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Dynamic State Estimation of Driving Style Based on Driving Risk Feature

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ABSTRACT: In this paper, a novel method is proposed to estimate the driving styles of other drivers based on a driving risk feature. This new feature is proposed using a dynamic potential field method wherein the distribution changes depending on the relative number of adjacent vehicles. A more appropriate description of driving risk is obtained compared to other indices. The proposed feature dramatically improves the accuracy of estimating the driving style. To estimate the driving styles, this study considers a problem of the fundamental model under a scenario wherein the target vehicle follows the preceding vehicle. The proposed estimation method is validated through experimental results.

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

1. Introduction

According to a survey conducted by the Japan Metropolitan Police Department, as much as 90 % of the car crashes have been due to human mistakes [(1)]. Many methods have been proposed to decrease the accident rate in the driving support system, such as automatic detection of lane changes of other drivers [(2)(3)]. These systems use machine-learning techniques and work by analyzing common patterns that drivers generally exhibit on an average. However, these approaches have limitations because of the differences in the driving styles of each driver. Generally, drivers have different driving styles influenced by several conditions such as personality, driving environment, and mentality. According to a previous research [(4)], driving styles were found to affect driving patterns in unique ways even if the drivers are under similar conditions, thus limiting the performance of intelligent support systems.

Many studies have been conducted to determine the driving style. Quintero et al. employed an approach to classify a driver as either aggressive or as moderate [(5)]. This method analyzes the changes in the longitudinal and lateral positions by using the throttle, brake, and steering as features. However, these features are specific to each vehicle, making it impossible to estimate the driving styles of other traffic participants. To prevent car crashes, it would be better to estimate the driving styles of other drivers than that of the primary driver.

Aljaafreh et al. defined driving styles and categorized them into below normal, normal, aggressive, and very aggressive [(6)]. They proposed a method to estimate the driving style based on acceleration patterns. The acceleration and deceleration in longitudinal and lateral directions were used as features. However, this method focused only on the movement of the target vehicle without considering the relationship with adjacent vehicles, which should have been considered valuable information in determining the driving styles.

The driving style can be explained using the driving risk, which is defined as an index used to evaluate the possibility of crashing into another vehicle. It is associated with improperly maintaining the position and inconsistent or excessive acceleration (deceleration) [(7)]. An aggressive driver often shows a risky driving pattern whereas a cautious driver maintains the appropriate velocity and distance to avoid crashing with other vehicles. Hence, it is important to appropriately evaluate the driving risk considering the relationship with adjacent vehicles to improve the accuracy of estimating the driving style. Many indices have been proposed to evaluate the driving risk. Among them, the time-to-collision (TTC) and K_{dB}, which is a perceptual risk index, are generally used in the cases wherein the concerned vehicle is following the preceding vehicle [(8)(9)(10)]. These indices are calculated using the relative velocity and the distance between the following and preceding vehicles. However, there are some limitations when the velocity of the following vehicle is equal to that of the preceding vehicle.

Considering the above limitations, we propose a novel feature to appropriately evaluate the driving risk and improve the accuracy of determining the driving style. Only the measurable information regarding the primary vehicle was used to determine the driving styles of other drivers. Moreover, it was possible to evaluate the driving risk without restricting specific conditions, as observed in previous indices. To satisfy these requirements, we employed a dynamic characteristic potential model [(11)]. This model helps in generating a drifted potential field depending on the velocity relative to adjacent vehicles. The proposed method is used to obtain the repulsive potential energy from the preceding vehicle as a feature. This repulsive potential energy makes it possible to overcome the limitations observed in previous indices. When the target vehicle is faster than the preceding vehicle at a close range, the target is at a high risk of crashing. In this case, it can be considered that the target driver shows an aggressive driving style. Using the proposed method, a high repulsive potential energy is generated in the preceding vehicle, which reflects a high driving risk. However, a low repulsive potential energy is generated when the target vehicle is slower than the preceding vehicle while maintaining a sufficient distance. In this case, it can be considered that the target driver is less likely to crash, i.e., the risk is low and the driving style is cautious. As described previously, our approach can be used to appropriately evaluate the driving risk regardless of the conditions, thus improving the accuracy of determining the driving style.

