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# Lane-Changing Feature Extraction Using Multisensor Integration

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**Abstract:** We propose a feature extraction method for lane changes of other traffic participants. 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 feature extraction method using the multisensor system which consists of a position sensor and a laser scanner with line markings information. For a lane change prediction of other traffic participants, the most effective features are a lateral position and velocity with respect to a center line. We installed the sensor system to the primary vehicle and measured positions of other traffic participants while the primary vehicle drives on a highway. We extracted the features as the distance with respect to the center line and the lateral velocity of other vehicles using the measurement data. We confirmed that our feature extraction method has an enough accuracy for the lane change prediction.

**Keywords:** Lane change prediction, Feature extraction, Multisensor integration

## 1. 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 some drivers do not 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. 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 as shown in Fig. 1. In [3], 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 [4], the lateral positions for the point 0 m, 10 m, 20 m, 30 m ahead of the vehicle are used. In these studies, it was assumed that the lateral position and velocity are the most effective features for the prediction of lane changes by others. However, almost of previous researches used data acquired by a simulator not a real vehicle. As the result, the feature extraction method has not been examined in any detail.

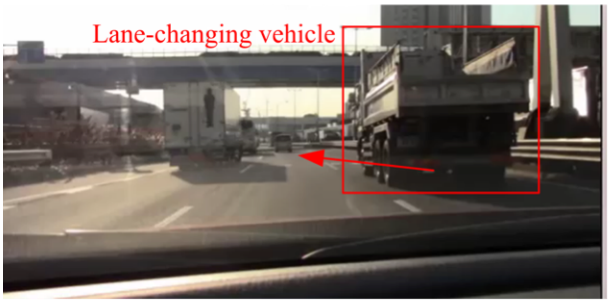


Fig. 1 Lane change of other traffic participant.

Considering these reports, we propose a method to extract features for the prediction of lane changes by other traffic participants. We construct the multisensor system which is able to extract the distance relative the center line and the lateral velocity of other vehicle using a real measurement data. Our system consists of a position sensor and a laser scanner with line marking information. The position sensor measures the position of the primary vehicle, and the laser scanner measures the relative positions of other vehicles from the primary vehicle. Line markings information are a map recorded the latitude and longitude of points each line. We use the distance with respect to the center line instead of the lateral position to account for road curvatures. Our method extracts the approximate curves of line markings, and the distance of other vehicles is calculated with the approximate curves. The lateral velocity can be calculated as the first derivative of the distance. This paper is organized as follows. Section 2 describes details about the proposed method. Section 3 presents the experimental results. Section 4 concludes and discusses future works.

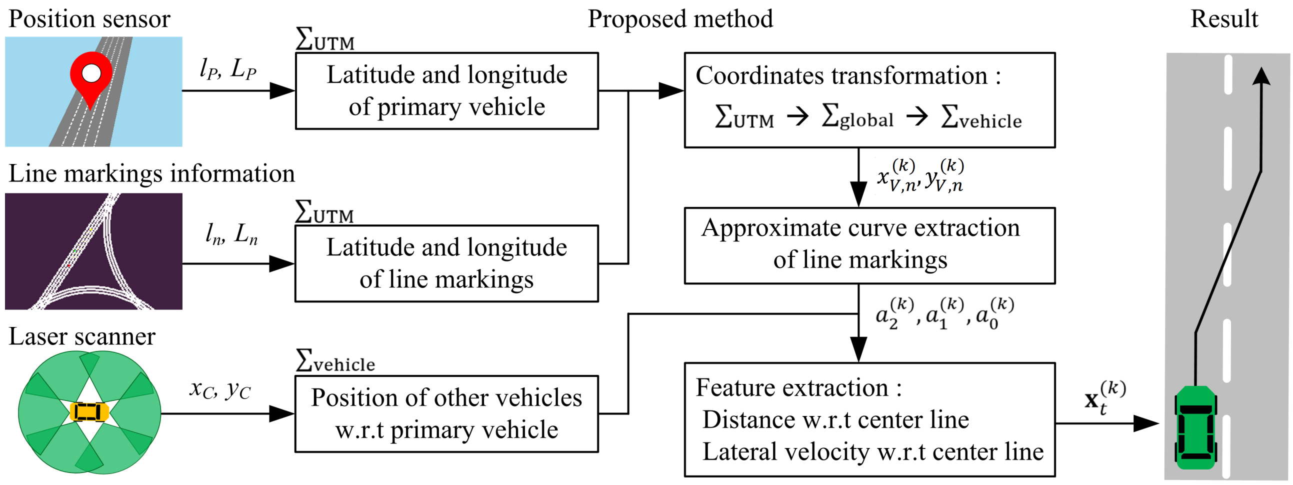

Fig. 2 Overview of proposed method.

