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# Cooperative Localization by using Knowledge of Self-organized Regularity

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*Abstract*: In this paper, a new localization approach for a team of robots which utilize emergent properties of their formation is proposed. At times, some of such a synchronized behavior generates spin-off effects that include geometric patterns on them. Therefore, it seems to be a reasonable question whether it is possible to utilize the pattern. Firstly, the authors discuss Takayama's control strategy which is proposed for target enclosure formation, which is a typical formation for Robocup. Then they propose a simple and useful expansion of Monte Carlo localization to utilize the emergent pattern of this formation. The proposed algorithms are confirmed by a series of computer simulations.

*Keywords*: Distributed Robots, Swarm Intelligence, Particle Filter

## I. INTRODUCTION

Localization is an important issue for mobile robotics. It requires to integrate a set of observed data captured by different sensors. Bayesian approach is one of the major approaches which sets up probabilistic mathematical framework. Particle Filter is a non-parametric probabilistic Bayesian approach which is adequate for non Gaussian distribution of particles. However, it needs larger amount of computational resources than others. Generally, localization accuracy is depended on robot's behavior and task so on. Therefore, when a robot cannot manage sufficient computational resource for its localization by itself multi robot cooperation seems to be a hopeful direction. However, current multi robot cooperation for localization methods indicates poor scalability.

In this paper, we discuss a new multi robot localization approach which complements this weakness. We assume that robots already know their collective behavior which are emerged while they are at work. Collective behavior is a bottom-up phenomena, for example, *Mexican wave*. Generally, the phenomena is more stable, the larger the group size is. Therefore, it can be possible to make a new cooperative localization approach by using this property which works well when the group size is large. In this paper, we show an good example and formulate its ability.

This paper is composed as follows. Firstly, we explain Takayama's target enclosure scheme which is adopted as their work to generate collective behavior. Also Monte Carlo Localization is explained which is the algorithm to estimate a robot's position. Then, a new multi robot localization algorithm is proposed. Then, the results of a series of computer simulation verify this idea. As a result, the proposed algorithm can use target as a new landmark with $1/\sqrt{n}$ times small variance.

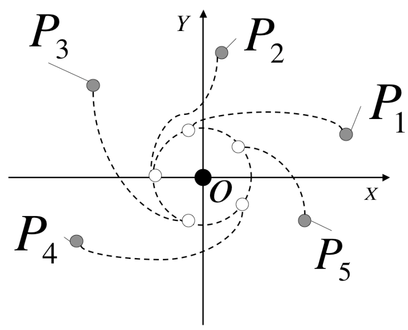


Fig.1. Takayama's Target Enclosure: dynamics

## II. COOPERATIVE LOCALIZATION

### 2.1. Particle Filter(MCL)

A bunch of sensor fusion methods are introduced. Multisensor fusion method based on particle filter is called as MCL(Monte Carlo Localization).

MCL is an implementation of Bayes Filter which a set of particles are used for representing probability distribution. Let's suppose current time is t. The set of particle at t is

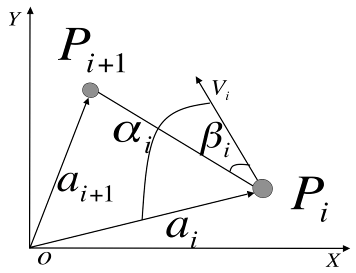


Fig.2. Takayama's Target Enclosure: rules

$$\chi_t := x_t^{[1]}, x_t^{[2]}, \ldots, x_t^{[M]} \quad (1).$$

Each particle represents a hypothesis about state of its robot. Here, a hypothesis means robot's position and direction in 2D space, namely $(x, y, \theta)$.

The a set of particle is updated by the step. A single update procedure is composed the following 3 sub procedures.

