Distortion Correction of Laser Scan Data from In-vehicle Laser Scanner based on Kalman Filter and NDT Scan Matching

Kimiaki Inui[1], Masahide Morikawa[1], Masafumi Hashimoto[2] and Kazuhiko Takahashi[2]

[1]Graduate School of Doshisha University, Kyotanabe, Kyoto 6100321, Japan
[2]Faculty of Science and Engineering, Doshisha University, Kyotanabe, Kyoto 6100321, Japan

Keywords: Laser Scanner, Laser-scan Data, Distortion Correction, Kalman Filter, NDT Scan Matching.

Abstract: This paper presents a Kalman-filter-based method of correcting distortion in 3D laser-scan data from in-vehicle multilayer laser scanner. A robot identifies its own 3D pose (position and attitude) in a laser-scan period using the normal-distributions transform (NDT) scan-matching method. Based on the pose information, the robot's pose is predicted and smoothed in a period shorter than the scan period using Kalman filter under the assumption that the robot moves at nearly constant linear and turning velocities. The predicted and smoothed poses of the robot are applied to map laser-scan data onto a world coordinate frame. Subsequently, the robot again identifies its own 3D pose from the mapped scan data using NDT scan matching. This iterative process enables the robot to correct the distortion of laser-scan data and accurately map the laser-scan data onto the world coordinate frame. Experimental results of mapping a signal light in a road environment validate the proposed method.

1 INTRODUCTION

Environment recognition using onboard laser scanners is an important issue in the fields of mobile robotics and vehicle automation (Mukhtar et al., 2015). Several recognition methods using single-layer or multilayer laser scanners have been proposed, such as simultaneous localization and mapping (SLAM) (Hess et al., 2016, Cadena et al., 2016), map building (Yokoyama et al., 2013), and moving-object tracking (Mertz et al., 2013, Kanaki et al., 2016).

In environment recognition systems using onboard laser scanners, laser measurements (laser-scan data) are captured in a sensor coordinate frame and mapped onto a world coordinate frame using the robot's pose information. The laser scanner obtains range measurements by scanning laser beams; thus, when the robot moves, all the scan data within a scan cannot be obtained at the same position of the robot. Therefore, if all the scan data obtained within one scan is mapped onto the world coordinate frame using the robot's pose information, a distortion arises in the scan data. To correct this distortion, the robot's pose should be determined more frequently than the laser-scan period, i.e., for every laser measurement in the scan.

Many methods for correcting distortion in scan data have been proposed. Brenneke (Brenneke, et al., 2003) corrected scan-data distortion by estimating the robot's pose in a short period based on the information from global navigation satellite systems (GNSSs) and inertial measurement units (IMUs). Other methods (Hong et al., 2010, Moosmann and Stiller, 2011, Zhang and Singh, 2014) have been proposed that reduce scan-data distortion by estimating the robot's pose using only the laser-scan data, i.e., without using GNSS and IMU data. These methods were used to calculate the robot's pose for each laser-scan period using the iterative closest-points (ICP) scan-matching method (Besl and McKay, 1992) and its variants and to estimate the robot's pose in a period shorter than the scan period using linear interpolation under the assumption that the robot moves at nearly constant velocity.

In this paper, we present a distortion-correction method for scan data using only laser scanner. Normal distributions transform (NDT) scan matching (Biber and Strasser, 2003) is applied to estimate the robot's pose. As the NDT scan matching method has a lower computational cost than the ICP method, it can easily process large amounts of scan data captured from a multilayer laser scanner. In addition, the robot's pose is estimated in a period

shorter than the laser-scan period using Kalman filter. Since the Kalman-filter-based robot localization is commonly used in mobile robotics and vehicle automation, the scan-data distortion in a Kalman-filter framework can be easily embedded into the self-localization system of the robot.

