemented within the drone, and the measurement accuracy was approximately 10 cm. The measurement rate was 25 Hz. The highway at location 1 has two lanes per direction, and the other locations have three lanes per direction. To validate the robustness of the proposed method with respect to driving conditions, performance was evaluated using the data of all locations. For the evaluation, 5,917 lane-keeping vehicles were considered excluding lane-changing vehicles.




(a)




(b)

Fig. 4. Examples of operation characteristic estimation using the proposed method: the green, red, and blue lines represent the three model parameters: $\alpha$, $l$, and $m$, respectively. The black line shows the reaction time. X axis indicates the time, and Y axis represents the estimated values of the operation characteristic variables. Figure (a) shows the successfully estimated result. Figure (b) represents the unstable estimation result. We consider that the unstable estimation can be caused by volatile driving of the *ego* vehicle. During the driving process, one vehicle can interrupt into the front space of the *ego* vehicle, consequently, the *ego* and *target* vehicles may be forced to decrease the speed unexpectedly.

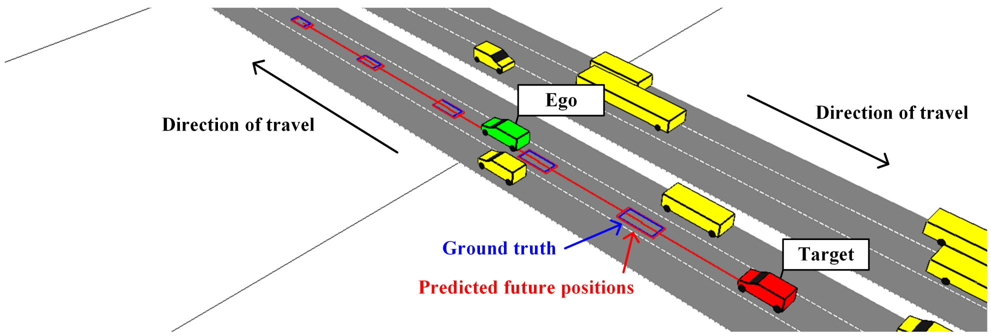



Fig. 5. Result of the trajectory prediction using the proposed method: the green vehicle depicts the *ego* vehicle, and the red one is the *target* vehicle. In addition, the five red rectangles represent the predicted future positions obtained by the proposed method at the five prediction terms: 0.4 s, 0.8 s, 1.2 s, 1.6 s, and 2.0 s, respectively. The blue rectangles show the ground truth. It can be seen that the proposed method has high accuracy.

### B. Criterion of the performance evaluation

As the evaluation criterion, the error between the ground truth and the predicted position of the *target* was considered. As the proposed method predicts the future positions until two seconds with increments of 0.04 s, the root mean-squared error (RMSE) of all predicted positions was considered as the criterion. Let $i$ be the index in the longitudinal direction, and then, RMSE can be calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}(x_i - \hat{x}_i)^2}, \tag{5}$$

where $x_i$ denotes the position at a time step $i$, and is used as the ground truth. $\hat{x}_i$ represents the predicted position obtained using the proposed method. However, the error of lateral positions was excluded from the evaluation scope. $N$ is the number of predicted positions. The future positions are predicted until two seconds with increments of 0.04 s, therefore, $N$ was determined equal to 50.

### C. Results of the operation characteristic estimation

Figure 4 (a) shows the result for a single case from the entire evaluation dataset. X axis depicts the time, and Y axis represents the estimated values of operation characteristic variables. The green line indicates $\alpha$, the red one is $l$, and the blue line shows $m$. These parameters do not have units. It is confirmed that stable values were estimated for all parameters. In addition, the black line indicates the reaction time (in seconds). In the figure, it can be seen that the reaction time gradually increased, and reached a value close to 2.1 s.

