Map generation in unknown environments by AUKF-SLAM using line segment-type and point-type landmarks

Sho Nishihta, Shoichi Maeyama, and Keigo Watanebe,

Graduate School of Natural Science and Technology, Okayama University,
3-1-1 Tsushima-naka, Kita-ku, Okayama 700-8350 Japan

nishihata-s@usmm.sys.okayama-u.ac.jp, {maeyama, watanabe}@sys.okayama-u.ac.jp

Abstract. Recently, autonomous mobile robots that collect information at disaster sites are being developed. Since it is difficult to obtain maps in advance in disaster sites, the robots being capable of autonomous movement under unknown environments are required. For this objective, the robots have to build maps, as well as the estimation of self-location. This is called a SLAM problem. In particular, AUKF-SLAM which uses corners in the environment as point-type landmarks has been developed as a solution method so far. However, when the robots move in an environment like a corridor consisting of few point-type features, the accuracy of self-location estimated by the landmark is decreased and it causes some distortions in the map. In this research, we propose AUKF-SLAM which uses walls in the environment as a line segment-type landmark. We demonstrate that the robot can generate maps in unknown environment by AUKF-SLAM, using line segment-type and point-type landmarks.

1. INTRODUCTION
In recent years, the development of an autonomous mobile robot that gathers information at disaster sites has been actively developed. It is difficult to give the map in advance in disaster sites where people cannot enter. Therefore, the robot needs to realize autonomous behavior not only in known environments with maps but also in unknown environments without maps. In order to enable robots to move under unknown environments, it needs to estimate the self-location, as well as to generate the map. This is called a Simultaneous Localization and Mapping (SLAM) problem[1][2]. As a method to solve the SLAM problem, an Extended Kalman Filter (EKF) and an Unscented Kalman Filter (UKF) which adopt stochastic concept, and an Augmented UKF (AUKF) was also proposed so as to treat systematic errors included in odometry, such as measurement errors in a wheel diameter and a tread are proposed[3][4]. In these methods, features in the environment such as corners where walls vertically intersect are registered as landmarks. Whenever the robot moves, it acquires a landmark and corrects the self-location from the positional relationship between the robot and the landmark. However, when the robot moves in an environment like a corridor consisting of few point-type features, the robot decreases the accuracy in the estimation of self-location and creates a distorted map.

There are several researches using line segments in SLAM research[5][6][7][8]. Therefore, the robot registers the wall as a landmark, which is the feature of the line segment in the environment, and uses it for the estimation of self-location. In this research, the present SLAM is assumed to use an AUKF indoors, and adopts walls as landmarks, as well as corners. Experiments are conducted using an
autonomous mobile robot, and it is verified that the line segment-type landmark is useful. In this paper, a SLAM problem is first described using an AUKF. A conventional point-type landmark and the proposed line segment-type landmark are next explained. Finally, experiments using an actual mobile robot are conducted to check the usefulness of the line segment-type landmark.

2. SLAM solution method using AUKF

Figure 1 shows the proposed AUKF-SLAM model. In figure 1, \((x_t, y_t, \theta_t)\) is the position and posture of the robot at time \(t\), \((R_R, R_L, T, S)\) are the right wheel radius, the left wheel radius, the tread, and the sensor mounting offset. Let the \(i\)th landmark information of the corner estimated by the robot be \((l_{xi}, l_{yi}, l_{si})\). Also, let the \(k\)th landmark information of the wall estimated by the robot be \((l_{x1k}, l_{y1k}, l_{x2k}, l_{y2k})\). Then, using the position, orientation and kinematic parameters of the robot and the landmark information, the state \(x_t\) of the robot is expressed by

\[
x_t = (x_t, y_t, \theta_t, R_R, R_L, T, S, l_{xi}, l_{yi}, l_{si}, \ldots, l_{x1k}, l_{y1k}, l_{x2k}, l_{y2k}, \ldots)
\]  

(1)

The state \(x_t\) is represented by the mean and covariance of a normal distribution to reduce the influence by noise. In the AUKF, those values are corrected by prediction and updating, and the appropriate estimated values are calculated. The following equations are defined as the motion model and the measurement model, respectively, which are necessary for estimation.

\[
x_t = g(u_t, x_{t-1}) + \delta_t
\]  

(2)

\[
z_t = h(x_t) + \epsilon_t
\]  

(3)

\(g\) and \(h\) in each model are nonlinear functions. \(z_t\) is the measured value and \(u_t\) is the control input. \(\delta_t\) is a motion noise vector, and \(\epsilon_t\) is a measurement noise vector. It is assumed that the noise is Gaussian with zero-mean and additively added.

3. Line segment-type and point-type landmarks

The landmark is a feature used by the robot to estimate the self-location and create a map. From the sensor data that measured the environment, the wall is used as a line segment-type landmark, and the corner at which the walls intersect is used as a point-type landmark. Increasing the types of landmarks eliminates the shortage of landmarks to be used by robots for estimation, so that it is thought to be able to cope with any environment. Here, we describe the acquisition method and its measurement model of each landmark.

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3.1. Line segment-type landmark

In the case of using line segment-type landmarks, it needs to group the sensor data into each wall. The grouping method of points is explained with figure 2. Assume that the group A, whose ith point is a terminal, is determined. Compare the group A and a point group, which is composed of from the (i+1)th point to Nnext ahead. If the angle $\theta_{\text{next}}$ formed by two straight lines is less than a threshold value, and the distance $d_{\text{next}}$ between the ith point and the (i+1)th point is less than a threshold value, unify them as a one group. On the other hand, when either $\theta_{\text{next}}$ or $d_{\text{next}}$ exceeds the threshold value, the group from the (i+1)th point is set as a group of different straight lines. After grouping is completed, the position at both ends of the obtained straight line ($l_{x1}$, $l_{y1}$, $l_{x2}$, $l_{y2}$) is registered as a line segment-type landmark.

