Dynamic Potential-Model-Based Feature for Lane Change Prediction

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***Abstract*—We propose a prediction method for lane changes in other vehicles. According to previous research, over 90 % of car crashes are caused by human mistakes, and lane changes are the main factor. Therefore, if an intelligent system can predict a lane change and alarm a driver before another vehicle crosses the center line, this can contribute to reducing the accident rate. The main contribution of this work is to propose a new feature describing the relationship of a vehicle to adjacent vehicles. We represent the new feature using a dynamic characteristic potential field that changes the distribution depending on the relative number of adjacent vehicles. The new feature addresses numerous situations in which lane changes are made. Adding the new feature can be expected to improve prediction performance. We trained the prediction model and evaluated the performance using a real traffic dataset with over 900 lane changes, and we confirmed that the proposed method outperforms previous methods in terms of both accuracy and prediction time.**

I. Introduction

According to a survey by the Japan Metropolitan Police Department, over 90 % of car crashes are caused by human mistakes [1]. Recently, autonomous car technologies and driving safety support systems have been attracting considerable attention as solutions to preventing car crashes. Implementation of intelligent technologies to assist drivers in recognizing situations around their own vehicle can be expected to decrease the accident rate. Car crashes often occur when traffic participants try to change lanes. Furthermore, the survey reported that only 40 % of drivers use direction indicators when they change lanes [2]. Based on these reports, a lane change prediction method is required to use information without direction indicators.

Lane change prediction can be classified into an estimation of the lane-changing (primary) drivers intention and that of other drivers. A method using a hidden Markov model (HMM) has been suggested to estimate the drivers intention [3]. The method uses the lateral relative position of a car in the lane and the steering angle as features. Almost 98 % accuracy was achieved using the assessment data collected on highways in Japan. In [4], a method was suggested that used only controller area network (CAN) bus signals. Features based on sequential forward floating selection (SFFS) were selected; steering angle, lateral velocity, lateral acceleration, braking pedal angle, and yaw rate were selected as the most effective features. In addition, eye movement data and head dynamics can improve the prediction accuracy according to previous research [5]. However, for the role of the solution in preventing car accidents, the prediction of lane changes by other drivers is the more crucial task than that of the primary driver. The above methods can only detect lane changes of the primary vehicle because of features that are unmeasurable from the outside.

In [6], the prediction method uses information that is directly measurable from the outside. In that study, the lateral offset to the lane center, the lateral velocity relative to the lane, and the relative velocity of the preceding car were selected as the most effective features. In [7], features that include the ratio of the average speed of vehicles in the original lane to the corresponding value in the target lane, the time to collision with the preceding vehicle, and the distance from the rear vehicle were selected to improve the prediction time. However, in these methods it was assumed that the preceding vehicle is slower than the target vehicle. For that reason, degradation of the prediction performance can occur under conditions that are not considered (e.g., in a case in which a driver changes a lane because the following vehicle gets closer rapidly). There is also the case in which the next lane is empty. With the exception of these cases, numerous conditions to change lanes exist. However, using the relative amounts from adjacent vehicles as features can degrade the prediction performance under unexpected conditions. Furthermore, previous research has demonstrated that it is important to use only the most effective set of features rather than a set of all possible features [8].

Considering these reports, we propose a method to predict lane changes of other vehicles using a feature that considers the relationship to adjacent vehicles. We focus on a dynamic characteristic potential model for the approach to extract a feature. Wolf and Burdick suggested a potential model that generates a concentrated potential field behind each adjacent vehicle [9]. However, since the model only considers front vehicles, it cannot generate the concentrated potential field forward. In contrast, Hoshino and Maki proposed a dynamic characteristic model that considers the direction of movement of obstacles, the velocity of obstacles, and the distance from

