Driver Classification in Vehicle Following Behavior by Using Dynamic Potential Field Method

Hanwool Woo[1], Yonghoon Ji[1], Yusuke Tamura[1], Yasuhide Kuroda[2], Takashi Sugano[3], Yasunori Yamamoto[3], Atsushi Yamashita[1], and Hajime Asama[1]

***Abstract*— In this paper, a novel method is proposed to classify drivers in vehicle following behavior. The main contribution of this work is to construct a method to classify drivers as the fundamental model to consider characteristics of each driver under a scene that the target vehicle follows the preceding vehicle. Many methods have been proposed using data-driven approaches, however, each driver has an own driving style and shows different characteristics to be influenced by traffic conditions. As the result, the performance of previous methods to detect common patterns trained by machine learning techniques may realize the limitation. The proposed method extracts a new feature to describe a driving style by using a dynamic potential field method, and it can be a significant feature to classify drivers. It is demonstrated that our new feature dramatically improves the accuracy of driver classification through experimental results.**

I. INTRODUCTION

According to a survey by the Japan Metropolitan Police Department, almost 90 % of car crashes have been caused by human mistakes [1]. Therefore, autonomous vehicles and intelligent driving support systems are attracting attention as the solution to decrease car accidents. These systems are already implemented to a real vehicle to measure surrounding environments, and it alarms a warning to the primary driver when a dangerous situation is predicted. It was reported that a lane change is the main factor of car crashes [2]. If it is possible to detect lane changes of other vehicles before lane crossing, it should be contributed to prevent car accidents.

We have proposed methods to detect lane changes of other vehicles through lane change detection that is treated as the classification problem by machine learning techniques [3]. This approach constructs a prediction model averaged by the training data. However, drivers have their own driving styles and show different characteristics to be influenced by traffic conditions (e.g., psychological situation, driving skills, and environment). Therefore, it is difficult to detect lane changes properly under several conditions by a common model. Our approach has focused on this problem. If it is possible to classify drivers based on a driving style, the prediction model can be adjusted depending on personal characteristics. As the result, it is expected that the performance of support systems is dramatically improved with respect to the common prediction model.

[1]H. Woo, Y. Ji, Y. Tamura, A. Yamashita, and H. Asama are with the Department of Precision Engineering, Graduate School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan. {woo, ji, tamura, yamashita, asama}@robot.t.u-tokyo.ac.jp

[2]Y. Kuroda is with the Mazda Motor Corporation, 2-5 Moriyacho, Kanagawa-ku, Yokohama 221-0022, Japan. kuroda.y@mazda.co.jp

[3]T. Sugano and Y. Yamamoto are with the Mazda Motor Corporation, 3-1 Shinchi, Akigun Fuchucho, Hiroshima 730-8670, Japan. {sugano.t, yamamoto.ya}@mazda.co.jp

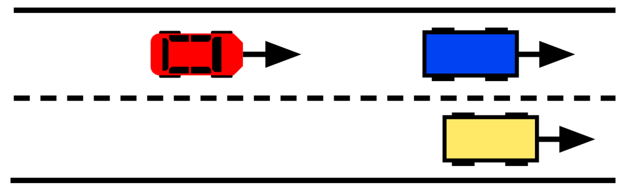


Fig. 1. Schematic illustration of target scene: we assume a scene that the target vehicle follows the preceding vehicle on a straight highway. A red vehicle represents the target, a blue one is the preceding vehicle, and a yellow one is the lead vehicle. Since the preceding and lead vehicles block off a road, the target vehicle is forced to follow them.

