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A POTENTIAL FIELD BASED APPROACH FOR MULTI-ROBOT TRACKING OF MULTIPLE MOVING TARGETS

Zheng LIU[1], Marcelo H. ANG Jr.[2], and Winston Khoon Guan SEAH[3]
[1]Dept. of Electrical & Computer Engineering and [2]Dept. of Mechanical Engineering,
National University of Singapore, [3]Institute for Infocomm Research, Singapore.
g0202255@nus.edu.sg, mpeangh@nus.edu.sg, winston@i2r.a-star.edu.sg

ABSTRACT

The "Museum" problem is a typical problem of collaborative multi-robot tracking of multiple moving targets (CMTMMT). The objective is to achieve collective tracking of multiple targets by multiple robots. In this paper, we present our conditional-weighted potential field based control algorithm to solve this problem. The essence of this algorithm is to make the robots move under the vector sum of the local forces imposed on it while encouraging collaboration. Additionally, some modifications are done to improve the performance. The simulation of our algorithm shows satisfactory performance and ability to achieve collective tracking in museum problem.

Key Words – multi-robot, multiple targets, potential field, tracking, collective robotics

I. INTRODUCTION

1.1. Overview of multi-robot system

In last two decades, multi-robot system is widely studied in a wide range of areas including materials transport, exploration, coordinated sensing, robot soccer, moving in formation, etc [1]. Compared with traditional single-robot system, multi-robot system has several advantages [2]:

- Multi-robot system can accomplish some inherently complex task that cannot be done by single-robot system.
- Multi-robot system can upgrade the performance by collectively working.
- Multi-robot system is more robust than single-robot system.
- The robots used in multi-robot system can be cheaper and simpler than the robot in single-robot system.

However, the implementation of multi-robot system is inherently more complex than single-robot system. To collectively accomplish a task, the multi-robot system needs to solve the following main problems:

- Task decomposition and allocation.
- Interaction among robots to collaborate.

There are two main solutions to task decomposition and allocation: centralized control and decentralized control. Centralized control is more like a single-robot system with a central controller. In a group of robots, there exists a "commander" to control the entire system. Decentralized control does not have such a leader robot: each robot controls itself equally (distributed) or unequally (hierarchy).

Interaction among robots is mostly by wireless communications, but some approaches use environment cues to share the information as form of communication.[3]

Most of the advantages of multi-robot system are achieved by collective work. Thus, how to realize collaboration among several robots is the essential problem in multi-robot system. The collaboration can be realized by centralized control. Centralized control, however, is difficult and not practical since all possible scenarios have to be predicted and corresponding actions programed for the robots to react accordingly. Furthermore, centralized control usually degrades the robustness of the system when an unanticipated event occurs, e.g., when the control center is crashed, the system can not continue to work even though some robots are functional. In addition, centralized control is computationally expensive, the control algorithm can not be feasible when the robot team is quite huge, e.g., more than 100 robots.

Current and more interesting and practical approaches are mostly focused on the distributed multi-robot system, because it can achieve the highest robustness and is more flexible than centralized and hierarchical control. However, most recent distributed control algorithms are hard to be both simple and scalable; especially when the task is quite complex [4] and the robot team is huge. More importantly, there seems to be no formal methodology to allow decentralized control and collective behavior. However, potential field based methods show promise and is therefore the focus of this paper.

1.2. Potential field based control algorithm

To realize collaboration, robustness, and computation efficiency, some distributed control algorithms have been developed. Among them, potential field based algorithm is quite simple and effective, especially in some applications, i.e., CMTMMT. CMTMMT is a typical problem in the research of multi-robot system. In [5], Parker provides a potential field based approach, called weighted local force vector control, to solve this problem, and some satisfactory results were obtained.