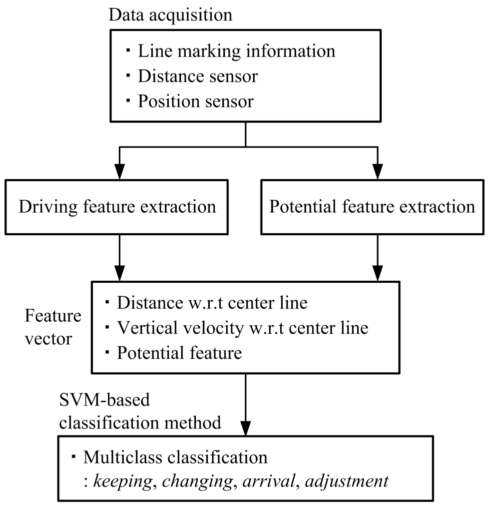


Fig. 1. Flowchart of the proposed method

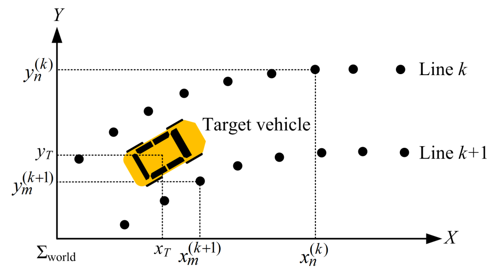


Fig. 2. Definition of coordinates

obstacles when it generates the repulsive potential fields for motion planning of mobile robots [10]. We apply a dynamic potential model to the vehicle driving model. The proposed method generates the potential field that changes the distribution depending on the relative amounts from adjacent vehicles. After the field is generated, the method extracts the feature by using the ratio of potential energy of the current lane to the corresponding value of the next lane. We define this feature as the potential feature. The potential feature can describe many lane change situations, including the cases in which the following vehicle gets closer rapidly, the preceding vehicle is slower than the target, and the next lane is empty. Furthermore, the case in which a driver suspends a lane change maneuver because of insufficient distance with other vehicles can be applied by using the potential feature.

We train and test the prediction model using real traffic data collected by the Federal Highway Administration [11]. For the assessment of our method, we compare the performance with previous methods by using the same testing dataset.

II. Overview of the Proposed Method

Figure 1 shows the flowchart of our proposed method. We assume that the primary vehicle has line marking information, a distance sensor, and a position sensor. Using data acquired by measurement, we can understand situations around the primary vehicle. We take two approaches to feature extraction. The first approach uses the position and velocity of the target (primary) vehicle that changes a lane. This approach focuses on only the target without considering other vehicles. The position and velocity of the target exhibit the same changing characteristics for all conditions of lane changes. For this reason, this information can be considered as the most effective set of features. We use the distance with respect to the center line instead of the position to take account of the curvature of the road as the first feature, and the vertical velocity with respect to the center line is calculated from the first derivative of the distance. We use the vertical velocity as the second feature. In this research, these features are defined as the driving features. The feature extraction method is explained specifically in Section III.

The second approach uses a dynamic characteristic potential method to consider the relationship to adjacent vehicles. Drivers may consider the relative distance and the relative velocity with respect to other vehicles at the moment a lane change is attempted. However, if the relative amounts are used directly as features without appropriate conversions, the feature extraction may degrade [6]. In this research, by using a dynamic potential model that changes the distribution by relative amounts, the potential feature that can describe a variety of conditions of lane changes can be extracted. The method of extracting the potential feature is discussed in Section IV. The proposed method uses the support vector machine (SVM) as a classification method. We define the lane-changing process as consisting of four steps: *keeping, changing, arrival,* and *adjustment*. In the proposed method, the target vehicle is judged as attempting to change lanes when the current feature vector is classified as *changing*. We explain the details of the classification scheme in Section V.

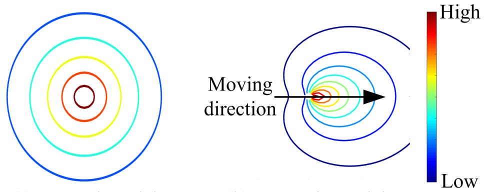
III. Driving Feature Extraction

A. Definition of the vehicle coordinates

In the following subsection, we explain the method of extracting the driving features: the distance with respect to the center line and the first derivative of the distance. We assume that the primary vehicle has map information about line markings that consists of points. Each point has information about a position as at the world coordinates Σ_{world}. The position of the target vehicle measured by the distance sensor installed on the primary vehicle is the vehicle coordinates Σ_{vehicle}. Therefore, the position of the target vehicle needs to be converted to the world coordinates. We define the position of the target vehicle at the world coordinates as (x_T, y_T), and define the position of n^{th} point at the k^{th} line marking as $(x_n^{(k)}, y_n^{(k)})$. The definitions are shown in Fig. 2.