Ly *et al.* proposed a driver classification method using only inertial sensors from the CAN bus [4]. They tested the information such as acceleration, braking, turning, and the combination of them as features. It was concluded that the combination of braking and turning was the most effective feature, and almost 65 % of the classification accuracy was achieved. In addition, Fernandez *et al.* employed an approach using a Fuzzy logic for the driver classification [5]. This method used the information about an age, acceleration, braking, and speed. However, the information used in above methods can be measured only in the primary vehicle, therefore, it cannot be applied to other vehicles. Otherwise, Doshi *et al.* analyzed the information which can characterize driving styles by experiments using a driving simulator and a real vehicle [6]. They proposed longitudinal acceleration, longitudinal jerk, lateral acceleration, lateral jerk, and time-to-crash as the information that characterize each driver. However, it was not discussed how accurate the classification can be performed.

Considering these situations, we propose a method to classify drivers while take into account the driving style. A problem scene is assumed that the target vehicle follows the preceding vehicle on a two-lane highway as shown in Fig. 1. A red vehicle represents the target, a blue one is the preceding vehicle, and a yellow one is the lead vehicle which is on the next lane. A driving style can be defined as an index to evaluate the probability to crash into other vehicles, which is associated with improper position maintenance, and inconsistent or excessive acceleration (deceleration) [7]. The proposed method estimates the driving style, and it works to characterize the target driver.

The main contribution of this work is to extract a novel feature that describes a driving style by using a dynamic potential field method. The dynamic potential field method generates a potential field that changes the distribution depending on the relative velocity with respect to the preceding vehicle [8]. The proposed method uses the repulsive potential energy generated from the preceding vehicle as a feature. When the target driver has an aggressive driving style, the vehicle would approach at a faster rate and keep a shorter distance from the preceding vehicle than cautious drivers. In this case, the target vehicle takes the high repulsive potential energy. On the other hand, when the target driver is cautious, he or she would take the low repulsive potential energy. As described above, our proposed feature is able to describe a driving style.

Moreover, a filtering method is also implemented to consider past classification results based on an assumption that the driver may not be changed within a short period. Kumar *et al.* implemented a Bayesian filter to the output of a SVM (Support Vector Machine) [9]. However, this method refers to the training dataset but the target driver, therefore, it has no effect when the target shows a different pattern with respect to the training dataset. In contrast, the proposed method focuses on the target, and it refers to the tendency shown in past estimation results until the current time. As the results, temporary errors that are different to the past tendency can be removed, and it is expected to improve the classification accuracy.

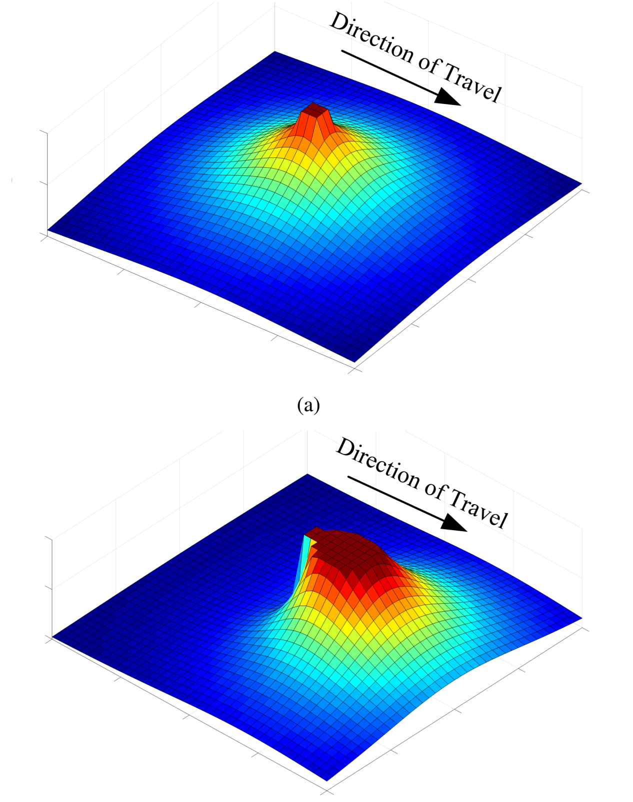
The reminder of this paper is organized as follows. Section II presents details of the proposed method, and Section III presents an experimental setup and evaluation. Finally, Section IV presents concludes and future works.