The rest of this paper is organized as follows. In Section 2, an overview of the experimental system is given. In Section 3, scan-data mapping based on NDT scan matching is summarized. In Section 4, a distortion-correction method for scan data using the Kalman filter is described. In Section 5, experimental results are presented, followed by conclusions in Section 6.

2 EXPERIMENTAL SYSTEM

Figure 1 shows the mobile robot equipped with a 32-layer laser scanner (Velodyne HDL-32E). The maximum range of the laser scanner is 70 m, the horizontal viewing angle is 360° with a resolution of 0.16°, and the vertical viewing angle is 41.34° with a resolution of 1.33°.

The laser scanner provides 384 measurements (the object's 3D position and reflection intensity) every 0.55 ms (at 2° horizontal angle increments). The period for the laser-scanner beam to complete one rotation (360°) in the horizontal direction is 100 ms, and 70,000 measurements are obtained in one rotation.

In this paper, one rotation of the laser-scanner beam in the horizontal direction (360°) is referred to as one scan, and the data obtained from this scan is referred to as scan data. Moreover, the laser scanner's scan period (100 ms) is denoted as τ and scan data observation period (0.55 ms) as $\Delta\tau$.

3 SCAN-DATA MAPPING

Figure 2 shows the process for scan-data mapping using NDT scan matching. First, the scan data related to the ground is removed based on the reflection intensity of the scan data, and the remaining scan data is mapped onto a 3D grid map (a voxel map) represented in the robot's coordinate frame, Σ_b . A voxel grid filter (Munaro et al., 2012) is applied to downsize the scan data. The voxel used for the voxel grid filter is a tetrahedron with a side-length of 0.2 m.

In the world coordinate frame, Σ_W , a voxel map with a voxel size of 1 m is used for NDT scan

Figure 1: Overview of the experimental robot.

matching. For the i-th ($i = 1, 2, \ldots n$) measurement in the scan data, we define the position vector in Σ_b as $\boldsymbol{p}_{bi}$ and that in Σ_W by $\boldsymbol{p}_i$. Thus, the following relation is given:

$$\begin{pmatrix} \boldsymbol{p}_i \\ 1 \end{pmatrix} = \boldsymbol{T}(\boldsymbol{X}) \begin{pmatrix} \boldsymbol{p}_{bi} \\ 1 \end{pmatrix} \tag{1}$$

where $\boldsymbol{X} = (x, y, z, \phi, \theta, \psi)^T$ is the robot's pose. $(x, y, z)^T$ and $(\phi, \theta, \psi)^T$ are the 3D position and attitude (roll, pitch, and yaw angles) of the robot, respectively, in Σ_W . $\boldsymbol{T}(\boldsymbol{X})$ is the following homogeneous transformation matrix:

$$T(X) =$$
$$\begin{pmatrix} \cos\theta\cos\psi & \sin\phi\sin\theta\cos\psi - \cos\phi\sin\psi & \cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi & x \\ \cos\theta\sin\psi & \sin\phi\sin\theta\sin\psi + \cos\phi\cos\psi & \cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi & y \\ -\sin\theta & \sin\phi\cos\theta & \cos\phi\cos\theta & z \\ 0 & 0 & 0 & 1 \end{pmatrix}$$
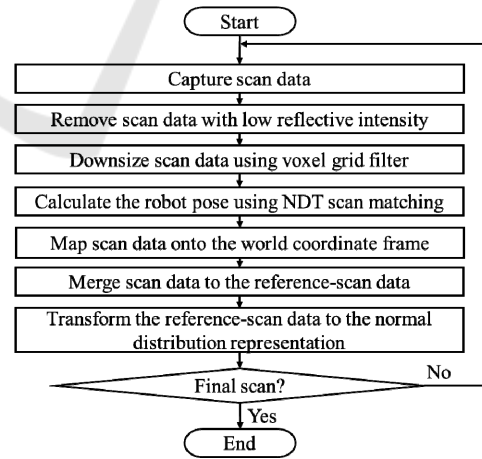

Figure 2: Process of scan data mapping using NDT scan matching.

