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Platooning Method for Multiple Mobile Robots Using Laser-Based SLAM

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Abstract: This paper presents a leader–follower platooning method for multiple mobile robots using laser-based simultaneous localization and mapping (SLAM). The leader broadcasts laser scan images and odometry information. The follower builds an occupancy grid map based on the leader's information and estimates leader's tracks using a correlation-based map matching method. Based on the leader's tracks, the follower generates its own target path using a smoothed cubic spline function. The follower is controlled so that it can move along the target path while maintaining a constant gap between itself and the leader. The experimental result of a three-robot platooning in an indoor environment validates the proposed method.

Keywords: Platooning, Formation control, Multi-mobile robots, Laser range sensor, SLAM.

1. INTRODUCTION

Platooning and formation control of multiple mobile robots and vehicles have been studied with much interest in many areas such as intelligent transport system (ITS), material handling system, utilities inspection, environmental surveillance, disaster monitoring, and rescue and scouting operation [1, 2, 3]. In this paper, we focus on a leader–follower type of multiple robot platooning.

In the leader–follower type of a multiple robot platooning, a leader robot navigates a robot team while the other robots, followers, maintain a desired posture (position and orientation) with respect to the leader. To maintain their formation, the followers need information of the posture of the leader relative to them. In most conventional leader–follower approaches, the leader is assumed to be always visible by the follower's sensors such as laser range sensor (LRS) or a vision sensor, and then the relative posture is directly measured by the sensors. However, in the real world, the leader is not always visible to the followers because the robots in the team and objects in environments obscure the leader; this deteriorates platooning performance. To cope with the problem, indirect sensing method such as scan matching and simultaneous localization and mapping (SLAM) [4, 5] are used, in which the leader's posture is indirectly estimated by the follower's sensors.

In this paper, we present a leader–follower platooning of multiple mobile robots using laser-based SLAM. This paper is organized as follows. Section 2 gives an overview of our experimental system. In Sections 3 and 4, we present our methods of robot's posture estimation and control. In Section 5, to validate our method, we describe a platooning experiment using three mobile robots in an indoor environment; we then present our conclusions in Section 6.

2. EXPERIMENTAL SYSTEM

Figure 1 shows the three mobile robots (one leader and two followers). Each robot has two independently-driven-wheels. Each robot is equipped with left and right wheel encoders to measure wheel velocities and a forward-looking LRS to sense environments. The LRS captures laser scan images represented by a sequence of distance samples in an area sweeping 270 [deg] in the horizontal plane. Wireless LAN is used to exchange information among the robots.

3. ROBOT'S POSTURE ESTIMATION USING SLAM

3.1. Overview

We apply occupancy-grid-map-based SLAM [7] to estimate the postures of the leader and followers in a common coordinate frame. We define three maps (Fig. 2): *leader measurement map* (LMM), *follower measurement map* (FMM), and *environmental map* (EM). In our experiments, we set the cell size at 0.2 [m] × 0.2 [m]. Robot postures are estimated by the following five steps:

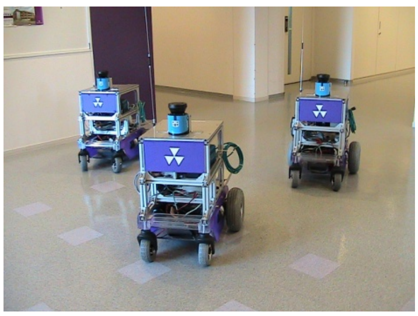

Fig. 1 Overview of mobile robots

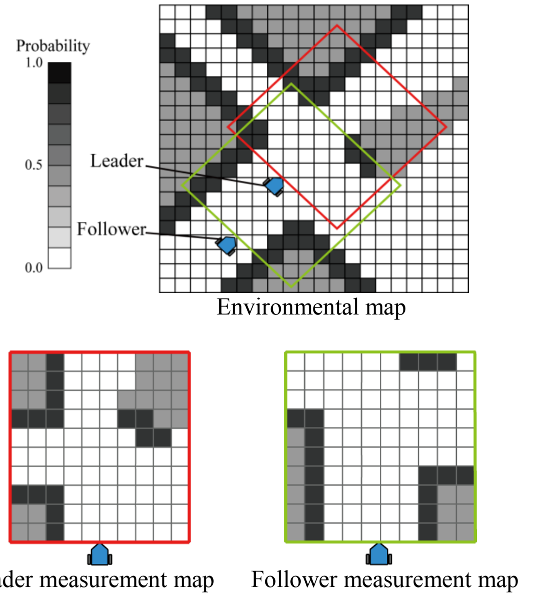

Fig. 2 Grid map. Darker cell indicates the cell occupied by static objects with a higher probability.

