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Fuzzy Logic in Collective Robotic Search

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Abstract—One important application of mobile robots is searching a geographical region to locate the origin of a specific sensible phenomenon. We first propose a fuzzy logic approach using a decision table. A novel fuzzy rule based was designed. And then a fuzzy search strategy is adopted by utilizing the three tier centers of mass coordination. Experimental results show that fuzzy logic algorithm is an efficient approach for the collective robots to locate the target source. In addition, noise and the position of the target affect the searching result.

1. INTRODUCTION

In recent years there has been growing interest in collective robotic search problem. A team of smaller and simpler collective robots, each with equal or similar capabilities, completes high-risk tasks for human beings [1]. The objective of the team of robots is to find the origin of a specific phenomenon with the maximum field intensity by sharing information between robots, and to aggregate around the phenomenon. For example, we may need to drive a large number of inexpensive, expendable sensory robots in hazardous or hostile environments, with a particular emphasis on sensing concentrations of hazardous chemicals in terrestrial environments. In case where human intervention through teleoperation is not available, the robot team must be deployed in a territory without supervision, requiring an autonomous decentralized coordination strategy. Mapping mine fields, extraterrestrial and undersea exploration, detecting the location of chemical and biological weapons, and the location of explosive devices are its important applications [2]. A lot of advantages have been achieved. First, low cost. As we know, several small and simple robots cost less than a single but much more complex robot; Second, high speed. Although a large robot with powerful sensors and a highly sophisticated search mechanism performs tasks more efficiently than a single and simpler robot, the collective robots can give a greater overall efficiency. Third and the most valuable advantage is the communication between the collective robots [3]. A robot receives information from other robots, decides which direction to move, and then proceeds ahead [4]. In addition, once a robot find the goal, all the other robots would jump to the goal.

Investigations of collective behavior are considerably rarefied, and studies involving collective search are rarer still.

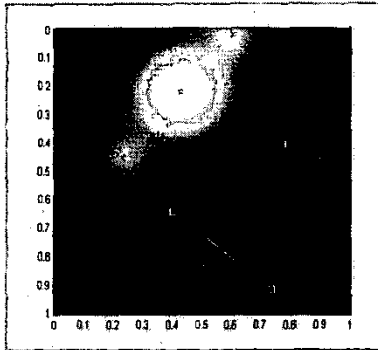
In [5], a decentralized *alpha-beta coordination* is proposed for an agent team searching for source targets. Its simulations confirm the ability of the team to find a source and stabilize the steady-state mean squared error. It has been shown how space-filling curves can enhance the efficiency and robustness of geographic search by robot collectives [6]. In [7], a control system employing an extended Kalman filter (EKF) and different styles of Global position System (GPS) is introduced to control a mobile robot to search a given rectangular area. In [8], the author discusses relevant results in robotics which are inspired by animal behavior. The foraging problem[9][10][11][12], in which robots collect objects scattered in the environment, is a canonical problem related to the source location problem. Recently, several experiments on robotic search algorithm have been reported. Wunsch and Zhang provided three different neural network algorithms: steepest ascent algorithm, combined gradients algorithm and stochastic optimization algorithm to solve the collective robotics search problem. The experimental results showed that the performance of steepest ascent method is better than that of combined gradient method, while the stochastic optimization method is better than steepest ascent method [13]. What's worth notice is that none of these previous research work adopt fuzzy logic based algorithm to accomplish the collective robotic search problem.

We propose two novel fuzzy logic algorithms to solve the collective robotic search problem. The robots can correctly identify the goal source, which is characterized by a maximum intensity, while incurring a low total cost.

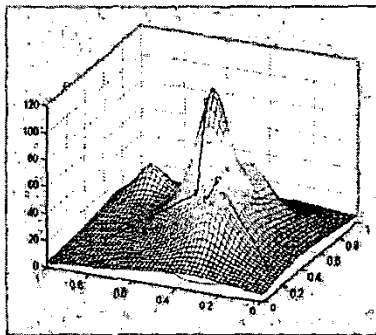
2. PROBLEM DESCRIPTION

Let's assume we have a two-dimensional bounded Euclidean space, as shown in Fig. 1. Five signal sources are randomly distributed in the domain. The brightest source is the target, which has the maximum signal intensity among all these sources, and others are classified as noises, which possess weaker intensities. Our goal is to locate the target source

correctly by sharing information among robots. Obviously, we have the maximum of total field intensities near the target source. We also presume there are no obstacles on this domain and each source emits the signal evenly in all directions. The searching procedure will end when all the robots converge to the target.