The relationship between a robot and a line segment-type landmark is shown in figure 3. The measured value $z_t$ obtained from the line segment-type landmark is the distance $r_t$ from the robot to the landmark, and the relative angle $\varphi_t$. Therefore, the measured value is expressed by the following equation.

$$z_t = \begin{bmatrix} r_t \\ \varphi_t \end{bmatrix} \quad (4)$$

Using the position ($x_t$, $y_t$), and attitude $\theta_t$ of the robot, and also using the linear parameters, i.e., (a, b, c) related to the line segment-type landmark, the measurement function $h$ in equation (2) is expressed by the following equation:

$$h = \begin{bmatrix} |ax_t+by_t+c| \\ \sqrt{a^2+b^2} \\ \tan^{-1}\frac{b}{a} - \theta_t \end{bmatrix} \quad (5)$$

Here, the linear parameters a, b, c of the line segment-type landmark used in equation (5) are expressed, using the position at both ends of the obtained straight line ($l_{x1}$, $l_{y1}$, $l_{x2}$, $l_{y2}$), by the following equations:
3.2. Point-type landmark

The position detection of point-type landmarks is explained with figure 4. First, compare the information on the wall acquired when the line segment-type landmark was measured. Next, the angle $\theta_{AB}$ formed between the walls is calculated using the linear parameters of the wall. When the angle $\theta_{AB}$ is around 90 deg, the intersection of the walls is estimated as a point-type landmark. Assuming that a straight line of group A is $a_x x + b_y y + c_A = 0$ and a straight line of group B is $a_x x + b_y y + c_B = 0$, the estimated point-type landmark position $(l_x, l_y)$ is expressed as follows:

$$a = l_y - l_y 1$$
$$b = -(l_x2 - l_x 1)$$
$$c = -(a_l x 1 + b_l y 1)$$

$$l_x = \frac{1}{(a_l x B - a_B x A)[a_B c_A - a_A c_B]} [b_A c_B - b_B c_A]$$

The relationship between the robot and a point type landmark is shown in figure 5. The measured value $z_t$ obtained from the point-type landmark is the distance $r_t$ from the robot to the landmark, the relative angle $\phi_t$ and its direction $s_t$. Therefore, the measured value is expressed by the following equation:

$$z_t = \begin{bmatrix} r_t \\ \phi_t \\ s_t \end{bmatrix}$$

The measurement function $h$ is expressed, using the position $(x_t, y_t)$, the attitude $\theta_t$ of the robot and the position $(l_x, l_y)$ and the direction $l_s$ of the point type landmark, by the following equation:

$$h = \sqrt{((l_x - x_t)^2 + (l_y - y_t)^2)}$$

$$\tan^{-1}\left(\frac{y_t - y_1}{l_x - x_1}ight) - \theta_t$$

4. Experiments

Figure 6 shows the robot used in this research. The experimental robot is a front wheel steering type mobile robot driven by a rear wheel. An encoder is attached to the driving wheels, and an odometry is calculated based on the information. The size of this robot is 85 cm in length, 60 cm in width and 65 cm in height. The mounted sensor has a 30 m range and 0.25 deg angular resolution from -135 deg to 135 deg.
The mobile robot autonomously moved in the environment composed of few point-type features. The robot does not possess the map information in advance, and automatically follows the route generated by using the DT method. Then, the robot carries out SLAM using only point-type landmarks, and similarly does SLAM using line segment-type and point-type landmarks, and then, the performances are compared each other. The robot corrects the self-location and updates a map every 250 ms.

Figure 7 shows a search result using only point-type landmarks. Since there were few point-type features, the robot was not able to correct the self-location when moving through the corridor. As a result, the map was distorted. The distortion was accumulated, so that the robot was not able to create a closed map. Consequently, the route was not able to be generated due to the gap between the map and the sensor data, and the robot was left in the unknown environment. On the other hand, figure 8 shows a map generated using both line segment-type and point-type landmarks. The self-location of the robot was able to be corrected from the wall by using a line segment-type landmark. For this reason, the distortion that occurred during the turning motion and the translational motion was corrected. As a result, the robot succeeded in searching for an unknown environment while generating a map without blocking the route.
Figure 9. The standard deviations of estimated parameters

The standard deviation of self-location is shown in figure 9. The standard deviations of $x$, $y$, and $\theta$ are increasing with lapse of time. Comparing the standard deviations of $x$ and $y$, it is found that the former is larger than the latter. In this environment, the robot is always moving along the wall. When using line segment-type landmarks, the robot estimates them in the direction perpendicular to the wall. Therefore, it was impossible to estimate them sufficiently in the $x$ direction where few walls exist. On the other hand, since the wall always existed in the $y$ direction, it is considered that the standard deviation of $y$ became smaller than that of $x$. There were many changes in the standard deviation of $\theta$ because the orientation of the robot changed frequently due to the turning motion and the adjustment for following the route. However, it was confirmed that the increase in the standard deviation of $\theta$ was suppressed by the correction using the line segment-type landmark. Furthermore, in near 470 s, the self-location was greatly corrected and the standard deviations became small by remeasuring the highly reliable landmark detected at the start. It was confirmed by this experiment that the line segment-type landmark was very useful in the environment where it was difficult to obtain the point-type features.

5. Conclusion
In this paper, we have described AUKF-SLAM, line segment-type and point-type landmarks. Next, we conducted experiments using an actual robot and verified that line segment-type landmarks were useful. In the future, we will conduct an experiment to verify the estimated kinematic parameters of the robot.

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