B. Approximate curve of line markings

The proposed method calculates the distance with respect to the center line instead of the lateral position to account for road curvature. For that reason, the approximate curves of line markings must be extracted. We assume that the measurable range of a distance sensor is 50 m. We use only the points



(a) Normal model (b) Dynamic model

Fig. 3. Potential field diagram

from each line within this range to make the approximation. A second-degree polynomial is approximated by the method of least squares. The approximate curve at the k^{th} line is

$$y^{(k)} = a_2^{(k)}(x^{(k)})^2 + a_1^{(k)}x^{(k)} + a_0^{(k)} \tag{1}$$

where $a_2^{(k)}, a_1^{(k)}$ and $a_0^{(k)}$ are coefficients at the k^{th} line. The approximation is conducted each time step of measurements.

C. Extraction of the driving feature

The distance with respect to the k^{th} line is defined as $d^{(k)}$. The distance $d^{(k)}$ is calculated by using the position of the target vehicle (x_T, y_T) and the k^{th} approximate curve. We generate points at a distance intervals of 0.1 m on the approximate curve and find the closest point from the target vehicle. The distance $d^{(k)}$ is calculated by using

$$d^{(k)} = \min_n \sqrt{(x_T - x_n^{(k)})^2 + (y_T - y_n^{(k)})^2} \tag{2}$$

where n is an index about the generated points. The distance $d^{(k)}$ is defined as the first feature. The vertical velocity with respect to the center line is calculated from the first derivative of the distance $\dot{d}^{(k)}$. We define it as the second feature. Because these features have units, in the absence of scaling the prediction result can be influenced by the differences of units. For that reason, we normalize the features using a maximum value. It is impossible to normalize by using the mean and variance values because the prediction is conducted in real time. The prediction can use only measurement values until the current time. We define the maximum value related to feature $d^{(k)}$ as the width of the lane center. The maximum value related to feature $\dot{d}^{(k)}$ is searched for during the training step.

IV. Potential feature extraction

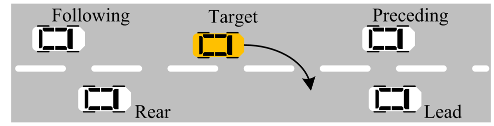
A. Dynamic characteristic of the potential method

The potential method is often used for robot navigation. This method generates attractive potential energy from a destination and repulsive potential energy from an obstacle. The normal model is

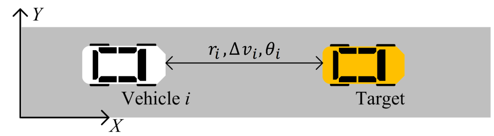
$$U = U_d + U_o \tag{3}$$

where U_d denotes the attractive potential energy from a destination, and U_o denotes the repulsive potential energy from an obstacle. The repulsive potential energy is calculated as

$$U_o = \frac{1}{2\pi\sigma^2}\exp[-\frac{r^2}{2\sigma^2}] \tag{4}$$



(a) Adjacent vehicles



(b) Relative amounts at vehicle i

Fig. 4. Definition of adjacent vehicles and relative amounts

where r is the distance from a robot to an obstacle, and σ is the variance of the distance. The normal model only considers the distance from obstacles. In contrast, the dynamic model considers the direction of movement and velocity of obstacles [10]. This method generates the drifted potential field toward the direction of movement of obstacles using the von Mises distribution.

The differences of potential fields generated by the normal model and the dynamic model are shown in Fig. 3. Our proposed method generates the potential field that changes the drift direction depending on the relative velocity, and the relative angle with respect to adjacent vehicles around the target vehicle. Figure 4 shows the adjacent vehicles and the relative amounts for each vehicle considered in this research. We define the target vehicle as $Target$, a vehicle ahead of the target in the current lane as $Preceding$, a vehicle behind the target in the current lane as $Following$, a vehicle ahead of the target in the next lane as $Lead$, and a vehicle behind the target in the next lane as $Rear$. In the following sections, we denote these vehicles by capital letters ($T, P, F, L,$ and R). The repulsive potential energy at vehicle i is generated by

