Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-22 (2016) 303–308

Multi-robot SLAM via Information Fusion Extended Kalman Filters

Toshiki Sasaoka * **Isao Kimoto** * **Yosuke Kishimoto** ** **Kiyotsugu Takaba** ** **Haya Nakashima** ***

* *Graduate School of Science and Engineering, Ritsumeikan University*
** *College of Science and Engineering, Ritsumeikan University 1-1-1 Noji-higashi, Kusatsu, Shiga, 525-8577 Japan (e-mail: ktakaba@fc.ritsumei.ac.jp)*
*** *Graduate School of Engineering, Osaka University*

Abstract: This paper is concerned with Simultaneous Localization and Mapping (SLAM) problem with multiple mobile robots. Each robot detects landmarks and other robots, and estimates their positions by the extended Kalman filters. To achieve good estimation accuracy, an optimal information fusion technique is adapted to the multi-robot SLAM problem. This technique involves the minimization of the estimation error covariance by weighted averaging of the state estimates from the extended Kalman filters. Simulation and experimental results are included to show the effectiveness of the present method.

Keywords: multi-agent system, SLAM, information fusion, extended Kalman filter

1. INTRODUCTION

In the last decades, a lot of attention has been paid to control of mobile robots in uncertain environment (see e.g. Thrun, Bugard and Fox (2006)). In particular, it has been a central issue to develop algorithms for a mobile robot to obtain precise information on both of its position and its environment. Such a problem is called *Simultaneous Localization And Mapping (SLAM)*. There have been a number of works reported on the SLAM with a single mobile robot (e.g. Whyte and Bailey (2006)). The estimation accuracy of the single-robot SLAM may often be degraded in some situations where, for example, some landmarks cannot be detected because of obstacles.

A method for overcoming this difficulty is to use multiple robots which cooperatively estimate their positions and the locations of landmarks. There have been several works reported on the SLAM algorithms using multiple robots (Howard (2006); Gil et al. (2010)). In most of the previous works, the base station collects the measurements from all the robots, and estimates the locations of the robots and landmarks. In this paper, we take another approach for the multi-robot SLAM problem based on the information fusion technique due to Sun and Deng (2004). The mobile robots carry out the extended Kalman filter based on their individual measurements, and send the estimated locations to the base station. The base station generates the optimal estimates by minimizing the estimation error covariance of a weighted average of the received estimates. The advantage of the present approach is to make use of the computational resource of the mobile robots.

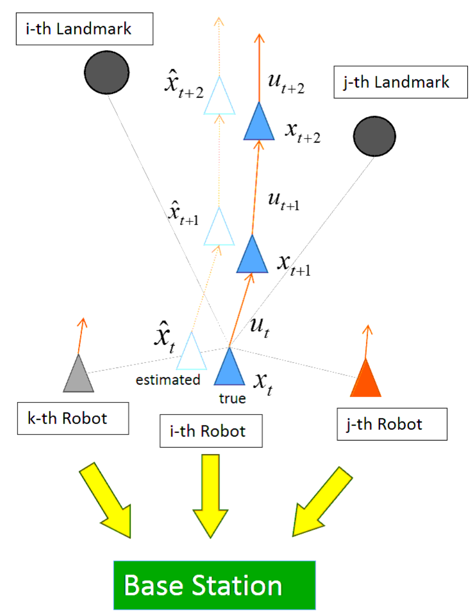

Fig. 1. Multi-robot SLAM Configuration

2. MODELING AND PROBLEM STATEMENT

Consider the system of M mobile robots and N landmarks as shown in Fig. 1.

The purpose of this system is to obtain accurate positions of all landmarks and all robots based on the sensor measurements of the robots. The detailed model of this system is described below.

