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이동로봇 항법용 형상지도 작성 및 형상의 위치불확실성 평가

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Building a Feature Map and Uncertainty Evaluation of a Feature Position for Mobile Robot Navigation

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ABSTRACT

Abstract A new feature-based map building model that uses only the footprints of sparse sonar data has been developed and implemented. An arc feature association model was developed, which associates two sonar footprints into an arc feature. The association model provides information on the regions of canter points of the arc feature. The information makes it possible to decide weather the two sonar footprints are associated with a line, point or arc. Lines, points, or arc features are extracted from more than two independent sonar footprints using the arc feature association model. We also propose a method that estimates the position uncertainties of the extracted features by considering both the pose uncertainty of the robot and the measurement uncertainty of the sonar sensor. This pose uncertainty is also used in the arc feature association process of the sonar footprints. The proposed method has been tested in a real home environment with a mobile robot.

Key words : Feature-based map building, sonar sensors, arc feature association, position uncertainty.

I. INTRODUCTION

The vital functions for mobile robot navigation are representation of a robot's environment, localization, and path planning. In most cases, representation of environment can be a basis of localization and path planning because it can provide the information on the location of objects. Building a sonar map from sonar range readings is the most common approach for the representation of the environment.

A sonar sensor can give direct depth information on the location of an object, but it suffers from a multipath phenomenon due to the effect of a specular reflection of a sonar beam[1]. This phenomenon together with a wide beam aperture

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makes it difficult to decide the location of objects from a single sonar measurement.

There are two different approaches to build a sonar map. The first one is the grid based sonar map in which the environment is sub-divided into several 2-D or 3-D cells. Each cell is represented by the probability of being occupied by an object [2]. A Bayesian updating model[3] and orientation updating model[4,5] are the typical ones for grid map building methods. The grid map is very efficient to represent the location of objects easily, but it needs a large amount of memories to build and maintain a map of wide space.

The other one is the feature-based map building method in which the environment is modeled by a set of geometric primitives such as lines, points and arcs. Crowley developed one of the earliest feature-based approaches to sonar, introducing the concept of the composite local model [6]. The composite local model is built by extraction straight-line segments from sonar data, and is matched to a previously stored global line segment map to provide localization. Christensen et al. developed TBF (Triangulation-based fusion) of sonar data [7]. This algorithm delivers stable natural point landmarks. Choset et al. developed ATM (Arc Transversal Median) and arc carving algorithm [8]. ATM and arc carving fuse multiple sonar readings to improve azimuth resolution.

A rotating sonar scanner has been used by Leonard and Durrant-Whyte to obtain densely scanned sonar data[9]. A simple threshold technique was presented to extract RCDs (Regions of Constant Depth) that were used to make the features such as lines and points.

In this paper, a feature-based map building model that uses only the footprints of sparse sonar data is presented. An arc feature association model is developed, which associates two sonar footprints into an arc feature. The association model provides information on the regions of canter points of the arc feature. This information makes it possible to decide weather the two sonar footprints are associated with a line, point or arc.

The position uncertainty of the feature is then estimated by considering pose uncertainty of the robot together with the measurement uncertainty of the sonar sensor. This pose uncertainty is also used in the arc feature association model.

II. DATA ASSOCIATION MODEL

2.1 Arc feature Association (Footprint-to-Footprint Association)

Sonar range readings generally have large amount of angular uncertainty because of the wide effective beam width. In addition, a sonar sensor can open gives a false reading due to the specular reflection. Association of more than two sonar readings is, therefore, very important in order to reduce the uncertainties of sonar data. A typical sonar footprint is illustrated in Fig. 1. θ_l and θ_u represent the minimum and maximum angles, r is the range, and β the effective beam width of the sonar sensor.

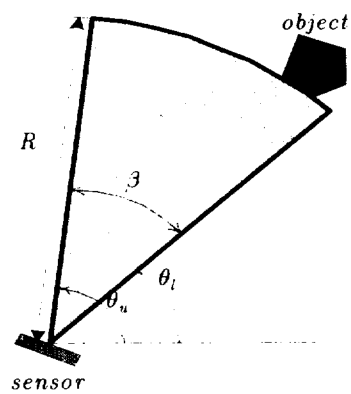

Fig. 1 Sonar footprint.

Fig. 2 shows sonar footprints corresponding to each type of target. Sonar footprints which correspond to a plane or cylinder should be all tangent to the plane or the cylinder. Sonar footprints that correspond to a corner or edge should all intersect in a point at the corner or edge. These are the data association constraints for each type of a feature. For the point or arc feature visible angles are defined as shown in the Fig. 2 and for line feature visible direction is defined.