In summary, potential field based algorithm is a real-time distributed control algorithm. It considers the robots and the targets as charges in a potential field. The robots carry a kind of charge, i.e., positive, and the targets an opposing charge, i.e. negative. Therefore, the targets will attract the robots and the robots will repulse each other to avoid collision of robots. Each robot moves under the vector sum of all the forces imposed on it. Thus the system can accomplish tracking. In CMTMMT, potential field based control algorithm has some advantages:

- The algorithm is quite simple. Each robot can make decision of its action using its own local processor.
- In system scale, the robots are collaborative because they can automatically implement task distribution and allocation.
- No intercommunication is needed. However, some additional intercommunication may upgrade the performance of tracking.

We advance this concept in a specific case of CMTMMT, which is the museum problem,. Our simulation results show promise. In Section II, we will explicitly introduce the museum problem and related works. In Section III, our potential field based control algorithm will be shown. In Section IV, simulation results and discussion will be presented. Finally, Section V summarizes our contributions and future work.

II. MUSEUM PROBLEM

2.1. Background

Collaborative multi-robot tracking of multiple moving targets is a typical problem of multi-robot system. In our research, we focus on the museum problem, which is a special case of the CMTMMT problem. The museum problem can be described as follows:

- The environment (museum) is a large "clean" 2D area containing no obstacles or only some simple convex obstacles. (This is a limitation of potential field based control algorithm, we will discuss this in the discussion section)
- There are some targets (visitors) moving randomly within the environment (museum).
- The robots (security guards) have local limited-range panoramic sensors, which can scan the objects within a circular area around the robot. The sum of the scannable areas of all the robots (security guards) is far less than then the entire area to be monitored; hence the robots have to move.
- The robots (security guards) can move within the entire area. They need to avoid collision with targets (visitors) and other robots (other security guards).
- The task of the robots (security guards) is to track targets (visitors). When a target (visitor) is within the sensor range of a robot (security guard), we think the target is being tracked. The more targets are tracked at a same time, the higher performance we get. In brief, the objective is to maximize the targets (visitors) that remain under tracking or observation by the robots (security guards).

Mathematically, the museum problem can be defined as follows:

Given:

S: a large 2D bounded area with no obstacles or only some simple convex obstacles.

V: a team of m robots (v_i , i = 1,2,..m) with panoramic sensors. The sensors have limited sense range: sensor_range (v_i) and the total scanable area is far less then the entire area:

$$\bigcup_{v_i \in V} sensor\_range(v_i) << S$$

O(t): a set of n targets ($o_j(t)$, j = 1,2,…,n), such that target $o_j(t)$ is within area *S* at time *t*.

A(t): an $m \times n$ matrix where:

$$a_{ij} = \begin{cases} 1, \text{ if a robot } v_i \text{ is tracking target } o_j(t) \\ 0, \quad \text{otherwise} \end{cases}$$

Let

$$h_j(A(t), j) = \begin{cases} 1, \text{ if there exists an } i \text{ s.t. } a_{ij} = 1 \\ 0, \quad \text{otherwise} \end{cases}$$

Then the objective of the control system is to maximize:

$A = \sum_{t=1}^{T} \sum_{j=1}^{n} \frac{h_j(A(t), j)}{T}$, where T is the total time.

2.2. Related work

There are many approaches to this problem. (In some papers, museum problem is also referred to as the “art gallery” problem.) However, most of them are by centralized control. Although these approaches can compute some optimal solutions in theory, they are computational expensive: museum problem is NP-hard in the number of targets and the number of robots [6], which means the computation load will increase exponentially. Previous centralized approaches also can not provide real-time solutions to solve museum problem.

Besides the centralized control algorithms, there are some distributed control algorithms to solve museum problem recently. In [7], Jung and Sukhatme introduce an approach, in which the robots move by calculating the center of mass of detected targets and following this point, not the targets themselves. The worst case of that approach is that when two targets are moving in opposite directions, the robot will be inclined to stop tracking and lose both targets. In [5], Parker shows a potential based control algorithm, which is called as A-CMOMMT. By using weighted local force vector control, the simulation result of A-CMOMMT is satisfactory.