Firstly, the motion of the i-th mobile robot is typically described by the two-wheeled vehicle model as

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.10.414

$$\dot{x}_i = v_i \cos\theta_i,$$
$$\dot{y}_i = v_i \sin\theta_i,$$
$$\dot{\theta}_i = \omega_i,$$

where $(x_i,\ y_i)$, and θ_i are the x-y coordinates and the heading angle of the i-th robot, and where the translational speed v_i and the angular velocity ω_i are the control inputs. By the Euler approximation, this continuous time model is discretized with sampling period δ as

$$\boldsymbol{x}^i_{\mathrm{r},t+1} = f_{\mathrm{r}}(\boldsymbol{x}^i_{\mathrm{r},t}, \boldsymbol{u}^i_t) + \boldsymbol{w}^i_{\mathrm{r},t}, \tag{1}$$

where

$$\boldsymbol{x}^i_{\mathrm{r},t} = \begin{bmatrix} x_i(t\delta) \\ y_i(t\delta) \\ \theta_i(t\delta) \end{bmatrix},\quad \boldsymbol{u}^i_t = \begin{bmatrix} v_i(t\delta) \\ \omega_i(t\delta) \end{bmatrix},$$
$$f_{\mathrm{r}}(\boldsymbol{x}^i_{\mathrm{r},t}, \boldsymbol{u}^i_t) = \begin{bmatrix} x_{i,t} + \delta v_{i,t}\cos\theta_{i,t} \\ y_{i,t} + \delta v_{i,t}\sin\theta_{i,t} \\ \theta^i + \delta\omega_{i,t} \end{bmatrix},\quad t = 0,1,2,\ldots$$

We have added the white Gaussian noise $\boldsymbol{w}^i_{\mathrm{r},t}$ with mean zero and covariance Q_i in order to apply the EKF method. Putting together the states of all robots, we obtain

$$\boldsymbol{x}_{\mathrm{r}t} = \begin{bmatrix} \boldsymbol{x}^1_{\mathrm{r},t} \\ \boldsymbol{x}^2_{\mathrm{r},t} \\ \vdots \\ \boldsymbol{x}^M_{\mathrm{r},t} \end{bmatrix},\quad \boldsymbol{u}_t = \begin{bmatrix} \boldsymbol{u}^1_t \\ \boldsymbol{u}^2_t \\ \vdots, \\ \boldsymbol{u}^M_t \end{bmatrix}.$$

Denote the x-y coordinates of the j-th landmark with $\boldsymbol{x}^j_{\mathrm{m}} = [\, x_{\mathrm{m}j}\ \ y_{\mathrm{m}j} \,]^\top$ to get

$$\boldsymbol{x}_{\mathrm{m},t} = \begin{bmatrix} \boldsymbol{x}^1_{\mathrm{m}} \\ \boldsymbol{x}^2_{\mathrm{m}} \\ \vdots, \\ \boldsymbol{x}^N_{\mathrm{m}} \end{bmatrix}.$$

Noting that every landmark does not move, w obtain the state equation

$$\boldsymbol{x}_{t+1} = f(\boldsymbol{x}_t, \boldsymbol{u}_t) + \boldsymbol{w}_t, \tag{2}$$

where

$$\boldsymbol{x}_t = \begin{bmatrix} \boldsymbol{x}_{\mathrm{r}t} \\ \boldsymbol{x}_{\mathrm{m}t} \end{bmatrix},\ f(\boldsymbol{x}_t, \boldsymbol{u}_t) = \begin{bmatrix} f_{\mathrm{r}}(\boldsymbol{x}_{\mathrm{r},t}, \boldsymbol{u}_t) \\ \boldsymbol{x}_{\mathrm{m}t} \end{bmatrix},\ \boldsymbol{w}_t = \begin{bmatrix} \boldsymbol{w}_{\mathrm{r},t} \\ \boldsymbol{0} \end{bmatrix}.$$

It may be noted that the noise $\boldsymbol{w}_t$ on the right-hand side of (2) is still a zero mean Gaussian white noise process with covariance $Q := \mathrm{diag}(Q_1, \ldots, Q_M,\ 0)$.

