Advanced Adaptive Cruise Control Based on Collision Risk Assessment

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***Abstract*— In this study, we propose the advanced adaptive cruise control for assessing the collision risk with surrounding vehicles and control the ego vehicle as a way to improve driving safety. Autonomous driving and advanced driver assistance systems (ADAS) have attracted attention as solutions to accident prevention. The ability to anticipate a situation and automatically control a maneuver to avoid a collision is expected to become a reality in the near future. Our research group has focused on the requirements of such ability, particularly lane changing, which is the main factor of traffic accidents. The advanced adaptive cruise control adjusts its distance from surrounding vehicles to minimize a collision risk in advance. The proposed method estimates the intentions of the surrounding traffic participants and predicts their future actions. Based on such prediction, a collision risk assessment is performed. It was demonstrated that the proposed control method can dramatically improve driving safety over human drivers.**

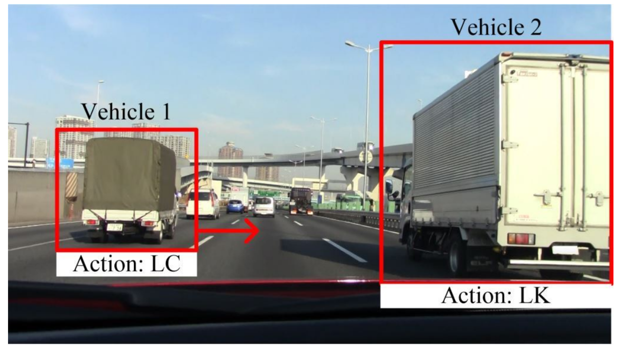

Fig. 1. Prediction of future action: Predicting future actions of the surrounding traffic participants for driving safety is strongly required. In the figure, LC indicates lane changing, and LK denotes lane keeping. The prediction of lane-changing actions and maintaining the distance from the vehicle in advance are expected to be achieved.

I. INTRODUCTION

According to a previous survey, it has been reported that human error cause almost 90 % of all car accidents [1]. Therefore, autonomous driving and advanced driver assistance systems (ADAS) have attracted attention as solutions to improving driving safety. These systems have already been implemented in real vehicles, and are being used to analyze dynamic scenes and issue warning alarms to a driver when a dangerous situation is predicted. Furthermore, in the near future it will become possible to anticipate certain situations and automatically control maneuvers to avoid a collision. It was reported that lane changes are the main factor in car crashes [2]. In the real world, there are drivers with an aggressive driving style, who may perform a risky lane change even when safety is not ensured. To prevent this type of dangerous situation, the prediction of future actions of the surrounding traffic participants is strongly required, as shown in Fig. 1. Moreover, automated maneuvers conducted to avoid collisions based on a prediction can dramatically improve driving safety.

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There have been many previous studies on trajectory prediction and collision risk assessments. Wolf and Burdick proposed a control method for autonomous driving based on a potential field method [3]. However, this method needs to be known in order to calculate the potential energy. As the result, it can only be applied to a self-trajectory. Therefore, their method is not suitable for the trajectory prediction of the surrounding vehicles. Houenou et al. proposed a method to integrate a motion model and a maneuver recognition model for trajectory prediction [4]. Their motion model predicts a trajectory with assuming constant yaw rate and acceleration. The maneuver recognition model determines whether the subject keeps or changes a lane by the comparison of the instantaneous path and the shape of the road. However, this method does not take into account adjacent vehicles when predicting a trajectory. Furthermore, the discussion only focused on the trajectory prediction, and a way to react to the behaviors of the surrounding vehicles to improve driving safety was not proposed.

In a collision risk assessment, the time-to-collision (TTC) and K_{dB}, which is a perceptual risk index, are generally used as an index to evaluate the possibility of crashing, wherein the vehicle of concern is following the preceding vehicle [5], [6]. These indices are calculated using the relative velocity and the distance between the following and preceding vehicles. However, they become less efficient for future behaviors. Laugier et al. proposed a method for a collision risk estimation [7], and is able to evaluate the future risk of surrounding vehicles by the trajectory prediction. However, avoidance of the behaviors of other traffic participants has not been discussed.