Our approach is mainly based on Parker’s work [5]. However, we do not use intercommunication and motion prediction as Parker, because we think these techniques are computationally expensive and will degrade the robustness of the system. In our approach, we add some new amendments, such as vector force weight rules, and then get a more feasible and practical solution for potential field based tracking. The details of our approach will be explicitly introduced in next section.

III. OUR POTENTIAL FIELD BASED APPROACH

3.1. Overview of our potential field based control

As introduced in the introduction section, potential field based algorithm assumes that robots and targets carry opposite charges, therefore there exist attractive force between robot and target, and repulsive force between robot and robot. Based on this assumption, our control strategy is to let each robot move under the vector sum of all the forces imposed on it, thus accomplish tracking, and avoid collision simultaneously. Obviously, there are two essential problems in this control strategy:

- calculating the attractive and repulsive forces (both are called local forces).
- calculating the vector sum of the local forces imposed on a robot.

In this section, we will explicitly explain the method we used to solve these two problems.

3.2. The calculation of local forces

In our approach, each robot is assumed to have a panoramic sensor, which can scan within a circular area around the robot. As shown in Fig. 1, target o_j and robot v_k ($k \neq i$) is within the sensor range of robot v_i. Then, robot v_i can sense their existence, and find the distance and orientation to them:

- To target o_j: the distance is r_{io_j}, the angle between the direction to o_j and the current moving direction is a_{ij}.
- To robot v_k: the distance is r_{ik}, the angle between the direction to v_k and the current moving direction is a_{ik}.

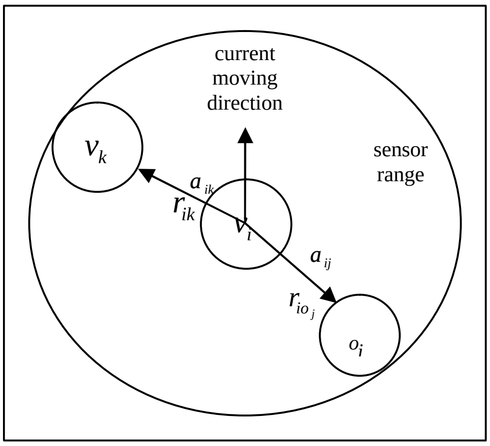

Fig. 1. Sensor Range of Robot v_i

We define the attractive force to be directed towards the target o_j, and the orientation of the repulsive force to be opposite to the direction of the other robot v_k, as shown in Fig. 2.

The magnitudes of the local forces can be calculated by functions shown in Figs. 3 and 4.

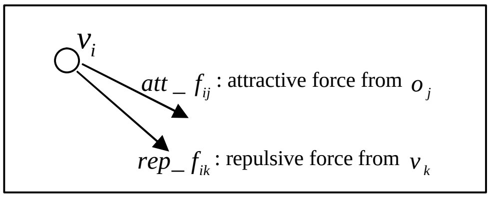

Fig. 2. The Orientation of the Local Forces Imposed on Robot v_i

Fig. 3 shows the function defining magnitude of attractive force imposed on a robot due to a target. Let r_{r-o} be the distance between the robot and the object/target. The magnitude of the attractive force depends on r_{r-o} according to:

- $r_{r-o} \le r_{o1}$: The magnitude is set as negative maximum. This is to avoid moving so close to the target, therefore avoiding the collision with the target.
- $r_{o1} < r_{r-o} \le r_{o2}$: The magnitude changes gradually from negative to positive, so that the repulsive force to avoid collision will continuously decrease and then becomes attractive.
- $r_{o2} < r_{r-o} \le r_{o3}$: In this segment, the magnitude is set maximum, so that the robot will be inclined to keep tracking the target within this range. We refer to this range as the preferred tracking range.
- $r_{o3} < r_{r-o} \le r_{sensor\_range}$: The magnitude will gradually decrease to zero until the target is beyond the sensor range.
- $r_{sensor\_range} < r_{r-o}$: The magnitude is set as zero because the target is beyond the sensor range of the robot, so that no more attractive force will be imposed to this robot from this target.