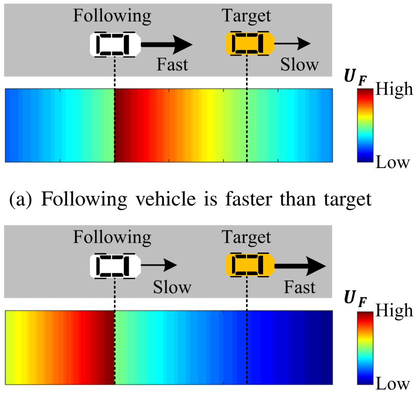
$$U_i = \frac{\exp[\eta(\Delta v_i)\cos\theta_i]}{2\pi I_0[\eta(\Delta v_i)]}\alpha\frac{\exp[-\frac{{r_i}^2}{2\sigma^2}]}{2\pi\sigma^2} \tag{5}$$

$$r_i = x_i - x_T \tag{6}$$

$$\Delta v_i = v_{i,x} - v_{T,x} \tag{7}$$

$$\theta_i = \begin{cases} 0 & (i\text{=}P,F) \\ \pi & (i\text{=}L,R) \end{cases} \tag{8}$$

where i is a vehicle index, r_i is the relative distance, σ is the variance of r_i, Δv_i is the relative velocity, θ_i is the relative angle, and α is a coefficient. The first term in Eq. (5) represents the von Mises distribution, and $I_0(\eta)$ is the 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 the angle θ_i. In this research, the parameter η is adjusted by the relative velocity Δv_i, then the drifted direction of the potential field is chosen. The relative angle θ_i becomes only zero or π in accordance with the preceding order. In



(a) Following vehicle is faster than target

(b) Following vehicle is slower than target

Fig. 5. Aspects of the potential field generated by the proposed method

Eq. (5), the second term denotes the repulsive potential energy, which is inversely proportional to the distance r_i. For this term, if the target vehicle drives close to adjacent vehicles, it is affected by a large repulsive potential energy.

Aspects of the potential fields generated by using the proposed method are shown in Fig. 5. If the following vehicle is faster than the target, the drifted potential field is generated toward the target. If the following vehicle is slower than the target, the potential field drifted backward does not interfere with the target. The proposed method generates a one-dimensional potential field because vehicles must drive following a lane. For that reason, the potential field does not depend on the lateral position. In the calculation for the next lane, we assume that the target vehicle drives at the same longitudinal position, then the relative amounts and potential energy are calculated.

B. Extraction of the potential feature

The potential fields from adjacent vehicles are integrated for each lane and then the potential feature is extracted by using the ratio of the potential energy of the current lane to that of the next lane. The potential energy is derived by using

$$U_C = \omega_P U_P + \omega_F U_F \quad (0 \leq U_C \leq 1) \tag{9}$$

$$U_N = \omega_L U_L + \omega_R U_R \quad (0 \leq U_N \leq 1) \tag{10}$$

where U_C denotes the potential energy of the current lane, U_N is the potential energy of the next lane, and ω_i is a weight coefficient at vehicle i. We define the ratio of potential energy as z,

$$z = \ln U_C - \ln U_N \tag{11}$$

and the value of p is calculated as

$$p = \varphi[z] \tag{12}$$

where $\varphi[\cdot]$ is the cumulative distribution function. We define the value p as the potential feature. The potential feature represents the possibility of changing lanes through a comparison of situations between the current lane and the next lane. Figure 6

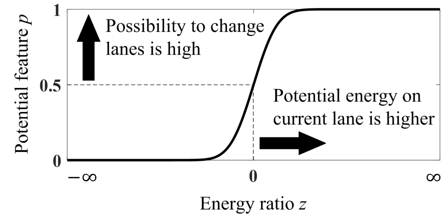


Fig. 6. Potential feature p

shows what the value of the potential feature means. If the potential energy of the current lane is higher than that of the next lane, the ratio z is greater than zero and the value of the potential feature becomes great than 0.5. This value means that a lane change gives the target advantages to drive.