The scan data obtained at the current time $t\tau$ ($t = 0, 1, 2, \ldots$), $\boldsymbol{P}_{b(t)} = \{\boldsymbol{p}_{b1(t)}, \boldsymbol{p}_{b2(t)}, \cdots, \boldsymbol{p}_{bn(t)}\}$ or $\boldsymbol{P}_{(t)} = \{\boldsymbol{p}_{1(t)}, \boldsymbol{p}_{2(t)}, \cdots, \boldsymbol{p}_{n(t)}\}$, are referred to as the new input scan, and the scan data obtained in the previous time

before $(t-1)\tau$, $\boldsymbol{P} = \{\boldsymbol{P}_{(0)}, \boldsymbol{P}_{(1)}, \cdots, \boldsymbol{P}_{(t-1)}\}$, is referred to as the reference scan.

NDT scan matching (Biber and Strasser, 2003) conducts a normal distribution transformation for the reference-scan points in each grid on a voxel map; it calculates the average value and covariance of the laser-measurement positions. By matching the new input-scan at $t\tau$ with the reference-scan data obtained prior to $(t-1)\tau$, the robot's pose, $\boldsymbol{X}_{(t)}$, at $t\tau$ is determined. The robot's pose is used for conducting a coordinate transform with Eq. (1), and the new input scan can then be mapped to Σ_W.

In this study, we use Point Cloud Library (PCL) for NDT scan matching (Rusu and Cousin, 2011). It should be noted that the downsized scan data is only used to calculate the robot's pose using NDT scan matching at small computational cost.

4 DISTORTION CORRECTION

4.1 Robot's Motion Model

As shown in Fig. 3, the robot's linear velocity in Σ_b is defined as V_b (the velocity in the x_b-axis direction), and the angular velocities about the x_b-, y_b-, and z_b-axes are defined as $\dot{\phi}_b$, $\dot{\theta}_b$, and $\dot{\psi}_b$, respectively.

If the robot is assumed to move at nearly constant linear and angular velocities, the following motion model can be used:

$$\begin{pmatrix} x_{(t+1)} \\ y_{(t+1)} \\ z_{(t+1)} \\ \phi_{(t+1)} \\ \theta_{(t+1)} \\ \psi_{(t+1)} \\ V_{b(t+1)} \\ \dot{\phi}_{b(t+1)} \\ \dot{\theta}_{b(t+1)} \\ \dot{\psi}_{b(t+1)} \end{pmatrix} = \begin{pmatrix} x_{(t)} + a_{1(t)}\cos\theta_{(t)}\cos\psi_{(t)} \\ y_{(t)} + a_{1(t)}\cos\theta_{(t)}\sin\psi_{(t)} \\ z_{(t)} - a_{1(t)}\sin\theta_{(t)} \\ \phi_{(t)} + \{a_{2(t)}\sin\phi_{(t)} + a_{3(t)}\cos\phi_{(t)}\}\tan\theta_{(t)} \\ \theta_{(t)} + \{a_{2(t)}\cos\phi_{(t)} - a_{3(t)}\sin\phi_{(t)}\} \\ \psi_{(t)} + \{a_{2(t)}\sin\phi_{(t)} + a_{3(t)}\cos\phi_{(t)}\}\dfrac{1}{\cos\theta_{(t)}} \\ V_{b(t)} + \tau w_{\dot{V}_b} \\ \dot{\phi}_{b(t)} + \tau w_{\ddot{\phi}_b} \\ \dot{\theta}_{b(t)} + \tau w_{\ddot{\theta}_b} \\ \dot{\psi}_{b(t)} + \tau w_{\ddot{\psi}_b} \end{pmatrix}$$