Step 1: Broadcast of the leader's sensor data

The leader broadcasts laser scan images obtained by its own LRS and odometry information to the followers.

Step 2: LMM and FMM generation

Each follower individually builds an LMM using current laser scan images sent from the leader. It also builds an FMM using its own current laser scan image.

Step 3: Leader's posture estimation

To determine the leader's posture in the EM, each follower matches the LMM with the EM using a correlation-based map matching algorithm [7].

Step 4: EM update

Each follower updates the EM by merging the previous EM with the current LMM. The map update is based on a binary Bayesian filter [7].

Step 5: Follower's posture estimation

Each follower determines its own posture by matching the FMM with the new EM using a correlation-based map matching algorithm.

3.2. Measurement map generation

Each follower generates two measurement maps (LMM and its own FMM) using the current laser scan images. As shown in Fig. 3, the laser distance samples are mapped onto the measurement maps. The number of laser distance samples mapped on cell (i, j) of the measurement map is denoted by $n_{(i,j)}$. Probability of the cell $p_{M(i,j)}$ is then given by [6]

$$\begin{cases} p_{M(i,j)} = 0.5 + p_{add} \times n_{(i,j)} & \text{for } n_{(i,j)} > 0 \\ p_{M(i,j)} = p_{\min} & \text{for } n_{(i,j)} = 0 \end{cases} \quad (1)$$

where $p_{add} = 0.05$ and $p_{\min} = 0.0001$. Probability of the cell being outside the sensing area is given as $p_{M(i,j)} = 0.5$.

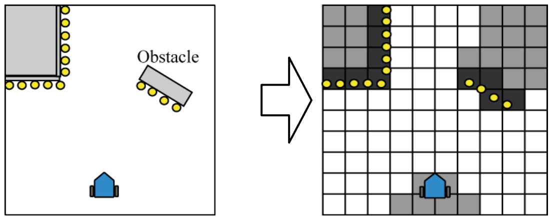

Fig. 3 Measurement map. Yellow point indicates the laser distance samples.

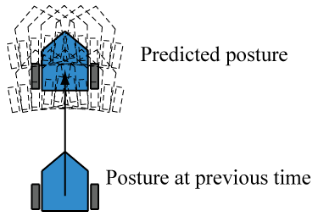

Fig. 4 Generation of robot postures by random sampling

3.3. Map matching

Each follower determines the leader's and its own postures using the correlation-based map matching algorithm. To explain our map matching, we determine the leader's posture. The follower's posture can be similarly determined. As shown in Fig. 4, the robot's posture at the current step is predicted based on dead-reckoning. Based on a random sampling technique, we generate fifty postures of the robot around the predicted posture.

To match the LMM with the EM, we define the following correlation function [7]

$$\lambda = \frac{\sum_{i,j}(b_{M(i,j)} - \bar{b}) \cdot (b_{E(i,j)} - \bar{b})}{\sqrt{\sum_{i,j}(b_{M(i,j)} - \bar{b})^2 \sum_{i,j}(b_{E(i,j)} - \bar{b})^2}} \quad (2)$$

where $b_{M(i,j)}$ and $b_{E(i,j)}$ are binary indices related to the LMM and the EM, respectively, and $\bar{b}$ is the average map value. These values are given by

$$b_{M(i,j)} = \begin{cases} 1 & \text{for } p_{M(i,j)} > 0.5 \\ 0 & \text{others} \end{cases} \quad (3)$$

$$b_{E(i,j)} = \begin{cases} 1 & \text{for } p_{E(i,j)} > 0.9 \\ 0 & \text{others} \end{cases} \quad (4)$$

$$\bar{b} = \frac{1}{2N} \sum_{i,j} (b_{M(i,j)} + b_{E(i,j)}) \quad (5)$$

where $p_{E(i,j)}$ is the probability of the cell being in the EM, and N is the number of cells in the LMM; in this experiment, $N = 10{,}000$.

