Active Ranging Sensors Based on Structured Light Image for Mobile Robot

Jin Shin and Soo-Yeong Yi

Abstract In this paper, we propose a ring array of active structured light image-based ranging sensors for a mobile robot. Since the ring array of ranging sensors can obtain omnidirectional distances to surrounding objects, it is useful for building a local distance map. By matching the local omnidirectional distance map with a given global object map, it is also possible to obtain the position and heading angle of a mobile robot in global coordinates. Experiments for omnidirectional distance measurement, matching, and localization were performed to verify the usefulness of the proposed ring array of active ranging sensors.

1 Introduction

Localization is the estimation of current position and heading angle, i.e., the posture of the mobile robot. Ranging sensors for the measurement of distances to surrounding objects are required for localization. There exist many kinds of ranging sensors, such as ultrasonic sensors, infrared laser sensors, laser scanners, stereo cameras, and active structured light image-based sensors [1]. Among these sensors, the structured light image-based sensor can effectively acquire distance

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information [2]. Bulky laser equipment and long image processing time have discouraged the use of the structured light image-based method in the past, but recent advancements in semiconductor laser equipment and faster processors have made this system more viable and economical.

In this paper, a new ring array of ranging sensors is presented for the localization of a mobile robot. The ring array sensor has four active structured light image-based ranging sensors attached to the mobile robot. It is clear that omnidirectional distance acquisition is much more useful for a mobile robot than unidirectional distance acquisition. A ring array structure of ranging sensors that covers all directions had been used with ultrasonic ranging sensors [1]. In case of the ultrasonic ring array of sensors, however, it is impossible to activate multiple ultrasonic sensors at the same time because of signal crosstalk, which slows the distance measurement rate. In contrast, the structured light image-based sensors in a ring array can measure omnidirectional distances in one shot, without any mutual interference. To alleviate the computational burden in the main controller of a mobile robot, we developed structured light image-based ranging sensor modules by embedded image processor and arranged them in a circular pattern on the mobile robot. Each ranging sensor module transmits distance data to the main controller of the mobile robot after structured light image processing, and the main controller estimates the posture of the robot by matching the omnidirectional distance data with a given global object map.

2 Structured Light Image-Based Distance Measurement with a Ring Array

As shown in Fig. 1, a structured light image-based ranging sensor consists of a camera and a structured light source. In order to obtain horizontal object distances under the assumption of robot motion on two-dimensional ground, a horizontal sheet of structured laser light is used in this study. By using the time difference of two images with modulated structured laser light, it is possible to extract the structured light pixel image, as shown in Fig. 2 [3].

Figure 2 shows the image illuminated by structured light and the extracted structured light pixel image obtained through image processing. From the center line of the image in Fig. 2b, structured light pixel distance p is detected in the vertical direction. From the pixel distance p, measurement angle ρ is given as follows:

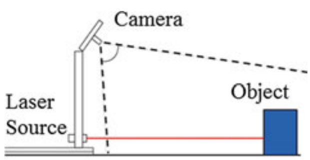


Fig. 1 Distance measurement based on structured light image

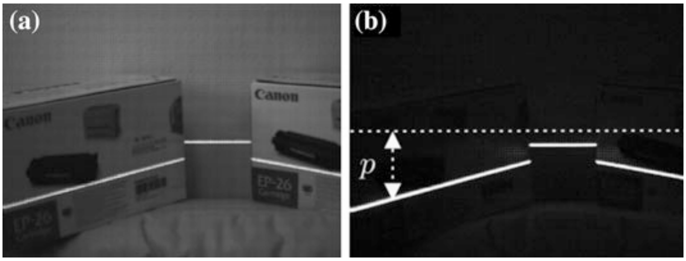


Fig. 2 Extraction of structured light pixel image: **a** structured light image. **b** Extracted structured light pixel image (*solid line*)

$$\rho = \tan^{-1}\left(\frac{p}{\lambda}\right) \tag{1}$$

where λ represents the focal length of the camera. From the distance measurement model in Fig. 3a, the distance l to an object can be obtained as follows:

$$l = b \cdot \cot\left\{\theta - \tan^{-1}\left(\frac{p}{\lambda}\right)\right\} \tag{2}$$

In Fig. 3a, λ is the camera focal length, θ represents the camera view angle, and b denotes the baseline.

The well-known CMUcam3 [4] and a 660 nm wavelength infrared semiconductor laser are adopted to develop the structured light image-based ranging sensor module. The embedded processor in CMUcam3 performs all of the image processing and only transmits the distance data to the main controller of the robot. Figure 3b shows the ring array of the ranging sensor modules attached to the mobile robot, which can measure omnidirectional object distances.