$$(2)$$

where $a_{1(t)} = V_{b(t)}\tau + \tau^2 w_{\dot{V}_b}/2$, $a_{2(t)} = \dot{\theta}_{b(t)}\tau + \tau^2 w_{\ddot{\theta}_b}/2$, and $a_{3(t)} = \dot{\psi}_{b(t)}\tau + \tau^2 w_{\ddot{\psi}_b}/2$. $w_{\dot{V}_b}$, $w_{\ddot{\phi}_b}$, $w_{\ddot{\theta}_b}$, and $w_{\ddot{\psi}_b}$ are the acceleration disturbances.
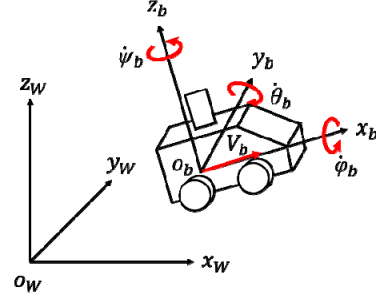
Equation (2) can be expressed in the vector form:

Figure 3: Notation related to robot motion.

$$\boldsymbol{\xi}_{(t+1)} = \boldsymbol{f}[\boldsymbol{\xi}_{(t)}, \boldsymbol{w}, \tau] \qquad (3)$$

where $\boldsymbol{\xi} = (x, y, z, \phi, \theta, \psi, V_b, \dot{\phi}_b, \dot{\theta}_b, \dot{\psi}_b)^T$ and $\boldsymbol{w} = (w_{\dot{V}_b}, w_{\ddot{\phi}_b}, w_{\ddot{\theta}_b}, w_{\ddot{\psi}_b})^T$.

We define the robot's pose obtained at $t\tau$ using NDT scan matching as $\boldsymbol{z}_{NDT(t)} \equiv \hat{\boldsymbol{X}}_{(t)}$. The measurement equation is then

$$\boldsymbol{z}_{NDT(t)} = \boldsymbol{H}\boldsymbol{\xi}_{(t)} + \Delta\boldsymbol{z}_{NDT(t)} \qquad (4)$$

where $\Delta\boldsymbol{z}_{NDT}$ is the measurement noise, and $\boldsymbol{H}$ is the measurement matrix,

$$\boldsymbol{H} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}$$

4.2 Distortion-correction Method

Figure 4 shows the process for scan-data distortion correction using the Kalman filter.

If the state estimate, $\hat{\boldsymbol{\xi}}_{(t-1/t-1)}$, and its associated error covariance, $\boldsymbol{\Gamma}_{(t-1/t-1)}$, are obtained at $(t-1)\tau$, the Kalman prediction algorithm gives the state prediction, $\hat{\boldsymbol{\xi}}_{(t-1,1/t-1)}$, and its associated error covariance, $\boldsymbol{\Gamma}_{(t-1,1/t-1)}$, at $(t-1)\tau + \Delta\tau$ according to

$$\left.\begin{aligned} \hat{\boldsymbol{\xi}}_{(t-1,1/t-1)} &= \boldsymbol{f}[\hat{\boldsymbol{\xi}}_{(t-1/t-1)}, 0, \Delta\tau] \\ \boldsymbol{\Gamma}_{(t-1,1/t-1)} &= \boldsymbol{F}_{(t-1/t-1)}\boldsymbol{\Gamma}_{(t-1/t-1)}\boldsymbol{F}_{(t-1/t-1)}^T \\ &\quad + \boldsymbol{G}_{(t-1/t-1)}\boldsymbol{Q}\boldsymbol{G}_{(t-1/t-1)}^T \end{aligned}\right\} \quad (5)$$

where $\boldsymbol{F} = \partial\boldsymbol{f}/\partial\hat{\boldsymbol{\xi}}$, $\boldsymbol{G} = \partial\boldsymbol{f}/\partial\boldsymbol{w}$, and $\boldsymbol{Q}$ is the covariance matrix of the plant noise, $\boldsymbol{w}$.