C. Definition of the feature vector

We define the feature vector as consisting of the driving features and the potential feature. The feature vector at time t can be represented as

$$\mathbf{x}_t^{(k)} = \left[\mathbf{d}_t^{(k)} \quad \dot{\mathbf{d}}_t^{(k)} \quad \mathbf{p}_t^{(k)}\right]^{\mathrm{T}} \tag{13}$$

$$\mathbf{d}_t^{(k)} = \left[d_{t-(N-1)}^{(k)}, ..., d_{t-1}^{(k)}, d_t^{(k)}\right] \tag{14}$$

$$\dot{\mathbf{d}}_t^{(k)} = \left[\dot{d}_{t-(N-1)}^{(k)}, ..., \dot{d}_{t-1}^{(k)}, \dot{d}_t^{(k)}\right] \tag{15}$$

$$\mathbf{p}_t^{(k)} = \left[p_{t-(N-1)}^{(k)}, ..., p_{t-1}^{(k)}, p_t^{(k)}\right] \tag{16}$$

where k is the index used to denote line markings. The proposed method can be adapted to both the left and the right sides of lane changes. k is chosen based on the lane-changing side and all features are calculated following the specified side.

Since a lane change is not a temporary process but a continuous one, the feature vector must consider transitions of the features. We set a moving window to capture the transitions, and N is the window size in Eq. (14). For example, $\mathbf{d}_t^{(k)}$ is a sequence that consists of N data until time t.

V. MULTICLASS CLASSIFICATION USING A SVM

The proposed method uses a SVM to classify the feature vector into the intention classes shown in Fig. 7. A driver's intentions may lie in a high-dimensional feature space and a SVM kernel can address this problem through a conversion of features from a low-dimensional space into a high-dimensional space [12]. The SVM determines the hyperplane parameters $\mathbf{w}$ and b that are used to classify the data:

$$\arg\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \tag{17}$$

such that

$$t_i(\mathbf{w}^{\mathrm{T}}\mathbf{x}_i - b) \geq 1, \;\; (i = 1, ..., m) \tag{18}$$

where m represents the total number of data, and t_i is a class label at the feature vector $\mathbf{x}_i$. Previous research has shown

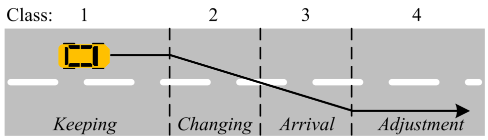


Fig. 7. Intention classes of the lane-changing process

that SVMs give reliable results in lane-change prediction [8][12]. We define the lane-changing process as consisting of four steps: *keeping, changing, arrival,* and *adjustment*. In the proposed method, the target vehicle is judged as attempting to change lanes when the current feature vector is classified as *changing*.

SVM performance depends largely on kernel selection; however, because a kernel selection method has yet to be suggested, the only way to select the best kernel at present is through a process of trial and error. We selected a radial basis function as a kernel through trial and error. A radial basis function is defined by

$$K(\mathbf{x}, \mathbf{x}') = \exp(-g\|\mathbf{x} - \mathbf{x}'\|^2) \tag{19}$$

where g is the kernel parameter. The proposed method uses one simple approach for the multiclass extension of the binary SVM using a one-versus-all strategy.

VI. Experimental results

A. Evaluation of the potential feature p

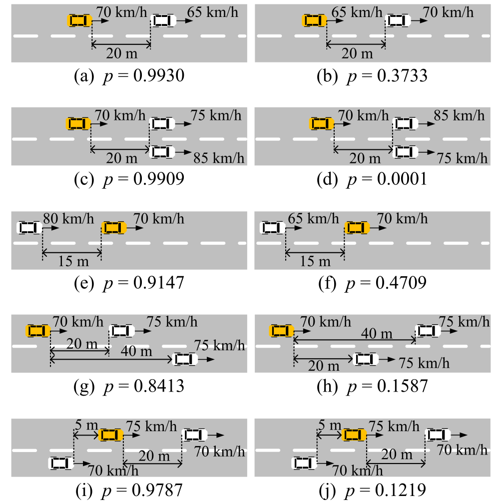
We calculated the values of the potential feature p in the following ten situations to evaluate its descriptive ability:

(a) The *preceding* vehicle is slower than the *target*.
(b) The *preceding* vehicle is faster than the *target*.
(c) The *lead* vehicle is faster than the *preceding* vehicle.
(d) The *lead* vehicle is slower than the *preceding* vehicle.
(e) The *following* vehicle is faster than the *target*.
(f) The *following* vehicle is slower than the *target*.
(g) The next lane is empty.
(h) The current lane is empty.
(i) The *rear* vehicle is slower than the *target*.
(j) The *rear* vehicle is faster than the *target*.

