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Simultaneous Pedestrian and Multiple Mobile Robots Localization Using Distributed Extended Kalman Filter

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***Abstract*— This paper is concerned with distributed extended Kalman filtering (DEKF) for simultaneous pedestrian and multiple mobile robots localization. Here, extended Kalman filter (EKF) is applied to the multiple robots for the pedestrian localization. The estimate from each robot is fused by distributed algorithm to improve the accuracy. Furthermore, we used multiple robots formation control to keep a triangle formation at the same time. The focus of this paper is to investigate the effect of the proposed algorithm on simultaneous localization accuracy. A Monte Carlo simulation result is presented to demonstrate the efficiency in localization accuracy of the distributed fusion of EKFs.**

***Index Terms*— Multirobot localization, Extended Kalman filter, Fusion formula, Distributed fusion**

I. INTRODUCTION

The localization problem for multiple robots (agents) system has been regarded as an important problem. It is a key component in many successful autonomous robot systems [1]. Robot navigation is the task of an autonomous robot to move safely from one location to another. The general problem of navigation can be formulated in three questions [2]. Where am I ? Where am I going ? How do I get there ? This means the robot has to find out its location relative to the environment. When we talk about location, pose, or position we mean the x and y coordinates and heading direction of a robot in a global coordinate system. We need to get its precise location.

There are numerous publications for localization of single mobile robot [3-5]. However multiple robots work in cooperation in common work space to perform specific tasks for many robotic applications. Multiple robots localization has been developed for tasks which can be accomplished more efficiently by a whole team of robots than just by single robot localization.

A distributed algorithm is one of solution to handle problem as many autonomous and independent robot localization tasks [6]. The advantage of a distributed algorithm is that the parallel structures would lead to increase the input data rates and make easy fault detection and isolation. Also, it has the reduced computational burden as compared to the centralized algorithm. The information that robots obtain using their sensors needs to be combined to determine what is going on in the environment.

In [7], a dead-reckoning system for mobile robot navigation and a wireless sensor network for a pedestrian navigation and their integration via EKF for the simultaneous localization were introduced. In this paper, we provide a distributed localization algorithm based on the EKF proposed in [8] and the optimal fusion formula with matrix weights [9-11] for the simultaneous localization [7]. It has a better accuracy than every local EKF.

Our problem in cooperative robotics is to maintain a geometric configuration such as line (robots move line-abreast), column (robots move one after the other) and triangle (robots move in a triangle formation) during movement. we used robot motion control to navigate the multiple mobile robots to its goal in an unknown environment without any collisions among them. Thus, we presented a triangle formation for a group of mobile robots using formation control in [12].

This paper is organized as follows. Single mobile robot and pedestrian simultaneous localization technique is described in Section II. The strategy of robot formation for a team of three mobile robots is introduced in Section III. Three mobile robot and pedestrian simultaneous localization technique with robot formation control is described in Section IV. In Section V, we present the main result regarding the DEKF for multiple robots environment. Here the key equations for cross-covariances between local EKF filtering errors are derived. In Section VI, an example of multiple robots system result is presented. Conclusion will be given in Section VII.

II. SINGLE MOBILE ROBOT AND PEDESTRIAN SIMULTANEOUS LOCALIZATION

In this section, we develop a simultaneous localization technique of pedestrian and single mobile robot. If the robot is able to measure a physical component of the object such as the relative distance or direction between object and robot, then we can design an integrated simultaneous localization system.

The system model of single mobile robot and pedestrian simultaneous localization is described by the following equations [7]:

$$X(k+1)=\begin{bmatrix} x^o(k+1)\\ y^o(k+1)\\ v_x^o(k+1)\\ v_y^o(k+1)\\ x^R(k+1)\\ y^R(k+1)\\ \theta(k+1)\end{bmatrix}$$
$$=\begin{bmatrix} x^o(k)+\Delta t\cdot v_x^o(k)\\ y^o(k)+\Delta t\cdot v_y^o(k)\\ v_x^o(k)\\ v_y^o(k)\\ x^R(k)+cos\,(\theta)\,\Delta l(k)\\ y^R(k)+sin\,(\theta)\,\Delta l(k)\\ \theta(k)+\Delta\theta(k)\end{bmatrix}+\begin{bmatrix} 0\\ 0\\ \Delta t\cdot a_x^o\\ \Delta t\cdot a_y^o\\ -cos\,(\theta)\cdot n_{\Delta l}\\ -sin\,(\theta)\cdot n_{\Delta l}\\ -n_{\Delta\theta}\end{bmatrix}, \tag{1}$$

where

- Δt a sampling interval
- (x^o, y^o) the position in x and y directions
- (v_x^o, v_y^o) the velocity in x and y directions
- (a_x^o, a_y^o) the acceleration in x and y directions
- Δl the output from the odometer sensor
- θ the output from a heading sensor like magnetic compass
- $\Delta\theta$ the angular variation which is determined from a heading reference sensor
- $n_{\Delta l}$ and $n_{\Delta\theta}$ the measurement noises which are uncorrelated white Gaussian noises

The position of the object can be measured by wireless sensor network.