By a similar calculation, the state prediction, $\hat{\boldsymbol{\xi}}_{(t-1,j/t-1)}$, and its associated error covariance, $\boldsymbol{\Gamma}_{(t-1,j/t-1)}$, at $(t-1)\tau + j\Delta\tau$, where $j = 1, 2, \ldots, 180$,
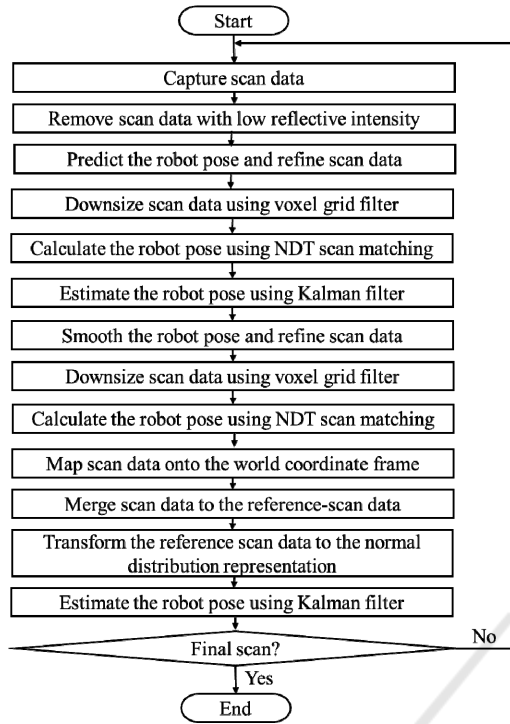
Figure 4: Process of distortion correction in scan data.

can be obtained. We denote the state prediction related to the robot's pose, (x,y,z,ϕ,θ,ψ), as $\hat{X}_{(t-1,j/t-1)} \in \hat{\xi}_{(t-1,j/t-1)}$.

Using Eq. (1), the scan data obtained at $(t-1)\tau+j\varDelta\tau$, $p_{bi(t-1,j)}$ where $i = 1, 2, \ldots n$, can be transformed to $p_{i(t-1,j/t-1)}$ as follows:

$$\begin{pmatrix} p_{i(t-1,j/t-1)} \\ 1 \end{pmatrix} = T(\hat{X}_{(t-1,j/t-1)}) \begin{pmatrix} p_{bi(t-1,j)} \\ 1 \end{pmatrix} \quad (6)$$

Using the state prediction, $\hat{X}_{(t/t-1)} = \hat{X}_{(t-1,180/t-1)}$, the scan data, $p_{i(t-1,j/t-1)}$, is re-transformed into the scan data in $\varSigma_b$ at $t\tau = (t-1)\tau + 180\varDelta\tau$ as follows:

$$\begin{pmatrix} p_{bi}^{*}(t) \\ 1 \end{pmatrix} = T(\hat{X}_{(t-1,180/t-1)})^{-1} \begin{pmatrix} p_{i(t-1,j/t-1)} \\ 1 \end{pmatrix} \quad (7)$$

To calculate the robot's pose, $z_{NDT}(t)$, NDT scan matching is performed using scan data, $P_b^{*}(t) = \{p_{b1}^{*}(t), p_{b2}^{*}(t), \cdots, p_{bn}^{*}(t)\}$, as the new input scan. Based on Eqs. (3) and (4), the Kalman estimation algorithm then gives a state estimate, $\hat{\xi}_{(t/t)}$, and its associated error covariance, $\varGamma_{(t/t)}$, as follows:

$$\left.\begin{array}{l} \hat{\xi}_{(t/t)} = \hat{\xi}_{(t-1,180/t-1)} + K_{(t)}\{z_{NDT}(t) - H\hat{\xi}_{(t-1,180/t-1)}\} \\ \varGamma_{(t/t)} = \varGamma_{(t-1,180/t-1)} - K_{(t)}H\varGamma_{(t-1,180/t-1)} \end{array}\right\}$$

$$(8)$$

where $K_{(t)} = \varGamma_{(t-1,180/t-1)}H^T S^{-1}(t)$ and $S_{(t)} = H\varGamma_{(t-1,180/t-1)}H^T - R$. R is the covariance matrix of $\varDelta z_{NDT}$.