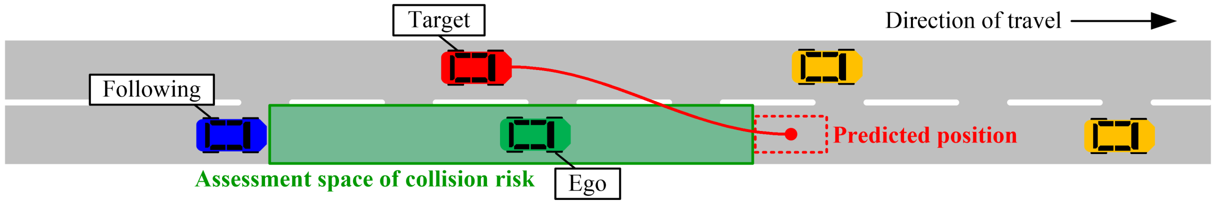


Fig. 2. Problem definition: The scene is modified to obtain an infinite and straight highway, which has only one side. The ego vehicle predicts the position of the target vehicle for a time horizon of 2 s, and the assessment space of collision risk is then defined between the predicted position and the following vehicle. The ego vehicle adjusts the position in advance to minimize the collision risk with respect to both vehicles before the target vehicle crosses the lane marking.

To solve these issues, we propose a novel method to assess a future collision risk and avoid a collision with a surrounding vehicle. Adaptive cruise control (ACC), which controls the velocity and maintains a safe distance from the preceding vehicle, is already implemented in real vehicles; however, it cannot handle future collision risk in its current stage. The proposed method predicts the trajectories of the surrounding vehicles, particularly those cutting the front space of the ego vehicle, and evaluates the collision risk for a time horizon of a few seconds. Moreover, it appropriately adjusts the distance to both the lane-changing vehicle and the following vehicle of the ego vehicle based on a risk indicator. The proposed method uses the risk index extracted by the dynamic characteristic potential field method, which changes the distribution depending on the relative distance and the relative velocity [8]. This index can be used to evaluate a collision risk without restricting specific conditions, as observed in TTC or K_{dB}. The proposed method adjusts the velocity of the ego vehicle to decrease the risk index while predicting the trajectories of the surrounding vehicles.

The contribution of the present research is as follows. Previous studies have certain limitations, as described in the previous paragraph. The proposed method is able to anticipate the future risk and control the vehicle to avoid a collision with the surrounding vehicles. This is a state-of-the-art approach, and demonstrates a significant performance as an advanced safety system.

The remainder of this paper is organized as follows. Section II presents the problem definition and an overview of the proposed method. Section III describes the details of the proposed method. Section IV details the experiments and presents the evaluation results. Finally, Section V presents some concluding remarks and areas of future work.

II. Overview

A. Problem definition

In this study, the scene is modified to obtain a straight and infinite highway, which has only one side, as shown in Fig. 2. The ego vehicle, indicated using a green color, houses measurement devices such as GPS and lidars. The vehicle predicts a trajectory of the target vehicle (shown in red). The proposed method focuses on a situation in which the target cuts in the front space of the ego vehicle, which is the main factor of an accident. The trajectory of the target vehicle and the collision risk are estimated for a time horizon of 2 s. The ego vehicle should consider the risk with respect to not only the target vehicle, but also the following vehicle. If it immediately decelerates to avoid the cut-in vehicle, a collision with the following vehicle would occur. Hence, the ego vehicle adjusts its position and velocity to minimize the risk toward the two vehicles. Only the measurable information regarding the ego vehicle is used, and all calculations are conducted within 0.1 s.

B. Overview

To overcome the limitation of the previous studies, a novel method based on a collision risk assessment for the ACC is proposed. Figure 3 shows a schematic of the proposed method, which comprises four parts: driving intention estimation, trajectory prediction, collision risk assessment, and risk minimization. Inputs of the method are the positions of the ego and surrounding vehicles. The position of the ego vehicle can be measured using GPS, whereas those of the surrounding vehicles can be acquired using lidars.