Fig. 3 shows how to associate two different sonar readings into an arc feature. z_1 and z_2 are the range values of the two sonar footprints. d is the separation between the two sensor locations. According to the data association constraints shown in Fig. 2 there should be at least one circumcircle of two sonar footprints if the two footprints correspond to a certain type of feature. Without loss of generation, we can assume the feature is an arc because a line or point can also be considered as a circle. If the feature is a line or a point, there is only one circumcircle, otherwise there are infinite number of circumcircles. In Fig. 3 the dashed line represents the trace of center points of circumcircles that satisfies the angle constraints of the two footprints.

The radius R of circumcircle is calculated using the law of cosines as follows,

$$R = \frac{z_1^2 - z_2^2 - 2d\cos(\phi_1)z_1 + d^2}{2(d\cos(\phi_1) + z_2 - z_1)} \tag{1}$$

where ϕ_1 is the bearing from the origin to the hypothesized center of the circumcircle. We can now set up an arc feature association rules. If R_{min} is very large or infinite, the two footprints are clustered into a line feature. On the other hand, if R_{max} is very small or zero, the footprints are clustered into a point. Otherwise, they are clustered into an arc feature.

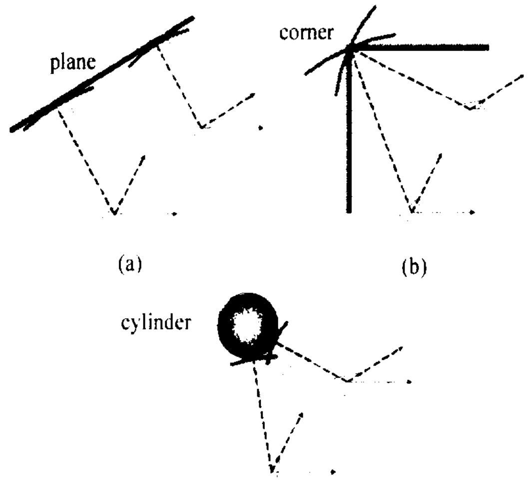

Fig. 2 Sonar footprints corresponding to (a) a plane, (b) a corner, and (c) a cylinder.

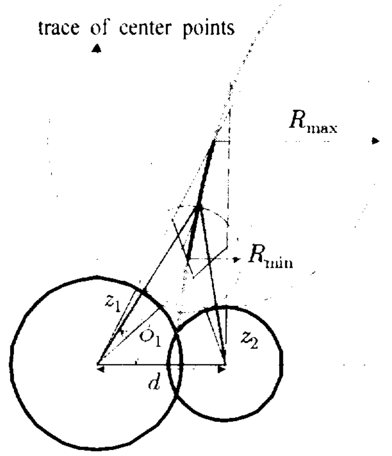

Fig. 3 The arc feature association model

2.2 Footprint-to-Feature Association

Using the arc feature association model stated above, all sonar readings that correspond to the same feature are clustered together. Clusters are promoted to a tentative or confirmed feature according to the number of sonar data that support the same feature. A promoted cluster whether it is tentative or confirmed one no longer need the footprint-to-footprint association, instead it need a footprint-to-feature association.

Footprint-to-feature association is to test whether the footprint is possible or not when it is assumed to be originated from the given feature[9]. This is, if the footprint satisfies the angle and range constrains below, then the footprint-to-feature association is successful.

$$|R-\hat{R}| \le \delta_R \text{ and } \theta_l \le \hat{\theta} \le \theta_u \tag{2}$$

In the above equation, $\hat{R}$ and $\hat{\theta}$ are predicted range and bearing, i.e, predicted footprint, respectively. δ_R and $\hat{\theta}_u$ are the parameters to be designed considering the sensor resolution.

Fig. 4 shows $\hat{R}$ and $\hat{\theta}$ for each type of a feature. The predicted footprint for line feature is computed as,

$$\hat{R} = P_V(P_R - x_s\cos(P_\theta) - y_s\sin(P_\theta)) \tag{3}$$

$$\hat{\theta} = P_\theta \tag{4}$$

where P_V is the visible direction, P_R is the normal distance from the origin to the line, x_s and y_s are the location of sensor, and P_θ is the angle of the plane. For a point feature.

$$\hat{R} = \sqrt{(P_x - x_s)^2 + (P_y - y_s)^2} \tag{5}$$

$$\tan(\hat{\theta}) = \frac{P_y - y_s}{P_x - x_s}, P_x \ne x_s \tag{6}$$

where P_x and P_y are the position of a point feature.