3 Posture Estimation from Omnidirectional Distance

From the structured light pixel images of the ranging sensor array shown in Fig. 4 and Eq. (2), it is possible to acquire a local omnidirectional distance map, as

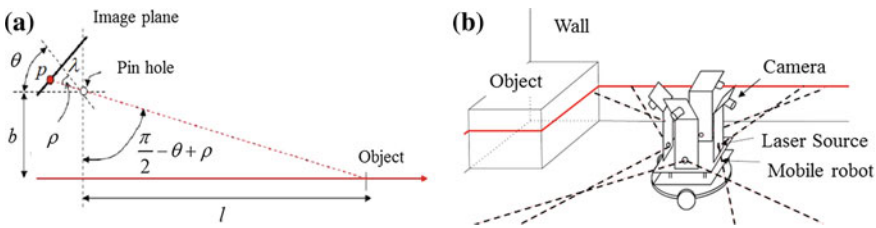


Fig. 3 Distance measurement model and omnidirectional ranging through ring array. **a** Distance measurement model. **b** Ring array of ranging sensor module

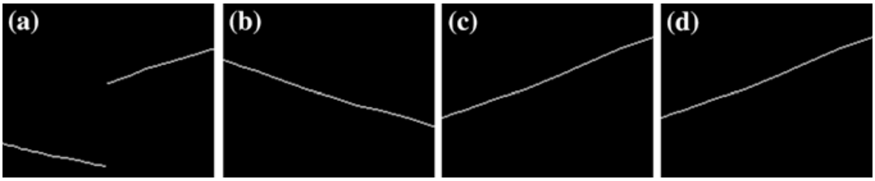
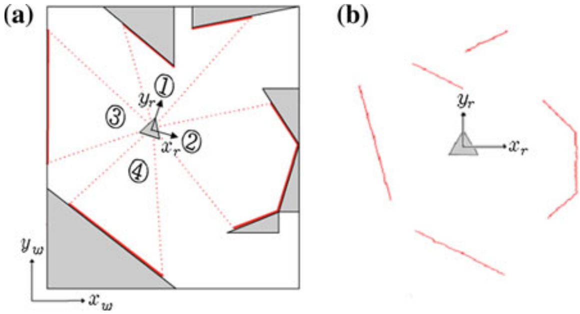


Fig. 4 Structured light pixel images from ranging sensor array. **a** From camera 1. **b** From camera 2. **c** From camera 3. **d** From camera 4

Fig. 5 Omnidirectional distance data. **a** Mobile robot environment. **b** Measured local distance map



shown in Fig. 6. In Fig. 5a, the circled numbers denote each camera in the ring array corresponding to each image in Fig. 4. Figure 5b shows the local distance map in the moving coordinates of the mobile robot. The local distance map consists of a set of measured points (x_m, y_m) in the moving coordinates. When the estimated posture of the robot is $(\widehat{x}_r, \widehat{y}_r, \widehat{\theta}_r)$ in world coordinates, the measured local distance data can be transformed into world coordinates as follows:

$$\begin{bmatrix} x_w \\ y_w \end{bmatrix} = R\left(\widehat{\theta}_r\right)\begin{bmatrix} x_m \\ y_m \end{bmatrix} + T\left(\widehat{x}_r, \widehat{y}_r\right) \tag{3}$$

where $R(\theta)$ and $T(x, y)$ represent the rotation and translation, respectively, as follows:

$$R(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}, T(x, y) = \begin{bmatrix} x \\ y \end{bmatrix} \tag{4}$$

Posture estimation should be updated by matching the real-time omnidirectional distance map with a given global object map. There have been many studies of the matching problem. In [5] and [6], a least-squared-error-based matching algorithm was suggested to associate real-time distance data with a given global map. Since the matching algorithm considers every measured points individually, it requires a significant number of computations. In order to improve computational efficiency, a matching algorithm is developed in this paper by modifying the algorithms in [5] and [6]: line segments are obtained from the measured local

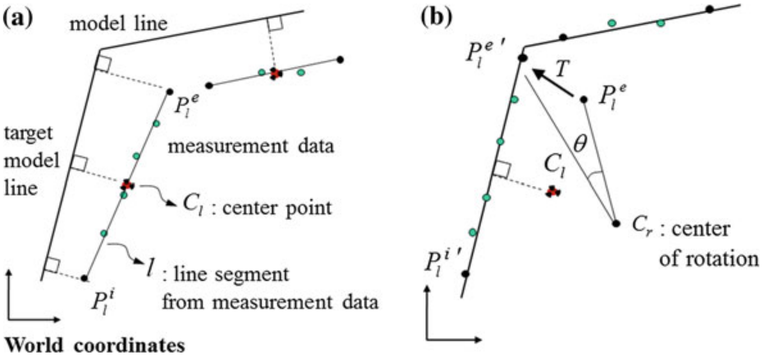


Fig. 6 Matching algorithm. **a** Before matching. **b** After matching

distance map first and only two end points of a line segment are matched with the global map, rather than all of the measured points.

