Automatic Detection Method of Lane-Changing Intentions

Based on Relationship with Adjacent Vehicles Using Artificial Potential Fields

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ABSTRACT: This paper presents a new method to detect lane changes of other vehicles automatically. The main contribution of this work is to propose a new feature using a potential field that changes the distribution depending on the relative number of adjacent vehicles. Previous researches have considered only some of limited situations, for example, that the preceding vehicle is slower than the target vehicle. Therefore, degradation of the detection performance can occur under conditions that were not considered. On the other hand, the new feature we propose is able to describe general lane-changing situations by applying a dynamic potential model. We trained an estimation model and evaluated the performance using a traffic dataset with over 900 lane changes. It was confirmed that the proposed method outperforms previous methods in terms of both accuracy and early detection.

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

1. Introduction

According to a survey conducted by the Japan Metropolitan Police Department, over 90 % of car crashes are caused by human errors ⁽¹⁾. Recently, autonomous driving technologies and driver support systems have been attracting considerable attention as solutions to prevent 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 detection method should not rely on direction indicators to predict lane changes.

Lane change detection can be classified into an estimation of the lane-changing (primary) driver's intention and the intention of the other drivers. A detection method using a hidden Markov model (HMM) has been suggested to estimate the driver's intention ⁽³⁾. This method uses the lateral 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. Li et al. suggested a method that uses only controller area network (CAN) bus signals ⁽⁴⁾. In this method, 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 detection

Fig. 1 Lane changes of other vehicle.

accuracy according to previous research ⁽⁵⁾⁽⁶⁾. However, to prevent car crashes, the detection of lane changes by other drivers is a more crucial task than the detection of lane changes by the primary driver, as shown in Fig. 1. The above methods can be only adapted to lane changes of the primary vehicle because of features that are not measurable from the outside (e.g., steering angle, eye movement).

Schlechtriemen et al. suggested a detection method that uses only directly measurable information from the outside ⁽⁷⁾. In their study, the lateral offset to the lane center, lateral velocity relative to the lane, and relative velocity of the preceding car were selected as the most effective features. Ding et al. suggested 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 to improve the early detection performance ⁽⁸⁾. However, in

Fig. 2 Overview of the proposed method.

these methods it was assumed that the preceding vehicle is slower than the target vehicle. Therefore, degradation of the detection performance can occur under conditions that were not considered. There are numerous conditions to change lanes in the real world with the exception that the preceding vehicle is slower than the target vehicle.

To overcome these limitations of conditions to change a lane, we propose a method to detect lane changes of other vehicles using a feature that considers the relationship between the target vehicle that conducts a lane change and adjacent vehicles. We focus on an artificial potential field 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, a dynamic characteristic model considers the direction of movement of obstacles, velocity of obstacles, and distance from obstacles when it generates the repulsive potential fields for motion planning of mobile robots ⁽¹⁰⁾⁽¹¹⁾⁽¹²⁾. We apply a dynamic potential model to the vehicle driving model. The proposed method generates a potential field that changes the distribution depending on a relative distance, a relative velocity, and a relative angle from adjacent vehicles. After the field is generated, this 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 proposed potential feature can describe many lane changing 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. In addition, we extract the driving features i.e., the distance with respect to the centerline and the lateral velocity.

The remainder of this paper is organized as follows. Section 2 presents the overview of the proposed method, and Section 3 presents the method of the driving feature extraction. Section 4 describes the method of the potential feature extraction, and Section 5 describes the estimation model of the driving intentions. Section 6 presents the evaluation results of the proposed method using real traffic data ⁽¹³⁾ and measurement data acquired by an experimental vehicle, which was installed with measurement devices. Finally, Section 7 presents conclusions and future work.

2. Overview of the Proposed Method

For the improvement of the detection performance, we propose a new feature that can describe the characteristics of lane changing. Figure 2 shows the flowchart of our proposed method. We take two approaches to extract features. The first approach uses the position and velocity of the target vehicle that conducts a lane change. 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. Therefore, this information can be considered as the most effective set of features. We use the distance with respect to the centerline instead of the position to take account of the curvature of the road as the first feature, and the lateral velocity with respect to the center line is calculated from the first derivative of the distance. We use the lateral 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 3.