Next, we correct the distortion in the scan data obtained at $(t-1)\tau+j\varDelta\tau$. The Kalman smoothing algorithm gives state-smoothed data at $(t-1)\tau+j\varDelta\tau$ as follows:

$$\left.\begin{array}{l} \hat{\xi}_{(t-1,j/t)} = \hat{\xi}_{(t-1,j/t-1)} \\ \quad + C_{(t)}\{\hat{\xi}_{(t-1,j+1/t)} - \hat{\xi}_{(t-1,j+1/t-1)}\} \\ \varGamma_{(t-1,j/t)} = \varGamma_{(t-1,j/t-1)} \\ \quad + C_{(t)}\{\varGamma_{(t-1,j+1/t)} - \varGamma_{(t-1,j+1/t-1)}\}C^{-1}(t) \end{array}\right\}$$

$$(9)$$

where $C_{(t)} = \varGamma_{(t-1,j/t-1)}F_{(t-1,j)}^T \varGamma_{(t-1,j+1/t-1)}^{-1}$.

It should be noted that, since a state estimate cannot be obtained at $(t-1)\tau+j\varDelta\tau$, Eq. (9) uses a state prediction.

Therefore, the scan data obtained at $(t-1)\tau+j\varDelta\tau$, $p_{bi(t-1,j)}$, can be transformed to $p_{i(t-1,j)}$ using

$$\begin{pmatrix} p_{i(t-1,j/t)} \\ 1 \end{pmatrix} = T(\hat{X}_{(t-1,j/t)}) \begin{pmatrix} p_{bi(t-1,j)} \\ 1 \end{pmatrix} \quad (10)$$

and subsequently re-transformed to obtain the scan data in $\varSigma_b$ at $t\tau$ using the following equation:

$$\begin{pmatrix} p_{bi(t)} \\ 1 \end{pmatrix} = T(\hat{X}_{(t/t)})^{-1} \begin{pmatrix} p_{i(t-1,j/t)} \\ 1 \end{pmatrix} \quad (11)$$

where $\hat{X}_{(t/t)}$ is the robot's pose estimated according to Eq. (8).

To calculate the robot's pose, $z_{NDT}(t)$, NDT scan matching is conducted based on the distortion-corrected scan data, $P_{b(t)} = \{p_{b1(t)}, p_{b2(t)}, \cdots, p_{bn(t)}\}$, as the new input scan. Then, Eq. (8) is used to determine $\hat{X}_{(t/t)}$, and Eq. (1) is used to map the new input scan onto $\varSigma_W$.

5 EXPERIMENTAL RESULTS

The robot turned at a T-junction on a road, as shown in Fig. 5. The maximum linear and turning velocities

were 11 m/s and 22°/s, respectively. Scan data was captured in 100 scans (10 s), and the distortion-correction method was evaluated by mapping a signal light onto the world coordinate frame, Σ_W.

Figure 6 shows the mapping result for the signal light based on scan data captured by the static laser scanner. The right figure in Fig. 6 shows the laser measurements for the pole part of the signal light (diameter 0.22 m); the mapping result of the signal light was plotted on the horizontal plane (x_w-y_w plane) in Σ_W.

Figure 7 shows the mapping result when the distortion in the scan data is not corrected. The robot's pose was estimated every 0.1 s by NDT scan matching, and mapping was conducted using scan data without distortion correction. The scan data is widely spread sideways and one signal light is recognized as two signal lights.