## 2. THE PROPOSED METHOD

Figure 2 shows the overview of our proposed method. The primary vehicle has a position sensor, line markings information, and a laser scanner. Using the position sensor and line markings information, we can calculate the relative position of line markings with respect to the primary vehicle. However, since acquired data by the position sensor and line markings information are the latitude and longitude at the Universal Transverse Mercator (UTM) coordinates, the coordinates transformation must be conducted to get data in meters. From the reason, the proposed method transforms the data to the global coordinates using the geodesic sailing method. Otherwise, the position data of other vehicles measured by the laser scanner are at the vehicle coordinates. As the differences of coordinates, the proposed method conducts the coordinate transformation for the position data of line markings from the global coordinates to the vehicle coordinates. To account for road curvature, the proposed method approximates a second-degree polynomial curve. The distance from the curve of other vehicles can be calculated using the approximate curves, and it is defined as the first feature. The lateral velocity with respect to the approximate curve is calculated from the first derivative of the distance. We use the lateral velocity as the second feature.

Details about the proposed method are presented in the following: (a) coordinates transformation, (b) approximate curves of line markings, and (c) feature extraction.

### 2.1 Coordinates transformation

In this research, we define three coordinates as the UTM coordinates $\Sigma_{\mathrm{UTM}}$, the global coordinates $\Sigma_{\mathrm{global}}$, and the vehicle coordinates $\Sigma_{\mathrm{vehicle}}$. The UTM coordinates consists of the latitude $l$ and longitude $L$. The proposed method transforms the position of the primary vehicle and all points each line at the UTM coordinates to the global coordinates using the geodetic distance $\rho$ and the azimuth $Z$. We define the global position of the 1$^{\mathrm{st}}$ point at the 1$^{\mathrm{st}}$ line marking as the origin point of the global coordinates. When the latitute and longitude of the origin point are $(l_0, L_0)$, the geodetic distance $\rho$ and azimuth $Z$ can be calculated using the Lambert-Andoyer method [5]. The geodetic distance $\rho$ is calculated by using

$$\rho = R_A\left(X + \frac{R_A - R_B}{8R_A}\Delta\rho\right), \tag{1}$$

$$X = \cos^{-1}[\sin\phi_0 \sin\phi + \cos\phi_0 \cos\phi \cos(L_0 - L)], \tag{2}$$

$$\Delta\rho = \frac{(\sin X - X)(\sin\phi_0 + \sin\phi)^2}{\cos^2\frac{X}{2}} - \frac{(\sin X + X)(\sin\phi_0 - \sin\phi)}{\sin^2\frac{X}{2}}, \tag{3}$$

$$\phi_0 = \tan^{-1}\left[\frac{R_B}{R_A}\tan l_0\right], \tag{4}$$

$$\phi = \tan^{-1}\left[\frac{R_B}{R_A}\tan l\right], \tag{5}$$

where $R_A$ and $R_B$ are the radius of the earth. We use the

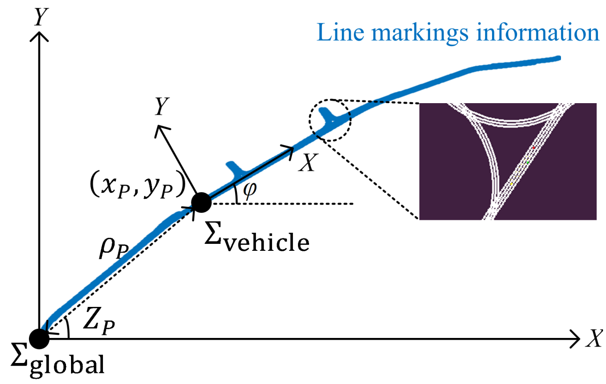

Fig. 3 Relationship with coordinates.

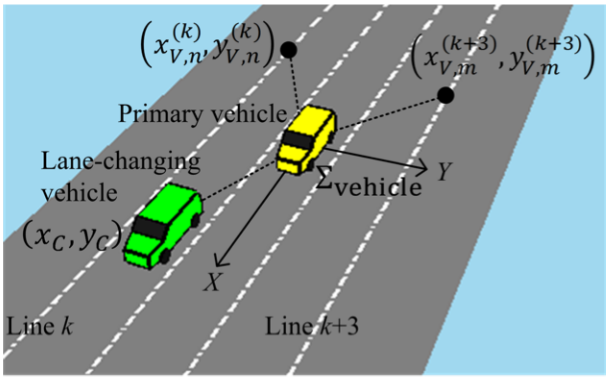


Fig. 4 Definition of vehicle coordinates.

