Cooperative Localization for Multi-robot Incorporating Proprioceptive/Exteroceptive Position Sensors*

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Summary. This paper presents a new method of cooperative localization for multiple robots utilizing correlation between GPS errors of common mode in shared workspace. Assuming that GPS data of individual robot are correlated strongly as the distance between robots are close, we utilize the differential position data between the robots to refine robot's position data. Under artificial environment for simulation with imposed model error to robot motion and GPS sensor data error, it is confirmed that the proposed method provides improved localization accuracy [9]. In addition, we present a practical solution to accumulated position error in traveling long distance.

1 Introduction

Mobile robots require capability to estimate their position in order to navigate autonomously in their work space. Consequently, localization by sensor-based method has been researched as one of the most essential problems in mobile robotics. In previous researches, a number of works on localization of single robot have been reported [1, 2]. However recently, many robotic applications require that robots work in collaboration in common workspace to perform a task. In such tasks as multiple robots operate in close, we need more precise absolute localization or relative localization of multiple robots in order to avoid collisions with each other.

The multiple robot system, in comparison with the single robot system, has the advantages of collecting and integrating multiple sensor data from different robots. Accordingly, the system can obtain better localization performance and increase the robustness of the localization accuracy for each robot by fusing collected multiple sensor data. In addition, if each robot is equipped with heterogeneous sensor, the system can improve the overall localization accuracy.

Despite of above-mentioned advantages, most existing localization researches for multiple robots have not utilized such advantages [3,4]. Even in multiple robot systems each robot estimates its position by its own sensor data.

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Recently, some research works start to focus on integrating the sensor data from multiple sources in order to remove the uncertainty of the absolute or relative position of mobile robot. Most of research commonly used methods include triangulation [7], Kalman filter [5], and MCL (Monte Carlo Localization) [8]. These approaches have improved position accuracy as contrast with the methods utilizing information from single robot. On the other hand, these approaches are relatively complex because they deal with statistic parameters. In addition, they are usually applicable to robots in indoor.

In our previous research, we presented an approach for cooperative multiple robot localization utilizing correlation between GPS errors of robots [9]. The proposed method was relatively simple compared with previously methods (include triangulation, Kalman filter, and MCL) and provided better localization accuracy compared with relying on the resource of each robot.

In this paper, we propose a practical solution to accumulated position error of cooperative multiple robot localization in traveling long distance. We define two operational parameters. One is the ratio of standard deviation between proprioceptive and exteroceptive position sensors. The other is a refresh interval to replace accumulated DR data with GPS data providing fixed standard deviation of position error. Determining the two operational parameters, we can improve the cooperative localization accuracy of multiple robots.

2 Cooperative Localization

2.1 Assumptions

In order to deal with localization problem for multiple robots, we assume the followings:

1) Each robot has GPS receiver, odometer, and gyro sensor in order to localize absolute position and relative position by model-based dead-reckoning.
2) The closer robots have the stronger correlation between GPS data errors.
3) All robots are equipped with communication devices that allow other robots or remote control station to receive position data measured from each robot.

2.2 Cooperative Localization Algorithm

Based on above-mentioned assumptions, we describe mathematical details of the proposed cooperative localization algorithm with the nomenclature shown in Table 1.

If m robots work in common space, the position of kth robot estimated by robot model at time i+1 as:

$$\hat{P}_{i+1}^{k} = \overline{P}_{i}^{k} + (V_{i+1} + e_{i+1})\delta t \qquad (1)$$

for $k = 1,\ldots,m$. And GPS data $\tilde{P}_{i+1}^{k}$ are sampled at time $i+1$.

