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Line Matching Algorithm for Localization of Mobile Robot Using Distance Data from Structured-light Image[1]

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Abstract. Distance measurement is essential for autonomous mobile robot. An active raging sensor based on the structured-light image obtains distance data of a set of object points on a laser stripe. This paper aims to propose an algorithm for extraction of line segments from the distance data and matching with a given global map of environment. By using this algorithm, a mobile robot is able to localize its position and heading angle in the environment. Experiments for matching and localization are conducted by using distance data from the active ranging sensors to verify the performance of the proposed algorithm.

Keywords: structured-light image, active ranging, matching, localization, mobile robot

1 Introduction

In order to achieve self-localization and autonomous navigation for a mobile robot, a distance measurement system is prerequisite to obtain spatial map of the robot's environment [1]. Among the many kinds of ranging sensors, the structured-light image based sensor has many advantages: efficient computation in image processing, robustness against ambient light and cost-effectiveness [2]. The structured-light imaging system projects a laser stripe onto environmental object and captures the reflected light by a camera. Distance of a set of object points on the laser stripe can be computed based on the triangulation.

Because the distance data contains the information about the environment, it is possible to localize a mobile robot by matching the measured distance data with a given environmental object map. Many studies are available on the matching algorithm for localization of a mobile robot [3], [4]. The environmental object map is generally given in the form of line segments. A curved object is possibly approximated by a set of line segments also.

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Main aim of this paper is to propose a line matching algorithm for a set of distance data from a structured-light image with a given environmental object map in the form of line segments. An efficient algorithm for extraction of a line segment from measured set of distance data is also proposed in this paper.

2 Line Segment Extraction

Fig. 1 shows an example of laser structured-light image. The ranging sensor based on the structured-light image obtains a set of distance data of points on a projected laser stripe[5],[6].

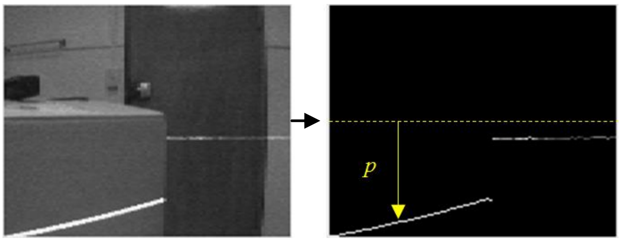


Fig. 1. An example of laser structured-light image and distance data of a set of points on a laser stripe

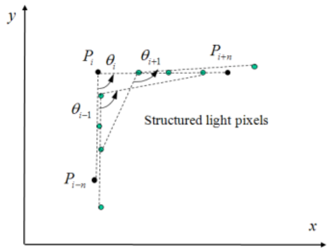


Fig. 2. Angle θ_i at P_i in case of $n = 4$

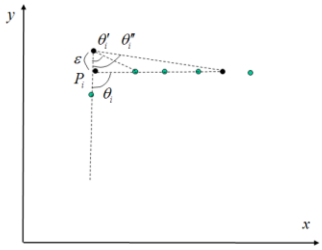


Fig. 3. Pixel noise on the angle

In order to represent the measured set of distance data with several line segments, two end points of a line segment should be determined. In case that there is a discontinuous point in the measured data, it is simple to determine the end point of a line segment. In the other case that two line segments are connected, a corner point should be found out as the end point of a line segment. As illustrated in Fig. 2, an angle θ_i at P_i between the vectors $\vec{r}_i = \overrightarrow{P_i P_{i-n}}$ and $\vec{f}_i = \overrightarrow{P_i P_{i+n}}$ are defined as follows:

$$\theta_i = \cos^{-1}\left(\frac{\vec{r}_i \cdot \vec{f}_i}{\left\|\vec{r}_i\right\| \left\|\vec{f}_i\right\|} \right) \tag{1}$$

where '·' denotes the inner product, P_i is the i^{th} pixel position in the measured data, and P_{i-n} and P_{i+n} are the $(i-n)^{th}$ and the $(i+n)^{th}$ pixel positions respectively with a fixed interval n. The criterion for P_i to be a corner point is described as follows:

$$\theta_{i-n} \geq \theta_{i-(n-1)} \geq \cdots \geq \theta_i \text{ and } \theta_i \leq \theta_{i+1} \leq \cdots \leq \theta_{i+n} \tag{2}$$