radius of the earth, $R_A = 6378140$ km and $R_B = 6356755$ km. The azimuth $Z$ is calculated by

$$Z = \tan^{-1}\left[\frac{\sin(L_0 - L)}{\cos\phi_0 \tan\phi - \sin\phi_0 \cos(L_0 - L)}\right]. \quad (6)$$

Figure 3 shows the relationship with the geodetic distance, azimuth, and the global position of the primary vehicle. We define the position of the primary vehicle at the global coordinates as $(x_P, y_P)$, and define the position of $n^{\text{th}}$ point at the $k^{\text{th}}$ line marking at the global coordinates as $(x_{G,n}^{(k)}, y_{G,n}^{(k)})$. The origin point of the vehicle coordinates is the global position of the primary vehicle. The direction of $X$ axis is defined by the driving direction of the primary vehicle as $\varphi$ in Fig. 3. The position of $n^{\text{th}}$ point at the $k^{\text{th}}$ line at the vehicle coordinates is shown in Fig. 4, and it can be calculated by using

$$\begin{bmatrix} x_{V,n}^{(k)} \\ y_{V,n}^{(k)} \end{bmatrix} = \begin{bmatrix} \cos(-\varphi) & -\sin(-\varphi) \\ \sin(-\varphi) & \cos(-\varphi) \end{bmatrix} \begin{bmatrix} x_{G,n}^{(k)} - x_P \\ y_{G,n}^{(k)} - y_P \end{bmatrix}. \quad (7)$$

### 2.2 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 tracking range of the laser scanner is 50 m. This range is that the laser scanner can detect and track around objects. We use only the points 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 $k^{\text{th}}$ line is

$$y^{(k)} = a_2^{(k)}(x^{(k)})^2 + a_1^{(k)} x^{(k)} + a_0^{(k)}, \quad (8)$$

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

### 2.3 Feature extraction

The distance with respect to the $k^{\text{th}}$ line is defined as $d^{(k)}$ as shown in Fig. 5. The distance $d^{(k)}$ is calculated by using the position of other vehicles $(x_C, y_C)$ and the $k^{\text{th}}$ approximate curve. We generate points at a distance intervals of 0.1 m on the approximate curve and find the closest point from other vehicles. The distance $d^{(k)}$ is calculated by using

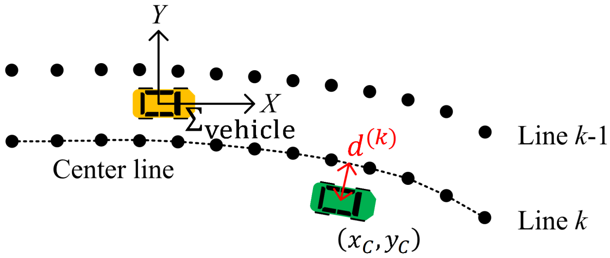


Fig. 5 Distance with respect to center line.

$$d^{(k)} = \min_n \sqrt{(x_C - x_n^{(k)})^2 + (y_C - y_n^{(k)})^2}, \quad (9)$$

where $n$ is an index about the generated points. The lateral velocity with respect to the center line is calculated from the first derivative of the distance $\dot{d}^{(k)}$.

Since the measurement data acquired by the sensor system include some noise, the proposed method conducts the filtering using the Kalman filter [6]. We define the feature vector at time $t$ with respect to the $k^{\text{th}}$ line as $\mathbf{x}_t^{(k)}$, and it is used as the state vector. The feature vector can be represented as

$$\mathbf{x}_t^{(k)} = \begin{bmatrix} d_t^{(k)} \\ \dot{d}_t^{(k)} \end{bmatrix}, \quad (10)$$

and it is filtered by using

$$\bar{\mathbf{x}}_t^{(k)} = \mathbf{A}\mathbf{x}_{t-1}^{(k)}, \quad (11)$$

$$\bar{\mathbf{P}}_t^{(k)} = \mathbf{A}\mathbf{P}_{t-1}^{(k)}\mathbf{A}^T + \mathbf{Q}, \quad (12)$$

$$\mathbf{K}_t^{(k)} = \bar{\mathbf{P}}_t^{(k)}\mathbf{H}^T\left(\mathbf{H}\bar{\mathbf{P}}_t^{(k)}\mathbf{H}^T + R\right)^{-1}, \quad (13)$$

$$\mathbf{x}_t^{(k)} = \bar{\mathbf{x}}_t^{(k)} + \mathbf{K}_t^{(k)}(z_t^{(k)} - \mathbf{H}\bar{\mathbf{x}}_t^{(k)}), \quad (14)$$

$$\mathbf{P}_t^{(k)} = (\mathbf{I} - \mathbf{K}_t^{(k)}\mathbf{H})\bar{\mathbf{P}}_t^{(k)}, \quad (15)$$