We next model the observation equation of the i-th robot. The i-th robot observes the information on the relative distances and directions of the landmarks as

$$h_{\mathrm{M}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{m}}) = \begin{bmatrix} r_{\mathrm{M}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{m}}) \\ \varphi_{\mathrm{L}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{m}}) \end{bmatrix} : \mathbb{R}^3 \times \mathbb{R}^2 \to \mathbb{R} \times \mathbb{R} \tag{3}$$

$$r_{\mathrm{M}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{m}}) = \sqrt{(x_i - x_{\mathrm{m}j})^2 + (y_i - y_{\mathrm{m}j})^2} \tag{4}$$

$$\varphi_{\mathrm{M}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{m}}) = \tan^{-1}\frac{y_i - y_{\mathrm{m}j}}{x_i - x_{\mathrm{m}j}} - \theta_i \tag{5}$$

In the same way, the j-th robot is observed from the i-th robot as

$$h_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{r}}) = \begin{bmatrix} r_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{r}}) \\ \varphi_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{r}}) \end{bmatrix} : \mathbb{R}^3 \times \mathbb{R}^3 \to \mathbb{R} \times \mathbb{R} \tag{6}$$

$$r_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{r}}) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{7}$$

$$\varphi_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^j_{\mathrm{r}}) = \tan^{-1}\frac{y_i - y_j}{x_i - x_j} - \theta_i \tag{8}$$

It thus follows that the observation of the i-th robot is summarized as

$$\boldsymbol{z}^i_t = \begin{bmatrix} h_{\mathrm{M}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^1_{\mathrm{m}}) \\ \vdots \\ h_{\mathrm{M}}(\boldsymbol{x}_{\mathrm{r}}, \boldsymbol{x}^N_{\mathrm{m}}) \\ \hline h_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^1_{\mathrm{r}}) \\ \vdots \\ h_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^{i-1}_{\mathrm{r}}) \\ h_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^{i+1}_{\mathrm{r}}) \\ \vdots \\ h_{\mathrm{R}}(\boldsymbol{x}^i_{\mathrm{r}}, \boldsymbol{x}^M_{\mathrm{r}}) \end{bmatrix} + \boldsymbol{v}^i_t \tag{9}$$

in short,

$$\boldsymbol{z}^i_t = h_i(\boldsymbol{x}_{\mathrm{r},t}, \boldsymbol{x}_{\mathrm{m},t}) + \boldsymbol{v}^i_t. \tag{10}$$

where $\boldsymbol{v}^i_t$ is the white Gaussian noise with zero mean and covariance R_i.

As a result, the multi-robot SLAM problem is formulated as the problem of estimating the state vector $\boldsymbol{x}_t$ based on the input and measurement data $\{\boldsymbol{u}_k,\ \boldsymbol{z}^1_k, \ldots, \boldsymbol{z}^M_k\}_{k=0,1,\ldots,t}$.

There are two approaches to compute the state estimate $\hat{\boldsymbol{x}}$. The simplest way is to collect all the measurements $\boldsymbol{z}^1, \ldots, \boldsymbol{z}^M$ and $\boldsymbol{u}$ at every time step, and then compute the Kalman filter for the overall system. Since this method requires large computational effort, we employ the second approach: all the mobile robots carry out the Kalman filters based on their individual measurements and send their state estimates to the base station which combines them to obtain the optimal estimate.

In the next section, we will briefly review the optimal information fusion technique for the second approach for a *linear* system (Sun and Deng (2004)).

3. OPTIMAL INFORMATION FUSION FOR MULTI-SENSOR STATE ESTIMATION

3.1 Multi-sensor State Estimation Problem

We wish to estimate the state of a linear discrete-time system defined by

$$\boldsymbol{x}_{t+1} = F_t\boldsymbol{x}_t + B_t\boldsymbol{u}_t + G_t\boldsymbol{w}_t \tag{11}$$

from M sensor measurements

$$\boldsymbol{z}^i_t = H^i_t\boldsymbol{x}_t + \boldsymbol{v}^i_t,\ \ i = 1, 2, \ldots, M,$$

where $\boldsymbol{x}_t \in \mathbb{R}^n$, $\boldsymbol{z}^i_t \in \mathbb{R}^m$, and $\boldsymbol{u}_t \in \mathbb{R}^p$ are the state, output, and inputs at time t. Moreover, $\boldsymbol{w}_t \in \mathbb{R}^r$ and $\boldsymbol{v}^i_t \in \mathbb{R}^m$ are process noise and measurement noise. F_t, B_t, G_t, and H^i_t are time-varying matrices with compatible dimensions.

We make the following assumption.