The predicted footprint for an arc feature is given by,

$$\hat{R} = \sqrt{(P_x - x_s)^2 + (P_y - y_s)^2} - P_R \tag{7}$$

$$\tan(\hat{\theta}) = \frac{P_y - y_s}{P_x - x_s}, P_x \ne x_s \tag{8}$$

where P_R is the radius of arc feature.

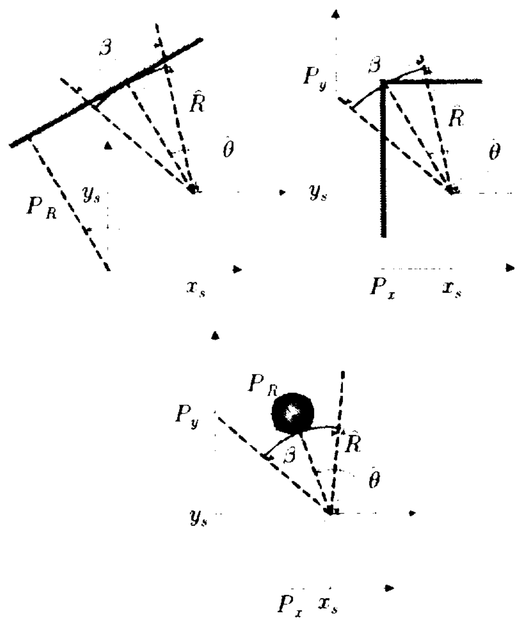

Fig. 4 The predicted footprint corresponding to (a) a plane, (b) a corner, and (c) a cylinder.

III. UNCERTAINTY EVALUATION OF A FEATURE

3.1. Position Uncertainty of a Robot

The position of a robot is represented by (x, y, θ) on a 2 dimensional work space where x and y are the coordinates of robot and θ is the heading of the robot as shown in Fig. 5. In the figure $d(n)$ is the distance increment and $\theta(n)$

is the rotation angle of the robot at $n+1$ step. The position of the robot can be estimated as follows[10].

$$X(n+1) = f(X(n), u(n)) + \omega(n), \quad \omega(n) \sim N(0, Q(n)) \tag{9}$$

where $w(n)$ is a zero mean Gaussian noise with covariance $Q(n)$, $u(n)$ is the control input, and $f(X(n), u(n))$ has of the form;

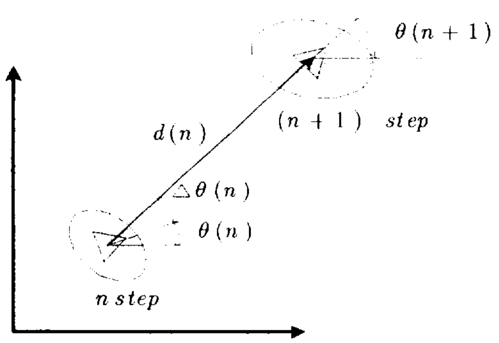

Fig. 5 Position uncertainty of a Robot.

$$f(X(n), u(n)) = \begin{pmatrix} x(n) + d(n)\cos\theta(n) \\ y(n) + d(n)\sin\theta(n) \\ \theta(n) + \Delta\theta(n) \end{pmatrix} \tag{10}$$

The uncertainty associated with this estimation can be represented as the covariance of $X(n+1)$ such that,

$$P(n+1) = JP(n)J^T + Q(n) \tag{11}$$

where J is the Jacobian of Eq. (10)

3.2. Position Uncertainty of a Feature

The position uncertainty of a feature depends on both the measurement uncertainties of the sensor and robot's pose uncertainty as shown in Fig. 6. Measurement uncertainties of the sonar sensing come from the range and angular error. We assume that the range and angular error of sensors are un-correlated each other and zero mean Gaussian noise. We also assume the robot's pose uncertainty and the measurement uncertainties are un-correlated.

The position of a feature shown in Fig. 6 can be written as,

$$X_t = F(x_t, y_t, \theta_t) = \begin{bmatrix} x_r + r\cos(\theta_r + \theta_s) \\ y_r + r\sin(\theta_r + \theta_s) \\ \theta_r + \theta_s \end{bmatrix} \tag{12}$$

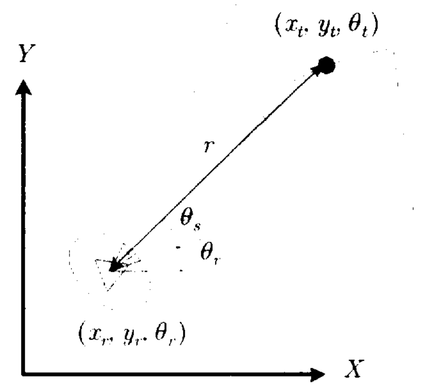

Fig. 6 Position uncertainty of a Feature.