In addition, an error correction is implemented based on the assumption that the driving style remains the same within a short period. Kumar et al. implemented a Bayesian filter at the output of the support vector machine (SVM) [12]. However, this method refers to the training dataset but the target driver. Therefore, this method is ineffective when the target vehicle shows a different pattern with respect to the training dataset. In contrast, the proposed method focuses on the target vehicle considering the tendency of the past estimation results until the current time. Thus, temporary errors different from the past tendency could be removed, which is expected to improve the estimation accuracy.

The remainder of this paper is organized as follows. Section 2 presents the problem setting and the overview of the proposed method. Section 3 explains the method of obtaining the new feature using the dynamic potential model. Section 4 describes the classification method. Section 5 presents the error correction. Section 6 explains the experiments using a driving simulator and presents the evaluation results. Finally, Section 7 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. 1. The primary vehicle, indicated using white color in Fig. 1 (a), houses measurement devices such as a GPS and laser scanners. The primary vehicle obtains the longitudinal vehicle gap D_x, relative velocity in the longitudinal direction $V_{r,x}$, and relative angle θ between the target and preceding vehicles as shown in Fig. 1 (b). The red vehicle is the target vehicle for which the driving style is estimated. The proposed method focuses on a situation wherein the target follows the preceding vehicle, indicated in blue color. The primary vehicle considers the movement of the target vehicle, the driving style of which is estimated at each time step.

The revision to previous studies shows a prevalence of driving style estimation using either two or three levels. In this paper, the driving style is categorized into three levels: *cautious*, *normal*, and *aggressive*, as observed in a previous study [13]. The proposed method is used to determine the type of driving style of the target among the three given levels.

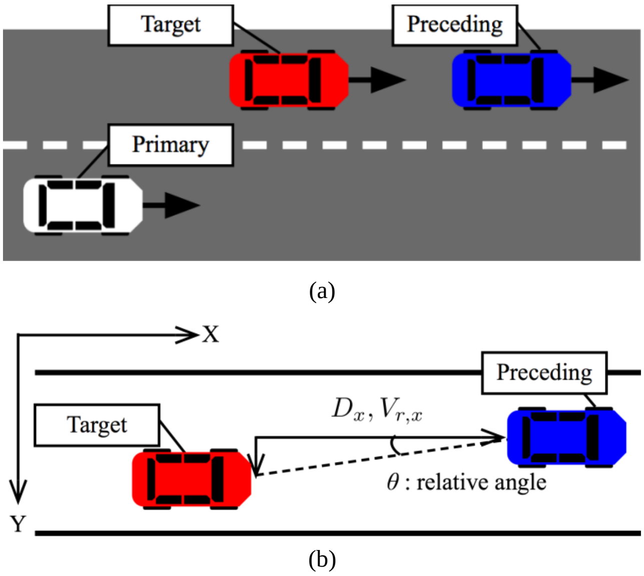


Fig 1 Problem setting: (a) relationship with vehicles adjacent to the primary vehicle, and (b) definition of proposed features.

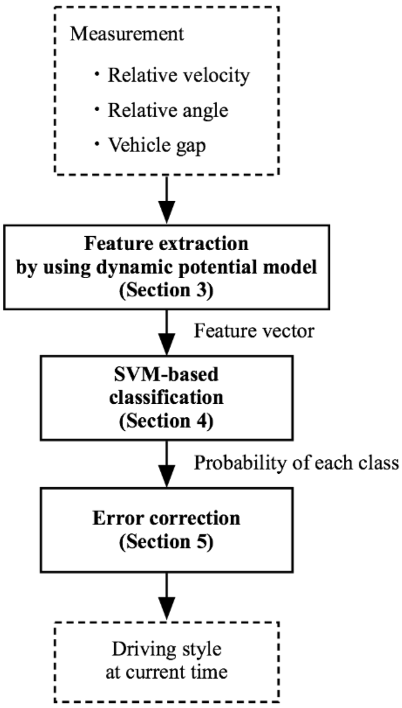


Fig. 2 Overview of proposed method.

2.2. Overview of Proposed Method

To overcome the limitation of the previous methods, the proposed method focuses on the driving risk and extracts a novel feature. Figure 2 shows the schematic of the proposed method. It comprises three parts: feature extraction using a dynamic potential model, SVM-based classification, and error correction. The relative velocity in the longitudinal direction $V_{r,x}$, relative angle θ, and vehicle gap D_x with respect to the preceding vehicle are obtained using measurement devices installed on the primary vehicle. Using this information, the feature is extracted. The proposed method considers the driving risk, which is defined as the possibility of crashing into a preceding vehicle. The dynamic potential model is used to evaluate the driving risk. The vehicle gap and the relative velocity with respect to the preceding vehicle are considered simultaneously in this approach using the dynamic potential model. The repulsive potential energy of the preceding vehicle is obtained, which is used as a feature. This part is the main contribution of this study. In Section 3, the feature extraction method is explained.