(a) Simulation domain with target, noise and collective robots in it.



(b) Field intensity of the target and noises

Fig. 1 Robot search region where there are five sources and four robots. Our experiments were carried out on this 1 by 1 length unit square domain. The red star with maximum intensity denotes the target, and the blue crosses with weaker intensity denote the noises, and the square blocks with different colors denote the robots. The lines indicate each step of individual robot. In (a), x-axis and y-axis denotes the coordination of sources and robots. The level of the field intensity can be observed easily in (b). In (b), x-axis and y-axis denotes the coordination of sources and robots while the z-axis denotes the field intensity of each source.

3. FUZZY LOGIC USING A DECISION TABLE

In this approach, a decision table determines the robots' behavior in a 2-dimensional space. It has two axes. The first is $f_i(k)$, which is the measured field intensity of the i th robot at the k th step. It is sensed by the sensor at each step. The second is $P_i(k)$, which is the estimated distance between the robot and the target source. The fuzzy rule base for the robotic search was chosen as shown in Table 1.

TABLE 1 THE FUZZY RULE BASE FOR ROBOTIC SEARCH

$P_i(k) \Rightarrow$	Small	Medium	Large
$f_i(k) \Downarrow$			
Small	M_{rs}	M_{dm}	M_{dl}
Medium	M_{ds}	M_{dm}	M_{dl}
Large	$70\%M_{ds}$ $30\%M_{-dm}$	M_{rs}	M_{rs}

where M denotes the robot movement, which is the length of a step; the subscript r represents a random movement; d indicates a specific direction towards the estimated location of the target source, which will be described later; $-d$ indicates the opposite direction; s , m , and l represent small action, medium action, and large action, respectively.

The robot calculates a gradient of the field intensity using its current measurement, $f_i(k)$, the previous measurement $f_i(k-1)$, and the positions at these two steps, and move along the gradient of the field intensity.

The estimation of $P_i(k)$ is given as below.

$$P_i(k) = \sqrt{(x_i(k) - \bar{x}_i(k))^2 + (y_i(k) - \bar{y}_i(k))^2} \quad (1)$$

where $x_i(k)$ is the x-coordinate of robot i at step k , $y_i(k)$ is the y-coordinate of robot i at step k , $\bar{x}_i(k)$ is the estimated x-coordinate of the center of mass of the collective robots, and $\bar{y}_i(k)$ is the estimated y-coordinate of the center of mass of the collective robots, which are given as follows.

$$\bar{x}_i(k) = \frac{\sum_{j \in C}^N f_j(k) \cdot x_j}{\sum_{j \in C}^N f_j(k)} \quad (2)$$

$$\bar{y}_i(k) = \frac{\sum_{j \in C}^N f_j(k) \cdot y_j}{\sum_{j \in C}^N f_j(k)} \quad (3)$$

where N is the total number of robots, $C = \{\text{the robots who communicate with the } i\text{th robot at time step } k\}$.

After both $f_i(k)$ and $P_i(k)$ are calculated, the problem is how to classify them into three categories (i.e. large, medium, and small). We proposed a dynamic classification method. For the field intensity, $f_i(k)$ classification, *large* field intensity is the value higher than $2/3$ of the largest field intensity previously recorded by any robot; field intensity is *small* if it is either less than 20% of the lowest measurement ever recorded, or less than $1/2$ of the current value. If the value doesn't fall into both of the categories, it is *medium*.

For the distance, $P_i(k)$ classification, it is classified as *large* if it is greater than $2/3$ of the largest distance between two robots; a distance is *small* if it is less than either the mean of the closest 20% robots or $1/2$ of the large distance, which ever is smaller. Any value in between is *medium*.

For the movement, M classification, it is classified as *large* if it is greater than $1/3$ of the largest distance between two robots; it is *small* if it is less than either the mean of the closest 10% robots or $1/4$ of the large movement, which ever is smaller. Any value in between is *medium*.