The second approach uses an artificial 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 ⁽⁷⁾. 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 4.

The proposed method uses the HMM as an estimation method. We initialize the model that has four internal states and an ergodic structure fully connected to all states. The estimation model is constructed by the training using traffic data. The constructed model outputs the state that has the maximum likelihood for each time step. We define the lane-changing process as consisting of four driver's intentions: *keeping*, *changing*, *arrival*, and *adjustment*. Each internal state of the HMM is assigned to a driving intention. In the proposed method, the target vehicle is judged as attempting to change lanes when the output state is estimated as *changing*. We explain the details of the estimation model by using the HMM in Section 5.

Fig. 3 Relationship between the global and vehicle coordinates.

3. Driving Feature Extraction

3.1. Definition of coordinates

In this research, we define the three coordinates as the Universal Transverse Mercator (UTM) coordinates $\{U\}$, the global coordinates $\{G\}$, and the vehicle coordinates $\{V\}$. The UTM coordinates consist of the latitude and the longitude. The proposed method transforms the position of the primary vehicle and all points on each line from the UTM coordinates to the global coordinates using the geodetic distance, ρ , and the azimuth, Z . We define the global position of the first point at the first lane marking as the origin point of the global coordinates. The coordinates transformation from the UTM coordinates to the global coordinates is conducted by using the Lambert-Andoyer method ⁽¹⁴⁾.

Figure 3 shows the relationship between the global coordinates and the vehicle coordinates. We define the position of the target vehicle with the vehicle coordinates as (x_T, y_T) , and the position of the n^{th} point at the k^{th} lane marking as $(x_n^{(k)}, y_n^{(k)})$. These definitions are shown in Fig. 4.

3.2. Approximate curve of lane markings

The proposed method calculates the distance from the centerline 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 from each line within this range to make the approximation, and a second-degree polynomial can be considered to be capable of representing the road curvature completely in this range ⁽¹⁵⁾. The approximate curve at the k^{th} lane marking is

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

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

3.3. Extraction of the driving feature

The distance with respect to the k^{th} lane marking 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 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

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

Fig. 4 Definitions of the vehicle coordinates.

Fig. 5 Definitions of adjacent vehicles.

where n is an index about the generated points. The distance, $d^{(k)}$, is defined as the first feature. The lateral velocity with respect to the centerline is calculated from the first derivative of the distance $d^{(k)}$. We define it as the second feature. Because these features have units, in the absence of scaling the detection performance can be influenced by the differences of units. For that reason, we conduct the scaling using a maximum value. We define the maximum value related to feature $d^{(k)}$ as half of the width of lane. The maximum value related to feature $\dot{d}^{(k)}$ is searched for during the training phase.

4. Potential Feature Extraction

4.1. Dynamic characteristic of the potential field

A potential field is often used for robot navigation ⁽¹⁶⁾⁽¹⁷⁾. This method generates the attractive potential energy from a destination and the repulsive potential energy from an obstacle. The normal potential model is

$$U = U_d + U_o, \quad (3)$$

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

$$U_d = K_d \cdot d, \quad (4)$$

$$U_o = \frac{1}{2\pi\sigma_o^2} \exp\left[-\frac{r^2}{2\sigma_o^2}\right], \quad (5)$$

where K_d is a coefficient, d is the distance from a robot to a destination, r is the distance from a robot to an obstacle, and σ_o represents the variance of the distance r . The normal model only considers the distance to obstacles. In contrast, the dynamic model considers the direction of movement and velocity of obstacles ⁽¹⁰⁾. This model generates the drifted potential field toward the direction of movement of obstacles using the von Mises distribution.

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. We define the target vehicle as *target*, a vehicle ahead of the target in the same lane as *preceding*, a vehicle behind the target in the same 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* as shown in Fig.5.

Fig. 6 Aspects of potential fields generated by the proposed method: (a) vehicle i drives with same velocity as the target, (b) vehicle i is faster than the target, (c) vehicle i is slower than the target.

