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A collaborative localization tolerant to recognition error by double-check particle exchange

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Abstract Statistical algorithms using particle filters for collaborative multi-robot localization have been proposed. In these algorithms, by synchronizing every robot’s belief or exchanging particles of the robots with each other, fast and accurate localization is attained. These algorithms assume correct recognition of other robots, and the effects of recognition errors are not discussed. However, if the recognition of other robots is incorrect, a large amount of error in localization can occur. This article describes this problem. Furthermore, an algorithm for collaborative multi-robot localization is proposed in order to cope with this problem. In the proposed algorithm, the particles of a robot are sent to other robots according to measurement results obtained by the sending robot. At the same time, some particles remain in the sending robot. Particles received from other robots are evaluated using measurement results obtained by the receiving robot. The proposed method is tolerant to recognition error by the remaining particles and evaluating the exchanged particles twice, and if there is no recognition error, the proposed method increases the accuracy of the estimation by these two evaluations. These properties of the proposed method are argued mathematically. Simulation results show that incorrect recognition of other robots does not cause serious problems in the proposed method.

Key words Multi-robot localization · Particle filter · Localization · Collaborative multi-robot system

1 Introduction

The localization of mobile robot using sensors is considered to be one of the most important problems in mobile robots, and probabilistic methods have been proposed.1 Probabilistic methods are expected to be robust for sensor noise or some inappropriate sensor information. The Kalman filter and Monte Carlo localization (MCL) are widely used for probabilistic localization.1 These are based on Markov localization.2–5 MCL uses a particle filter that consists of the possible positions of a robot.6–8

In a multi-robot system, each robot can recognize other robots as mobile landmarks for localization, and know the relative positions of other robots by using sensors, and each robot can acquire estimated locations from other robots via communication devices. In this situation, the accuracy of localization can be increased and the calculation time can be decreased by using the information of the robots in collaboration. For example, some collaborative methods utilize the geometrical group configuration of the robots. Nakamura et al.9 have proposed a localization method for mobile robots using geometrical constraints of observed robots and landmarks in the environment. Furthermore, Kurazume et al.10 have proposed a cooperative positioning system (CPS) in which robots are divided into two groups. While robots in one group are moving, robots in the other group are stationary and act as landmarks.

On the other hand, there are methods in which the localization of robots is unified. In these methods, first each robot determines its own position independently without information about other robots. Then the localization information of the robots is exchanged and unified. Using a Kalman filter, Bahr et al.11 have proposed a method for cooperative localization. This method combines multiple estimations. In general, the Kalman filter assumes the distribution of noise to be Gaussian. For the particle filter, there are few assumptions about the distribution of noise. In this article, robot localization using a particle filter is discussed.

Fox et al.12,13 have proposed a method for collaborative multi-robot localization using a particle filter. In their method, each robot’s belief is synchronized whenever one robot detects another robot. Through this collaboration, faster calculations and a higher localization accuracy are obtained. Gassparri et al.14 have proposed another method,
in which particles and sensor information are exchanged if their weights exceed a certain threshold.

In the above probabilistic collaborative multi-localization algorithms that use particle filters, recognition of other robots is assumed to be correct, and the effects of recognition errors by other robots are not considered. However, recognition of other robots is difficult in some cases. For example, if a robot uses laser range sensors to recognize other robots, and if the shapes of the robots are similar, it is difficult to distinguish the robots. This may cause a serious problem in localization.

To cope with this problem, a new algorithm for probabilistic collaborative multi-robot localization is proposed. In the proposed algorithm, the particles of a robot are sent to other robots according to measurement results obtained by the sending robot. At the same time, some particles remain in the sending robot. Particles received from other robots are evaluated using measurement results obtained by the receiving robot. By using the remaining particles, the localization results are expected to be tolerant to incorrect recognition of other robots. Because the exchanged particles are evaluated twice, by the sending robot and by the receiving robot, a high accuracy is expected. These properties of the proposed method are argued mathematically and confirmed by simulation.

### 2 Outline of conventional algorithms for collaborative multi-robot localization

First, an outline of MCL without collaboration is presented. Here, only one robot is considered. MCL is a probabilistic method and uses a particle filter to represent the probability distribution of the robot’s location, which is called belief. Belief is the probability of the robot at the time of robot motion model.

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### 3 The problem of recognition error of other robots

Conventional collaborative multi-robot localization methods assume that the recognition of robots by other robots is correct. That is, the robot number of robot i is recognized as i correctly by robot j. In a typical multi-robot system, many robots with the same shape are used. In that case, recognition of one robot by another robot is difficult. If the initial positions of all robots are known, a robot can recognize other robots by successively tracing the positions of the other robots with laser sensors. However, if two other robots are very near, these robots cannot be distinguished by the first robot and recognition errors can occur.

In the method proposed by Fox et al., the probabilities of localizations for all robots are collected and multiplied, and the probability of localization for one robot is obtained as in Eq. 1. However, if the recognition of one robot by another robot is incorrect, the probability collected from an incorrectly recognized robot is very small, and the probability of localization for the robot is also very small. In Eq. 1, if robot i is incorrectly recognized as robot i',

\[
bel(x_i) = p(x_i | d_{i'}) p(x_i | d_{i})
\]

which can become very small.

If the recognized robot is far away from the correct robot, the probability of localization becomes almost zero. In this case, the probability of localization cannot be calculated correctly, the estimated location of a robot may be very far from its correct location, and this causes a serious problem.

In a case where the incorrectly recognized robot is near the correct robot, the error in the estimated location is not large. However, as the distance between the correct robot location and the incorrectly recognized robot increases, the error in the estimated location increases.

### 4 Proposed algorithm

To cope with the problem described in the previous section, a new algorithm for collaborative multi-robot localization