Next, a machine-learning technique is used for the classification. The SVM is used in the proposed method, which is reliable for low-dimensional classification. The driving style of the target is outputted at each time step. The details are described in Section 4.

Finally, the error correction is performed to improve the estimation accuracy based on the assumption that the driving style remains unchanged within a short period. In the proposed method, the probability of each class in the SVM is used, and the probability of each driving style is updated using the statistics of past estimation results. Using this approach, temporary errors that are different from the tendency of the past results could be eliminated. The details of these approaches are discussed in Section 5.

3. Feature Extraction

3.1. Driving Risk Feature

The driving risk can be evaluated using the relationship between the target and preceding vehicles. When the target is faster than the preceding vehicle, despite the small vehicle gap, it is assumed that the target driver is driving with a high risk. In this case, the target driver is considered to show an *aggressive* driving style. However, when the target vehicle is slower than the preceding vehicle with a sufficient vehicle gap, it is considered that the target driver is driving with a low risk, which is categorized as the *cautious* driving style.

As mentioned in Section 1, several indices have been proposed to evaluate the driving risk. Among them, 1/TTC and K_{dB} are generally used. However, they cannot be employed when the relative velocity is zero with respect to the preceding vehicle. 1/TTC is calculated as follows.

$$1/\mathrm{TTC} = \frac{V_{r,x}}{D_x}, \tag{1}$$

where $V_{r,x}$ represents the relative velocity between the target and preceding vehicles, and D_x is the distance between the two vehicles. K_{dB} is derived as follows [8][9].

$$K_{\mathrm{dB}} = 10\log_{10}\left(\left|4\times 10^7 \times \frac{V_{r,x}}{D_x^3}\right|\right)\mathrm{sgn}\left(V_{r,x}\right), \tag{2}$$

The distance between the vehicles does not affect the indices in the case wherein the velocity of the target vehicle is equal to that of the preceding vehicle, even though this case is often observed during a following behavior.

To solve this problem, a novel feature is proposed using a dynamic potential field method to simultaneously consider both the vehicle gap and the relative velocity. Using this approach, the driving risk could be evaluated without restricting the situation observed in the previous indices.

The potential field method is generally used for robot navigation [14]. This method helps in generating a repulsive energy from an obstacle to avoid a collision. In a normal potential model, only the distance between the robot and the obstacle is considered whereas both the relative velocity and the distance are considered in the dynamic model [15]. By applying this dynamic model for driving, a method of generating a drifted potential field depending on the relative velocity was proposed [11]. In the proposed method, the repulsive potential energy of the preceding vehicle is used as a feature to evaluate the driving risk. The greater the repulsive potential energy, the higher is the driving risk. The repulsive potential energy U can be derived as follows.

$$G\left(V_{r,x},\theta\right) = \frac{1}{2\pi I_0\left(k\left(V_{r,x}\right)\right)}\exp\left[k\left(V_{r,x}\right)\cos\theta\right], \tag{3}$$

$$H\left(D_x\right) = \frac{1}{2\pi\sigma}\exp\left[-\frac{D_x^2}{2\sigma}\right], \tag{4}$$

$$U = \alpha G\left(V_{r,x},\theta\right)H\left(D_x\right), \tag{5}$$

where θ represents the relative angle, σ is the variance of the vehicle gap, and α is a coefficient. The relative angle is the angle between the relative position of the target with respect to the preceding vehicle. Equation (3) represents the von Mises distribution, and $I_0(\cdot)$ is the modified Bessel function of order zero. This distribution is uniform with a circular shape when the parameter k is zero. If the parameter k is large, the distribution tends to angle θ. In this study, the parameter k is adjusted using the relative velocity $V_{r,x}$. The drifted direction of the potential field is then determined.