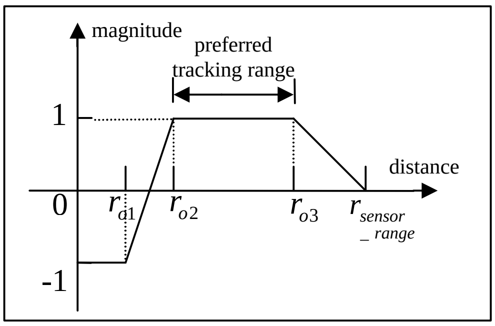

Fig. 3. Magnitude of Attractive Force Imposed on a Robot Due to a Target.

Fig. 4 shows the function defining magnitude of repulsive force imposed on a robot due to another robot. (Note the orientation is opposite the one for the attractive case.) Let r_{r-r} be the distance between two robots. The magnitude of the repulsive force depends on r_{r-r} acoording to:

- $r_{r-r} \le r_{r1}$: The magnitude is set as maximum. In this segment, the repulsive force is strongest, so that two nearby robots will leave apart rapidly.
- $r_{r1} \le r_{r-r} \le r_{r2}$: The magnitude decreases gradually to zero, so that the repulsive force will continuously decrease too.
- $r_{r2} \le r_{r-r}$: In this segment, the magnitude is set zero because two robots are already far apart enough. There will be no repulsive force between two robots any more.

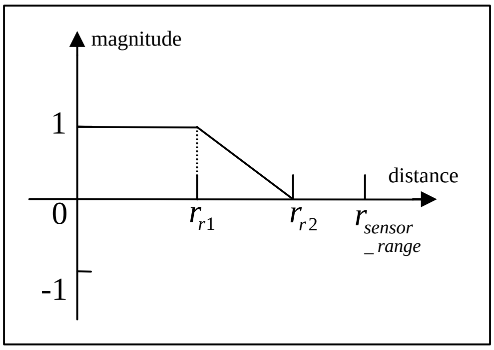

Fig. 4. Magnitude of Repulsive Force Imposed on a Robot Due to another Robot.

3.3. The calculation of vector sum of local forces

As described before, the robot will move under the vector sum of the forces imposed on it. However, equally adding these vectors, (referred to as pure potential field based control) may degrade the performance of the system. For example, in Fig. 5, two robots are following the same target simultaneously. In this case, the two robots and the target will keep a triangle pattern to move until another robot or target appears and disturbs the balance among them. Obviously, there is a waste of resources because one of the robots can search and follow another target without tracking a target already being followed.

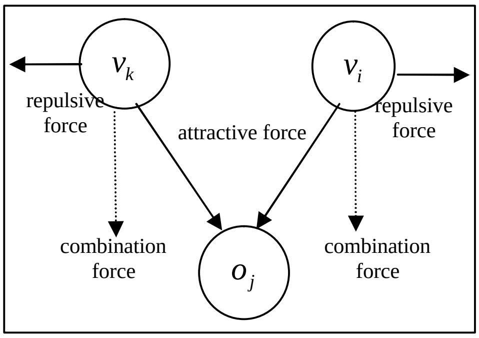

Fig. 5. Two Robots Follow One Target Simultaneously

To avoid the deficiency of pure potential field based control algorithm, we find a solution: setting weights to the attractive force vectors before adding them up. We name this as weighted potential field based control algorithm. In our approach, the sum of weighted local force vectors can be expressed as Eq. 1.

$$F_{i\_sum} = \sum_{j=1}^{n} w_{ij} att\_f_{ioj} + \sum_{k=1,k\neq i}^{m} rep\_f_{ik} \qquad (1)$$

In Eq. 1, w_{ik} represents the weight of target o_j to robot v_i. Normally, the weight is set as 1 except another robot is also found to follow the same target. In this case, the weight of that target will be deduced to avoid the situation in Fig. 5. In Parker's approach [5], the weight is deduced whenever another robot is found nearby the target. But this strategy may lead to a problem: supposing two robots are almost at the same distance from a target, and these two robots find each other. Then, they will both decrease the weight of the attractive force from the target. Finally, maybe both of them will give up tracking the target any more. Obviously, this result is not our expectation.