We denote these vehicles by capital letters (T , P , F , L , and R). The repulsive potential energy at vehicle i is generated by

$$U_i = \frac{\exp[\varepsilon(\Delta v_i)\cos\theta_i]}{2\pi I_0[\varepsilon(\Delta v_i)]} \alpha \frac{\exp\left[-\frac{r_i^2}{2\sigma_i^2}\right]}{2\pi\sigma_i^2}, \quad (6)$$

where i is a vehicle index, r_i is the relative distance, σ_i 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. (6) represents the von Mises distribution, and $I_0(\varepsilon)$ is the modified Bessel function of order 0. The distribution is uniform when the parameter ε is zero. If the parameter ε is large, the distribution drifts toward the angle θ_i . In this research, the parameter ε is adjusted by the relative velocity Δv_i ; then, the drifted direction of the potential field is chosen. The relative angle θ_i denotes the angle between the relative position with respect to the *target* and the driving direction of the *target*. In Eq. (6), the second term denotes the repulsive potential energy, which is inversely proportional to the distance r_i . For this term, if the *target* 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. 6. If the vehicle i drives with the same velocity as the *target*, the potential field does not drift in any direction. However, the drifted potential field is generated toward the *target* when the vehicle i is faster than the *target*. Otherwise, if the vehicle i is slower than the *target*, the potential field drifting backward does not interfere with the *target*. In the calculation for the next lane, we assume that the *target* drives in the same longitudinal position into the next lane; then the relative amounts and potential energy are calculated with respect to the *lead* and the *rear* vehicle.

4.2. Extraction of the potential feature

The potential energies U_i ($i = P, F, L$, and R) 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 energies are derived by

$$U_C = \omega_P U_P + \omega_F U_F \quad (0 < U_C \leq 1), \quad (7)$$

$$U_N = \omega_L U_L + \omega_R U_R \quad (0 < U_N \leq 1), \quad (8)$$

Fig. 7 Meaning of the potential feature p .

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 energies as z ,

$$z = \ln U_C - \ln U_N, \quad (9)$$

and the value of p is calculated as

$$p = \varphi[z], \quad (10)$$

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. 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 greater than 0.5 as shown in Fig. 7. When the value of the potential feature is greater than 0.5, it is advantageous for the target to change lanes. On the other hand, a value of the potential feature of less than 0.5 means that keeping the current lane is recommended.

4.3. 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

$$\mathbf{x}_t^{(k)} = [d_t^{(k)} \quad \dot{d}_t^{(k)} \quad p_t^{(k)}]^T, \quad (11)$$

where k is the index used to denote the centerline. The proposed method can be adapted to both a left lane change and a right lane

change. k is chosen based on the lane-changing side and all features are calculated following the specified side.

Since the measurement data acquired by the sensor system include noise, the proposed method conducts filtering by using a Kalman filter⁽¹⁸⁾. We define the feature vector as the state vector, and the distance with respect to the centerline $d_t^{(k)}$ is filtered by using the Kalman filter. After that, the proposed method also applies the moving average filter to $d_t^{(k)}$. In the filtering, only the measurement values until the current time are used. The lateral velocity $\dot{d}_t^{(k)}$ is calculated after the filtering. However, the filtering is not adapted to the potential feature $p_t^{(k)}$.

5. Estimation Method

5.1. Construction of the estimation model

The proposed method uses the HMM to estimate the driving intention using the extracted features. The HMM is able to directly estimate unmeasurable hidden states using measurable information. This model deals with problems stochastically that are expected to affect the variability, like differences of drivers. Then, it constructs a statistical model that is capable of treating the uncertainty. The proposed method uses the ergodic structure, as shown in Fig. 8, and the state transition probability, a_{ij} , from state i to state j is initialized as a uniform distribution. In addition, we assume that the emission probability, $b_i(x)$, has a Gaussian distribution. The emission probability is calculated as

$$b_i(x) = \frac{1}{\sqrt{(2\pi)^k |\Sigma_i|}} \exp \left[-\frac{1}{2} (x - \mu_i)^T \Sigma_i^{-1} (x - \mu_i) \right], \quad (12)$$