Figure 8 shows the mapping result obtained by the proposed method: distortion correction of the scan data using the Kalman filter. For comparison purposes, the distortion in the scan data was also corrected using a linear extrapolation and interpolation method, where the extrapolation and interpolation algorithms correspond to the Kalman

prediction and smoothing algorithms, respectively, used in the proposed method. The mapping result obtained by the conventional linear extrapolation and interpolation method is shown in Fig. 9.

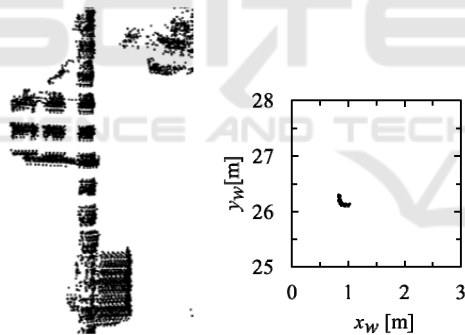Figure 5: Photo of the environment and signal light used for an experiment.

Figure 6: Mapping result of the signal light when the robot stops.
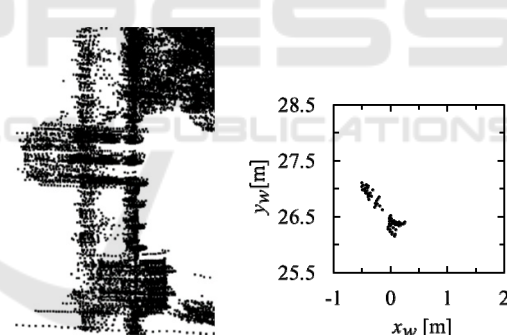

Figure 7: Mapping result without distortion correction.
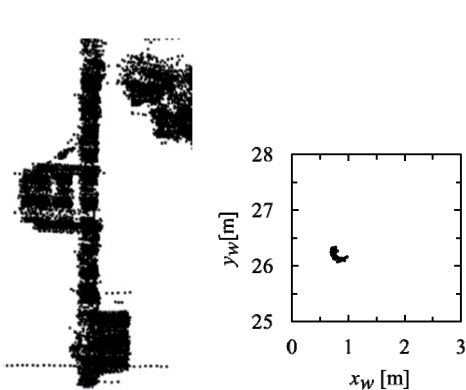

Figure 8: Mapping result obtained by the proposed method.
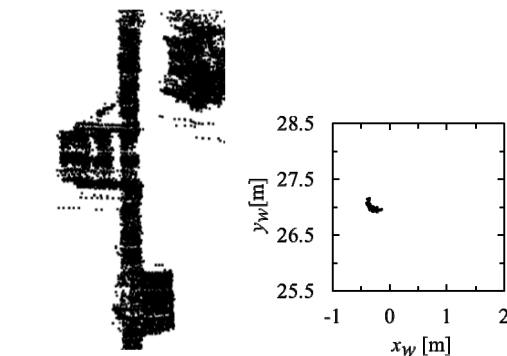

Figure 9: Mapping result obtained by the linear extrapolation and interpolation method.

It is clear from Figs. 6–9 that the distortion correction of the laser-scan data provides a better mapping result.

The laser-mapping position obtained using the Kalman filter (the right figure in Fig. 8) is closer to the actual position shown in Fig. 6, compared with that obtained using the linear extrapolation and interpolation method (the right figure in Fig. 9). This indicates that the mapping performance of the proposed method is superior to that of the conventional linear extrapolation and interpolation method.

6 CONCLUSIONS

In this paper, we presented a distortion-correction method for laser-scan data obtained from in-vehicle multilayer laser scanner. The method was achieved by Kalman prediction, estimation, and smoothing of the robot's pose data using NDT scan matching. Experimental results of mapping a signal light in a road environment showed the effectiveness of the proposed method.

Future research will aim at evaluating the performance of SLAM and moving-object tracking systems using scan data where the distortion is corrected using the proposed method.

ACKNOWLEDGEMENTS

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