In our approach, we only decrease the weight of the attractive force between the farthest robot and the target. As shown in Fig. 6, when robot v_i find its peer v_k and the target o_j, it will compute the distance r_{koj} between v_i and the target o_j. Comparing the r_{koj} and r_{ioj}, robot v_i will decide whether it needs to decrease the weight of the attractive force to the target o_j: If r_{koj} is larger than r_{ioj}, the weight will not change, else the weight will be decreased. The other robot v_k will also do the same thing at the same time. Finally, only one robot (v_i) will follow the target, and the other one will leave (because of the repulsive force between robots) and try to track a new target..

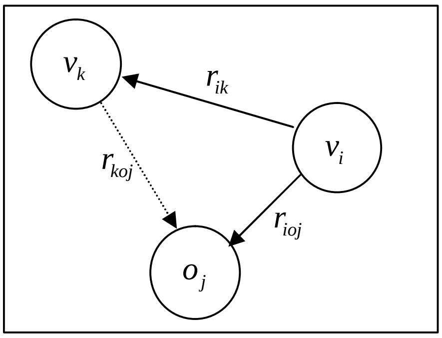

Fig. 6. Example: Decrease Weight Adaptively by Computing the Distance. If r_{koj} is smaller than r_{ioj}, v_i will set the weight w_{ij} = 0.1 or less, else w_{ij} = 1.

Another case needs to be considered is when a robot is tracking two oppositely moving targets, as shown in Fig. 7. In this case, the attractive forces will counteract each other, and then the robot will have little motivation to track (we call this as "hesitation"). Especially when the two targets are at the edge of the sensor range, "hesitation" may cause the robot to lose both targets. In [5], Parker thinks that the noise of the real sensors will avoid this case because balance of the attractive forces is impossible to happen in the real world. However, from our experience, when the moving speed of the robot is only a bit faster than the targets, "hesitation" behavior may badly affect the tracking performance.

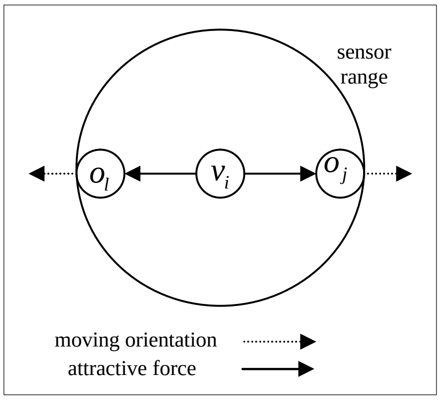

Fig. 7. A Robot Tracking Two Oppositely Moving Targets

To avoid the "hesitation" behavior, we add a restriction to the calculation of the vector sum of the local forces:

- If one target is already within "good" range (a range within the sensor range),

the robot will move under the weighted vector sum F_{i_sum} calculated by Eq. 1.
- If no target is within good range, the robot will move under the strongest attractive force and the repulsive forces, or search for target randomly (when nothing is within the sensor range).

This restriction will avoid "hesitation" behavior by forcing the robot to give up following one target in the condition shown in Fig. 7. We refer to this control algorithm with this restriction as "conditional weighted" potential field based control algorithm. In this control strategy, however, we need to decide on how to set an appropriate value for the "good" range.. If good range is too small, the performance of the system will be badly degraded because the robot can not follow more than one target before one target is already within the good range. If the good range is too big and near the sensor range, the "hesitation" behavior will still happen.

In our simulation and discussion section, we will test and compare the performance of these algorithms:
- Pure potential field based control algorithm.
- Weighted potential field based control algorithm.
- Conditional weighted potential field based control algorithm.