The measurement model containing a relative distance from the robot to pedestrian as l is given by

$$Z(k)=\begin{bmatrix} x^o(k)\\ y^o(k)\\ \theta(k)\\ l(k)\end{bmatrix}+\begin{bmatrix} n_x^o(k)\\ n_y^o(k)\\ n^\theta(k)\\ n^l(k)\end{bmatrix}, \tag{2}$$

where the measurement noises $w = \left[n_x^o,\ n_y^o,\ n^\theta,\ n^l\right]^T$ are uncorrelated white Gaussian noises and the distance l between the robot and object is shown in Fig. 1,

$$l=\sqrt{\left(x^o-x^R\right)^2+\left(y^o-y^R\right)^2}.$$

III. ROBOT FORMATION CONTROL

Fig. 2 shows that relative motion among three robots. The strategy is to have a leader (robot 1) guide followers (robot 2 and 3). We assume that the robots are identical, and don't fail during travel. The lead robot has to acquire the main targets, while the follower robots maintain a formation.

Let θ_{leader} is the angle of robot 1, according to Fig. 2, and the desired positions for the configurations triangle is:

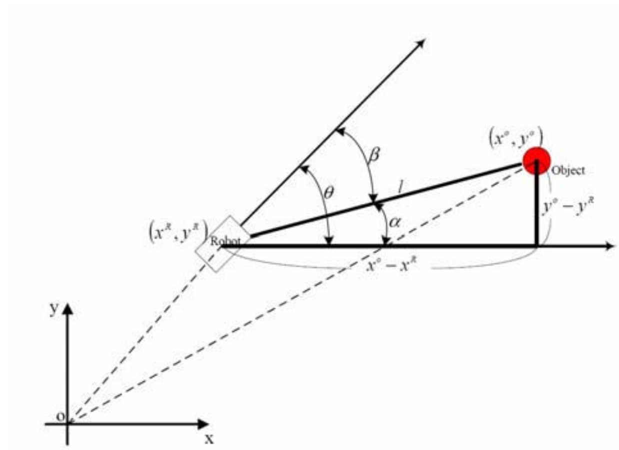

Fig. 1. Relative motions of robot and object

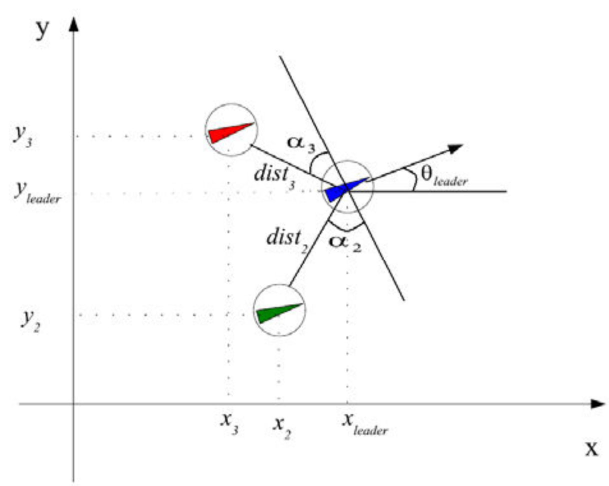

Fig. 2. Relative motion among three mobile robots

$$\begin{cases} x_2 = x_1 + dist_2\cdot sin\,(\theta_{leader}-\alpha_2)\,,\\ y_2 = y_1 - dist_2\cdot cos\,(\theta_{leader}-\alpha_2)\,,\end{cases} \tag{3}$$

$$\begin{cases} x_3 = x_1 - dist_3\cdot sin\,(\theta_{leader}+\alpha_3)\,,\\ y_3 = y_1 + dist_3\cdot cos\,(\theta_{leader}+\alpha_3)\,,\end{cases} \tag{4}$$

where (x_1, y_1) is the position of robot 1, (x_2, y_2) is the position of robot 2, and (x_3, y_3) is the position of robot 3. Furthermore, $dist_2$ and $dist_3$ are the distances of the robot 2 and 3 (followers) relative to the robot 1 (leader), respectively, α_2 is angle between robot 1 and robot 2, α_3 is angle between robot 1 and robot 3 as shown in Fig. 2.