Table 1. Nomenclature for Cooperative Localization Algorithm

Symbol	Description
$\overline{P}_i^k$	Position of *k*th robot estimated by cooperative localization algorithm at time *i*
$\hat{P}_i^k$	Position of *k*th robot estimated by robot model at time *i*
$\tilde{P}_i^k$	Position of *k*th robot estimated by GPS data at time *i*
V_i	True velocity of robot between of time *i*-1 and time *i*
e_i	Velocity error caused by slip between robot wheels and ground between of time *i*-1 and time *i*
δt	Sampling period
W_i^{kj}	Weight factor for compensation between *k*th robot and *j*th robots at time *i*
ΔP_i^k	GPS data error of *k*th robot estimated by difference between GPS data and robot model at time *i*
l_i^{kj}	Differential position data between *k*th robot and *j*th robot at time *i*
L_i^k	Parameter determined from total distance between robots at time *i*

Then, the key idea of proposed cooperative localization algorithm is described as follows:

$$\overline{P}_{i+1}^k = \tilde{P}_{i+1}^k - \sum_{j=1}^{m} (W_{i+1}^{kj} \Delta P_{i+1}^k) \tag{2}$$

$$W_{i+1}^{kj} = \frac{1/(l_{i+1}^{kj} + 1)}{L_{i+1}^k} \tag{3}$$

$$L_{i+1}^k = \sum_{j=1}^{m} 1/(l_{i+1}^{kj} + 1) \tag{4}$$

$$l_{i+1}^{kj} = | \hat{P}_{i+1}^k - \hat{P}_{i+1}^j | \tag{5}$$

$$\Delta P_{i+1}^k = \tilde{P}_{i+1}^k - \hat{P}_{i+1}^k \tag{6}$$

for $k = 1,\ldots,m$.

The main idea is motivated from the concept of DGPS which compensates error by comparing true data and noisy sensed data. In this approach we adopt the quasi true value as $\hat{P}_i^k$ and noisy data as $\tilde{P}_i^k$. And we find the cases where our algorithm can be applied in view point of statistic parameters of the sensors.

Both the weight term, W_{i+1}^{kj}, and the reciprocal term of total distance between robots, L_{i+1}^k, include $1/(l_{i+1}^{kj}+1)$ term. When compensate GPS errors, we fuse the compensation quantity according to the distance between the robots, $1/(l_{i+1}^{kj}+1)$. Note that the closer robots contribute more than the farther robots in the fusion.

2.3 Refresh Interval

Most mobile robot applications employ two basic position estimation methods: absolute/relative positioning or proprioceptive/exteroceptive position. Absolute positioning methods usually rely on landmark, map matching, satellite-based GPS data, or navigation beacons. In this paper, we assume that robots can receive the GPS data for absolute positioning, but it doesn't care the other proprioceptive sensors.

Relative positioning method is usually Dead Reckoning (DR) based on odometer and gyro. Odometer and gyro are inexpensive, simple, and easy to accomplish in real time. On the other hand, odometer has its unbounded accumulation of errors, and also gyro has relatively large drift rates which cause unbounded growth in orientation errors. Therefore, it is necessary to update absolute position periodically in order to reduce potential for unbounded growth of errors.

In proposed method, we have found the proper period called refresh interval to update GPS position data. The localization performance of the proposed method can be improved by replacing $\hat{P}_i^k$ with $\tilde{P}_i^k$, when errors of the $\hat{P}_i^k$ are bigger than errors of the $\tilde{P}_i^k$.

3 Simulation Results

In this section, we simulate the proposed cooperative localization algorithm according to the virtual position. The traveling space for multiple robots is a square 40 meter on a side. We limited the maximum gap between robots to 1 meter in order to avoid collisions between the robots. The robots for simulation were assumed to cylindrical shape with a radius of 50 centimeter. The maximum velocity of robots limits 1 meter per second. There are 10 mobile robots traveling randomly on a 2D-flat platform.

We compare the proposed cooperative localization (CL) method for multiple robots with the single robot localization (SL) method by fusing dead reckoning data and the GPS data relying on the resource of each robot. In addition, we present examples to prevent position data estimated by proposed method from accumulating errors.