II. PROPOSED METHOD

The proposed method uses a machine learning technique and constructs a classification model. The classification performance largely depends on the feature selection, as the result, it was reported that an improper feature causes the performance degradation [10]. Our approach is to consider a driving style, and it appropriately works to classify drivers as a valuable feature. The proposed method takes into account the relation between the target vehicle and the preceding vehicle in order to estimate a driving style. When the target driver has an aggressive driving style, the vehicle would approach at a faster rate and keep a shorter distance from the preceding vehicle than cautious drivers. Otherwise, when the target driver is cautious, he or she would take a long distance and get closer slowly. The proposed method uses a dynamic potential field method to consider both the vehicle gap and the relative velocity with respect to the preceding vehicle.

A. Dynamic Potential Field Method

The potential method is generally used for robotics [11]. This method generates attractive potential energy from a destination and repulsive potential energy from an obstacle.



(a)

(b)

Fig. 2. Differences between normal model and dynamic model: (a) the potential field generated by the normal model has the uniform distribution in all direction, (b) the dynamic model generates the drifted potential field depending on the moving direction.

The normal model is

$$U^{(n)} = U_a^{(n)} + U_r^{(n)}, \tag{1}$$

where $U_a^{(n)}$ denotes the attractive potential energy from a destination, and $U_r^{(n)}$ denotes the repulsive potential energy from an obstacle. The attractive and repulsive potential energy are calculated as

$$U_a^{(n)} = K_d \cdot d, \tag{2}$$

$$U_r^{(n)} = \frac{1}{2\pi\sigma^2} \exp[-\frac{r^2}{2\sigma^2}], \tag{3}$$

where K_d is a coefficient, d is a distance from a robot to a destination, r is the distance to an obstacle, and σ is the variance of the distance r. The normal model only considers the distance from obstacles. In contrast, the dynamic model considers both the distance from obstacles the moving direction of obstacles [12]. This method generates the drifted potential field toward the moving direction using the von Mises distribution.

The differences of potential fields generated by the normal model and the dynamic model are shown in Fig. 2. The normal model has the uniform distribution in all direction as shown in Fig. 2 (a) while the dynamic model generates the potential field that changes the drift direction depending on the movement as shown in Fig. 2 (b).

The proposed method changes the drift direction of potential fields considering the relative velocity with respect with the preceding vehicle. The repulsive potential energy at time t is derived as

$$G(V_r) = \frac{\exp[-\epsilon(V_r)]}{2\pi I_0[\epsilon(V_r)]}, \tag{4}$$

$$H(D_g) = \frac{\exp[-\frac{D_g^2}{2\sigma^2}]}{2\pi\sigma^2}, \tag{5}$$

$$U_t^{(d)} = \alpha G(V_r) H(D_g), \tag{6}$$

where V_r is the relative velocity between the target vehicle and the preceding vehicle, D_g is the vehicle gap, σ is the variance of D_g, and α is a coefficient. Equation (4) represents the von Mises distribution, and $I_0(\epsilon)$ is the modified Bessel function of order 0. It can be adjusted how largely the distribution is drifted by the parameter ϵ. The distribution is uniform when the parameter ϵ is zero. If the parameter ϵ has a large value, the distribution is largely drifted forward or backward with respect to the preceding vehicle. In this research, the parameter ϵ is adjusted by the relative velocity V_r, then the drifted direction of the potential field is chosen. Equation (5) denotes the repulsive potential energy, which is inversely proportional to the vehicle gap D_g. For this term, if the target vehicle drives close to the preceding vehicle, it is affected by a large repulsive potential energy.