Figure 3 shows the conditions of the vehicles with regard to the generated potential field based on the relative velocity. The red and blue vehicles are the target and preceding vehicles, respectively. With regard to the colors of the generated potential field, the red and blue circles indicate the high and low repulsive potential energies, respectively. When the velocity of the target is equal to that of the preceding vehicle, the potential field is uniform depending only on the vehicle gap as shown in Fig. 3 (a). When the target is faster than the preceding vehicle, the potential field drifts toward the target as shown in Fig. 3 (b). Consequently, the target is affected by the large potential energy, implying that the target is at a high risk of crashing with the vehicle ahead. In contrast, when the target is slower than the preceding vehicle, the potential field is generated forward as shown in Fig. 3 (c). Even if the target drives close to the preceding vehicle, the driving risk is low because of the relative velocity. The low driving risk is reflected in the small repulsive potential energy. Equation (4) expresses the repulsive potential energy, which is inversely proportional to the vehicle gap. This equation shows that if the target drives close to the preceding vehicle, it is affected by the large repulsive potential energy. However, if the target is farther away, the repulsive potential energy is lower.

If the target driver exhibits a *cautious* driving style, the driver would maintain a considerable distance from the preceding vehicle and drive slowly. In this situation, it can be considered that the driver is driving with a low risk, which is reflected in the low

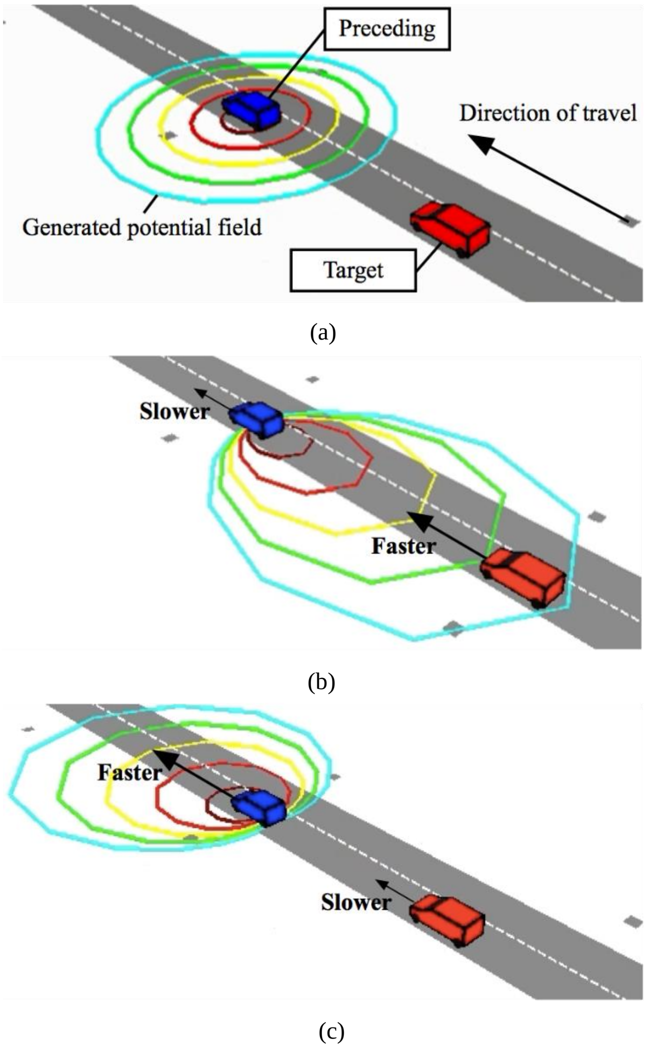


Fig. 3 Generated potential field using dynamic potential model: (a) the relative velocity is zero between the target and preceding vehicles, (b) the target is faster than the preceding vehicle, and (c) the target is slower than the preceding vehicle. The distribution of the potential field changes depending on the relative velocity.

repulsive potential energy. However, when the target driver has an *aggressive* driving style, the driver closely follows the preceding vehicle with a high risk of crashing. Moreover, the driver would rapidly approach the preceding vehicle. Therefore, the target is affected by the high repulsive potential energy.

As explained previously, our approach using the dynamic potential model makes it possible to evaluate the driving risk regardless of the relative velocity while simultaneously considering the vehicle gap. The repulsive potential energy generated by the preceding vehicle is defined as the driving risk feature (DRF), which is used as the feature.

