거리매칭에 기반한 다수로봇 위치추정

제홍모°, 김정태, 김대진

포항공대

invu71@postech.ac.kr, postman@postech.ac.kr, dkim@postech.ac.kr

Multi-Robot Localization based on Distance Mapping

Hongmo Je°, Jungtae Kim, Daijin Kim

POSTECH

ABSTRACT

This paper presents a distance mapping-based localization method with incomplete data which means partially observed data. We make three contributions. First, we propose the use of Multi Dimensional Scaling (MDS) for multi-robot localization. Second, we formulate the problem to accomodate partial observations common in multi-robot settings. We solve the resulting optimization problem using 'Scaling by Majorizing a Complicated Function (SMACOF)', a popular algorithm for iterative MDS. Third, we not only verify the performance of MDS-based multi-robot localization by computer simulations, but also implement a real world localization of multi-robot team. Using extensive empirical results, we show that the accuracy of the proposed method is almost similar to that of Monte Carlo Localization(MCL).

1. Introduction

Localization is an important problem in mobile robotics, and the literature is rich with solutions to variants of the problem. In recent years, there has been increased activity in the area of collaborative approaches to multi-robot localization. A simple approach for cooperative localization system with no infrastructure was first proposed in [1]. This approach used a 'station-mover' strategy which divided all robots into two groups. At any given time, one group is stationary and the other is moving. Moving robots are thus able to use stationary robots as landmarks to correct for odometry error. The groups interchange roles and iterate until all robots reach their targets.

A dominant modern approach is the probabilistic Monte Carlo Localization (MCL) [2] utilizing an independence property to estimate the position of the individual robots. A study [3] on the influence of different group trajectories on the accuracy of MCL showed that through appropriate cooperation, localization error decreases while the number of robots increases. Other approaches taking advantage of relative inter-robot range and bearing observations also have been proposed [4, 5, 6]. A maximum likelihood estimation-based approach is given in [7], and an Extended Kalman Filter [8] using relative observations of range and bearing is described.

In general, most of robot localization methods, which have been proposed in recent, have concentrated on a question that is ``Where am I?" in an environment with known/unknown map, however, we regarded multi-robot localization problem as a task of finding relative positions of each robot in multi-robot team.

In this paper we propose a distance mapping approach to multi-robot localization with partially observed inter-robot distances as the relative observations. We apply Multi-dimensional scaling (MDS) to this problem. MDS is a well-studied distance mapping method with a history of application in many fields such as pattern classification, data visualization, mathematical psychology, and so on. We use an iterative MDS algorithm called SMACOF [12] which can minimize a stress function of both full distance and incomplete distance matrix through an optimization technique. In addition we utilize the motion information of robots to improve the performance on both convergence and stability by predicting likely positions of robots when direct inter-robot range estimates are unavailable.

At each iteration of our algorithm if range measurements are unavailable, we experiment with three choices to estimate the missing information - random, where no information is passed from one step to the next, previous, where at each iteration a missing range value is substituted by the value at the previous iteration, and prediction, where the value at the previous iteration is combined with the current motion information to produce an estimate of the current missing value. We performed extensive simulations to verify which choice is good. Our experiments show that the prediction strategy is the best choice for initialization

2. Distance Mapping

A distance mapping is that one takes a set of objects and a distance metric and maps those objects to a space in such a way that the distances among objects are approximately preserved. Consider a set of objects $S = \{s_1, s_1, \ldots, s_N\}$ and a distance function δ where for any two object $s_i, s_j \in S$, $\delta(s_i, sj)$ (denoted δ_{ij}) represents the distance between s_i and s_j. The function δ can be a Euclidean or a general distance metric. A general distance metric δ must satisfy the following properties:

- Nonnegative : $\delta(s,s) = 0$
- Symmetry : $\delta(s,t) = \delta(t,s)$
- Triangle inequality : $\delta(s,t) \le \delta(s,w) + \delta(w,t)$

where s, t, w are objects. Assuming the target p dimensional space (usually p=2 or p=3) is $T \in R^p$, the distance mapping finds a embedding function $\varphi : S \mapsto T$ satisfying $\delta(s_i, s_j) = d(\varphi(s_i), \varphi(s_j))$ where δ is a metric of space S and d is a metric of space T.