where μ_i represents the mean vector at the state i , and Σ_i is the covariance matrix at the state i . The mean vector and the covariance matrix at each state are set by the random value. After the initialization, the parameters of the HMM are re-estimated by the training dataset. In this research, we use the Baum-Welch algorithm as the re-estimation method of the parameters⁽¹⁹⁾. The state transition probability a_{ij} from the state i to j is represented as

$$a_{ij} = P(s_{t+1} = j | s_t = i), \quad (13)$$

where s_t means the state at time t . The feature vector sequence until time t is defined as $\mathbf{X}_{1:t} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_t]$, and the probability that the model M reaches state i at time t is represented as

$$\alpha_t(i) = P(\mathbf{X}_{1:t}, s_t = i | M), \quad (14)$$

and it is derived as

$$\alpha_t(i) = [\sum_{j=1}^N \alpha_{t-1}(j) a_{ji}] b_i(x_t), \quad (15)$$

This probability is called as the forward probability. Otherwise, there is the backward probability, and it is represented as

$$\beta_t(i) = P(\mathbf{X}_{t+1:T} | s_t = i, M), \quad (16)$$

where T is the last time of the sequence. The backward probability can be derived as

$$\beta_t(i) = \sum_{j=1}^N a_{ij} b_j(x_{t+1}) \beta_{t+1}(j). \quad (17)$$

By using the forward probability and the backward probability, the parameters of the HMM can be re-estimated by the following equations.

Fig. 8 Ergodic structure of HMM.

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \alpha_t(i) a_{ij} b_j(x_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^{T-1} \alpha_t(i) \beta_t(i)}, \quad (18)$$

$$\bar{\mu}_i = \frac{\sum_{t=1}^T \alpha_t(i) \beta_t(i) x_t}{\sum_{t=1}^T \alpha_t(i) \beta_t(i)}, \quad (19)$$

$$\bar{\Sigma}_i = \frac{\sum_{t=1}^T \alpha_t(i) \beta_t(i) (x_t - \bar{\mu}_i)(x_t - \bar{\mu}_i)^T}{\sum_{t=1}^T \alpha_t(i) \beta_t(i)}. \quad (20)$$

The proposed method re-estimates the parameters that have the maximum likelihood of occurring by the repetition of the above calculations.

5.2. Estimation of driving intention

The proposed method estimates the state of the driving intention at the current time. The proposed method uses the Viterbi algorithm for the state estimation⁽²⁰⁾. The maximum probability $\delta_t(i)$ reached in state i at time t is represented as

$$\delta_t(i) = \max_i P[\mathbf{S}_{1:t-1}, s_t = i, \mathbf{X}_{1:t} | M], \quad (21)$$

where $\mathbf{S}_{1:t-1}$ denotes the state sequence until time $t-1$. The maximum probability $\delta_t(i)$ can be calculated as

$$\delta_t(i) = \left\{ \max_j P[\delta_{t-1}(j) a_{ji}] \right\} b_i(x_t), \quad (22)$$

The maximum likelihood state, s_t , at time t is derived as

$$s_t = \arg \max_i \delta_t(i). \quad (23)$$

When the state s_t is estimated as the state *changing*, the proposed method judges that the target vehicle would try to change a lane.

6. Experiments

6.1. Evaluation of the potential feature

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

- The *preceding* vehicle is slower than the *target*.
- The *preceding* vehicle is faster than the *target*.
- The *lead* vehicle is faster than the *preceding* vehicle.
- The *lead* vehicle is slower than the *preceding* vehicle.
- The *following* vehicle is faster than the *target*.
- The *following* vehicle is slower than the *target*.
- The next lane is empty.
- The current lane is empty.
- The *rear* vehicle is slower than the *target*.
- The *rear* vehicle is faster than the *target*.

Figure 9 shows the results. The value of the potential feature calculated was greater than 0.5 for cases in which a lane change is

Fig. 9 Value of potential feature in ten situations.