IV. SIMULATION AND DISCUSSION

4.1. Simulation configuration and methodology

To test our potential field based control algorithm, we conducted simulation under following conditions:
- The museum: a 5m*5m square area with walls on the boundary. In our simulation, there was no obstacle within this area.
- Visitors (targets): 9 targets were represented by virtual robot Khepera (a mini cylinder robot). It moved randomly within the interest area (museum). If its way was blocked by something, such as the wall, the other targets, or the robot security guards, it could change its moving direction to avoid collision.
- Security guards (robots): 3 robots were represented by virtual robot Khepera. Their sensor range were set to 0.5m. Therefore the highest overall scannable area was about 9.42% of the entire area.
- For the function defined in Figs. 3 and 4, we selected following parameter settings: r_{o1} = 0.1m, r_{o2} = 0.3m, r_{o3} = 0.4m; r_{r1} = 0.2m.
- Different values of good range were tested: 0.30m, 0.35m, 0.40m, 0.45m, and 0.50m .

We define the system performance P as the average number of the targets being tracked, i.e. P = 3.2 means in average there were 3.2 targets being tracked during the simulation time. Regarding each parameter set, we ran the simulation 50 times and got the average performance P. However, in the calculation of P, something should be noted: during the initial period of simulation, the robots need some time to find the targets, and before some targets is found, our potential field based control algorithm will not work. We called the initial time for searching targets as "warm up" period. To eliminate the influence of "warm up" period, we discard the data of the first 5000 simulation steps in each simulation run. Since each run is 50000 steps, the performance P is the result of the last 45000 simulation steps.

4.2. Simulation results

In our simulation, we test and compare the system performance in following conditions:
- Pure potential field based control without adaptively setting weight: in Eq. 1, let $w_{ij} \equiv 1$.
- Weighted potential field based control: in Eq. 1, adaptively decreasing w_{ij} by the method introduced in previous section. In our simulation, the reduction ratio was 0.1.
- Conditional weighted potential field based control: adaptively select one or all the attractive forces to follow by the method introduced in previous section. In our simulation, the good range was set as 0.30m, 0.35m, 0.40m, 0.45m, and 0.50m.

Fig. 8 and Fig. 9 show the simulation results. In Fig. 8, we compare the system performance of the 3 control algorithms. In Fig. 9, we compare the influence of the value of good range in conditional potential field based control algorithm. These results will be discussed next.

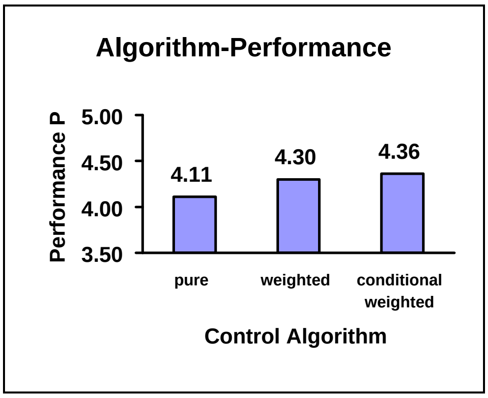

Fig. 8. Performances under Different Control Algorithms

Fig. 9. The Relation between the Value of Good Range and the Performance

4.3. Discussion

Fig. 8 shows that our potential field based approach is effective. While the total scannable area is only 9.42% of the entire area, the system performance P of 4.36 can be achieved , which means in average one robot was tracking about 1.45 targets at the same time. In addition, the simulation results also prove that our two modifications to pure potential field based control, adaptively changing weight and setting good range, are effective. They can improve about 6% of the system performance. In our approach, the distributed control is accomplished by less computational efforts compared with traditional centralized control. And that is a real time control algorithm, which is more practical and feasible. Therefore, we may draw a conclusion that our potential field based control algorithm is a promising methodology in solving the museum problem.

To make our conditional weighted potential field based control algorithm work better, something should be noted, i.e. the selection of the value of the good range. From Fig. 9, we can find that value has influence on the system performance. The smaller the value, the smaller chance that the robot can follow two targets simultaneously, thus losing the advantage of potential field based control. The bigger the value, the bigger the chance that the robot will present some "hesitation" behavior, thus the robots may lose the targets. From our simulation, we find that about 90% of the sensor range is a nice choice for the value of good range.