**Step1) sampling**

The new particle set $x_t^{[m]}$ is generated by the last particle set $x_{t-1}^{[m]}$ and the control signal at t $u_t$. We supposed that each robot has crawler so that $x_t^{[m]}$ is calculated by [2] and $u_t = (v, \omega)$. The set of new particles are called as $\bar{\chi}_t$

**Step2) Evaluation**

In this step each particle of $\bar{\chi}_t$ is evaluated. The likelihood of each particle $w_t^{[m]}$ is calculated. Let's suppose there are J landmarks on map L, which location is known. The $w_t^{[m]}$ is calculated by the probability $p(z_t | x_t^{[m]}, L_j)$ of observing $z_t = (r, \phi)$ about j-th landmark $L_j\,(1 \le j \le J)$ when it locates $x_t^{[m]}$ as follows.

$$w_t^{[m]} * = prob(r - \hat{r}) \cdot prob(\phi - \hat{\phi}) \quad (2)$$

where $(\hat{r}, \hat{\phi})$ is the true valu of j-th landmark $L_j$ and *prob* indicates a error function.

**Step3) Resampling**

The new set of particle $\chi_t$ is generated by $\bar{\chi}_t$ We adopt roulette selection. The selection probability of m-th particle is $w_t^{[m]}$.

### 2.2. Particle Filter(MCL)

A bunch of sensor fusion methods based on Bayesian approach are introduced [1]. Relative distance[3], rendezvous probability[4] transmitted are utilized for new evaluation criteria of equation (2). [5] proposes a camera system which uses transmitted particle for new candidates. It works well but all of these previous works supposed that each robot can identify all other robots. It makes serious problems when robots move fast and when they work in closed order. Basically, larger number of robots there are in a team, it makes harder to recognize a particular teammate.

## III. THE PROPOSED ALGORITHM

### 3.1. Collective Behavior and Bottom Up Properties

By the above summary the following idea comes up naturally. If some properties which get more reliable as increase of the number of robots are utilized, the robots can expect more accurate localization by using equation(2). Generally speaking, collective phenomena is occurred when many objects interact, for example, jam, Mexican wave. As known well, it is more difficult to emerge such character when the number of people in stadium is small so that this collective phenomena seems to be a good candidate for the robust property for localization of dense robots. For this purpose, we assume the following. Normally, these phenomena occur by chance and it is not intentional act. However, in this paper, we suppose that all of robots agree that they take some action to generate such collective pattern. More over, all of them know the bottom up pattern before hand.

### 3.2. Target Enclosure Behavior

In this paper, target enclosure behavior proposed by takayama [6] is adopted in exemplification of this new multi robot localization framework. Takayama proposes interesting simple rule for target enclosure in 2D plane. Let's suppose that n nonholonomic robots try to enclose a target at origin (see Fig.1). These robots are numbered counterclockwise. They propose the following control method.

$$v_i = f\beta_i \quad (3)$$

$$\omega_i = v_i / \bar{r} - k \cos \alpha_i \quad (4)$$

The $P_i$ , $v_i$ and $\omega_i$ denote i-th robot , its control speed $v_i$, and angular velocity respectively. This rule uses 2 angle information, $\alpha_i, \beta_i$(see Fig.2) and relative distance to the target. $k, f > 0$ are gain parameters. According this rule, the robots form a circle path around the target(see Fig.3).

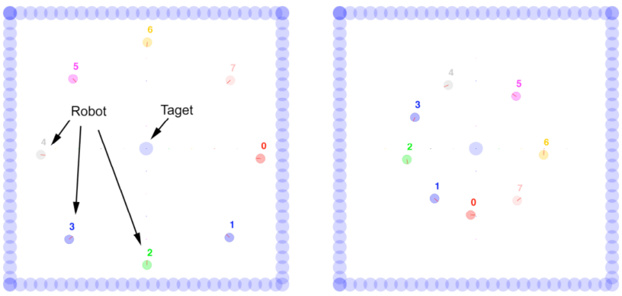


Fig.3 a scene of the target enclosure behavior. (i) An initial state (ii) A convergence state

Therefore, the following characteristics could be observable when this circular formation succeeds.