Although MDS has its origins in psychometrics and was originally proposed to help understand people's judgments of the similarity of members of a set of objects, it has found applications in diverse fields as marketing, sociology, physics, political science, biology, and engineering. MDS is a generic term that includes many different specific types. These can be classified according to whether the data are qualitative or quantitative, the number of similarity matrices, the nature of the MDS model, and the implementation of the algorithm to solve the MDS problem. In this paper, we assum that MDS-based multi-robot localization is a classical-metric-unweighted MDS problem because a distance on Euclidean space must be quantitative, may be an unweighted matrix, and can be treated with only one similarity matrix. As one of the distance mapping, MDS finds a embedding function which minimize a 'stress'. The stress function of classical-metric-unweighted MDS can be expressed as a naive least-squares equation as follows

$$\phi = \sum_{i,j}^{N} (\delta_{ij} - d_{ij})^2. \tag{1}$$

We can modify the stress function ϕ in Eq. (1) into matrix form as follows

$$\begin{aligned} \phi(X) &= \sum_{i,j} (\delta_{ij} - d_{ij}(X))^2 \\ &= \sum_{i,j} \delta_{ij} + \sum_{i,j} d_{ij}(X) - 2\sum_{i,j} \delta_{ij} d_{ij}(X) \\ &= \sum_{i,j} \delta_{ij} + tr(X^T \Gamma X) - 2tr(X^T \Omega(X) X) \end{aligned} \tag{2}$$

where $\Gamma = NI_{N*N} - 1_{N*N}$ and

$$\Omega = \omega_{ij}(X) = \begin{cases} -\dfrac{\delta_{ij}}{d_{ij}}(X), \; i \ne j, \; d_{ij}(X) \ne 0 \\ -\sum_{k \ne i} \omega_{ik}, \; i = j \end{cases} . \tag{3}$$

2.1 Iterative MDS

Iterative MDS minimizes the stress function using numerical optimization techniques. Line search and trust-region methods can find a local optimum, whereas a genetic algorithm, tabu search, and simulated annealing can achieve global optimum. This paper considers only line search methods for optimization because of both efficiency and speed of convergence. The procedure of generic iterative MDS is summarized as follows:

$k = 0$

Step 0: Start with a guess $X^{(0)}$: Initialization.

Step 1: Determine a direction $\Delta^{(k)}$ and a step size $\alpha^{(k)}$

Step 2: Update

$$X^{(k+1)} = X^{(k)} + \alpha^{(k)} \Delta^{(k)} \quad s.t. \, \phi(X^{(k+1)}) \le \phi(X^{(k)})$$

Step 3: Goto step 1 until stop condition is satisfied. The popular choice of a descent direction is a gradient descent

$$\Delta^{(k)} = -\nabla \phi(X^{(k)})$$

2.2 SMACOF

Unfortunately, the stress function ϕ is non-convex so it is impossible to find a global minimum. Majorization is a method which minimizes a majorizing function $\psi(X,Z)$ instead of the stress $\phi(X)$. $\psi(X,Z)$ must be quadratic by mazorization and satisfy $\phi(X) \le \psi(X)$. Following the formulation in [12] for stress majorization (SMACOF: Scaling by Majorizing a Complicated Function), we define a quadratic majoring function for stress as follows.

$$\psi(X,Z) = \sum_{i,j}\delta_{ij} + tr(X^T\Gamma X) - 2tr(X^T\Omega(Z)Z)$$

$$\ge \sum_{i,j}\delta_{ij} + tr(X^T\Gamma X) - 2tr(X^T\Omega(X)X) = \phi(X).$$

The gradient of $\psi(X,Z)$ w.r.t X is

$$\nabla_X\psi(X,Z) = 2\Gamma X - 2\Omega(Z)Z. \quad (4)$$

We have X by rewriting $\Gamma X = \Omega(Z)(Z)$,

$$X = \Gamma^{\dagger}\Omega(Z)Z = \frac{1}{N}\Omega(Z)Z. \quad (5)$$

If we set $X^{(k)} = Z^{(k)}$ then the gradient of the stress $\phi(X)$ (instead of Eq. ((4))) is given by

$$\nabla\phi(X) = 2\Gamma X - 2\Omega(X)X. \quad (6)$$

From the Eq. ((5))((6)), the majorization update rule can be derived as

$$\begin{aligned} X^{(k+1)} &= \Gamma\ \Omega(X)X \\ &= X^{(k)} - X^{(k)} + \Gamma\ \Omega(X)X \\ &= X^{(k)} - \frac{1}{2}\Gamma^{?}(2\Gamma X^{k)} - 2\Omega(X)X) \\ &= X^{(k)} - \frac{1}{2}\Gamma^{?}\nabla\phi(X^{k)}) \\ &= X^{(k)} - \frac{1}{2N}\nabla\phi(X^{(k)}). \end{aligned} \quad (7)$$