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 the potential feature was greater than 0.5 because the *rear* vehicle was slower than the *target*. In case (j), since the *rear* vehicle is faster than the *target*, the value of the potential feature was calculated as less than 0.5. The results prove that the potential feature describes numerous situations of lane changes appropriately, while previous methods consider only limited conditions where the *preceding* vehicle is slower than the *target*.

6.2. Criteria of performance evaluation

We trained and tested the proposed method using a real traffic dataset published by the Federal Highway Administration 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 six 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 measurements. We evaluated the performance by the *k*-fold cross-validation to use the insufficient dataset efficiently. After all of lane-changing data were divided to ten sets, training of the estimation model and testing of the detection performance were conducted by each set. By this testing method, all data can be used for the evaluation.

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

$$\tau_d = \tau_c - \tau_j, \quad (24)$$

where τ_c is the moment at which the *target* crosses the centerline, and τ_j is the moment at which the proposed method judges that the *target* would change a lane. A large value of τ_d means a high early detection performance. We defined the following criteria using the detection time τ_d :

Fig. 10 The proposed estimation model: (a) constructed structure by training, (b) driving intentions assigned to internal states.

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

Generally, a lane change takes 3.0 to 5.0 s according to previous research⁽²¹⁾. We judged cases in which $\tau_d \geq 5.0$ s as false alarms.

Second, the F_1 score is defined as

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}, \quad (25)$$

$$\text{precision} = \frac{TP}{TP + FP}, \quad (26)$$

$$\text{recall} = \frac{TP}{TP + FN}, \quad (27)$$

where *TP* denotes the true positive rate, *FP* denotes the false positive rate, and *FN* denotes the false negative rate. Including precision in the F_1 score allows for the evaluation of the false alarm rate when the proposed method judges a case where the vehicle does not change a lane as an incorrect lane change, and recall represents the failure rate, the most dangerous case, in which the proposed method judges a case should be a lane changing case as a lane keeping case. For that reason, the lane change detection method must satisfy recall with 100 % accuracy.

6.3. Evaluation of detection performance and feasibility

We show the constructed estimation model from the training using the traffic dataset in Fig. 10. We selected the model that has the maximum likelihood of occurrence, and we assigned each internal state of the HMM to the driving intentions: *keeping*, *changing*, *arrival*, and *adjustment* referenced the value of mean vector μ_i . The model had been constructed as a the left-to-right structure. However, it contains a state transition from state 2 (*changing*) to state 1 (*keeping*). This state transition means that a driver stops changing a lane despite attempting a lane change. There are some situations in which a lane change must be stopped like the case where the *rear* vehicle gets closer rapidly. This result shows that the estimation model was constructed considering those types of cases. We show a record of the scaled features and the detection results obtained by using the proposed method for one lane-changing event among the testing dataset as shown in Fig. 11. The black dashed line represents τ_c which is given by the dataset.

Fig. 11 Evaluation result for one lane-changing event: (a) record of features, (b) estimated state by the proposed method.

Table 1 Performance comparison with previous methods.

Method	Precision [%]	Recall [%]	F_1 [%]	τ_d [s]
Mandalia ⁽²²⁾	81.6	78.1	79.8	1.36
Schlechtriemen ⁽⁷⁾	92.8	100	96.3	1.74
Proposed method	94.6	100	97.2	1.88

The estimated state found by using the proposed method is represented as shown in Fig. 11 (b). The moment at which state 1 (*keeping*) is changed to state 2 (*changing*) is τ_j . We can see that τ_j was earlier than τ_c ; in other words, the proposed method detected a lane change before the *target* crossed the centerline. In this case, the detection time τ_d was 2.9 s. We can also confirm that the value of the potential feature (the red line) increases at the same time that the *target* starts to change lanes in Fig. 11 (a). The value stays above 0.5 during a lane change, and that means that the potential feature described the condition to change a lane appropriately.