To consider a continuous process but a temporary one, the proposed method calculates an average during the constant time. The new feature at time t is extracted by

$$p_t = \Sigma_{k=0}^{N} \frac{U_{t-k}^{(d)}}{N}, \tag{7}$$

where N is the constant time. This feature represents a driving risk or characteristic that the target driver may have. If the target driver has a cautious driving style, he would take a long distance with the preceding vehicle and drive slowly. Therefore, the small repulsive potential energy is generated as shown in Fig. 3 (a). In contrast, if the target driver has an aggressive driving characteristic, he follows the preceding vehicle closely in spite of high driving risks. As the result, it is represented as the large repulsive potential energy as shown in Fig. 3 (b).

The feature vector is defined as consisting of the relative velocity, the vehicle gap, and the repulsive potential energy. The feature vector at time t can be represented as

$$\mathbf{x}_t = \left[\mathbf{V}_t,\ \mathbf{D}_t,\ \mathbf{P}_t\right]^{\mathrm{T}}, \tag{8}$$

$$\mathbf{V}_t = \left[V_{r,t-(W-1)}, ..., V_{r,t-1}, V_{r,t}\right], \tag{9}$$

$$\mathbf{D}_t = \left[D_{g,t-(W-1)}, ..., D_{g,t-1}, D_{g,t}\right], \tag{10}$$

$$\mathbf{P}_t = \left[p_{t-(W-1)}, ..., p_{t-1}, p_t\right], \tag{11}$$

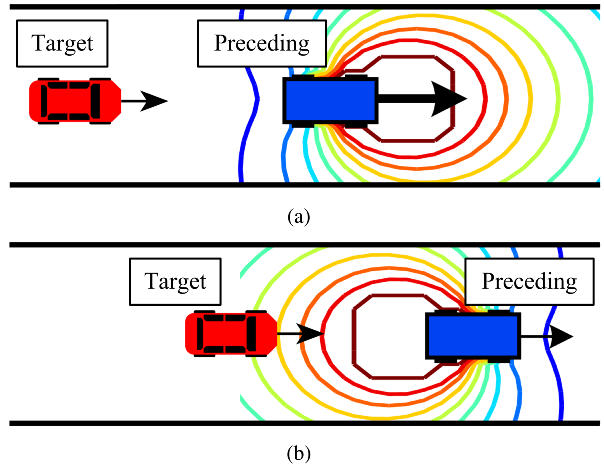


Fig. 3. Generated potential field depending on relative velocity with preceding vehicle: (a) the distribution of the potential field when the target is slower than the preceding vehicle, (b) the distribution of potential field when the target is faster than the preceding vehicle. The red vehicle is the target, and the blue one is the preceding vehicle.

where W is a constant size of the moving window to consider a continuous process. This feature vector is input to the classification model for both of training and testing. Because these features have units, in the absence of scaling the classification performance can be influenced by the differences of units. For that reason, the proposed method conducts the normalization using an average and a standard deviation that are calculated for the training phase.

B. Classification Method

The proposed method uses the SVM to classify the feature vector into the driver classes. In this research, a driver is defined as a class, and the driver recognition is solved as the multiclass classification. In this research, the radial basis function is selected, which is known as the best kernel function in the low dimensional classification. The radial basis function is defined by

$$K(\mathbf{x}, \mathbf{x}') = \exp(-\gamma \|\mathbf{x} - \mathbf{x}'\|^2), \tag{12}$$

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.

C. Filtering Method Considering Past Classification Result

The proposed method considers past classification results to decrease misclassification. The SVM always outputs only one class even if they have small differences among the probabilities of classes. To overcome this limitation, the proposed method takes an approach to refer to the past classification results when it is difficult to convince the result. If the correction is conducted to all cases, the biased result would be acquired to the initial outputs. The proposed method adjusts the probability of output class of the SVM as follow

$$P'(\mathbf{X}_{0:t}|c_t \in A) = P(\mathbf{X}_{0:t}|c_t \in A)\frac{f(A)}{\Sigma_{i=1}^{M} f(i)}, \tag{13}$$