We calculate the correlation for all postures generated by random sampling. We then determine the current posture of the leader to maximize the correlation.

3.4. Environmental map update

We update the EM using the binary Bayesian filter by employing Eqs. (6) and (7). To reduce the computational cost, we update the probability of only the cells overlapping between the old EM and the LMM.

$$p_{newE(i,j)} = \frac{S}{1+S} \tag{6}$$

$$S = \frac{p_{M(i,j)}}{1-p_{M(i,j)}} \cdot \frac{p_{E(i,j)}}{1-p_{E(i,j)}} \tag{7}$$

4. PLATOONING CONTROL

4.1. Path generation

As shown in Fig. 5, to obtain the robot formation pattern, we define two positions of each follower relative to the leader: offset distance d_1 and gap d_2.

Based on the SLAM technique described in the above section, the leader's tracks are estimated every 0.3 [s] (the period of the laser scan). The tracks consist of multiple position data (coordinates) in the EM, and the distance between two adjacent coordinates is very short. Generating a target path for the follower based on all position data of the tracks requires a large computational time. For this reason, we select several coordinates (knots) from the tracks.

Each follower determines knots that set offset distance d_1 from leader's tracks. We apply a cubic (third-ordered) spline to generate the follower's target path based on the knots [5]. Knot position data are noisy because of factors such as sensor noise. We therefore smooth the path generated from noisy knot position data by introducing a smoothed cubic spline. The target path generated using the smoothed cubic spline makes the path curvature continuous, allowing the follower to avoid wheel slippage.

4.2. Tracking control

We design a tracking controller based on Ackerman geometry so that the follower can move without any slippage along the target path while maintaining a constant gap d_2 between itself and the leader [5].

As shown in Fig. 6, we define lateral position error y_d and orientation error θ_d relative to the target path. We determine target turning velocity $\dot{\theta}^*$ so that the follower can pursue the target path:

$$\dot{\theta}^* = v^*\left[\frac{-1}{\cos\theta_d}(K_1 y_d + K_2 \sin\theta_d) + \frac{\cos\theta_d}{\rho_d - y_d}\right] \tag{8}$$

where v^* is the target linear velocity of the follower. K_1 and K_2 are control gains, and ρ_d is the path curvature calculated from the target path.

To maintain a constant gap d_2 between the leader and the follower, target linear velocity v^* is given by feed-

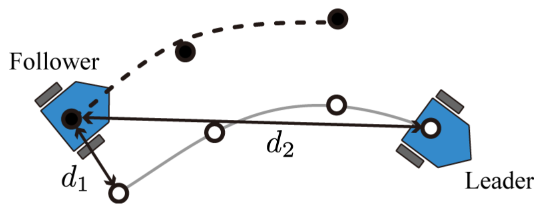

Fig. 5 Path generation. Open and closed circles indicate the knots of the leader and the follower, respectively. Thin and broken lines indicate the tracks of the leader and the target path of the follower, respectively.

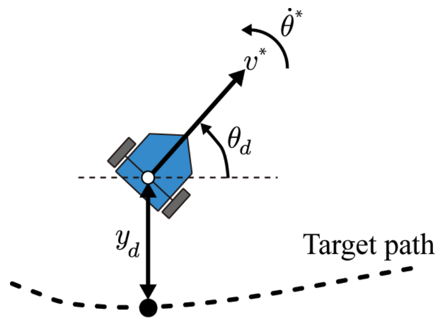

Fig. 6 Path tracking control

forward and PI feedback controls:

$$v^* = v_t + K_3(l_t - d_2) + K_4\sum_{t=1}^{t}(l_t - d_2) \tag{9}$$

where K_3 and K_4 are control gains, l_t is the current gap. v_t is the current velocity of the leader sent from the leader.

5. EXPERIMENTAL RESULTS

To validate our method, we conducted an experiment in an indoor environment, as shown in Fig. 7. The leader moved at a velocity of 0.15 [m/s]; the followers were controlled so that the three robots could form the pattern shown in Table 1. The robots captured their own scan images by LRSs every 0.3 [s].