3.1 Virtual Position Error

In order to simulate the proposed cooperative localization method, it is necessary to construct simulation environment of a piece assumptions mentioned in section 2. We have to make two kinds of errors. One is the GPS errors of all robots respectively according to probability distribution of proper standard deviation. The other is the model errors of all robots generated by cause such as slip between the wheels of robot and the ground.

First, we assume that the GPS data of individual robot are correlated strongly as the distance between robots are close. In other words, we assume that the GPS data error of individual is correlated linearly as the distance between robots. It is described how to make GPS data error in previous research [9].

Seconds, we assume that robot model error is generated as maximum 0.1m and minimum 0m per 1m in traveling distance. It means that the model errors between 0 and 0.1m are the same probability. It is possible to calculate standard deviation from continuous probability distribution. The calculated standard deviation is about 0.02887m per 1 second. In this paper, we simulate the cooperative localization method using this standard deviation value for model error.

3.2 The Ratio of Standard Deviation between Sensors

In previous case studies [9], we have found that the proposed method is valid in the proper ratio. The valid ratio ranges of standard deviation between the DR error and GPS error per unit time are about 1:2 ~ 1:5 in Fig.1.

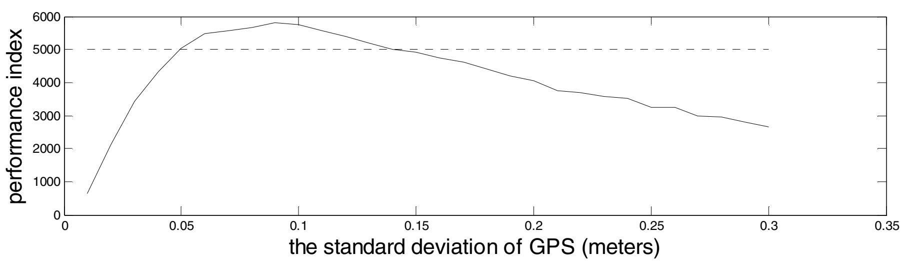

Fig. 1. The localization performance of proposed method according to the standard deviation of GPS when the standard deviation of DR is 0.02887m. The range below dot is valid.

3.3 Case 1 : $\sigma_{DR} = 0.02887m$, $\sigma_{GPS} = 0.08661m$, Operating Time : 300s, and Refresh Interval : 100s

In this case, there are robots' operating time of 300 seconds and compensating period of 100 second. Fig. 2 and Fig. 4 show the real trajectory and position errors for robot 6 during 300s respectively. Fig. 3 shows the comparison of the accumulated distance