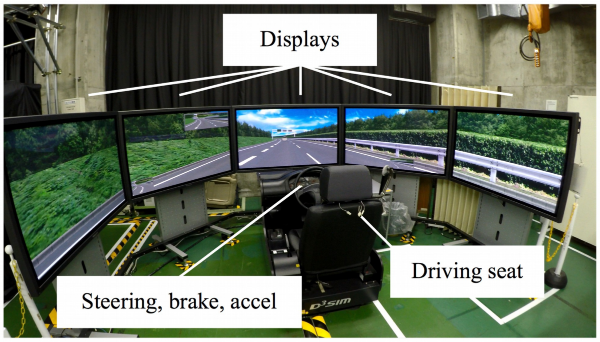


Fig. 4. Experimental setup of driving simulator: we used a driving simulator (DS) named as "D3 Sim (Mitsubishi Precision CO., LTD.)" to acquire the training data for the model construction and the testing data for the evaluation. Display devices consists of five monitors, and a driving seat is located to center of the 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.

where c_t is the output from the SVM at time t, $f(A)$ represents numbers of cases that the target is classified to driver A, i is the index of driver classes, and M is numbers of candidates. Finally, the classification result after the filtering, c_t', is calculated as

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

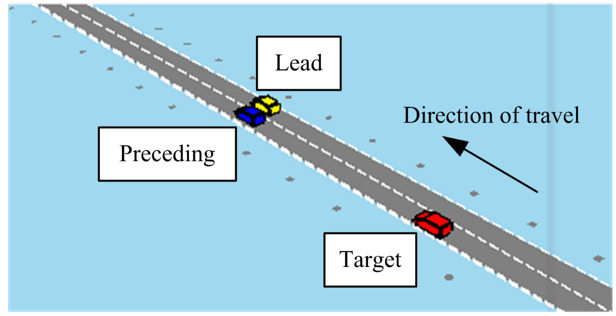
By implementation of the proposed filtering method, it can be expected that errors are eliminated and the classification accuracy is improved.

III. EXPERIMENTS

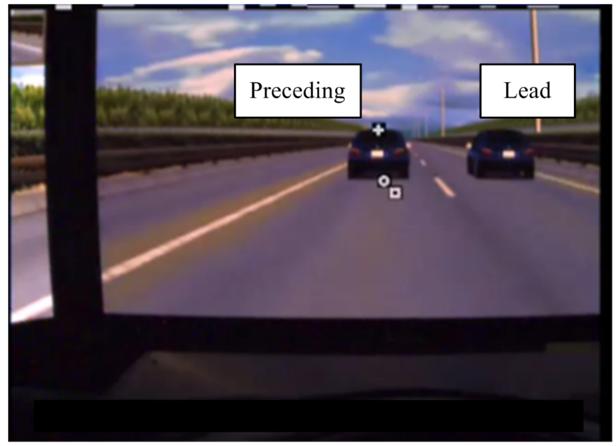
A. Experimental Setup

In this research, a driving simulator (DS) named as "D3 Sim (Mitsubishi Precision CO., LTD.)" was used in order to collect the training data to construct for the classification model and the testing data for evaluation. This simulator showed visual information on display devices which consist of five monitors as shown in Fig. 4. In addition, a driving seat was composed of a steering wheel, an acceleration pedal, and a brake pedal. The data was recorded per 120 Hz. A total of four subjects (driver A, B, C, and D) participated in the experiment, of varying age, simulator experience, and driving experience. Their informed consent was obtained before starting the experiments.

An experimental scene was modified to use a straight two-lane highway infinitely which had only one side as shown in Fig. 5 (a). In this particular experiment, there were no other vehicles on the highway in order to prevent the influence of interactions. A red car represents the target vehicle that subjects operate, a blue one is the preceding vehicle, and a yellow one represents the lead vehicle which drives on the next lane. As shown in Fig. 5 (b), the preceding and lead vehicles blocked off roads of the target vehicle while they changed the velocity randomly. Therefore, it was not allowed that the target vehicle overtakes them. As the result, the target was forced to follow the preceding vehicle for 60 s per one trial. A total of 20 trials were conducted per subject. It was instructed that subjects did not try to change a lane during the following before starting of the experiments. After 60 s, one of the two, the preceding and lead vehicle, accelerated, then, the target vehicle tried to overtake the remained vehicle which did not accelerate. Since the accelerating vehicle was determined randomly, subjects could not ready to overtake during the following. However, as this research only focused on the following behavior, the data after the acceleration was not used for both of the training and testing.