In contrast, Fig. 4 (b) shows the result for the case when the unstable values were estimated. The configuration is to that of provided in Fig. 4 (a). It is shown that the values of the three model parameters were unstable during the first three seconds. The reaction time was stable for the first 1.2 s; however, it gradually became unstable between 3 s and 5 s. We consider that unstable estimation was caused by volatile driving of the *ego* vehicle. During the driving process, one vehicle may interrupt into the front space of the *ego* vehicle, consequently, the *ego* and *target* vehicles may be forced to decrease the speed unexpectedly. The lane-changing event may affect the operation process of the *target* driver, and it may lead to the unstable operation characteristics.

### D. Results of the trajectory prediction

Figure 5 shows an example of the predicted future positions of the *target* vehicle obtained using the proposed method. The green vehicle indicates the *ego* vehicle, while

TABLE I
PREDICTION ERROR OF THE PROPOSED METHOD.

| Prediction term | Location 1 | Location 2 | Location 3 | Location 4 | Location 5 | Location 6 |
|---|---|---|---|---|---|---|
| 0.4 s | 0.027 m | 0.023 m | 0.025 m | 0.025 m | 0.031 m | 0.028 m |
| 0.8 s | 0.043 m | 0.040 m | 0.038 m | 0.043 m | 0.052 m | 0.049 m |
| 1.2 s | 0.066 m | 0.065 m | 0.058 m | 0.067 m | 0.083 m | 0.077 m |
| 1.6 s | 0.109 m | 0.109 m | 0.092 m | 0.107 m | 0.136 m | 0.119 m |
| 2.0 s | 0.182 m | 0.176 m | 0.144 m | 0.165 m | 0.219 m | 0.181 m |
| Average | 0.065 m | 0.062 m | 0.055 m | 0.062 m | 0.079 m | 0.070 m |

TABLE II
COMPARISON OF PREDICTION ERROR OF THE PROPOSED METHOD AGAINST THAT OF THE PREVIOUS METHODS.

| | Heyes [11] | Ozaki [12] | Aron [13] | Proposed (constant reaction time) | Proposed |
|---|---|---|---|---|---|
| Average | 0.139 m | 0.189 m | 0.183 m | 0.065 m | 0.065 m |
| Standard deviation | 0.032 m | 0.028 m | 0.034 m | 0.008 m | 0.008 m |

the red one is the *target* vehicle. In addition, the red rectangles show the predicted future positions, and the blue ones represent the ground truth. In this paper, the figure shows the future positions at five prediction terms: 0.4 s, 0.8 s, 1.2 s, 1.6 s, and 2 s. Accuracy can be evaluated based on the error between the ground truth and the predicted positions. From this figure, it can be confirmed that the future positions of the *target* vehicle were predicted accurately.

The errors at the five terms were calculated using the entire dataset. Table I shows the evaluation results obtained using the proposed method. First, it is confirmed that the accuracy in the case of short term prediction was better than that of long-term prediction. Second, it should be noted that for $\Delta =$ 2 s, the error was less than 0.2 m. Therefore, the proposed method showed appropriate performance regardless of the location. This result confirms that our approach is able to appropriately account for the change in driving conditions. At all locations, the average errors observed were less than 0.08 m. As a result, it was demonstrated that the proposed method is able to predict the future positions of the *target* vehicle with high accuracy.

To evaluate the effectiveness of the proposed method, the prediction accuracy was compared to that of the previous methods that have constant values of the operation characteristic variables as shown in Table II. In addition, performance was compared against that one estimated for the case when the proposed method was applied with the fixed reaction time of 1 s to confirm whether the reaction time is considered in the model correctly. Table III shows the determined values of operation characteristic variables in the previous methods. It is clearly evident that the proposed method with the adjustment of operation characteristics is able to significantly improve the prediction accuracy. Compared to the results obtained using the previous methods, the proposed method considerably reduced the errors in almost the half of the number of errors within the previous method in [11]. The average error of the proposed method was 0.065 m, while that of [11] was 0.139 m.