Figure 8 shows the results. The value of p calculated was greater than 0.5 for cases in which a lane change is advantageous (a, c, e, and g) and less than 0.5 when a lane change is not advantageous (b, d, f, and h). Cases (i) and (j) are situations used to evaluate risks during a lane change. If the rear vehicle gets closer rapidly, a lane change can be dangerous even if it is advantageous. In case (i), the value of p was greater than 0.5 because the rear vehicle is slower than the target. In case (j), since the rear vehicle is faster than the target, the value of p was calculated as less than 0.5. The results prove that the potential feature describes numerous situations of lane changes appropriately.

B. Criteria of performance evaluation

We trained and tested the proposed method using a real traffic dataset published by the Federal Highway Administration



(a) $p = 0.9930$ (b) $p = 0.3733$ (c) $p = 0.9909$ (d) $p = 0.0001$ (e) $p = 0.9147$ (f) $p = 0.4709$ (g) $p = 0.8413$ (h) $p = 0.1587$ (i) $p = 0.9787$ (j) $p = 0.1219$

Fig. 8. Values of potential feature p in ten situations

of the United States. The dataset was collected on eastbound I-80 in the San Francisco Bay Area. The measurement area was approximately 500 m in length and consisted of 6 freeway lanes. The dataset consisted of measurements taken per 0.1 s for 15 min, for a total of three times. Data from 5,678 vehicles were collected and 958 vehicles changed lanes during the measurement. We used 300 lane-changing data for the training and 658 lane-changing data for the test.

We used two evaluation criteria: the prediction time and the F_1 score. First, we defined the prediction time as

$$\tau_p = \tau_c - \tau_j \tag{20}$$

where τ_c is the moment at which the target vehicle crosses the center line, and τ_j is the moment at which the proposed method judges that the target would change lanes. A large value of τ_p means a high prediction performance. We defined the following criteria using the prediction time τ_p:

- Success: $0 < \tau_p < 5.0$ (judged within the time limit).
- Failure: $\tau_p \leq 0$ (judged too late).
- False alarm: $\tau_p \geq 5.0$ (judged too early).

Generally, a lane change takes 3.0 to 5.0 s according to previous research. We judged cases in which $\tau_p \geq 5.0$ s as false alarms by reference to the previous survey.

Second, the F_1 score is defined as

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{21}$$

$$\text{precision} = \frac{TP}{TP + FP} \tag{22}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{23}$$

where *TP* denotes the true positive rate, *FP* denotes the false positive rate, and *FN* denotes the false negative rate. The precision can evaluate the false alarm rate which the proposed method classifies *keeping* to *changing* incorrectly, and the

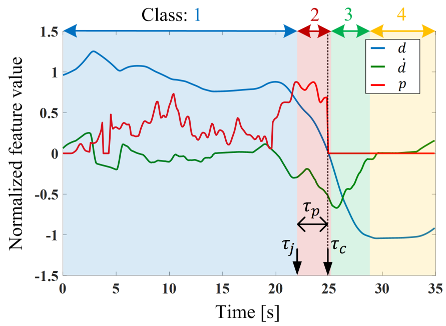


Fig. 9. Prediction results obtained by using the proposed method

TABLE I
PERFORMANCE COMPARISON WITH PREVIOUS METHODS

Method	Precision [%]	Recall [%]	F_1 [%]	τ_p [s]
Mandalia [8]	83.9	77.2	80.4	1.37
Schlechtriemen [6]	94.4	99.3	96.8	1.68
Proposed method	95.9	100	97.9	1.89

recall represents the failure rate, the most dangerous case, in which the proposed method classifies *changing* to *keeping*.