3. Localization

This section illustrates a detailed explanation of the proposed localization technique. We assumed each robot is equipped with a range sensor such as a laser finder, sonar, or camera to identify distance to other robots. We also assume that each robot is equipped with a set of inertial sensors (e.g. a compass and odometer) to compute its own motion. Define the configuration $x_i(t) = [x_{ix}(t) \quad x_{iy}(t)]$ as the current position of robot i at time t. The state we want to estimate is

$$X(t) = [x_1(t), x_2(t), x_3(t), \ldots, x_N(t)]. \quad (8)$$

3.1 Initialization

At each optimization step, the algorithm can be initialized. We implement three strategies for this:

• Random -- If we have no prior about the environment and the dynamics of each robot, coordinates obtained at random are set as initial point.

$$X^{(0)}(t) \sim N(\mu, \sigma^2)$$

This policy is very simple but unstable from the point of view of convergence. To make matters worse, it causes mapping inconsistency like the flip ambiguity.

• Previous -- When the movement of each robot is comparably small or the iteration time step is short, it may be desirable to set initial locations to the previous coordinates.

$$X^{(0)}(t) = X(t-1)$$

• Prediction -- The system is initialized with the predicted value of the current pose by applying a motion model to the previous pose.

$$X(t) = X(t-1) + \rho X(t)$$

It is difficult to know the true motion dynamics $\rho X(t)$, but $\rho\tilde{X}(t)$ can be estimated from motion sensors. Combining the previous coordinates with this $\rho\tilde{X}(t)$ we can set

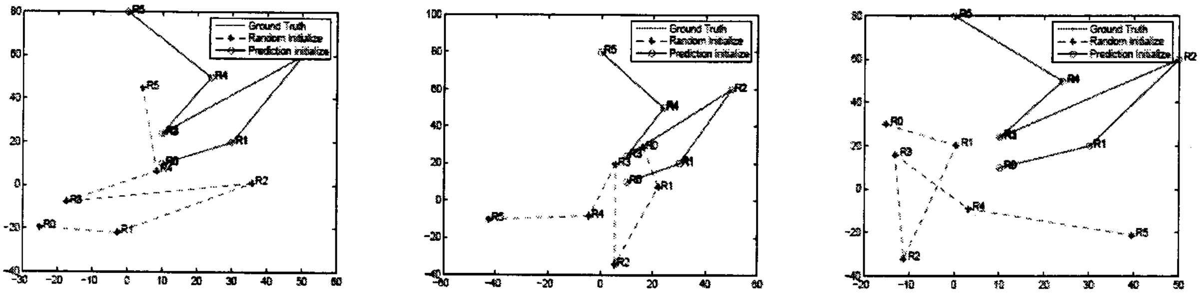
$$X^{(0)}(t) = X(t-1) + \rho\tilde{X}(t).$$

4. Experiments and Results

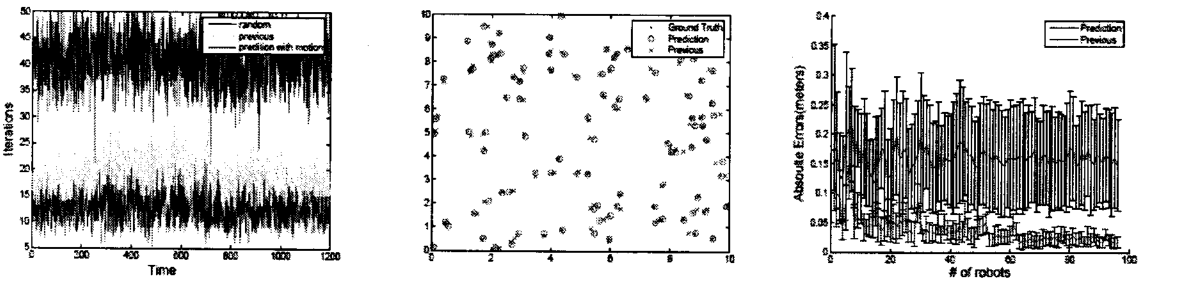
We performed several experiments to validate the proposed multi-robot localization.

Case I: No missing distance

Starting in a basic environment, there are 6 robots marked $R0$ to $R5$. We assumed that all inter-robot distances are available and motion dynamics can be obtained via odometry on each



(a) Translation and Rotation.
(b) Translation, Rotation, and Flip.
(c) Fail to optimize.



(a) Comparison of convergence.
(b) The embedding results for 100 robots; initializing with both prediction and previous.
(c) Absolute error plots.

Fig. 1. Embedding results of random initialization.
Fig. 2. The results for the 'no missing data' case

robot which has Gaussian noise($\sigma = 0.2$) as the measurement error. Robots are made to move randomly for 1200 time steps.