First, the proposed method indicates that drivers have four intentions, namely, lane *keeping*, *changing*, *arrival*, and *adjustment*. Each intention is defined as a class, and an estimation is treated as a multiclass problem using a support vector machine (SVM). The method is based on the lateral movement of the target vehicle. Details of this method are provided in our previous articles [9], [10]. The output of this part is the intention at each time step.

Second, the trajectory prediction applies the estimated driving intention to identify the strategies that drivers may execute while driving. In general, drivers perform different strategies with different 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 the vehicles in the other lanes. On the other hand, when drivers have intentions such as *changing* and *arrival*, they aim at the front of the adjacent lane, and must take into account surrounding vehicles on not only the current lane but also the adjacent lane. As the result, drivers must consider the surrounding vehicles according to their driving intentions. The proposed method changes the strategy according to the intention. Two prediction methods are used in each direction. The prediction in the longitudinal direction is conducted using the potential field method, whereas that in the lateral direction uses the sinusoidal model. Details of the trajectory prediction method are described in Section III. *A*.

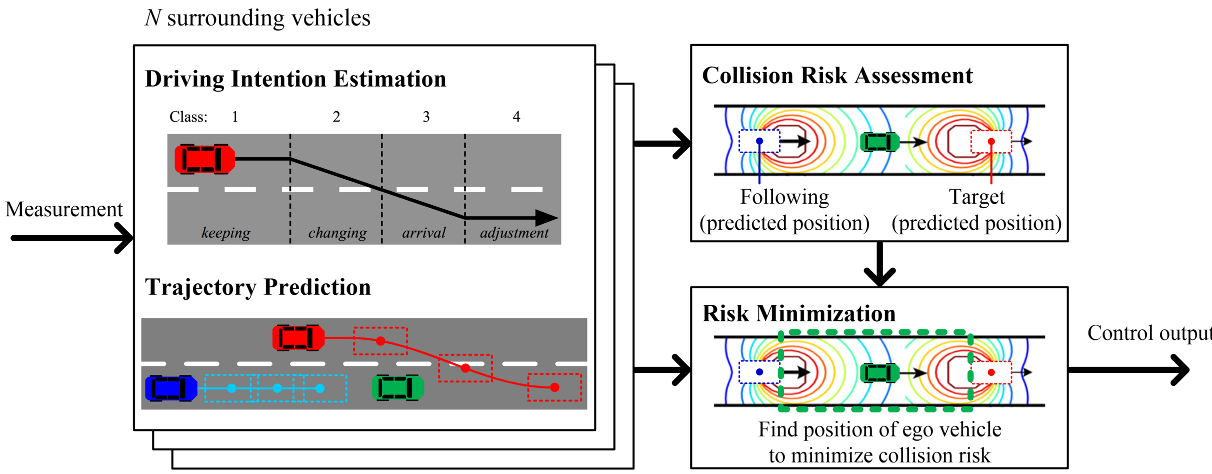


Fig. 3. Overview of the proposed method: The proposed method comprises four parts: driving intention estimation, trajectory prediction, collision risk assessment, and risk minimization. Inputs of the method are the positions of the ego vehicle and surrounding vehicles measured by sensors, which are installed in the ego vehicle. The output of the proposed method is the value of control of the ACC.

Third, a collision risk assessment is conducted. As described in Section I, the collision risk is evaluated using the dynamic potential field method in which the distribution is determined depending on the vehicle gap and relative velocity. The repulsive potential energy from the surrounding vehicle to the ego vehicle is defined as the risk index. If two vehicles rapidly near each other, it is reflected in the large amount of energy produced. On the other hand, when the ego vehicle keeps a safe vehicle gap and adjusts its velocity with respect to the surrounding vehicle, the low collision risk is reflected in the small repulsive potential energy that occurs. The details of this are described in Section III. *B*.