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \quad (16)$$

$$\mathbf{Q} = \begin{bmatrix} {\sigma_d}^2 & 0 \\ 0 & {\sigma_{\dot{d}}}^2 \end{bmatrix}, \quad (17)$$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad (18)$$

where $\mathbf{P}_t^{(k)}$ represents the corresponding covariance, $\mathbf{K}_t^{(k)}$ is the Kalman gain, $R = \sigma_z^2$ denotes the measurement noise, and $z_t^{(k)}$ is the measurement value of the distance with respect to the $k^{\text{th}}$ line at time $t$. Equation (11) means the prediction of the state. Equation (14) represents the filtered features by using the measurement $z_t^{(k)}$. The proposed method can be adapted to both the left and right sides of lane changes. $k$ is chosen based on the lane-changing sides and all feature are calculated following the specified side.

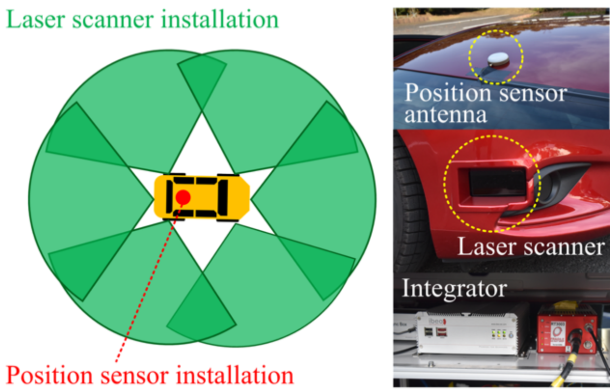


Fig. 6 Measurement devices installation.

## 3. EXPERIMENTS

The experimental vehicle was installed with the position sensor, the laser scanner, and line markings information as shown in Fig. 6. The equipped position sensor is RT3003 (Oxford Technical Solution), the inertial and GNSS system, which has up to 2 cm position accuracy. Six laser scanners (ibeo LUX) were also installed which has the 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, and we measured adjacent vehicles while we made a round trip. We collected 40 lane-changing vehicle data. The feature extraction was conducted off-line after the measurement.

Figure 7 (a) shows the position $y_C$ at the vehicle coordinates that was acquired by the laser scanner, and the extracted feature $d$ by using the proposed method is shown in Fig. 7 (b). This result is one of all 40 lane-changing data. As our experiment area was the straight way, the position $y_C$ has similar pattern with the feature $d$. However, if the experiment is conducted on a curved road, it would have quite different pattern. We can see that the position $y_C$ includes three times spike noise caused by the laser scanner accuracy. This noise can be the cause of false prediction of lane changes. Otherwise, the extracted feature about the distance shows stable values by the effect of the Kalman filter. Figure 7 (c) represents the first derivative of the position $y_C$. We can see that it is affected by noise, as the result, it is difficult to be used as a feature. Otherwise, Figure 7 (d) represents the lateral velocity, and it shows stable records. This result demonstrates that the proposed method can extract the stable features as the distance and the lateral velocity with respect to the center line to predict lane changes of other vehicles successfully.

## 4. CONCLUSION

In this research, we proposed a feature extraction method for lane changes of other traffic participants. By

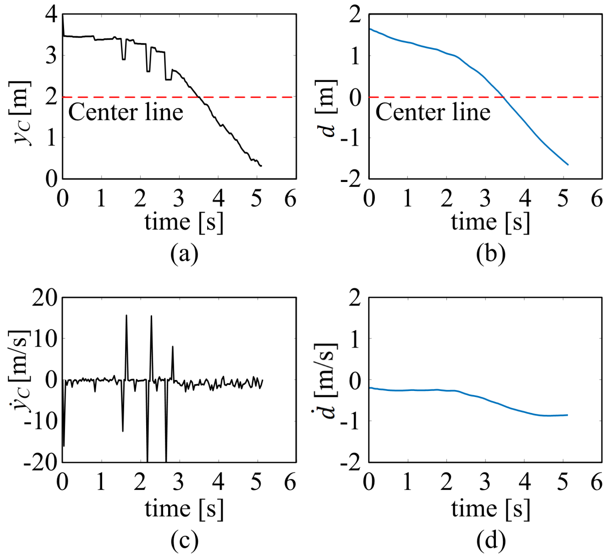


Fig. 7 Result of feature extraction: (a) position $y_C$, (b) distance w.r.t center line, (c) first derivative of position $y_C$, and (d) lateral velocity w.r.t center line.

the integration of a position sensor, a laser scanner, and line markings information, we confirmed that the most effective features, the distance and the lateral velocity with respect to the center line, can be extracted using data acquired by a real vehicle. Future work will focus on the lane change prediction method using our feature extraction system.

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