IV. THREE MOBILE ROBOTS AND PEDESTRIAN SIMULTANEOUS LOCALIZATION

Now, we reformulate the simultaneous localization and tracking problem with cooperative scheme using three mobile robots in the previous section.

Let us consider three mobile robots and pedestrian simultaneous localization. In this case, each robot has their own system and measurement model. The relative motion of robots in Fig. 2 is represented as (3), (4). Using these two equations, then (1) and (2) can be rewritten in the following form

$< System\ Model >$

$$X^i(k+1) = \begin{bmatrix} x^o(k+1) \\ y^o(k+1) \\ v_x^o(k+1) \\ v_y^o(k+1) \\ x^{R^i}(k+1) \\ y^{R^i}(k+1) \\ \theta^{R^i}(k+1) \end{bmatrix} = \begin{bmatrix} x^o(k) + \Delta t \cdot v_x^o(k) \\ y^o(k) + \Delta t \cdot v_y^o(k) \\ v_x^o(k) \\ v_y^o(k) \\ x^{R^i}(k) + cos\left(\theta^{R^i}\right)\Delta l(k) \\ y^{R^i}(k) + sin\left(\theta^{R^i}\right)\Delta l(k) \\ \theta^{R^i}(k) + \Delta\theta^{R^i}(k) \end{bmatrix}$$
$$+ \begin{bmatrix} 0 \\ 0 \\ \Delta t \cdot a_x^o \\ \Delta t \cdot a_y^o \\ -cos\left(\theta^{R^i}\right)\cdot n_{\Delta l}^i \\ -sin\left(\theta^{R^i}\right)\cdot n_{\Delta l}^i \\ -n_{\Delta\theta}^i \end{bmatrix},\ i = 1,2,3\ , \tag{5}$$

where

$$\begin{cases} x^{R^2}(k) = x^{R^1}(k) + dist_2 \cdot sin\left(\theta^{R^1}(k) - \alpha_2\right), \\ y^{R^2}(k) = y^{R^1}(k) - dist_2 \cdot cos\left(\theta^{R^1}(k) - \alpha_2\right), \end{cases} \tag{6}$$

$$\begin{cases} x^{R^3}(k) = x^{R^1}(k) - dist_3 \cdot sin\left(\theta^{R^1}(k) + \alpha_3\right), \\ y^{R^3}(k) = y^{R^1}(k) + dist_3 \cdot cos\left(\theta^{R^1}(k) + \alpha_3\right). \end{cases} \tag{7}$$

$< Measurement\ Model >$

$$Z^i(k) = \begin{bmatrix} x^{o^i}(k) \\ y^{o^i}(k) \\ \theta^{R^i}(k) \\ l^i(k) \end{bmatrix} + \begin{bmatrix} n_x^{o^i}(k) \\ n_y^{o^i}(k) \\ n^{\theta^{R^i}}(k) \\ n^{l^i}(k) \end{bmatrix},\ i = 1,2,3\ , \tag{8}$$

where the relative distance l^i is

$$l^i = \sqrt{\left(x^{o^i} - x^{R^i}\right)^2 + \left(y^{o^i} - y^{R^i}\right)^2},\quad i = 1,2,3\ .$$

V. DISTRIBUTED EXTENDED KALMAN FILTER

The fusion formula [9-11] can serve as the basis for designing of a distributed fusion filter. A new suboptimal distributed extended Kalman filter (DEKF) is described as follows: first, the local sensor measurements $Z^i(k), i = 1,2,3$ are processed separately by using the EKF [8]. Second, the obtained local estimates are fused in an optimal linear combination.