The matching algorithm is described in Fig. 6 where P_l^t and P_l^e denote the two end points of a line segment l from the measured local distance map and $P_l^c = \left(P_l^i + P_l^e\right)/2$ is the center point of the segment. Here, we assumed that those points are described in world coordinates by the transformation (3). Among the all model line segments from the given global map, the target model line segments nearest to the center point of a segment can be found. The target line segment satisfies the following (5).

$$P \cdot \mathbf{u}_l = r_l. \tag{5}$$

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

Rotation by $\Delta\theta$ about the present estimated position, $C_r = \left[\widehat{x}_r \quad \widehat{y}_r\right]^t$, of the robot and translation by $(\Delta x, \Delta y)$ makes two end points of segment l as follows:

$$P_l^{'} = R(\Delta\theta)(P_l - C_r) + C_r + T(\Delta x,\, \Delta y). \tag{6}$$

where P_l and $P_l^{'}$ represent two end points before and after the transformation in world coordinates. Then, the total matching error is defined by the sum of the squared distance between the transformed points $P_l^{'}$ of the all line segments l and the target line (5) as follows:

$$S = \sum_l \left(P_l^i \cdot \mathbf{u}_l - r_l\right)^2 + \left(P_l^e \cdot \mathbf{u}_l - r_l\right)^2 \tag{7}$$

By the well-known gradient method to minimize the total matching error (7), it is possible to get the transformation parameters, $(\Delta x, \Delta y, \Delta\theta)$, which is used to update the estimation of robot's posture as follows:

$$(\widehat{x}_r, \widehat{y}_r, \widehat{\theta}_r) \leftarrow (\widehat{x}_r + \Delta x,\ \widehat{y}_r + \Delta y,\ \widehat{\theta}_r + \Delta\theta) \tag{8}$$

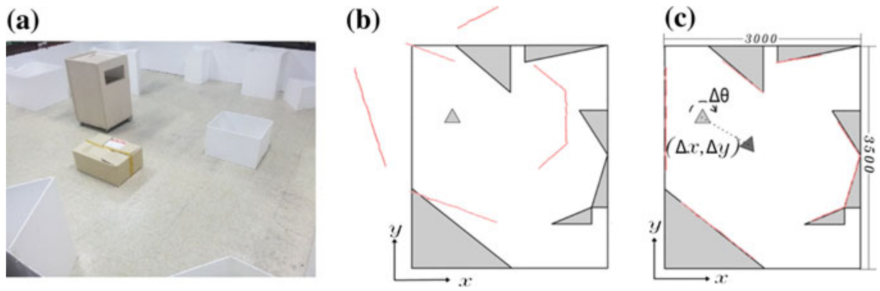


Fig. 7 Data matching experiment. **a** Experimental environment. **b** Before matching. **c** After matching

4 Experimental Results

We performed experiments to verify the effectiveness of the proposed ring array ranging sensor and the matching algorithm. As shown in Fig. 7a, some polygonal objects are placed in the mobile robot's environment. The omnidirectional distance data measured at an unknown robot posture are depicted in Fig. 7b, c and shows the resultant robot posture after matching and updating by the algorithm described in (5) through (8). In Fig. 7b, the transformation parameters to update the robot's posture are $(\Delta x, \Delta y, \Delta\theta) = (630, 320, 16.54°)$, as obtained from the matching algorithm.

5 Conclusion

The ring array of the structured light image-based ranging sensors proposed in this paper is able to obtain omnidirectional distances in one shot for fast localization of a mobile robot. Compact cameras with embedded processors used for the ring array of the ranging sensor in this paper send only final distance data to the main controller of the robot, thereby lowering its computational burden. Matching between the omnidirectional distance data from the proposed ranging sensors and the given global object map is required for localization of the mobile robot. A least-squared error-based algorithm was developed in this paper to associate line segments extracted from the omnidirectional distance data with the polygonal model of the global object map. Since the matching algorithm in this paper uses only two end points of a measured line segment to associate with the reference line segment of the polygonal world model, efficiency of computation is greatly improved. The proposed ring array of active structured light image-based ranging sensors and the matching algorithm in this paper were verified through experiments on local omnidirectional distance data acquisition, localization.

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