3.2. Feature Vector

The feature vector comprises three features: the vehicle gap with respect to the preceding vehicle, the relative velocity with respect to the preceding vehicle, and the DRF. The feature vector $\mathbf{x}_t$ at time t can be represented as follows.

$$\mathbf{x}_t = [\mathbf{D}_t\,,\ \mathbf{V}_t\,,\ \mathbf{U}_t]^{\mathrm{T}}, \tag{6}$$

$$\mathbf{D}_t = \left[D_{x,t-(W-1)}\,,\ \ldots,\ D_{x,t-1}\,,\ D_{x,t}\right], \tag{7}$$

$$\mathbf{V}_t = \left[V_{r,x,t-(W-1)}\,,\ \ldots,\ V_{r,x,t-1}\,,\ V_{r,x,t}\right], \tag{8}$$

$$\mathbf{U}_t = \left[U_{t-(W-1)}\,,\ \ldots,\ U_{t-1}\,,\ U_t\right], \tag{9}$$

where W is the size required to capture a continuous process. The proposed method considers the transition of the features. For example, $\mathbf{D}_t$ is a sequence comprising W data until time t.

In the absence of scaling, the estimation accuracy is largely influenced by the differences in the values. Thus, the proposed method conducts normalization using an average and a standard deviation, which are calculated during the training phase.

4. SVM-Based Classification

In the proposed method, the SVM is used to determine the class of the feature vector among the three defined driving styles. The proposed method deals with the driving style as a class in the SVM, and the driving style is determined via a multiclass classification.

In the proposed method, the radial basis function (RBF), which is the most effective kernel for low-dimensional classification, is selected. The RBF is defined as follows.

$$K(\mathbf{x}, \mathbf{x}') = \exp(-\gamma\|\mathbf{x} - \mathbf{x}'\|^2), \tag{10}$$

where γ is the kernel parameter. The proposed method uses an approach for the multiclass extension of the binary SVM using a one-versus-one strategy. The estimated driving style S_t at time t can be derived as follows.

$$S_t = \underset{j}{\operatorname{argmax}}\, y_j(\mathbf{x}_t), \tag{11}$$

where j represents the index of the driving styles. The driving style S_t denotes the output from the SVM without the error correction, explained in Section 5.

5. Error Correction

The proposed method conducts the filtering based on the past estimation results when it is not convinced of the output of the estimation model. The SVM always outputs at least one class among the candidates even if there is no significant difference in the probability of each class. To overcome this limitation, the past estimation results are referred to in the proposed method when it is difficult to establish the output from the SVM. The probability of each class in the SVM is calculated using a method proposed by Platt [16].

The proposed method refers to the past results until the current time, as shown in Fig. 4. Thus, the proposed filtering method has a higher adaptability to the target than the Bayesian filter [12]. The

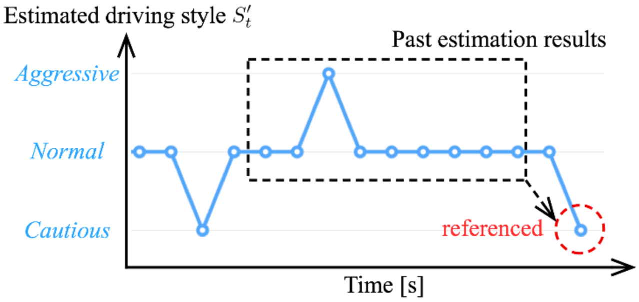


Fig. 4 Error correction based on past estimation results.

proposed method adjusts the probability of the output class of the SVM as follows.

$$P'(\mathbf{X}_{0:t}|S_t \in A) = P(\mathbf{X}_{0:t}|S_t \in A)\frac{f(A)}{\sum_j^M f(j)}, \quad (12)$$

$$\mathbf{X}_{0:t} = [\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_t], \quad (13)$$

where $f(A)$ represents the number of cases that the estimated driving style belongs to class A until time t, j is the index of the driving style class, and M is the number of candidates. Finally, the corrected driving style S_t' is derived as follows.

$$S_t' = \underset{j=1,2,\ldots,M}{\operatorname{argmax}}\, P'(\mathbf{X}_{0:t}|j). \quad (14)$$

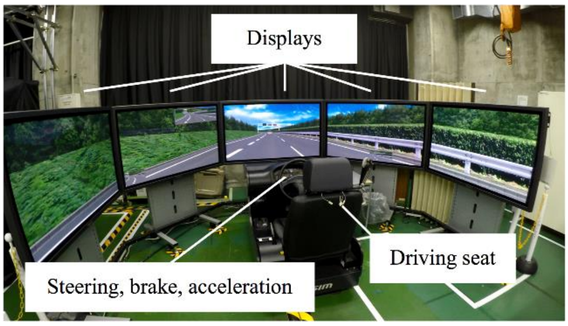
Compared to S_t given in Section 4, S_t' is a more accurate result because the temporary errors that are different from the tendency of the past estimation results could be removed using the filtering technique.