Let us denote local estimate of the state based on the individual sensor $Z^i(k)$ by $\hat{X}^i(k)$ To find local estimate $\hat{X}^i(k)$ we can apply the EKF to system (1) with sensor $Z^i(k)$ [7, 8, 12]. We obtain the following recursive equations:

$$\begin{aligned} \hat{X}^i(k+1) &= f\left(\hat{X}^i(k), U(k)\right) \\ &\quad + K^i(k+1)\left[Z^i(k) - \nabla_{\hat{X}} H^i f\left(\hat{X}^i(k), U(k)\right)\right], \\ P^{(ii)}(k+1) &= M^{(ii)}(k+1) \\ &\quad - K^i(k+1)\nabla_{\hat{X}} H^i M^{(ii)}(k+1),\ i = 1,2,3\ , \\ M^{(ii)}(k+1) &= \nabla_{\hat{X}} f(k) P^{(ii)}(k)\left(\nabla_{\hat{X}} f(k)\right)^T + Q(k), \\ K^i(k+1) &= \\ &\begin{cases} M^{(ii)}(k+1)\left(\nabla_{\hat{X}} H^i\right)^T\left(\nabla_{\hat{X}} H^i M^{(ii)}(k+1)\left(\nabla_{\hat{X}} H^i\right)^T + R(k+1)\right)^{-1}, & if\ Z^i\ is\ available \\ 0\ , & else \end{cases} \end{aligned} \tag{9}$$

where

$$f\left(\hat{X}^i(k), U(k)\right) = \begin{bmatrix} \hat{x}^o(k) + \Delta t \cdot \hat{v}_x^o(k) \\ \hat{y}^o(k) + \Delta t \cdot \hat{v}_y^o(k) \\ \hat{v}_x^o(k) \\ \hat{v}_y^o(k) \\ \hat{x}^{R^i}(k) + cos\left(\theta^{R^i}\right)\Delta l(k) \\ \hat{y}^{R^i}(k) + sin\left(\theta^{R^i}\right)\Delta l(k) \\ \hat{\theta}^{R^i}(k) + \Delta\theta^{R^i}(k) \end{bmatrix},$$

$$\hat{X}^i(k) = \left[\ \hat{x}^o(k), \hat{y}^o(k), \hat{v}_x^o(k), \hat{v}_y^o(k), \hat{x}^{R^i}(k), \hat{y}^{R^i}(k), \hat{\theta}^{R^i}(k)\ \right]^T,$$

$$U(k) = \left[\ \Delta l(k),\ \Delta\theta(k)\ \right]^T,$$

$$H^i = \left[\ x^{o^i}(k), y^{o^i}(k), \theta^{R^i}(k), l^i\ \right]^T.$$

Then the DEKF estimate $\hat{X}^{DEKF}(k)$ is constructed by using the fusion formula, i.e.,

$$\begin{aligned} \hat{X}^{DEKF}(k) &= \sum_{i=1}^{3} W^i(k)\hat{X}^i(k), \\ \sum_{i=1}^{3} W^i(k) &= I_3, \end{aligned} \tag{10}$$

where I_3 is the 3×3 identity matrix, $W^1(k), \ldots, W^3(k)$ are the time-varying weighted matrices determined by the mean square criterion.

Theorem [8, 9]. The optimal weights $W^1(k), \ldots, W^3(k)$ satisfy the linear algebraic equations

$$\begin{aligned} &\sum_{i=1}^{3} W^i(k)\left[P^{(ij)}(k) - P^{(i3)}(k)\right] = I_3, \\ &\sum_{i=1}^{3} W^i(k) = I_3,\ j = 1, 2\ , \end{aligned} \tag{11}$$

where $P^{(ij)}(k)$ is local cross-covariance [8, 9],

$$\begin{aligned} &P^{(ij)}(k) = cov\left\{\widetilde{X}^{(i)}(k),\ \widetilde{X}^{(j)}(k)\right\}, \\ &\widetilde{X}^{(i)}(k) = X^{(i)}(k) - \hat{X}^{(i)}(k),\quad i \neq j. \end{aligned} \tag{12}$$

VI. EXAMPLE

In this simulation test, it is assumed that the radio frequency identification system is used to obtain the relative distance of the pedestrian with respect to the robot. The total simulation time is 200 seconds and the sampling time Δt is given as 1 second. To make the simulation practically meaningful, the robot tracks the pedestrian. For this purpose it is required to drive the robot to follow the pedestrian. In this test, Δl and $\Delta\theta$ are controlled as [7]:

$$\begin{aligned} &\Delta l = 0,01\sqrt{\left(x^o - x^R\right)^2 + \left(y^o - y^R\right)^2}, \\ &\Delta\theta = 0.2\left[tan^{-1}\left\{\left(y^o - y^R\right)/\left(x^o - x^R\right)\right\}\right. \\ &\qquad \left. -tan^{-1}\left(y^R/x^R\right)\right]\ . \end{aligned}$$

These two figures show the estimated pedestrian and robot trajectories using proposed algorithm. Fig. 3 shows pedestrian trajectory tracking. Green dot's ($\circ$ marker) represent the object trajectory using single robot. Red dot's ($\times$ marker) represent the object trajectory using 3 robots. We see that simultaneous localization using 3 robots gives more accurate estimate than using single robot.