Figure 8 shows the results of the generated environment map and the tracks of three robots. The maximum errors in path tracking and gap controls were

Table 1 Transition of formation pattern

Time[s]	Follower #1		Follower #2	
	offset d_1	gap d_2	offset d_1	gap d_2
0−403	0.0[m]	1.5[m]	0.0[m]	3.0[m]
403−525	0.0	2.0	0.0	4.0
525−645	0.0	1.5	0.0	3.0
645−687	1.0	1.5	-1.0	3.0
687−722	1.0	2.0	-1.0	2.0

0.24 [m] and 0.16 [m], respectively. From these results, it is clear that the followers can follow the leader while maintaining the formation.

6. CONCLUSIONS

This paper presented a leader–follower platooning method for multiple mobile robots using laser-based SLAM. The experimental result demonstrated the effectiveness of our method. Our research is directed toward designing a fault-tolerant platooning such that multiple mobile robots can maintain the platooning even when their own sensors partially fail.

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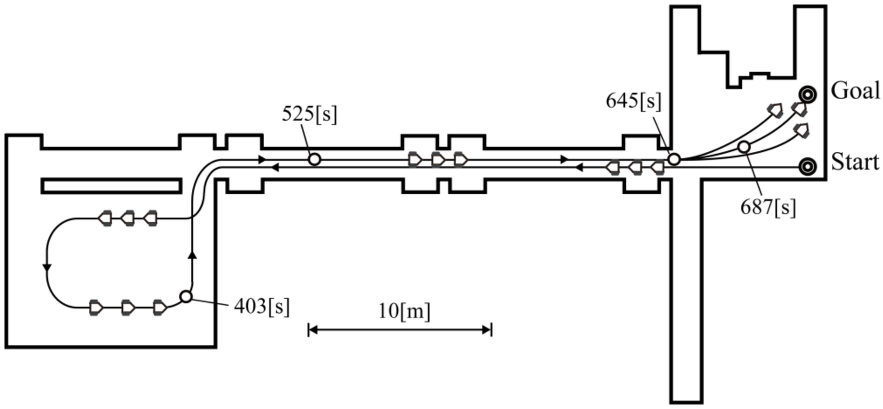

Fig. 7 Moving path of the leader in the experiment.

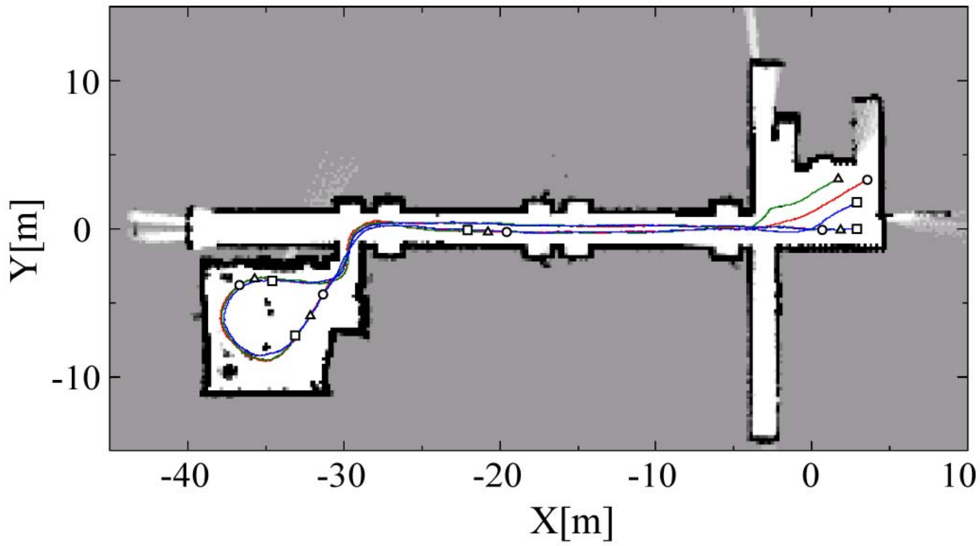

Fig. 8 Generated environmental map and tracks of three robots. Red, green, and blue lines indicate tracks of the leader, follower #1, and follower #2, respectively.