6. Results

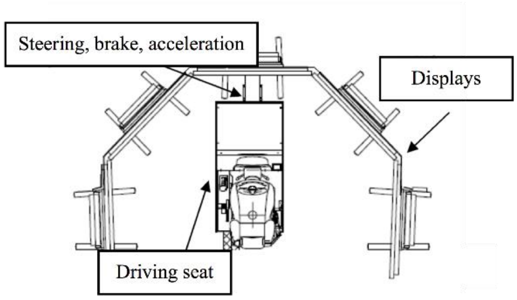
6.1. Experiments

In this study, a driving simulator (DS) named as "D3 Sim (Mitsubishi Precision Co., LTD.)" was used to collect the training dataset to develop the estimation model and the testing dataset for evaluation. This simulator showed visual information on display devices comprising five monitors as shown in Fig. 5 (a). In addition, the driving seat comprises a steering, an acceleration pedal, and a brake pedal as shown in Fig. 5 (b). The data was recorded at 120 Hz. A total of ten subjects (drivers *A*, *B*,..., and *J*) of different ages participated in the experiment with different simulator and 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, as shown in Fig. 6 (a). The red car is the vehicle operated by the subjects in the experiments, which is the target in the driving style estimation. The blue car is the preceding vehicle, and the yellow car represents the lead vehicle, which is on a lane adjacent to that of the target. Both the preceding and lead vehicles blocked the roads of the subject vehicle as shown in Fig. 6 (b) 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. The driving style was instructed to the subjects before the measurement. The order

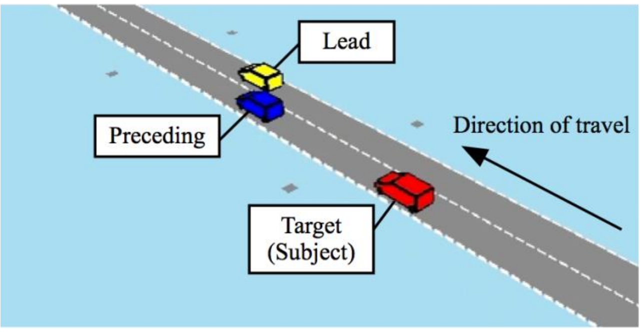


(a)

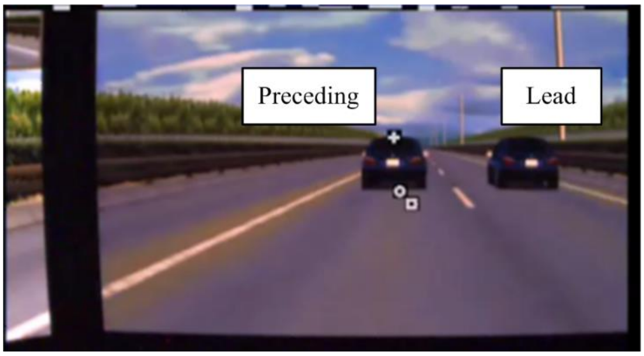


(b)

Fig. 5 Experimental setup: (a) driving simulator, and (b) system diagram.