C. Evaluation results

We show the prediction results obtained by using the proposed method for one lane-changing event among the testing dataset in Fig. 9. The black dashed line represents τ_c which is given by the dataset. The predicted class found by using the proposed method is represented by colors:blue means *keeping*, red means *changing*, green means *arrival*, and yellow means *adjustment*. The moment at which *keeping* changes to *changing* is τ_j. We can see that τ_j was earlier than τ_c; in other words, the proposed method predicted a lane change before the target vehicle crossed the center line. We can also confirm that the value of the potential feature p (the red line) increases at the same time that the vehicle starts to change lanes. The value stays above 0.5 during a lane change.

We repeated the same evaluations for the entire testing dataset and compared the performance with two previous methods that we chose. The first method uses the variance of the lateral position within a constant window size as features [8]. This method uses the SVM as a classification method but only focuses on the driving feature. The second method uses the lateral velocity relative to the lane, the lateral offset from the lane center, and the relative velocity of the preceding car [6]. This method uses the naive Bayes algorithm, which estimates the driver's intentions. Through the comparison with these previous methods, we can expect to prove the effectiveness of the potential feature. We implemented the previous methods and evaluated them using the same testing dataset. Table 1 gives the results in terms of the average precision, recall, F_1 score and prediction time τ_p. We can see from the table that the proposed method outperforms previous methods in terms of both the F_1 score and the prediction time. The proposed method achieved 97.9 % accuracy, and it can predict lane changes on average 1.89 s before the target vehicle crosses the center line. Specially, the proposed method predicted all of the lane changes correctly, so the recall was 100 % accurate. In contrast, the previous methods failed to detect several lane-changing cases. This result demonstrates that the potential feature can improve the prediction performance.

VII. CONCLUSION

In this research, we proposed a lane change prediction method considering the relationship to adjacent vehicles. For the describing the relationship appropriately, we presented the potential feature extracted by using a dynamic characteristic potential method. Using real traffic data, we trained and tested the proposed method, confirming that the proposed method achieved 97.9 % accuracy average F_1 score. Furthermore, the method can predict a lane change on average 1.89 s before the target vehicle crosses the center line. We demonstrated that the proposed method outperforms previous methods through evaluation using the same testing dataset. Future work will focus on evaluating the proposed method using real data collected by vehicle installed measurement devices. Both measurement accuracy and noise must be tested for this implementation.

REFERENCES

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

[2] R. Dang, F. Zhang, J. Wang, S. Yi, and K. Li, "Analysis of chinese driver's lane change characteristic based on real vehicle tests in highway", *Proceedings of the 2013 IEEE International Conference on Intelligent Transportation Systems*, pp. 1917-1922, 2013.

[3] N. Kuge, T. Yamamura, O. Shimoyama, and A. Liu, "A driver behavior recognition method based on a driver model framework", *SAE Technical Paper*, no. 2000-01-0349, 2000.

[4] G. Li, S. E. Li, Y. Liao, W. Wang, B. Cheng, and F. Chen, "Lane change maneuver recognition via vehicle state and driver operation signals - results from naturalistic driving data", *Proceedings of the 2015 IEEE International Conference on Intelligent Vehicle Symposium*, pp. 865-870, 2015.

[5] A. Doshi and M. M. Trivedi, "On the roles of eye gaze and head dynamics in predicting driver's intent to change lanes", *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 3, pp. 865-870, 2009.

[6] J. Schlechtriemen, A. Wedel, J. Hillenbrand, G. Breuel, and K. D. Kuhnert, "A lane change detection approach using feature ranking with maximized predictive power", *Proceedings of the 2014 IEEE International Conference on Intelligent Vehicle Symposium*, pp. 108-114, 2014.

[7] J. Ding, R. Dang, J. Wang, and K. Li, "Driver intention recognition method based on comprehensive lane-change environment assessment", *Proceedings of the 2014 IEEE International Conference on Intelligent Vehicle Symposium*, pp. 214-220, 2014.

[8] 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.

[9] M. T. Wolf and J. W. Burdick, "Artificial potential functions for highway driving with collision avoidance", *Proceedings of the 2008 IEEE International Conference on Robotics and Automation*, pp. 3731-3736, 2008.

[10] 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.

[11] The Federal Highway Administration, "Next Generation Simulation", http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm (accessed:10 May 2015).

[12] 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 Vehicle Symposium*, pp. 797-802, 2013.