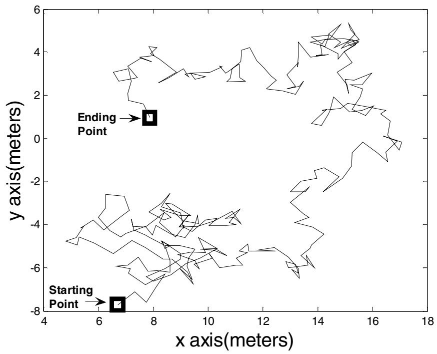

Fig. 2. Trajectory of a robot 10 in case 1

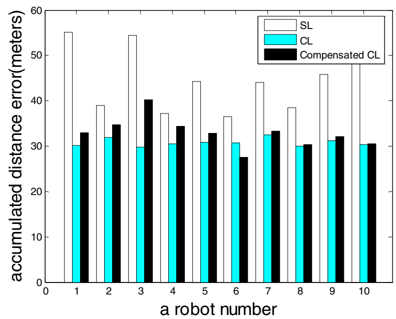

Fig. 3. Accumulated position errors of 10 robots in case 1

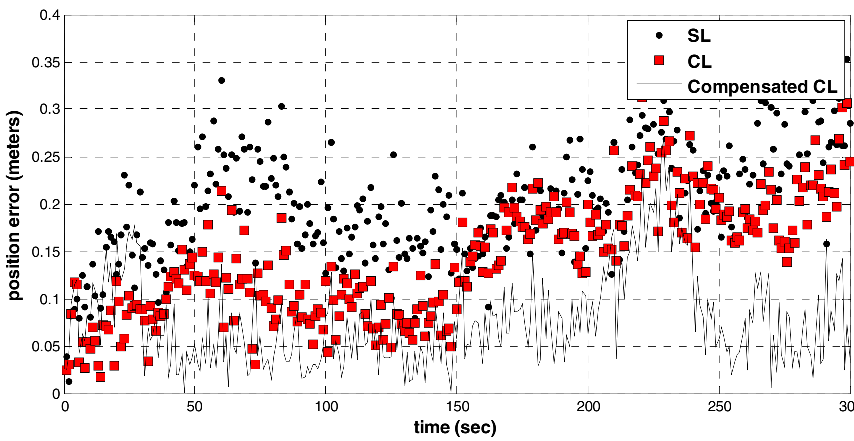

Fig. 4. Position errors of robot 6 in case 1

errors for 10 robots obtained by three different localization methods. From the results of this case, we know that it doesn't suitable for most robots to replace accumulated DR data with simultaneous GPS data per 100 Seconds.

3.4 Case 2 : $\sigma_{DR} = 0.02887m$, $\sigma_{GPS} = 0.08661m$, Operating Time : 300s, and Refresh Interval : 50s

In this case, there are robots' operating time of 300 seconds and refresh interval of 50 second. Fig. 5 and Fig. 7 show the real trajectory and position errors for robot 9 respectively. Fig. 6 shows the comparison of the accumulated distance errors for 10 robots obtained by three different localization methods. From the results of this case, we present the effect of replacing DR data accumulated with simultaneous GPS data per 50 Seconds.