(a)



(b)

Fig. 5. Experimental aspects: (a) we set a straight highway that consisted of 2 lanes of only one side. The preceding and lead vehicles blocked off a road to make the target follow them, therefore, it was impossible to overtake the preceding and lead vehicles during. (b) it shows an actual view displayed to monitors during experiments.

B. Evaluation

In the data collected by the DS, half of them were used for the training to construct the classification model, and the remained data was used for evaluation. Table I shows classification results by the proposed method. Based on the assumption that normally a driver is not changed within a driving session, a majority count system can be implemented that the most classified class is finally judged at the end of that trial. For example, if the driver A has been the most classified in that trial, the trial is finally classified as driver A even though it happened to be classified as other driver classes during the trial. A total of ten trials per subject was used for the testing data. Therefore, if the classification was conducted without errors, the number of classification result will be 10 in each subject. In Table I, it is clearly

TABLE I

CLASSIFICATION RESULTS BY MAJORITY COUNT

		Result			
		A	B	C	D
	A	8	0	0	2
Ground	B	0	2	0	8
truth	C	0	0	10	0
	D	0	2	0	8

TABLE II

CLASSIFICATION RESULTS AT EACH TIME STEP

		Result			
		A	B	C	D
	A	25,763	5,149	4,881	7,964
Ground	B	2,994	14,392	542	25,855
truth	C	635	1,304	41,816	225
	D	5,486	14,343	94	24,019

confirmed that driver C was perfectly classified. Otherwise, the case of driver B showed a poor result which is 20 % of the accuracy. The reason of the low performance can be considered that driver B and driver D may have a similar driving characteristic. The accuracy of driver A was 80 %, and driver D also showed the same value. With the majority count system, the proposed method achieved an average of 70 % for the classification accuracy in all testing data of four subjects.

For the specific analysis, it was evaluated that the classification results at each time step. Since the data was collected per 120 Hz, the classification was also conducted per the same cycle. The result is shown in Table II. In cases of driver B and driver D, it was shown that the classification accuracy was quite low. In the case of driver B, too many cases were classified to diver D compared to other subjects. The case of driver D also had many errors that it was classified as diver B. These results demonstrate that they have a similar driving characteristic when they follow the preceding vehicle. However, if they have a similar driving characteristic, it may not be a problem since they would require a similar support by the intelligent driving system. In this point, it is an invaluable task how to define a driving characteristic. Moreover, it should be considered how to classify drivers to the defined driving characteristics. We have planned to construct a method to take into account driving characteristics as a future work. In addition, it can be a solution to optimize the parameters of the SVM. In this research, the proposed method used the radial basis function as the kernel, however, the possibility still remains that other kernel functions are more suitable to solve this problem.

To evaluate the proposed feature which is extracted by using the dynamic potential field method, the performance of the proposed method was compared with a basic model.

TABLE III

PERFORMANCE COMPARISON

	Basic	Proposed
Accuracy	65 %	70 %

The basic model used only two features that were the relative velocity and the vehicle gap with the preceding vehicle. Except the proposed feature not included, other parameters and methods were completely same. The comparison result is shown in Table III. It was demonstrated that the proposed method achieved the higher classification accuracy than the basic model. In addition, according to the previous research of Ly *et al.*, it was reported that the accuracy to classify two drivers was almost 65 % [4]. Incidentally, this method also used the SVM as the classification method. Although this comparison is not strict because of different testing data, it can be a reference value to evaluate the performance. As those results above, it has been demonstrated that the proposed method is significantly effective to improve the accuracy for driver classification.