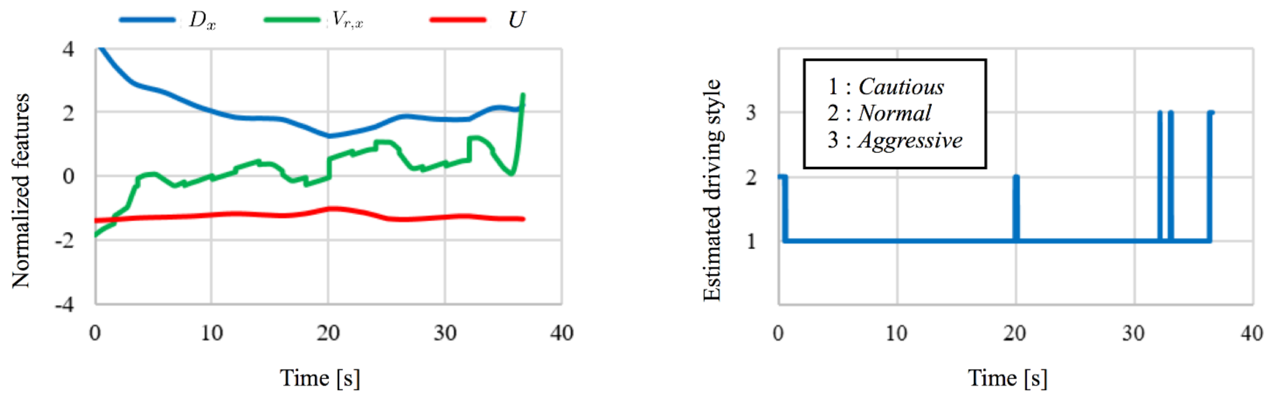


(a)



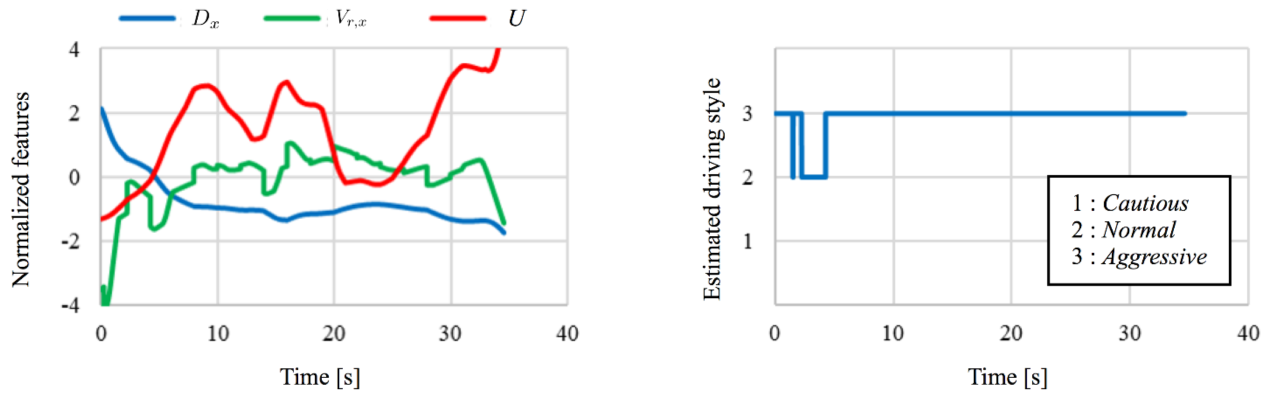
(b)

Fig. 6 Aspects of experiments: (a) experimental scenario, and (b) displaying scene to subjects.



(a) (b)

Fig. 7 Estimation results of one event where the ground truth is *cautious*: (a) proposed features, and (b) driving style estimated using proposed method.



(a) (b)

Fig. 8 Estimation results of one event where the ground truth is *aggressive*: (a) proposed features, and (b) driving style estimated using proposed method.

of the instructed driving style was *normal*, *cautious*, and then, *aggressive*. First, the subjects drove the vehicle under no specific instruction, and the data were recorded as *normal* driving style. Second, the subjects were instructed to “drive cautiously,” and the data obtained were classified as the *cautious* driving style. Thereafter, the subjects were instructed to “hurry,” and the data were recorded as the *aggressive* driving style. Twenty trials were conducted under each driving condition. Totally, 600 trials were conducted in the experiments.

Table 1 Average of features for each driving style.

	Cautious	*Normal*	*Aggressive*
D_x [m]	66.1	56.5	36.1
$V_{r,x}$ [m/s]	-0.905	-0.871	-0.871
U [J]	0.148	0.224	0.479

6.2. Estimation Results

Figures 7 and 8 show the results of one trial among the testing dataset. The ground truth in Fig. 7 is *cautious*, and the ground truth in Fig. 8 is *aggressive*. In Figs. 7 (a) and 8 (a), the X and Y axes denote the time and normalized features, respectively, used in the proposed method. The blue, green, and red lines indicate the vehicle gap, relative velocity, and DRF, respectively. The greater the values, the wider is the gap, the faster is the velocity, and higher is the repulsive potential energy, respectively. It is confirmed that the driver maintained a wider vehicle gap D_x under the *cautious* driving style than that under the *aggressive* style. Similarly, the *cautious* driver was influenced by the low repulsive potential energy U, the DRF, whereas the *aggressive* driver was influenced by the high repulsive potential energy. In contrast, there was no difference in the relative velocity $V_{r,x}$ between the two driving styles. Table 1 presents the average of the features under each condition.