Finally, the proposed method determines an acceleration/deceleration to minimize the collision risk. In the minimization, both the target and following vehicles should be considered. Furthermore, because inconsistent or excessive acceleration (deceleration) can cause an accident with the following vehicle, such action is prohibited. The output of the proposed method is the value of control for the ACC. The details of this part are discussed in Section III. *C*.

III. Proposed Method

A. Trajectory prediction

The proposed method predicts a trajectory according to the estimated driving intention of the surrounding drivers. First, when the estimated intention is *keeping* or *adjustment*, the goal is set to the front of the current lane. The surrounding vehicles generate the repulsive potential energy, which causes the vehicle of concern to maintain a safe margin from the front and back. However, the driver does not pay attention to the vehicles on the adjacent lane. On the other hand, when the estimated intention is *changing* or *arrival*, the driver aims at the front of the adjacent lane and may check the gap with the vehicles in both lanes. The proposed method uses a 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.

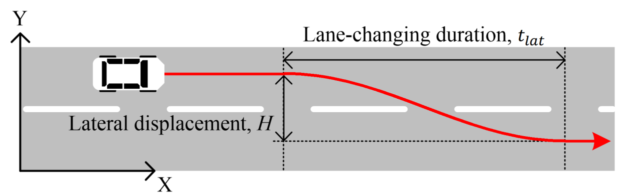


Fig. 4. Sinusoidal model for lane-changing trajectory: This model generates a lane-changing trajectory in the lateral direction.

For a prediction of lateral movement during a lane change, the proposed method uses the sinusoidal model [11]. This model is able to generate a lane-changing trajectory such as a sine curve, as shown in Fig. 4, and does not require a particular parameter. The acceleration in the lateral direction can be derived as

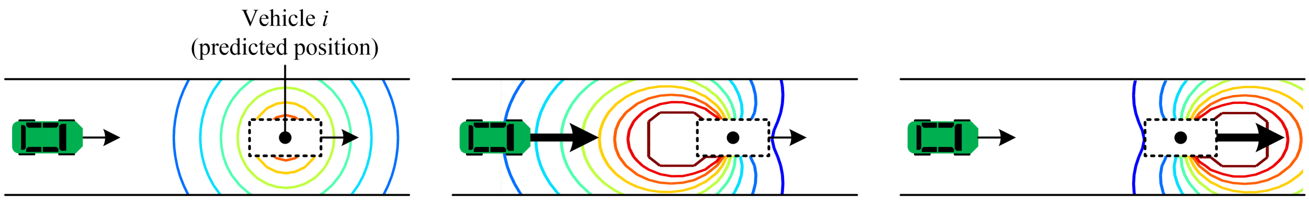
$$a_{lat}(t) = \frac{2\pi H}{t_{lat}^2} \sin \frac{2\pi}{t_{lat}} t, \tag{1}$$

where a_{lat} indicates a lateral acceleration, t is the time from the beginning of a lane change, 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 applying any particular parameters.

The proposed method predicts the longitudinal movement based on the potential field method. It defines two potential energies and generates a trajectory from the current position of the target vehicle to its goal while avoiding crashes. The total potential energy at the position x is derived as

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

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



(a) (b) (c)

Fig. 5. Generated potential fields using dynamic potential model: (a) The ego vehicle drives with the same velocity as vehicle i, (b) the ego vehicle is faster than vehicle i, and the ego vehicle is slower than the vehicle i.

goal is calculated as

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

where ω_g is the weight coefficient. The value of ω_g determines the acceleration/deceleration tendency when there are no surrounding vehicles. A large value creates sudden changes in velocity, and makes closes the vehicle gap between the target and preceding vehicles.

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

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

where ω_s is the weight coefficient, σ is the standard deviation of a vehicle gap from the surrounding vehicles, and i is the index of the vehicles. In this paper, the vehicles are denoted by capital letters (T:target, E:ego, and F:following). When the proposed method calculates the repulsive potential energy from the ego vehicle, it is assigned as $i = E$. The values of ω_s and σ determine how the vehicle of concern takes a gap from vehicle i.