Eq. (2) implies that θ_i is a local minimum within $i-n \leq i \leq i+n$. Fig. 3 shows the influence of pixel noise on the angle θ_i in accordance with n. When there is not any noise on pixel P_i, the angle should be θ_i in the figure. If the amount of noise on P_i is ε in y axis, the angle becomes θ_i' or θ_i'' in case of $n=1$ or $n=4$ respectively as shown in the figure. Thus, the influence of pixel noise on the angle become smaller as the interval n is increased. However, if n is set too large, it may cause a loss of corner point in a short line segment. Thus, the size of n should be determined by taking the amount of pixel noise into consideration. Fig. 4 is the graph of the angle θ_i by applying (1). From two end points of a line segment, the center of the line segment and the number of measured data points on the line segment can also be obtained.

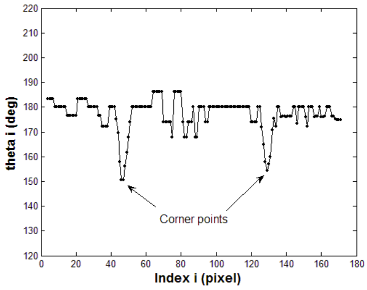


Fig. 4. Angle θ_i with respect to i at $n=4$

3 Matching and Localization

In Fig. 5 (a), P_l^i and P_l^e denote two end points of a line segment l. The center of the segment is $P_l^c = \frac{P_l^i + P_l^e}{2}$ and n_l is the number of data points on the segment l. It is assumed that the global map is modeled by the polygonal objects. The model line in Fig. 5 represents a side line of a polygonal object in the environment.

As explained in Fig. 5, the nearest model line is chosen as a target for each measured line segment l. To choose the target line, the shortest distance between a model line and the center of a line segment is used. The target line is described as

$$P \cdot \mathbf{u}_l = r_l \tag{3}$$

where P is a point on the target line, $\mathbf{u}_l$ is the unit normal vector, and r_l is a certain real number.

Rotation by $\Delta\theta$ and translation by $(\Delta x, \Delta y)$ with respect to the reference position C_r of the robot make the end points of the segment l as

$$P_l' = R(\Delta\theta)(P_l - C_r) + C_r + T(\Delta x, \Delta y) \tag{4}$$

where P_l and P_l' represent an end point before and after the transformation respectively. The squared distance between the transformed end point and the target line (3) is defined as the matching error as follows:

$$\begin{aligned} s_l = &\left[\left\{R(\Delta\theta)(P_l^i - C_r) + C_r + T(\Delta x, \Delta y)\right\} \cdot \mathbf{u}_l - r_l\right]^2 \\ &+ \left[\left\{R(\Delta\theta)(P_l^e - C_r) + C_r + T(\Delta x, \Delta y)\right\} \cdot \mathbf{u}_l - r_l\right]^2 \end{aligned} \tag{5}$$

where P_l^i and P_l^e are the two end points of the line segment. Then, the total matching error is represented by sum of the weighted matching errors of all line segments:

$$\begin{aligned} S &= \sum_l n_l s_l \\ &= \sum_l n_l \left[\left\{R(\Delta\theta)(P_l^i - C_r) + C_r + T(\Delta x, \Delta y)\right\} \cdot \mathbf{u}_l - r_l\right]^2 \\ &\quad + \sum_l n_l \left[\left\{R(\Delta\theta)(P_l^e - C_r) + C_r + T(\Delta x, \Delta y)\right\} \cdot \mathbf{u}_l - r_l\right]^2 \end{aligned} \tag{6}$$

The weight n_l is the number of all data points on a line segment l. In order to get the amount of rotation $\Delta\theta$ and translation $(\Delta x, \Delta y)$ that minimizes the total matching error (6) by the least-square method, the rotational matrix $R(\Delta\theta)$ is linearized as follows[11]:

$$R(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \approx \begin{bmatrix} 1 & -\Delta\theta \\ \Delta\theta & 1 \end{bmatrix} \tag{7}$$