We repeated the same evaluation for the entire testing dataset and compared the performance with two previous methods that we chose. The first previous method uses the variance of the lateral position within a constant window size as features⁽²²⁾. This method only focuses on the driving feature without considerations about the lane-changing conditions. The second previous method only considers the relationship with the *preceding* vehicle⁽⁷⁾. We implemented the previous methods and evaluated them using the same testing dataset. Table 1 gives the results in terms of the average of precision, recall, F_1 score, and detection time τ_d calculated by the k -fold cross-validation. We can see from the table that the proposed method outperforms previous methods in terms of both the F_1 score and the detection time. The proposed method achieved 97.2 % accuracy, and it can detect lane changes, on average, 1.88 s before the *target* crosses the centerline. In contrast, the first method failed to detect several lane-changing cases. This method has shown problems with detecting slow lane changes, therefore the most dangerous case can occur without warning to the

Fig. 12 Measurement devices.

driver. Compared to the second previous method, our method reduced the false alarm rate by almost 25 %, and the early detection performance was also improved at the same time.

To confirm whether there are significant differences between the proposed method and the second previous method, we conducted the Wilcoxon signed-rank test. As the sample size is not greater than ten, the test statistic value was compared to the critical value at 0.05 level. By this test, it was confirmed that there are significant differences between the proposed method and the second previous method in terms of both the F_1 score and the detection time. These results prove the effectiveness of the proposed method.

6.4. Evaluation of feasibility of proposed method

To confirm the feasibility of our method, we conducted experiments to measure lane changes of other vehicles. Our experimental vehicle kept a lane and never try to change a lane during the measurement while the vehicle collected data that other vehicles changed lanes. Only one driver was employed during the whole experiments. The experimental vehicle was installed with a position sensor and a laser scanner, as shown in Fig. 12. The equipped position sensor was the RT3003 (Oxford Technical Solution), with an inertial and GNSS system, which has up to 2 cm position accuracy. Six laser scanners (ibeo LUX) were also installed, which have a sensing range of 200 m at 32 fps. The experimental vehicle is able to measure the position of adjacent vehicles with 360° field of view. The measurement data was collected on the Metropolitan expressway in Odaiba, Tokyo, Japan. The measurement area was approximately 550 m in length. We measured the distance of adjacent vehicles using the laser scanners while we made a round trip. The feature extraction and the lane change detection by the proposed method were conducted off-line, after the measurement. Since it is assumed that acquired data include noise caused by measurement devices, the filtering was conducted before the feature extraction. We show the detection results of the proposed method using two lane-changing cases among the measurement data as shown in Fig. 13. Figures 13 (a), (b), and (c) are the result of one lane-changing case. Figures 13 (d), (e), and (f) show the result of another case. Figures 13 (a) and (d) show records of the feature d that is the scaled distance from the centerline for each lane changing case. The blue line represents the feature value without the filtering, the green line denotes the values by using the Kalman filter, and the red line depicts the filtered values by using both the Kalman filter and the moving average filter. We can see that the noise was clearly removed by using the Kalman filter and the moving average filter. We used the results filtered by the Kalman filter and the moving average filter. Figures 13 (b) and (e) show records of the all features that were scaled. The black dashed line represents τ_c . We can see that the potential feature (the red line) stays above 0.5 before a lane change. Figures 13 (c) and (f) represent the estimated state by the proposed method. We can confirm that the state transition from *keeping* to *changing* occurred before τ_c . This means that the proposed method can be implemented to the real vehicle system.

Fig. 13 Evaluation results: (a) and (d) results of the filtering, (b) and (e) records of all features, (c) and (f) estimation results.

7. Conclusions

In this research, we proposed a automatic detection method of lane-changing intentions considering the relationship to adjacent vehicles. For describing the relationship appropriately, we presented the potential feature extracted by using an artificial potential method. Using real traffic data, we trained and tested the proposed method, confirming that the proposed method achieved an average of 97.2 % for the F_1 score. In addition, the method can detect a lane change on average 1.88 s before the target vehicle crosses the centerline. We demonstrated that the proposed method outperforms previous methods through evaluation using the same testing dataset. Furthermore, we evaluated the feasibility of our method using the measurement data acquired by the real vehicle. We confirmed that the proposed method could be adapted to the real vehicle system from the result. As future work, we plan to evaluate the detection performance of our method with larger measurement data.

8. References

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