The trajectory prediction is performed for a time horizon of 2 s because it is commonly recognized as the reaction times of the driver and vehicle [12]. As a result, the output is the sequence of positions of other traffic participants for 2 s in advance.

B. Collision risk assessment

Based on the predicted trajectories, a collision risk assessment is conducted. As described in Section II, the proposed method defines the dynamic potential energy as the risk index. This model has no relationship with the potential field method for trajectory prediction, as described in Section III. *A*. The repulsive potential energy generated by the vehicle i can be derived as

$$f(\Delta V_i, \theta_i) = \frac{1}{2\pi I_0(\eta(\Delta V_i))} \exp\bigl(\eta(\Delta V_i)\cos\theta_i\bigr), \tag{5}$$

$$h(G_i) = \frac{1}{2\pi\sigma_i} \exp\bigl(-\frac{G_i^2}{2\sigma^2}\bigr), \tag{6}$$

$$R_i = f(\Delta V_i, \theta_i) h(G_i), \tag{7}$$

where

$$\theta_i = \begin{cases} \pi & (i = T) \\ 0 & (i = F) \end{cases}. \tag{8}$$

Here, ΔV_i indicates the relative velocity between the ego and vehicle i, and G_i is the vehicle gap between the two vehicles. Equation (5) represents the von Mises distribution, and $I_0(\eta)$ is a modified Bessel function of order 0. The distribution is uniform when the parameter η is zero. If the parameter η is large, the distribution drifts toward angle θ_i. In this study, the parameter η is adjusted based on the relative velocity ΔV_i; the drifted direction of the potential field is then chosen. Equation (6) denotes the repulsive potential energy, which is inversely proportional to the vehicle gap.

Figure 5 shows the conditions of the vehicles with regard to the generated potential field based on the relative velocity. With regard to the colors of the generated potential field, the red and blue circles indicate high and low repulsive potential energies, respectively. When the velocity of the ego vehicle is equal to that of vehicle i, the potential field is uniform depending only on the vehicle gap, as shown in Fig. 5 (a). When the ego vehicle is faster than vehicle i, the potential field drifts toward the ego vehicle, as shown in Fig. 5 (b). Consequently, the ego vehicle is affected by the large potential energy, implying that the ego vehicle is at a high risk of colliding with the vehicle ahead. In contrast, when the ego vehicle is slower than vehicle i, the potential field is generated in the forward direction, as shown in Fig. 5 (c). Even if the ego vehicle closely approaches vehicle i, the collision risk remains low because of the relative velocity. The low collision risk is reflected in the small amount of repulsive potential energy. Equation (6) expresses the repulsive potential energy, which is inversely proportional to the vehicle gap. This equation shows that if the ego vehicle drives close to vehicle i, it is affected by the large amount of repulsive potential energy. However, if the ego vehicle is farther away, the potential energy is lower.

The proposed method assesses the collision risk toward both the target and following vehicles. Therefore, vehicle i is the target vehicle when the collision risk with respect to the target is assessed. On the other hand, vehicle i is the following vehicle when the collision risk with the following vehicle is evaluated. Finally, the collision risk at position (x, y) can be derived as

$$R(x, y) = \sum_{i=T,F} R_i, \tag{9}$$

where T represents the target vehicle, and F denotes the following vehicle.