TABLE III
PARAMETER SETTING IN THE PREVIOUS METHODS.

| Variable | Heyes [11] | Ozaki [12] | Aron [13] |
|---|---|---|---|
| $\alpha$ | 0.8 | 1.1 | 2.45 |
| $l$ | 1.2 | 1.0 | 0.676 |
| $m$ | -0.8 | 0.9 | 0.655 |
| $\Delta T$ | 1 s | 1 s | 1 s |

Considering the results of the three previous methods, it can be seen that performance is largely affected by the values of the parameters. Among the previous methods, the values of the operation characteristic variables in [11] showed the best accuracy. Otherwise, the values in [12] showed the error, which was increased almost 30% compared to that of [11]. Hence, the constant values cannot handle the variation of individual characteristics, which may lead to a deterioration of the performance. In contrast, the proposed method showed the robust performance owing to the real time estimation of the parameter values. The standard deviation was derived from the changes of locations where the data were acquired. The standard deviation of the proposed method was 0.008 m, while that of the method proposed by [11] was 0.032 m. Hence, the proposed method achieved the best accuracy as compared to the previous methods. Based on this comparison, it was demonstrated that the real-time optimization of the operation characteristic variables is significantly effective in improving the robustness of the trajectory prediction with respect to the change of locations.

However, the effectiveness of the reaction time estimation was not evaluated as a comparison to the results of the method to estimate only three model parameters with a constant reaction time. RMSE of the proposed method was approximately similar to that shown in Table II. Generally, there is no need to accelerate or decelerate at a high rate, while following the vehicle. Therefore, the influence of the reaction time would be insignificant in terms of the trajectory prediction. To confirm the validity of the approach used to estimate the reaction time, different driving conditions such as lane-changing events are considered. It is required to consider the case when the *ego* vehicle movement is interrupted by the lane-changing of other vehicles. In this case, the *ego* vehicle may decelerate to avoid a collision with the interrupting vehicle, and it may force the *target* driver to react to the sudden event. We plan to confirm the effectiveness of the reaction time estimation under various driving conditions. This evaluation is to be a part of our future studies.

To obtain better performance, there are three points to be improved future studies. First, the proposed method defines the moving window of the constant size for the operation characteristic estimation and performs a moving average within the window. In the evaluation, the size of the window was set as 1 s. However, there were some cases of unstable estimation results as shown in Fig. 4 (b). Generally, the operation characteristics do not change in the short term. Hence, if it is possible to eliminate unstable estimation, performance of the proposed method should be considerably improved.

The second point is to consider the change in the speed of the *ego* vehicle. In the trajectory prediction, it was assumed that the *ego* vehicle keeps the current speed until two seconds in the future. However, it is obvious that the speed of the *ego* vehicle is not constant, and the information can be acquired using the CAN bus. As the position and speed of the *ego* vehicle have the large influence on the prediction result, this point should be addressed.

In addition, we expect that driving styles could be derived from the operation variables. If it is possible to identify such classes (e.g., cautious or reckless), it can significantly contribute to develop the safety system. In our previous work [20], the classification method of driving styles has been proposed. However, this method is based on machine learning techniques, therefore, the performance largely depends on training data. To overcome the limitation, the meaning of each operation variable should be defined.

## VI. CONCLUSIONS

In this paper, we proposed a novel method to predict the future positions of the following vehicle, until two seconds in future, while estimating the operation characteristics of the driver. The methods suggested previously have the limitation of keeping the constant values of parameters related to driving, though each driver has the different, individual operation characteristics. As compared to previous approaches, it was confirmed that the proposed method can considerably improve the accuracy of the trajectory prediction by updating the changes in the driving conditions. At all test locations, the proposed method achieved a minimum prediction error of 0.065 m compared to that of the optimal previous method, which was 0.139 m. Moreover, the standard deviation of the proposed method was 0.008 m, while that of the same optimal previous method was 0.032 m. Based on the observed results, it was demonstrated that our approach ensures the robustness of the trajectory prediction with high accuracy.

As future works, three points should be considered. The first point is to eliminate the cases of unstable estimation, and the second point is to consider the change in speed of the *ego* vehicle. Moreover, we try to identify driving styles based on the operation variables.

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