4. FUZZY LOGIC USING THREE TIER CENTER OF MASS COORDINATION

We design a different fuzzy logic approach to locate the target source using the three tier centers of mass coordination [15]. The membership function of field intensity is designed as shown in Fig. 2. The field intensity can be represented as a membership function of small, medium or large.

Once each robot has assigned itself a level in the three tier hierarchy, positions of the three centers of mass are calculated for all large, medium, and small field intensity robots, respectively, which are denoted as $V_{cml}(k)$, $V_{cmm}(k)$, and $V_{cms}(k)$, respectively. Two fuzzy rules are used to calculate the next position of the robots, as shown in (4). $V_i(k)$ is the position of the robot i relative to the origin at time step k .

$$V_i(k+1) = V_{cml}(k), \quad \text{if } F \text{ is small}$$

$$V_i(k+1) = (V_{cml}(k) - V_{cms}(k)) + V_i(k), \quad \text{otherwise}$$

(4)

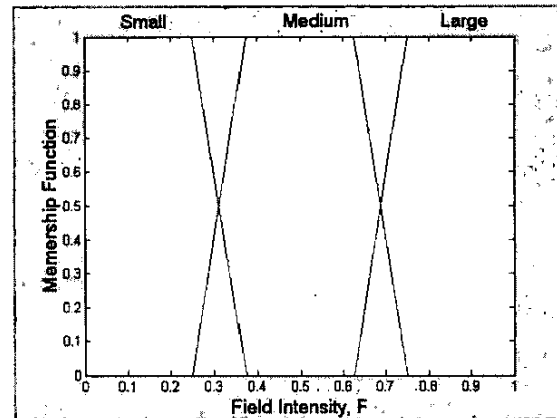


Fig. 2 Membership functions of the field intensity. F is the value that a robot has sensed.

Since initial positions of the robots are randomly chosen, they can be evenly distributed around the target, or group completely on one side of the target. Therefore, once the robots encounter a significant decrease in field intensity they stop and wait for new data. From (4), we can see that, for the robots on small field intensity sources, they will immediately jump to the center of mass of the robots with large field intensities; for the robots on large or medium field intensity sources, they will proceed in the direction between the center of mass of the robots with large field intensities and that of the small center of mass. The upper formula in (4) is most useful when the robots are distributed around the target. Because the large field intensity center of mass might be the target, or very near the target. The other formula in (4) is useful if all the robots are on one side of the target.

5. EXPERIMENTAL RESULTS

5.1 Experiment 1: Fuzzy Logic Using a Decision Table

We use the Intel Pentium IV processor up to 2.2GHz, and 1GB memory PC to do the experiments. The simulations are conducted in a domain free of obstacles. In this experiment, we experiment on the fuzzy logic approach using a decision table. The simulation is made on a domain of size 1 by 1 length units with 1000 trials. We put one target source, two noise sources, and five robots in the domain. Robots are initially distributed randomly in the domain. Fig. 3 shows the search routes of the robots in a trial.

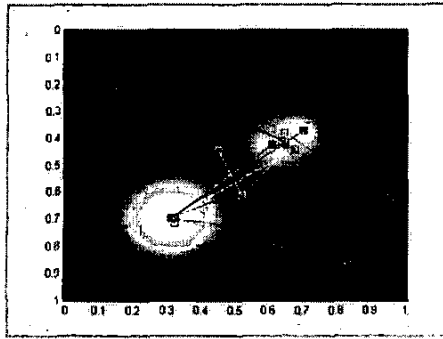


Fig. 3 Search route of the collective robots. There are one target source, two noise sources, and five robots in the domain. The brightest signal is the target source, and the other two signals with weaker field intensity are noise sources, which are overlap in this trial. The square denotes the robot.

Two parameters are used to evaluate the performance. One is the amount of covered domain, and the other is the number of failures. The failure is defined as any trial where the robots cover more than 100% of the domain, or when the robots stop. The experimental results are shown in Table 2.

TABLE 2 EXPERIMENTAL RESULTS

	Target Fixed at (0.5,0.5)	Random Target
Noiseless Environment	18.9% area covered, 1.5% failures	27.2% area covered, 2.4% failures
Noisy Environment	22.8% area covered, 5.3% failures	27.7% area covered, 19.1% failures

5.2 Experiment 2: Fuzzy Logic Using Three Tier Center of Mass Coordination

In this experiment, we experiment on the fuzzy logic approach using three tier centers of mass coordination. The simulation is made on a domain of size 1 by 1 length units with 1000 trials. We put one target source, two noise sources, and five robots in the domain. Robots are initially distributed randomly in the domain. The experimental results are shown in Table 3.