By inserting (7) into (6) and taking a derivative with respect to $\Delta\theta$ and $(\Delta x, \Delta y)$, it is possible to get the amount of translation and rotation that minimizes the total matching error as follows:

$$\begin{bmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{bmatrix} = \begin{bmatrix} A_{2\times 2} & B_{2\times 1} \\ C_{1\times 2} & D_{1\times 1} \end{bmatrix}^{-1} \cdot \begin{bmatrix} E_{2\times 1} \\ F_{1\times 1} \end{bmatrix} \tag{8}$$

where

$$\begin{aligned} A_{2\times 2} &= \sum_l n_l \mathbf{u}_l \mathbf{u}_l^t \\ B_{2\times 1} &= \sum_l n_l \left\{M(P_l - C_r) \cdot \mathbf{u}_l\right\} \mathbf{u}_l \\ C_{1\times 2} &= B_{2\times 1}^t \\ D_{1\times 1} &= \sum_l n_l \left\{M(P_l - C_r) \cdot \mathbf{u}_l\right\}^2 \\ E_{2\times 1} &= \sum_l n_l (r_l - P_l \cdot \mathbf{u}_l)\, \mathbf{u}_l \\ F_{2\times 1} &= \sum_l n_l (r_l - P_l \cdot \mathbf{u}_l) \left\{M(P_l - C_r) \cdot \mathbf{u}_l\right\} \end{aligned} \tag{9}$$

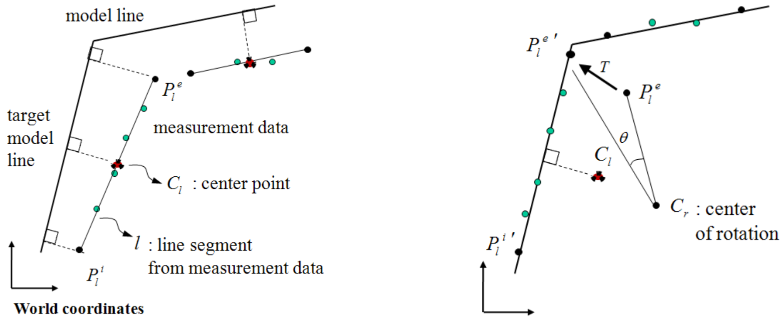
In (9), M is given by

$$M = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \tag{10}$$

When the amount of transformation $(\Delta x, \Delta y, \Delta\theta)$ is obtained from (8), the estimated posture $(\hat{x}_r, \hat{y}_r, \hat{\theta}_r)$ should be updated as follows:

$$(\hat{x}_r, \hat{y}_r, \hat{\theta}_r) \leftarrow (\hat{x}_r + \Delta x,\ \hat{y}_r + \Delta y,\ \hat{\theta}_r + \Delta\theta) \tag{11}$$

The matching process from (3) through (11) should be repeated until the matching error (9) becomes smaller than a predefined value.

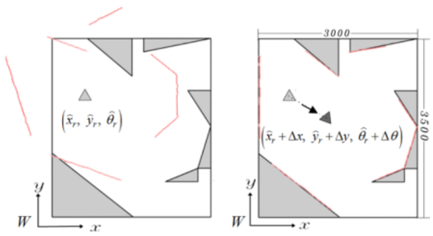


(a) Before matching (b) After matching

Fig. 5. Matching algorithm

4 Experiments

To verify the performance of the proposed matching algorithm and the result of localization, experiments are conducted by using an array of ranging system based on the laser structured-light. Fig. 6 shows the result of the map matching and the localization algorithm. The omnidirectional distance data measured at an unknown robot posture is depicted by red line segments in Fig. 6 (a) and the resultant robot posture after the matching is represented by a dark triangle in Fig. 6 (b). The amount of transformation to update the robot posture is $(\Delta x, \Delta y, \Delta\theta) = (630.0, 320.0, 16.54°)$ from the matching algorithm.



(a) Before matching (b) After matching and update

Fig. 6. Data matching and the self-localization

5 Conclusion

For the localization of a mobile robot in unknown environment, a ranging sensor is required to measure a distance to an environmental object. The active ranging sensor based on the structured-light image obtains a set of distance data on a laser stripe. In order to match the measured distance with an environment object map given in the form of line segments, line segments should be extracted from the measured data set. In this paper, an efficient line extraction and a matching algorithm are proposed based on a least-squared error. The matching algorithm developed in this paper to associate between line segments extracted from the measured omnidirectional distance data and polygonal model of the global object map. Since the matching algorithm used only two end points of a line segment to associate with an edge of the polygonal model, it is efficient in computation than a conventional point to point matching algorithm. The proposed line extraction and matching algorithms were verified through experiments by using ranging sensors based on the structured-light image.

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