Figures 7 (b) and 8 (b) show the estimated driving styles at each time step obtained using the proposed method. The driving style was successfully estimated based on the ground truth. The results demonstrate that the driving style could be estimated correctly using the proposed method.

6.3. Feature Evaluation

The effectiveness of the DRF was compared with the previous indices, 1/TTC and K_{dB}. The evaluation as a single variable classifier is one of the general methods for feature selection. The accuracy was calculated for the features, and they were compared with each other. The F_1 measure was used as an evaluation metric. The F_1 measure is represented for every class against the remaining two classes as follows. It can be derived as follows.

$$\text{precision} = \frac{TP}{TP+FP}, \tag{15}$$

$$\text{recall} = \frac{TP}{TP+FN}, \tag{16}$$

$$F_1 = 2 \times \frac{\text{precision}\times\text{recall}}{\text{precision}+\text{recall}}, \tag{17}$$

where *TP*, *FP*, and *FN* denote the *true positive*, *false positive*, and *false negative*, respectively. Among the 600 trials of the dataset, 300 trials were used for training and the remaining was used for the evaluation. Table 2 lists the results sorted with the features based on their estimation accuracies.

It is clearly confirmed that the DRF, which is the proposed feature, is the most valuable feature for determining the driving style compared to the other indices K_{dB} and 1/TTC. The accuracy of the DRF was the highest among the candidates, which was 53.4 %. Moreover, 1/TTC and K_{dB} exhibited largely the same or lower accuracy with respect to the vehicle gap. The results prove that these indices cannot consider the vehicle gap and the relative velocity simultaneously. Despite the increased amount of information, the performance decreased in the case of K_{dB}. In most cases, cautious drivers maintain a considerable distance from the preceding vehicle compared to aggressive drivers as shown in Table 1. The vehicle gap achieved an estimation performance with an accuracy of 51.8 % whereas the relative velocity showed the lowest performance with an accuracy of 27.9 %. Using this evaluation, we demonstrated that the DRF is significantly effective in determining the driving style.

6.4. Evaluation of Estimation Performance

It was confirmed that the DRF is the most effective feature as a single variable classifier. However, there is a possibility that the best set of features do not contain the best individual feature. Hence, it is possible to obtain a better estimation performance with 1/TTC or K_{dB}, though the DRF is the most effective feature as a single variable classifier. The performance of the proposed method was compared with set 1 (the vehicle gap, relative velocity, and 1/TTC) and set 2 (the vehicle gap, relative velocity, and K_{dB}). Table 3 lists the results of the estimation performance for each set of features. This comparison was conducted under the same conditions, except the features. The accuracies of the sets 1 and 2 were 63.8 % and 65.1 %, respectively, whereas the proposed features achieved the highest performance with an accuracy of 71.0 %. Thus, it was proven that the DRF is not only the best individual feature but also included in the best set of features for the driving style estimation.

Table 2 Estimation performance of features.

Ranking	Feature	F_1
1	DRF (proposed)	53.4 %
2	1 / TTC	51.9 %
3	Vehicle gap	51.8 %
4	K_{dB}	47.5 %
5	Relative velocity	27.9 %

Table 3 Performance comparison.

Feature set	F_1
Set 1 (vehicle gap, relative velocity, 1/TTC)	63.8 %
Set 2 (vehicle gap, relative velocity, K_{dB})	65.1 %
Proposed (vehicle gap, relative velocity, DRF)	71.0 %

Using the above evaluations, we demonstrated that the DRF, our proposed feature, is the most effective feature for estimating the driving style, outperforming the previous indices in estimating the accuracy.

7. Conclusion

In this study, a novel feature was proposed to evaluate the driving risk using a dynamic potential field method and determine the driving styles of other traffic participants. The experimental results demonstrate that the proposed method outperforms previous indices in terms of the estimation accuracy. The proposed feature was evaluated as a single variable classifier. The proposed feature was significantly more effective than 1/TTC and K_{dB}. In addition, the best set of features was evaluated, and the proposed features achieved an average of 71.0 % for the F_1 measure. The results show that the proposed method is very effective in determining the driving styles of other drivers.

In the future, the parameters optimization will be discussed for the DRF. The effectiveness of the DRF depends on the values of the parameters. We plan to propose a method to determine the parameters without the trial-and-error process.

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