TABLE 3 EXPERIMENTAL RESULTS

	Target Fixed at (0.5,0.5)	Random Target
Noiseless Environment	19.2% area covered, 1.7% failures	27.5% area covered, 3.1% failures
Noisy Environment	21.5% area covered, 5.9% failures	28.1% area covered, 18.7% failures

6. CONCLUSION

We proposed two novel fuzzy logic approaches for robotic search in a world free of obstacles. Experimental results show that fuzzy logic approach is an efficient approach for the

collective robots to locate the target source. Noise and the position of the target have an impact on the searching result. In a noisy environment, the robots occur more failures and cover more area to locate the target than in the environment free of noise. This might because the robots are nearer to the noise sources than to the target source. On the other hand, if the position of the target is at the center of the domain, the robots can locate the target with few failures, and less covering area. However, if the location of the target is randomly chosen, the robots cover much more area, and thus more failures may occur. This might because the target locates on one side of all the robots.

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REFERENCES

- [1] Y. Uny Cao, Alex S. Fukunaga, Andrew B. Kahng, and Frank Meng, "Cooperative Mobile Robotics: Antecedents and Directions," *Proceedings of 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems 95, 'Human Robot Interaction and Cooperative Robots'*, vol. 1, pp. 226 - 234, 1995.
- [2] S. Gross and J.Deneubourg, "Harvesting by a Group of Robots," *Proceedings of European Conference on Artificial Intelligence*, 1992.
- [3] C. Kube and H. Zhang, "Collective Robotics: From Social Insects to Robots," *Adaptive Behavior*, vol. 2 (2), 1993.
- [4] D. Gage, "How to Communicate with Zillions of Robots," *Proceedings of SPIE Mobile Robots VIII*, Boston MA, vol. 2058, pp. 250-257, 1993.
- [5] Steven Y. Goldsmith and Rush Robinett, "Collective Search by Mobile Robots Using Alpha-Beta Coordination," *Collective Robotics Workshop '98*, Agent World, Paris, 1998.
- [6] Shannon V. Spires and Steven Y. Goldsmith. "Exhaustive Geographic Search with Mobile Robots Along Space-Filling Curves," *Proceedings of the first International Workshop, CRW '98*. Paris, France, July 1998.
- [7] Brad Bauer and Gerald Cook. "Algorithm and Simulation Development of Autonomous Robotics Search," *Proceedings of the 23rd International Conference on Industrial Electronics, Control and Instrumentation*, vol. 3, pp. 1278-1283, 1997.
- [8] In-Keun Yu, C. S. Chou, Y.H. Song. "Application of the Ant Colony Search Algorithm to Short-term Generation Scheduling Problem of Thermal unites," *Proceeding of 1998 International Conference on Power System Technology*, vol. 1, pp. 552-556, 1998.

- [9] R. Arkin and J. Hobbins, "Dimensions of Communication and Social Organization in Multi-agent Robotic Systems," *Proceedings of Simulation of Adaptive Behavior*, 1994.
- [10] S. Goss and J. Deneubourg, "Harvesting by a group of robots," *Proceedings of European Conference of Artificial Life*, 1992.
- [11] M. Mataric, *Interaction and Intelligent Behavior*. MIT AI Lab Tech Report AITR-1495, 1994.
- [12] L. Steels, *Cooperation between distributed agents through self-organization*. European Workshop on Modeling Autonomous Agents in a Multi-Agent World, 1990.
- [13] Nian Zhang, Alexander Novokhodko, Donald C. Wunsch II, and Cihan H. Dagli, "A Comparative Study of Neural Networks Based Learning Strategies on Robotic Search Problems," *Proceedings of the SPIE Application and Science of Computational Intelligence Conference*, vol. 4390, pp. 214-235, Orlando, Florida, April 2001.
- [14] George Shortley and Dudley Williams. *Elements of Physics*. Prentice Hall, Englewood Cliffs, N.J. 1961.
- [15] Timothy J. Ross, *Fuzzy Logic with Engineering Applications*, McGraw-Hill, Inc. 1995. ISBN: 0-07-053917-0.