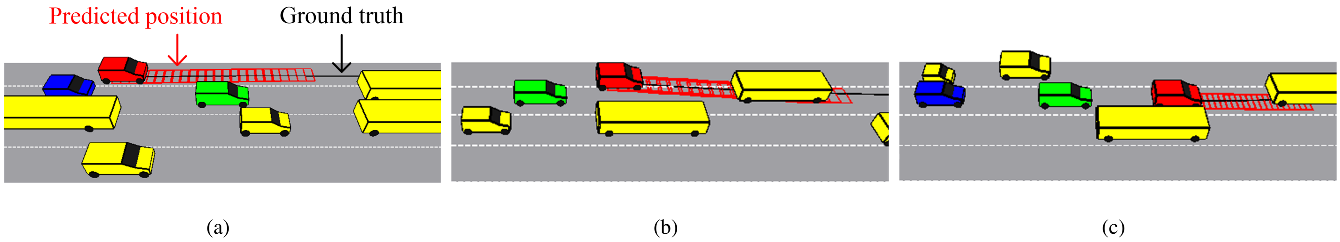


Fig. 6. Results of trajectory prediction by proposed method: (a) When the target vehicle maintains the current lane, (b) when the target changes a lane, (c) and when the target finishes lane changing. The red rectangle depicts the predicted position at each time step, and the black line shows the ground truth. Red indicates the target, green shows the ego vehicle, blue represents the following vehicle, and yellow indicates other vehicles that are not considered. It was clearly shown that the proposed method accurately predicted the trajectory compared with the ground truth.

C. *Risk minimization*

Based on the collision risk, the ego vehicle adjusts the vehicle gaps with respect to both the target and the following vehicles. The proposed method finds the optimal position between the two vehicles to minimize the collision risk. However, it can conversely cause an accident when applying an inconsistent or excessive acceleration (deceleration) because it surprises the surrounding drivers. Hence, the proposed method limits the acceleration (deceleration) to within ± 0.5 m/s^2. When there is no cut-in vehicle, the ego vehicle adjusts the position between the preceding and following vehicles in the same lane. If lane changes are predicted, the ego vehicle maintains a certain distance from the predicted position of the target vehicle for a time horizon of 2 s. The position used to minimize the collision risk can be determined as

$$(x^*, y^*) = \underset{x,y}{\operatorname{argmin}}\, R(x, y), \tag{10}$$

where

$$x_F < x < x_T. \tag{11}$$

In the equation, x_F represents the longitudinal position of the following vehicle, and x_T indicates that of the target vehicle. Finally, the control value is determined as the ego vehicle arrives at the position (x^*, y^*) 2 s in advance.

IV. RESULTS

The proposed method was trained and tested using a real traffic dataset collected from eastbound I-80 in the San Francisco Bay Area. This dataset has been published by the Federal Highway Administration of the United States [13]. The measurement area was approximately 500 m in length and consisted of six freeway lanes. The data was recorded in 0.1 s increments for 15 min. Data from 5,678 vehicles were collected. Among them, 747 lane-changing data were used for the evaluation. A evaluation period of 5 s was defined based on the moment at which the target vehicle crosses the lane marking. The errors in trajectory prediction and collision risk were calculated during this period.

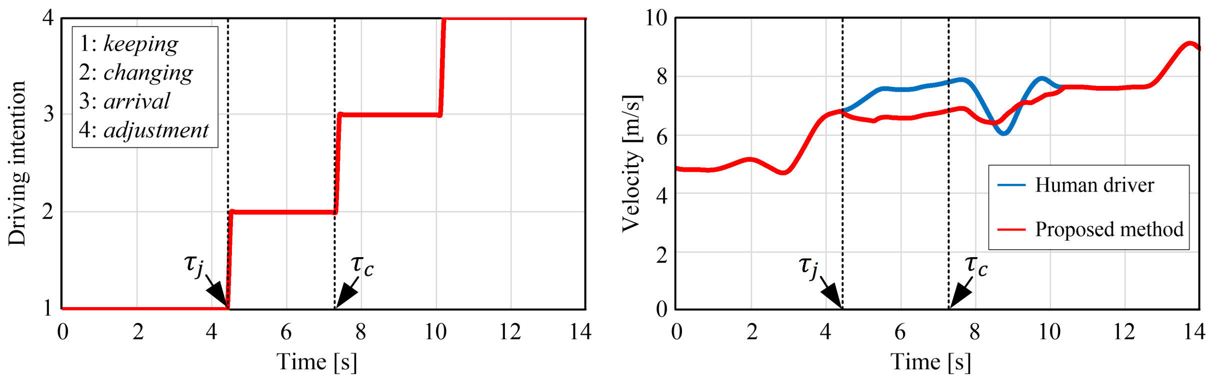
First, the performance of the driving intention estimation was evaluated. Cases in which the proposed method determined that a lane change would occur when in fact the vehicle did not change lanes were judged a false alarm. Otherwise, cases in which the proposed method predicted a lane-keeping state when the vehicle performed a lane change were judged a failure. A failure is the most dangerous case, and thus, the lane-change detection system must achieve a recall with 100 % accuracy. The performance was evaluated based on the F_1 score, which is defined as