As noted in Section, we applied three strategies for initialization at each optimization step. Fig. 2-(a) shows the plot of convergence for each policy. The figure tell us that initializing with the prediction procedure, which is generated by adding the previous coordinates to the motion information, is more than 3 times faster than random initialization. The previous procedure was more than 2 times faster than the random case.

Table I. Relative location error and convergence speed

	Random	Previous	Prediction
Iterations (converge)	40.92	18.20	12.46
σ	5.15	3.75	2.87
Relative errors	0.0156	0.0143	0.0134
σ	0.0023	0.0026	0.0029

To check the accuracy of the proposed distance mapping with the three initialization strategies, we evaluated the mean of the relative errors between the real position and the computed position in 2D coordinate space. The error is defined in Eq. (9).

$$RelErr = \frac{\|\delta(P) - \delta(\hat{X})\|}{(N-1)^2} \tag{9}$$

, where $\delta(P)$, $\delta((\hat{X}))$ are distance matrices for the real position $P = [p_1, p_2, \ldots, p_N]$ and the embedded(computed) position $\hat{X} = [x_1, x_2, \ldots, x_N]$.

The relative errors are compared in Table I. Even though it seems like their accuracy have little difference in the terms of the relative error, the random initialization has some problems. When it is required to reconstruct the absolute position, the random initialization needs more than two or three robots to have known positions. Fig. 1-(a) represents the case of translation and rotation requiring at lest two. Fig. 1-(b) indicates the case of translation, rotation, and flip requiring at least three. Fig. 1-(c) shows the worst case where a solution was not found due to divergence. For absolute localization, Fig. 2-(c) shows results in an environment where we experimented with between 5 and 100 robots performing wandering.

The absolute error is defined as $AbsErr = \|P - \hat{X}\|$. As shown in Fig. 2-(a), prediction is more accurate than previous. The number of robots might not affect the performance of absolute localization.

Case II : Partially observed distance

To better reflect a real situation, we performed experiments on the Player/Stage simulator [14] with 9 robots. We configured a world with complex corridors causing occlusions at most time step. Each robot has a laser finder which can observe other objects within 5 meters range in an 180 degree angle, a odometry device to calculate its motion, and a fiducial bar-code to be identified by other robots. We used the prediction technique for initialization at each optimization step. Fig. 4 indicates the multi-robot team consisting of five robots. All members of the robot team can communicate each other via wireless network. Instead of using a range sensor such as ultra sonic or laser scanner, we use only omnidirectional camera or pan-tilt-zoom(PTZ) camera. Therefore, we take both distance and ID information of the others simultaneously. The robot named *commander* must keep all information for localization and previous positions of all members of the multi-robot team. It first collects data from other robots, and then it generate relative positions of the team using MDS localization. Finally, *commander* broadcasts the result of localization to all members.

5. Discussion and Conclusion

In this paper, a global localization and map building is not described, but a relative multi-robot localization is presented since we have only focused on relative positions of multi-robot team. We make three contributions - we propose the use of Multi Dimensional Scaling (MDS) for multi-robot team localization; we formulate the problem to accomodate partial observations common in multi-robot settings; and we verify the performance of MDS-based multi-robot localization via both simulations and real implementation.

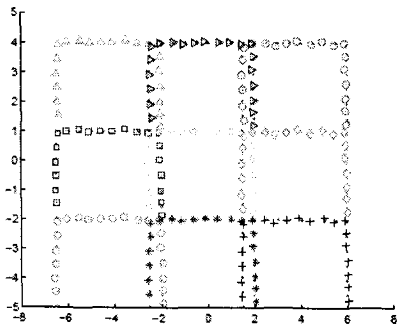


Fig. 3. The trajectory of the ground truth (represented as dots '.') and the embedding by the proposed method (represented as symbols).

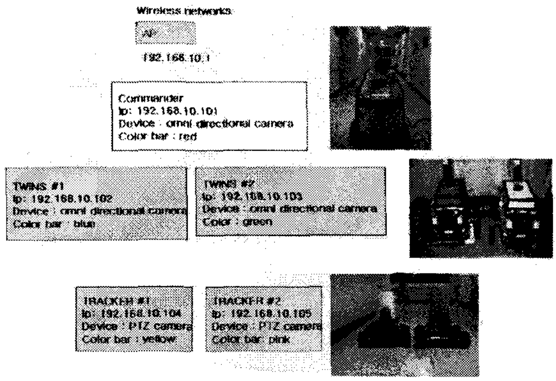


Fig. 4. Implemented Robot Team having 5 robots

We take advantage of the motion information of robots to help the optimization procedure. Three policies are compared at each time step: random, previous, and prediction (constructed by combining the previous pose estimates with motion information). Using extensive empirical results, we show that the initialization by the *prediction* method results in better performance in terms of both the accuracy and speed when compared to the other two initialization techniques. In addition we verify the performance of both MCL-based and MDS-based multi-robot localization are almost same.