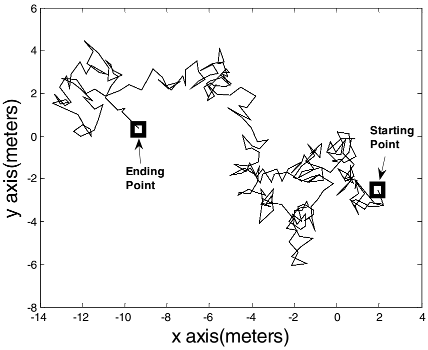

Fig. 5. Trajectory of a robot 5 in case 2

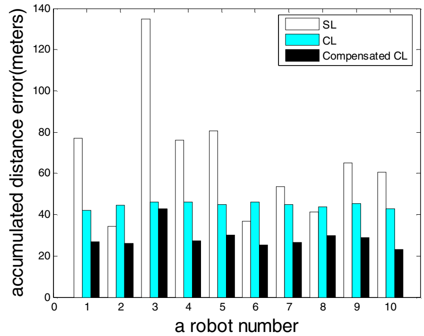

Fig. 6. Accumulated position errors of 10 robots in case 2

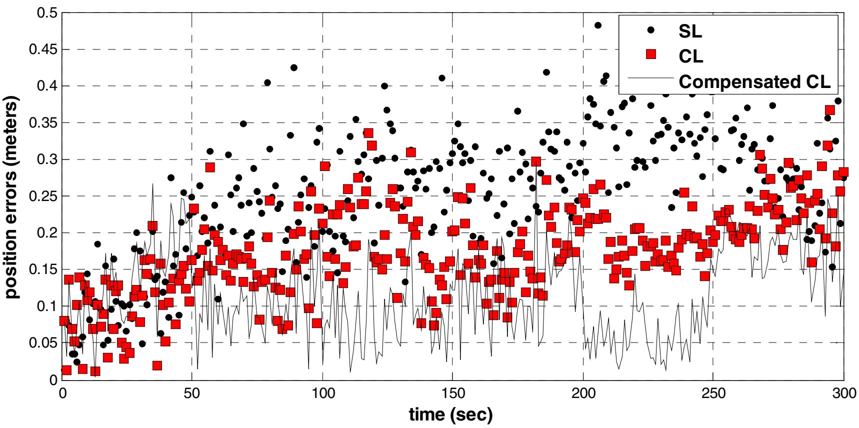

Fig. 7. Position errors of robot 9 in case 2

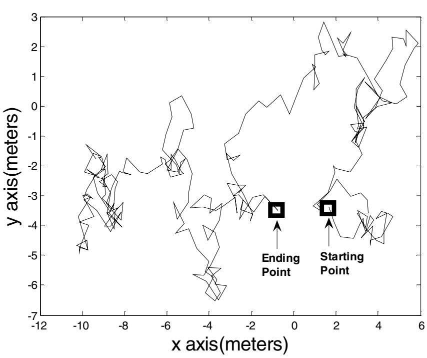

Fig. 8. Trajectory of a robot 5 in case 3

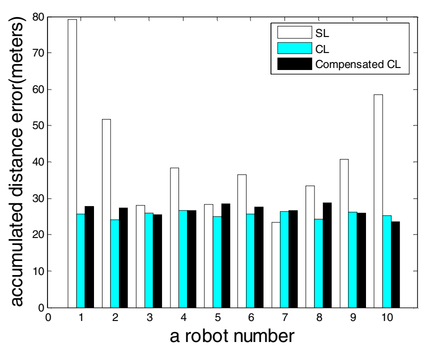

Fig. 9. Accumulated position errors of 10 robots in case 3

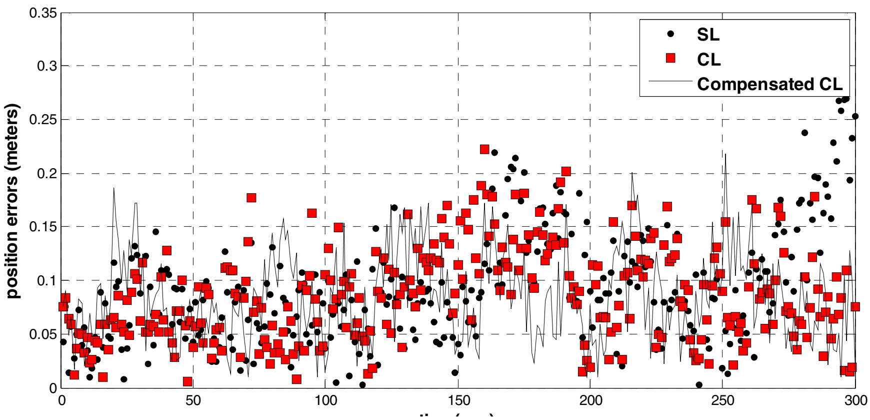

Fig. 10. Position errors of robot 3 in case 3

3.5 Case 3 : $\sigma_{DR} = 0.02887m$, $\sigma_{GPS} = 0.08661m$, Operating Time : 300s, and Refresh Interval : 10s

In this case, refresh interval is 10 second. Fig. 8 and Fig. 10 show the real trajectory and position errors for robot 3 during 300s respectively. Fig. 9 shows the accumulated distance errors for 10 robots. In this case, Fig. 9 shows that the errors of all robots aren't reduced. In this case, refresh interval of 50 seconds is more suitable than that of 10 seconds. As a result, we know that proposed method was able to improve localization accuracy in proper refresh interval (about 30s ~ 80s).

4 Conclusion and the Future Study

In this paper, the proposed method is motivated from the concept of DGPS which utilizes correlation between errors in common mode, and summarized in simple mathematical formula compared with existing methods. Simulation results show that the proposed method can achieve better localization performance in such cases as replacing the accumulated DR data with the GPS data providing fixed standard deviation for position error by proper refresh interval. In the future study, we will apply proposed cooperative localization algorithm to real multiple robot system.

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