Our potential field based control algorithm is satisfactory in the museum problem. However, there is some deficiency that can not be neglected. In our definition of museum problem, we assume the interest area (museum) is a "clean" area, where exists no obstacles or only little convex obstacles. That is because potential field based control algorithm has difficulties in overcoming concave obstacles. This problem is called as local minimum problem [8]. For example, if there is a concave obstacle between the robot and the target, the attractive force from the target and the repulsive force from the obstacle may make the robot "stuck" in the concave. In some papers, i.e. [8] and [9], some methods are mentioned to solve this problem. However, there is no formal solution for local minimum problem up to now. This deficiency needs more consideration in future study on potential field based control algorithm.

V. CONCLUSION AND FUTURE WORK

5.1. Conclusion

Museum problem is a traditional problem in multi-robot system. Its essential problem is to achieve collective work among the robots. In this paper, we present our conditional weighted potential field based control algorithm, which is a simple, low computational cost, real time algorithm. In our approach, the robots are moving under the vector sum of the local force imposed on it, therefore accomplish collaboration. Additionally, some modifications are done to improve the performance. Finally, our simulation results dhow the efficacy of our algorithms. Potential field based control algorithm is a promising algorithm to solve the problems of multi-robot system.

5.2. Future work

As mentioned before, the potential field based control has a deficiency, which is the local minimum problem. This problem confines the usage of this algorithm in some certain case, i.e. "clean" area without concave obstacles. Obviously, local minimum problem is one of the further problems need consideration.

Another problem in museum problem is in the searching part. Both in Parker's paper [5] and this paper, we ignore the initial part of the museum problem: searching for the targets. Potential field based control can achieve tracking when some targets is within the sensor range. However, it can not help in the search part. How to find an effective method to search and find targets in the museum problem is not trivial. This is a subject of our current research.

REFERENCES

[1] Tucker Balch and Lynne E. Parker, "*Robot Teams: From Diversity to Polymorphism*". Natick, Massachusetts: A K Peters Ltd., 2002.

[2] Y. Uny Cao, Alex S. Fukunaga, Andrew B. Kahng, and Frank Meng, "*Cooperative Mobile Robotics: Antecedents and Directions*". Proc. of EIII/RSJ International Conference on Intelligent Robots and Systems, vol. 1, pp. 226-234, 1995.

[3] C. Ronald Kube and Hong Zhang, "*Collective Robotics: From Social Insects to Robots*". Adaptive Behavior, Vol. 2(2), pp.189-219, 1993.

[4] G. Sen Gupta, C.H. Messom and Sng H.L., "*State Transition Based Supervisory Control for a Robot Soccer System*". Proc. of the First IEEE International Workshop on Electronic Design, Test and Applications (DELTA'02), New Zealand, pp. 338-342, 2002.

[5] Lynne E. Parker, "*Distributed Algorithm for Multi-Robot Observation of Multiple Moving Targets*". Autonomous Robots, Vol. 12(3), pp. 231-255, May, 2002.

[6] Lynne E. Parker and Brad A. Emmons, "*Cooperative Multi-robot Observation of Multiple Moving Targets*". Proc. of International Conference on Robotics and Automation, Vol. 3, pp. 2082-2089. Albuquerque, New Mexico, USA, 1997.

[7] Boyoon Jung and Gaurav S. Sukhatme, "*Cooperative Tracking using Mobile Robots and Environment-Embedded, Networked Sensors*". Proc.of IEEE International Symposium on Computational Intelligence in Robotics and Automation, pp206-211, 2001.

[8] Xiaoping Yun and Ko-Cheng Tan, "A Wall-Following Method for Escaping Local Minima in Potential Field Based Motion Planning". Proc. of 8th International Conference on Advanced Robotics, pp. 421-426, Monterey, CA, July, 1997.

[9] Liu Chenqing, Marcelo H. Ang Jr, Hariharan Krishnan, Lim Ser yong, "Virtual Obstacle Concept for Local-minimum-recovery in Potential-field Based Navigation". Proc. of the 2000 IEEE International Conference on Robotics & Automation, San Francisco, USA, 2000.