**(E1)** the relative distance to the target should be kept $\bar{r}$ .

(**E2**) the relative angle $\alpha_i$ to the target should be kept $\pi/2$ (by tangent line theorem).
(**E3**) the relative angle to its neighborhood should be equalized.

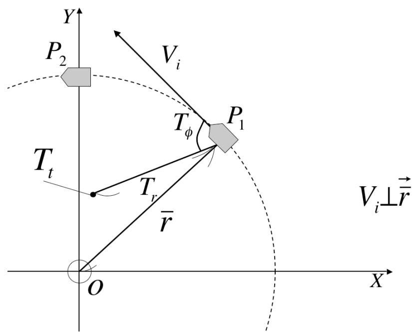


Fig.4. The proposed algorithm

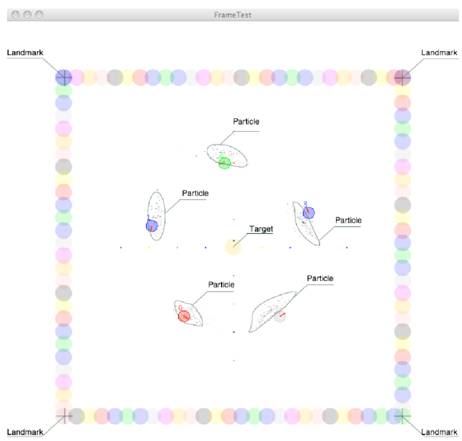


Fig.5. The simulation environment

### 3.3. Proposed algorithm

By these 3 information, the localization algorithm is proposed(Fig.4). This algorithm composes of 3 stages. Firstly, each robot $P_i$ deduces its position $\overline{xi_t}$ by average of its own particles $xi_t^{[m]}$. Next, by transmitting the deduced position each other, the position of target $T_t$ is estimated by averaging the set of position of them, namely $T_t = 1/n \Sigma \overline{xi_t}$.

At the third step, in MCL, the particle $x_t^{[m]}$ is evaluated by this information about the target and its observation $z_t$ more than the landmark information $L_j$.

$$w_t^{[m]} = prob(T_r - \bar{r}) \cdot prob(T_\phi - \pi/2) \cdot prob(r - \hat{r}) \cdot prob(\phi - \hat{\phi}) \quad (5)$$

$$T_r = \sqrt{(T_x - x)^2 + (T_y - y)^2} \quad (6)$$

$$T_\phi = atan2(T_y - y, T_x - x) - \theta \quad (7)$$

where $T_t$ is the distance to the target when $P_i$ locates at $x_t^{[m]}$, and $T_\phi$ indicates the angle to the target $T_t$ when $P_i$ is at $x_t^{[m]}$.

## IV. EXPERIMENTS

### 4.1. Accuracy of the target position

Our algorithm consists of 3 steps, and the first 2 steps estimates the target location by averaging of all of robots position. Firstly, the results of estimation of the target location are shown(Table.3.2).

We build the simulation (see Fig.5). Each robot is simplified as a 40cm diameter cylinder. The 12m x 12m rectangle field is surrounded by the same shape objects as wall. There are 4 landmarks at each corner of this field. At the center of the field, the target is set. The $\bar{r}$ sets 3m. All sensors installed at a robot contains realistic nose. Any measure of the distance suffers Gaussian nose with variance of 1m $N(0,1.0)$, on the other hand, $N(0,0.01rad)$ Gaussian noise comes to be mixed in any measure of angle.

Fig.6 shows the error of the estimation of target location by the proposed method (blue) and the error of the estimation by an isolated robot (red). The x axis means the time progress (step). Table 1 shows the statistic of the result.

Fig.6 says that the proposed method can estimate the target location more accurate than that of a single robot. Additionally, this method can provide the good quality information immediately on starting to enclose the target.