IV. CONCLUSION

In this research, we proposed a method for the driver classification. A scene is assumed that the target follows the preceding vehicle, and the following behavior was used for the features. The proposed feature which is extracted by using the dynamic potential field method is able to describe driving characteristics. In addition, the filtering method considering past classification results was also proposed. Experiments using a driving simulator was conducted to collect the training and testing data by four subjects. As the result of evaluation, it has been demonstrated that the proposed method is significantly effective to improve the classification accuracy. The proposed method achieved an average of 70 % for the classification accuracy using all testing data of four subjects.

As a future work, it has been still remained as a problem that some cases showed a quite low performance when drivers have similar driving characteristics. In this point, it is required how to classify and categorize drivers to driving characteristics. We have planned to take account of driving characteristics. Additionally, more driving data should be collected in order to construct a reliable model. It has been conducted using not only a driving simulator but also a real vehicle installed with measurement devices. It is expected that the proposed method is implemented to a experimental vehicle and the classification is conducted online.

REFERENCES

[1] Japan Metropolitan Police Department, States of occurrence of traffic accidents, 2014.

[2] U.S. Department of Transportation, Lane change/merge crashes: problems size assessment and statistical description, 1994.

[3] H. Woo, Y. Ji, H. Kono, Y. Tamura, Y. Kuroda, T. Sugano, Y. Yamamoto, A. Yamashita, and H. Asama, Lane-change detection based on vehicle-trajectory prediction, IEEE Robotics and Automation Letters, Vol. 2, No. 2, pp. 1109-1116, 2017.

[4] M. V. Ly, S. Martin, and M. M. Trivedi, Driver classification and driving style recognition using inertial sensors, Proceedings of the 2013 IEEE International Conference on Intelligent Vehicles Symposium, pp. 1040-1045, 2013.

[5] S. Fernandez and T. Ito, Driver classification for intelligent transportation system using fuzzy logic, Proceedings of the 2016 IEEE International Conference on Intelligent Transportation Systems, pp. 1212-1216, 2016.

[6] A. Doshi and M. M. Trivedi, Examining the impact of driving style on the predictability and responsiveness of the driver: real-world and simulator analysis, Proceedings of the 2010 IEEE International Conference on Intelligent Vehicles Symposium, pp. 232-237, 2010.

[7] G. A. M. Meiring and H. C. Myburgh, A review of intelligent driving style analysis systems and related artificial intelligence algorithms, Sensors, Vol. 15, No. 12, pp. 30653-30682, 2015.

[8] H. Woo, Y. Ji, H. Kono, Y. Tamura, Y. Kuroda, T. Sugano, Y. Yamamoto, A. Yamashita, and H. Asama, Automatic detection method of lane-changing intentions based on relationship with adjacent vehicles using artificial potential fields, International Journal of Automotive Engineering, Vol. 7, No. 4, pp. 127-134, 2016.

[9] P. Kumar, M. Perrollaz, S. Lefevre, and C. Laugier, Learning based approach for online lane change intention prediction, Proceedings of the 2013 IEEE International Conference on Intelligent Vehicles Symposium, pp. 797-802, 2013.

[10] H. Mandalia and D. Salvucci, Using support vector machine for lane-change detection, Proceedings of the 2005 IEEE International Conference on Human Factors and Ergonomics Society, pp. 1965-1969, 2005.

[11] H. Chiang, N. Malone, K. Lesser, M. Oishi, and L. Tapia, Path-guided artificial potential fields with stochastic reachable sets for motion planning in highly dynamic environments, Proceedings of the 2015 IEEE International Conference on Robotics and Automation, pp. 2347-2354, 2015.

[12] S. Hoshino and K. Maki, "Safe and efficient motion planning of multiple mobile robots based on artificial potential for human behavior and robot congestion", *Advanced Robotics*, Vol. 29, No. 17, pp. 1095-1109, 2015.