Our current work is in establishing principled techniques for comparing our approach with MCL. In general we are trying to find relations and distinctions between probabilistic approaches and distance mapping-based localization with motion information. Furthermore, we are interested in a theoretical analysis of error bounds and uncertainty of this approach.

ACKNOWLEDGMENT

This work is financially supported by the Ministry of Education and Human Resources Development(MOE), the Ministry of Commerce, Industry and Energy(MOCIE) and the Ministry of Labor(MOLAB) through the fostering project of the Lab of Excellency, and also performed for the Intelligent Robotics Development Program, one of the 21st Century Frontier R&D Programs funded by the Ministry of Commerce, Industry and Energy (MOCIE).

REFERENCES

[1] R. Kurazume, S. Nagata,and S. Hirose. "Cooperative positioning with multiple robots", In *Proc. of the IEEE ICRA*, vol. 2, pp. 1250–1257, May 1994.

[2] D. Fox, W. Burgard, and H.Thrun, "A Probabilistic Approach to Collaborative Multi-Robot Localization", *Autonomous Robots*, vol. 8, pp. 325–344, 2000.

[3] I. M. Rekleitis, G. Dudek, and E. E. Milios, "Multi -robot Cooperative localizations: a study of trade-off between efficiency and accuracy", In *Proceedings of the 2002 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, vol. 3, Lausanne Switzland, pp. 2690–2695, Oct. 2002.
[4] H. Sugiyama, "A method for an autonomous mobile robot to recognize its position in the global coordinate system when bulding a map", In *Proceedings of the 1993 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, vol. 3, Yokohama Japan, pp. 2186–2191, 1993.
[5] J. Hyams, M. W. Powell, and R. Murphy, "Cooperative Navigation of micro-rovers using color segmentation", In *Proceedings of the IEEE Intl. Symp. on Comp. Intelligent Robotics and Automation*, pp. 195–201, 1999.
[6] A. Howard, M. J. Mataric, G. S. Sukhatme, "Putting the 'I' in 'Team': An Ego-Centric Approach to Cooperative Localization", In *Proceedings of the IEEE International Conference on Robotics an Automation (ICRA03)*, pp. 868–892, Taipei, Taiwan, September 2003.
[7] A. Howard, M. J. Mataric, and G. S. Sukhatme, "Localization for Mobile Robot Teams Using Maximum Likelihood Estimation", In *Proceedings of the 2002 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, vol. 3, Lausanne Switzland, pp. 2849–2854, Oct. 2002.
[8] S. I. Roumeliotis and G. A. Bekey, "Distributed Multirobot Localization", *IEEE Transaction On Robotics And Automation"*, vol. 18, no. 5, Oct. 2002.
[9] A. Martinelli, F. Font, and R. Siegwart, "Multi-Robot Localization Using Relative Observations", In *Proceedings of the 2005 IEEE Int. Conf. on Robotics and Automation*, Barcelona Spain, pp. 2808–2812, April 2005.
[10] J. Xi and H. Zha, "Sensor Positioning in Wireless Ad-hoc Sensor Networks Using Multi Dimensional Scaling", In *Proceedings of the 23rd Conference of the IEEE Communicatons Society (Infocom 2004)*, Hong Kong, Mar. 2004.
[11] Y. Sang and W. Ruml, "Improved MDS-based Localization", In *Proceedings of the 23rd Conference of the IEEE Communicatons Society (Infocom 2004)*, Hong Kong, Mar. 2004.
[12] J. de Leeuw, "Applications of convex analysis to multidimensional scaling", In *Recent developments in statistics*, Amsterdam, The Netherlands: North-Holland, pp. 133–145, 1977.
[13] J. C. Gower, "Some distance properties of latent root and vector methods used in multivariate analysis", *Biometrika*, vol. 53, pp. 325–338, 1966.
[14] B. P. Gerkey, R. T. Vaughan, A. Howard, "The Player/stage Project:Tools for Multi-Robot and Distributed Sensor Systems", In *Proceedings of the International Conference On Advanced Robotics (ICAR 2003)*, pp. 317–323, Coimbra Portugal, Jun. 2003.
[15] P. Chang, "Robust Tracking and Structure from Motion with Sampling Method", doctoral dissertation, tech. report CMU-RI-TR-02-33, Robotics Institute, Carnegie Mellon University, February, 2003.