The estimation of target location is average of members' location. Therefore, the improvement seems to be getting large as the increase of the number of robots. Let's suppose that the standard deviation of error of distance to one of landmark is $\sigma_L$. Also $\sigma_X$ and $\sigma_T$ denote the standard deviation of error of localization of a robot and estimation of the target, respectively. An isolated robot uses landmarks only to estimate its position so that

$$\sigma_X = \sigma_L \quad (8)$$

If each of the above estimation is independent, $\sigma_T{}^2$ can be written as follows,

$$\sigma_T{}^2 = \frac{1}{n} \Sigma \sigma_X{}^2 \quad (9).$$

Then, we get

$$\sigma_T = \sigma_X / \sqrt{n} \quad (10)$$

Therefore, we can conclude that the proposed method can provide a $1/\sqrt{n}$ time more stable target location estimation than that by a single isolated robot.

Table 1 shows the results of that by a single robot (left column), by 5 robots team(the center column), and 8 robots team (the right column). $\sigma_T$ of single robot is 0.5004. On the other hand, $\sigma_T$ of 5 robots team and 8robots team are 0.2323 and 0.1836 respectively. These results about the improvement fit the above discussion because $1/\sqrt{5}$ =0.4472 ≒ 0.4642=(0.2323/0.5004) and $1/\sqrt{8}$ =0.3535 ≒ 0.3669=(0.1836 /0.5004)

Therefore, the proposed algorithm in n robots can estimate the target location with $\sigma_L/\sqrt{n}$ deviation.

### 4.2. Accuracy of Proposed localization Algorithm

Finally, we show the total performance of the proposed method. $\bar{r}$ =3m. A simulation runs 3000 steps. Table 2 shows the statistics of the robot's location estimation error of the last 2000 steps. The left column indicates localization error by a single isolated robot. The center and the right column mean that by 5 robots team and by 8 robots team, respectively. The 5 robots team can get better estimation (0.2618 m) than that of a single robot.(0.3356 m) Moreover, the 8 robots team can get more better estimation than that of 5 robots team.

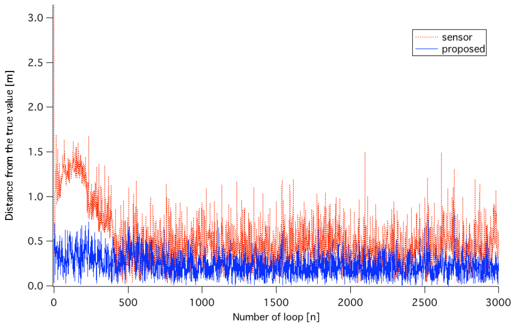


Fig.6. The error of the estimation of the target location by the proposed method.

Table 1. The statistics of the estimation error of the target location by the proposed method.

| (meter) | estimation by an isolated robot | the proposed by 5 robot team | the proposed by 8 robot team |
|---|---|---|---|
| error average | 0.5004 | 0.2323 | 0.1836 |
| deviation of error | 0.311 | 0.124 | 0.111 |
| distribution of error | 0.097154 | 0.015556 | 0.012502 |
| the number of samples | 3000 | 3000 | 3000 |
| the worst error | 3.1432 | 0.7945 | 0.9241 |
| the best estimation | 0.0243 | 0.0011 | 0.0023 |

Table 2. The statistics of the estimation error of robot location.

| (meter) | an isolated robot | the proposed(5 robots) | the proposed(8 robots) |
|---|---|---|---|
| error average | 0.3356 | 0.2618 | 0.2574 |
| deviation of error | 0.021274 | 0.021094 | 0.023420 |
| the worst error | 0.9005 | 0.9856 | 1.0394 |
| the best estimation | 0.0069 | 0.0023 | 0.0053 |

## V. CONCLUSION

In this paper, we proposed a new multi robot localization approach by using collective behavior which are emerged while they are at work. The results of a series of computer simulation based on Takayama's target enclosure scheme verify this idea. Then this cooperative localization approach by using this bottom-up property which works well. Especially, the proposed algorithm can use target as a new landmark with $1/\sqrt{n}$ times small variance. Therefore, we hope that this framework could complement the low scalability of traditional multi robot cooperative localization.

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