where x_t, y_t, and θ_t are the position and the direction of the feature, r is the sonar range, and θ_s is the relative angle of the sensor to the bearing of the robot. The position of feature can be estimated as,

$$F(\hat{x}_t, \hat{y}_t, \hat{\theta}_t) = \begin{bmatrix} \hat{x}_r + \hat{r}\cos(\hat{\theta}_r + \hat{\theta}_s) \\ \hat{y}_r + \hat{r}\sin(\hat{\theta}_r + \hat{\theta}_s) \\ \hat{\theta}_r + \hat{\theta}_s \end{bmatrix} \tag{13}$$

where hat represent the estimated values. Linearization of Eq. (13) using Taylor Series yields,

$$X_t = F(\hat{x}_t, \hat{y}_t, \hat{\theta}_t) + J\Delta X_t \tag{14}$$

where J is the Jacobian of the Eq. (12) given by,

$$J = \begin{bmatrix} 1 & 0 & -r\sin(\theta_r + \theta_s) & \cos(\theta_r + \theta_s) & -r\sin(\theta_r + \theta_s) & 0 \\ 0 & 1 & r\cos(\theta_r + \theta_s) & \sin(\theta_r + \theta_s) & r\cos(\theta_r + \theta_s) & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix} = (H | K) \tag{15}$$

If we let $\tilde{X}_t$ be the position error of the feature, we can get the covariance matrix, C_t, associated with the estimation as follows.

$$C_t = E\left[\tilde{X}_t \tilde{X}_t^T\right] = JE\left[\Delta X_t \Delta X_t^T\right]J^T = HC_r H^T + KC_s K^T \tag{16}$$

where C_r is the covariance related to the robot's position uncertainty, i.e.,

$$C_r = HP(n)H^T + Q(n) \tag{17}$$

C_s is the covariance of the measurement uncertainty of the sensor given by,

$$C_s = \begin{bmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_{\theta_s}^2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{18}$$

where σ_r is the standard deviation of range error, and σ_{θ_s} is the standard deviation for angular error of the measurement. σ_{θ_s} can be replaced by σ_θ, i.e., the robot's bearing uncertainty, because angular uncertainty of the measurement considering many range data depends only on the robot's bearing uncertainty.

IV. EXPERIMENTAL RESULTS

The map building and uncertainty evaluation methods developed have been implemented and tested in a real home environment with real robot. The robot is Pioneer 3-DX that has a ring of 16 Polaroid ultrasonic sensors. Fig. 7 shows the experimental environment that is composed sofas, tables, chairs, clothes chest, bookshelf, ashtray, and fire extinguisher. The widths of the table legs and the chair legs are about 6 cm and 3 cm respectively. The robot was run following the dashed line in Fig. 7 using remote controller, and no localization was performed.

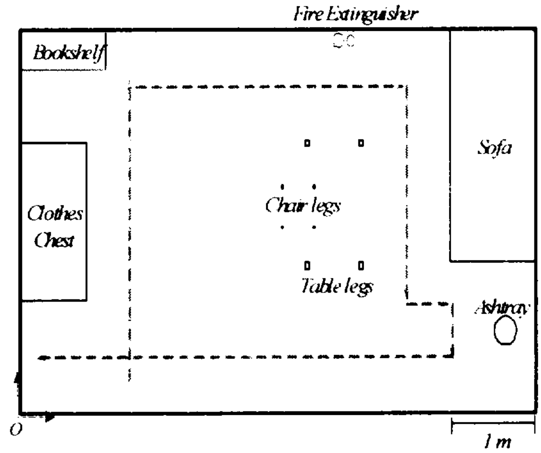

Fig. 7 Configuration of the experimental environment

Fig. 8 shows the results of mapping after the robot made a complete turn in the environment. In the figure, the ellipses represent the position uncertainties of the extracted features. One can see the ashtray is estimated as an arc feature, but the radius error is comparatively large. This is because there were not enough data to estimate the arc feature completely.

There are some unexpected line features in the resulting map. These false line features can be appear when the distance between any two point features is very small. In our experiment, small legs of the table and chair in the middle of the environment were estimated as false line features. Considering the uncertainties of sonar sensors and sparse sonar data, it can be said that the quality of the resulting map is comparatively good for the navigation of the mobile robot.