Fig.4 shows robot trajectory tracking. Simulation result demonstrates a group of robots is tracking a pedestrian and keeping a triangle formation at the same time without collision among them. The leader robot has to acquire the main targets, while the follower robots maintain formation.

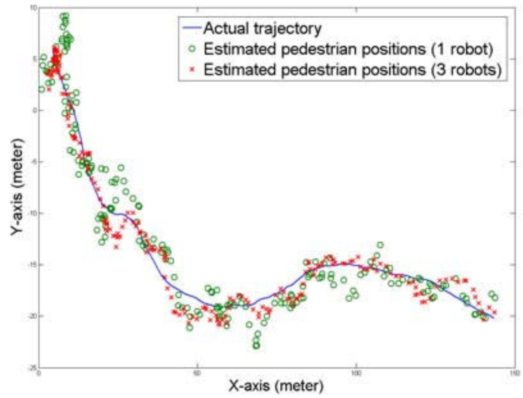

Fig. 3. Object trajectory tracking

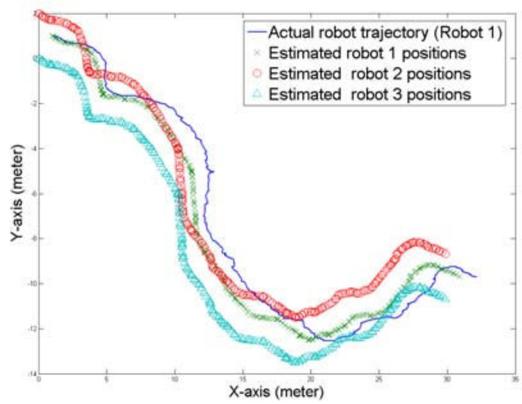

Fig. 4. Robot trajectory tracking

The estimation accuracy of the filters can be more clearly compared through the absolute distance error in Fig. 5. The absolute distance error ε_d is defined as distance between the actual and estimated pedestrian positions. It can be written in the following equation:

$$\varepsilon_d(k) = \sqrt{\left[x^o(k) - \hat{x}^o(k)\right]^2 + \left[y^o(k) - \hat{y}^o(k)\right]^2}. \tag{13}$$

Here the absolute distance error ε_d is calculated through Monte-Carlo method with 1000 runs. ε_d using single robot is remarkably larger than using 3 robots. Clearly, from Fig. 5, there is a performance improvement. This means that for our proposed algorithm can produce good results.

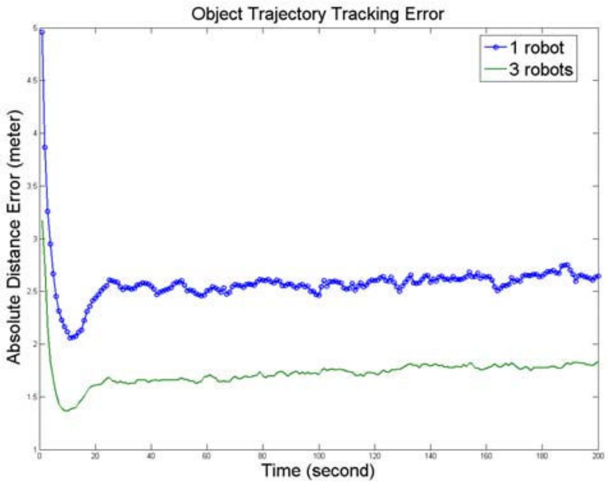

Fig. 5. Absolute distance error from simultaneous localization

VII. Conclusion

In this paper, a new distributed extended Kalman filter (DEKF) is proposed to cope with pedestrian localization problem using multiple mobile robots. It represents the weighted sum of the local estimate of EKFs. The minimum mean square error criterion is used to derive fusion rule for DEKF.

For avoiding collision among three mobile robots, we used robot formation control. We have decomposed the problem of formation control into: 1) control of a leader robot and 2) control of two follower robots in the group. Fig. 4 demonstrates pedestrian localization, avoiding collision and maintaining triangle formation.

Furthermore, simulation analysis and comparison with the single mobile robot verifies the effectiveness of the proposed DEKF. The results of our paper will be used in our actual experimental test in the near future and the results will be reported thereafter.

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