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}. \tag{12}$$

Including the precision in the F_1 score allows for an evaluation of the false-alarm rate, and the recall represents the failure rate. The proposed method achieved 98.3 % accuracy. Among 747 events, false alarms occurred in 26 cases, and no failures occurred, which is a higher level of performance than that of previous methods.

Figure 6 shows the results of trajectory prediction in one lane-changing event from the test dataset. The red rectangle represents the predicted position of the target vehicle at each time step, and the black line shows the ground truth. Figure 6 (a) shows the result at a position in which the target kept its current lane. Fig. 6 (b) shows the result at a point in which the target conducted a lane change. Fig. 6 (c) represents the result when the target vehicle finished changing lanes. It was shown that the predicted trajectory is quite consistent with the ground truth. The error in trajectory prediction by the proposed method was calculated during a lane change for the entire testing dataset. The average lateral error was 0.16 m, whereas the average longitudinal error was 1.72 m. The prediction in the lateral direction was better than the longitudinal movement because the displacement in the lateral direction was smaller during a lane change. From this evaluation, it was demonstrated that the proposed method can accurately predict the trajectories of the surrounding vehicles.

An example of improved driving safety using the proposed method for an entire testing dataset is illustrated in Fig. 7. Figure 7 (a) shows the results of driving intention estimation using the proposed method. In the figure, τ_j represents the moment at which the proposed method judges that the target vehicle will change a lane, and τ_c indicates the moment at which the target vehicle crossed the lane marking. It was shown that the proposed method appropriately estimated the driving intentions and predicted a lane change in advance.



(a)

(b)

Fig. 7. Results of the proposed method: (a) the results of driving intention estimated using the proposed method. In the figure, τ_j represents the moment at which the proposed method judges that the target vehicle will change its lane, and τ_c is the moment at which the target vehicle crosses the lane marking, and (b) represents a comparison of the velocity of the ego vehicle used in the example. It can be confirmed that a human driver abruptly decelerated after the target vehicle crossed the lane marking. On the other hand, the proposed method predicted the lane change and decelerated in advance.

TABLE I

COMPARISON OF COLLISION RISK.

	Human drivers	Proposed method
Collision risk [J]	1.52	1.27

Figure 7 (b) compares the velocity of the ego vehicle in the example. It can be confirmed that a human driver abruptly decelerated after the target vehicle crossed the lane marking. In this case, an accident did not occur; however, the rapid deceleration could cause a collision with the following vehicle. On the other hand, it was shown that the proposed method predicted the lane change and decelerated in advance. As a result, the ego vehicle suitably adjusted the velocity without a rapid deceleration. The same evaluation for the entire testing dataset was repeated, and the collision risk was compared. Table I shows the results in terms of the average of the collision risk. It was demonstrated from the table that the proposed method decreased the collision risk and dramatically improved the driving safety. The above results prove the effectiveness of the proposed method.

V. CONCLUSION

In this study, we proposed advanced adaptive cruise control to assess the collision risk with the surrounding vehicles and control the ego vehicle to improve driving safety. In particular, the proposed method focused on a lane change in which the surrounding vehicle cut-in on the front space of the ego vehicle. The proposed method estimated the intention of the target driver and predicted its trajectory. Based on the prediction, the collision risk assessment was performed, and the ego vehicle then adjusted its distance to minimize the risk. It was demonstrated that the proposed cruise control method improves the driving safety when compared with a human driver. As future work, we plan to implement the proposed method in a real vehicle and conduct experiments to evaluate its performance.

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