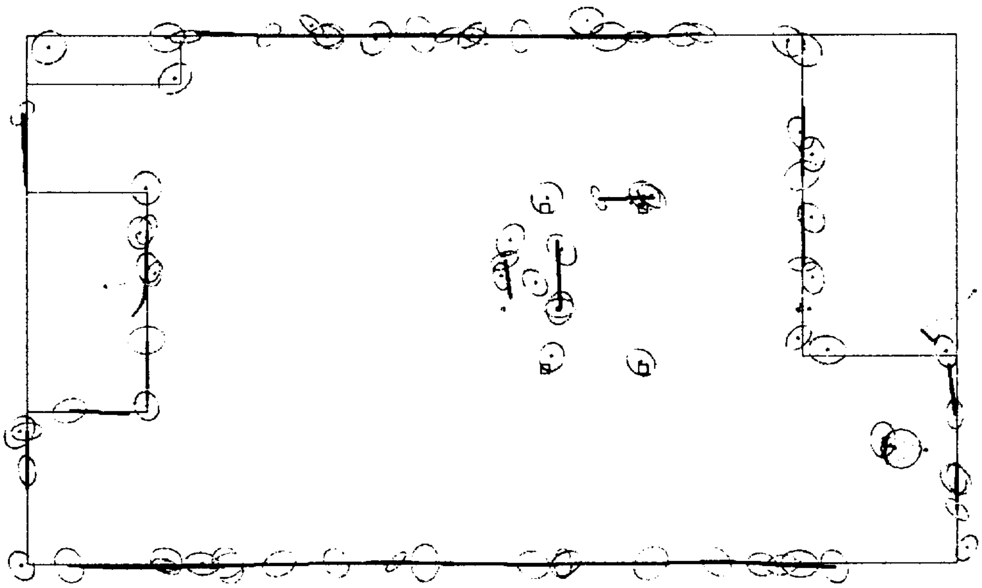

Fig. 8 Results of map building and position uncertainties. (thin lines : true map boundaries, thick lines : line features, points : point features, arcs : arc features, ellipse : position uncertainty)

V. CONCLUSION

A new feature map building method with only sparse sonar data has been developed and implemented. The method is based on an arc feature association model that associates two different sonar footprints together. Using the model some geometric primitives such as line, point, and arc features can be estimated. We also developed the method that estimates the position uncertainty of the extracted feature by combining the pose uncertainty of the robot and the measurement uncertainty of the sensor.

The developed methods were implemented and tested in a real home environment with a real robot. The results have shown that the quality of the resulting map is comparatively good for the navigation of the mobile robot. Consequently, the proposed methods of feature map building and evaluation of position uncertainty can be applied for Simultaneous Localization And Mapping(SLAM) of a mobile robot.

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REFERENCES

1) J. H. Lim and D. W. Cho, 1994, Specular reflection probability in the certainty grid representation, Trans. Of the ASME, vol. 116, pp. 512-520.
2) A. Elfes and H. P. Moravec, 1985, High resolution maps from wide angel sonar, IEEE

REFERENCES

1) J. H. Lim and D. W. Cho, 1994, Specular reflection probability in the certainty grid representation, Trans. Of the ASME, vol. 116, pp. 512-520.

2) A. Elfes and H. P. Moravec, 1985, High resolution maps from wide angel sonar, IEEE Intl. Conf. on Robotics and Automation, pp. 116-121.

3) D. W. Cho, 1990, Certainty grid representation for robot navigation by a Bayesian method, ROBOTICA, vol. 8, pp. 159-165.

4) J. H. Lim and D. W. Cho, 1996, Multipath Bayesian map construction model from sonar data, ROBOTICA, Vol.14, pp.527-540.

5) J. H. Lim, 1994, Map construction, exploration, and position estimation for an autonomous mobile robot using sonar sensors, Ph.D thesis, Pohang Institute of Science and Technology, Korea.

6) J. L. Crowley, 1985, Navigation for an intelligent mobile robot, IEEE Jour. of Robotics and Automation, RA-1(1), pp. 31-41.

7) O. Wijk and H. I. Christensen, 2000, Triangulation-based fusion of sonar data with application in robot pose tracking, IEEE Trans. on Robotics and Automation, vol. 16, no. 6, pp. 740-752.

8) K. Nagatani, N. A. Lazar, and H. Choset, 1999, The arc-transversal median algorithm: an approach to increasing ultrasonic sensor accuracy, IEEE Int. Conf. on Robotics and Automation, pp. 644-651.

9) J. J. Leonard, Direct sonar sensing for mobile robot navigation, Kluwer Academic Publishers, 1992.

10) Y. Bar-Shalom and T. E. Fortmann, 1988, Tracking and data association, Academic Press.