Influence Analysis of Setting Thresholds on Dynamical Sequential Task Allocation and Reallocation Methodology

Guanghui Li, Yusuke Tamura and Hajime Asama

Abstract—**We previous proposed a dynamical sequential task allocation and reallocation method to resolve a new task assignment domain: dynamical mobile task allocation, by which tasks can move randomly before they are assigned robots to execute, is the condition in which tasks and robots are allowed to be time-dependent before assigned robots to accomplish the relational tasks. It was demonstrated that our method improved the efficiency for the whole multi-robot coordination system to accomplish all tasks. Moreover, it was more conducive to reduce the numerous computational times and communication costs compared to the existing investigated task assignment methods, while the setting thresholds: large distance threshold and small distance threshold are assigned as a priori values. In this paper, we mainly focus on studying the influence of setting thresholds on our dynamical sequential task allocation and reallocation methodology. Various kinds of large and small distance threshold values and their combination are simulated. The simulation results suggest that it is better to assign both large distance threshold and small distance threshold to a relatively small value according to environment area, the large distance threshold is about one-tenth of environment's length and width, the small distance threshold is below half of large distance threshold, respectively. The results are very significant for us to choose and adjust the values of thresholds to adapt different environment scale.**

I. Introduction

ROBOT market will inevitably expand in recent few decades due to robotics industry are in a stage of infancy as a new high-technology industry to address needs of society such as limited production means for widely various products, labor shortages accompanying the reduction in younger population, and longer lifespan of humans in the coming aged society. The METI and NEDO expect the robot industry to have a market value over $29 billion by 2020, $97 billion by 2035 in Japan [1]. In particular, service robot will account for 36% of the market value by the year 2020, and 51% by 2035 respectively. Previously, service robots of many kinds were developed, such as transport robots, nursing and medical service robots, and assistant robots for disabled and elderly people, in addition to cleaning robots. An autonomous omni-directional mobile robot system MKR (Muratec Keio Robot) has been developed for transport application in a human-robot coexistence environment: hospital domain [2,3]. They employ MKR to transfer luggage, important specimens and other medical materials. It is noteworthy that they have developed some kinds of user interface such as panel display, display scrolling a message to interact with human. Results showed that robots can transport pharmaceuticals safely and effectively to a destination. The EU-funded DustBot Project: networked and cooperating robots for urban hygiene have been researched by [4]. They have developed and tested a system for improving the management of urban hygiene, based on a network of autonomous and cooperating robots, embedded in an ambient intelligence infrastructure (AmI). The robots are used to carry out two main services: one is door-to-door garbage collection on demand. Another is street cleaning and sweeping. The first museum tour-guide robot is called Rhino [5], and installed in mid-1997 in the Deutsches Museum Bonn (Germany). They have designed the software architecture of an autonomous tour-guide robot and a user interface tailored towards non-expert users, which was essential for the robot's success in the museum. The next year, a second-generation museum tour-guide robot Miverva has been developed [6], which improved based on Rhino to specifically address issues such as safe navigation in unmodified and dynamic environments. The key difference between both robots is that Minerva is much more effective in attracting people and making progress. Recently, a conceptual Guide-Dog Robot prototype to lead and to recognize a visually-handicapped person has developed and discussed in [7]. The key designed features of this Guide-Dog Robot include a movable platform, human-machine interface and capability of avoiding obstacle.

As described in this paper, we present a mobile task allocation and reallocation method for a guidance service system in which multiple autonomous mobile robots guide multiple targets at a shopping mall, museum, or exhibition. In one scenario, when walking into a large museum or exhibition, a person needs somebody to provide guidance service. Because there are few guides and numerous visitors, a person has little choice but to stand at a specified area and wait for a guide. If one leaves the specified area, then guides will not know that guidance services are needed. However, during the time spent waiting for services, it is impossible to do anything

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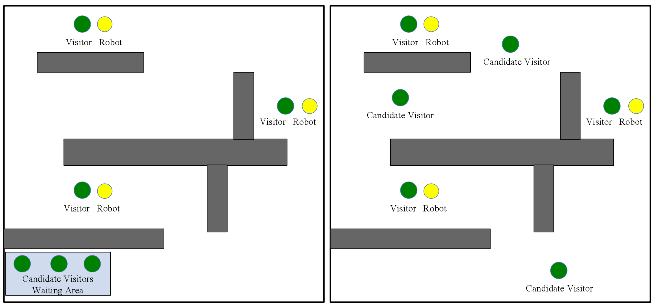
but wait, as shown in Fig. 1 (a). In other circumstances (Fig. 1 (b)), with many visitors and few guidance robots at the museum or exhibition using guidance robots for guiding services, before a robot provides a service, a person can move freely instead of merely standing at a specified area to wait for a guidance robot because robots can find a person and provide services with some order. This is an important advantage of using guidance robots at a museum or exhibition.



(a) Museum tour-guide (b) Museum tour-guide robot

Fig. 1. Illustration of museum tour-guide.

The remainder of this paper is structured as follows. The next section presents a formal definition of the dynamical mobile task assignment problem. Section III details related works and disadvantages of those methods used to resolve the new domain. Section IV describes and illustrates notion about body expansion behavior, setting two distance thresholds for robot decision-making, in addition to the proposed algorithm. Section V presents a discussion of simulation results. Finally, section VI explains the conclusions and outlines future work.

II. Formal Definition

As described in this paper, the task assignment problem is studied for multiple, fully distributed, initially homogeneous mobile robots. We should develop a novel task allocation and reallocation method to deal with a dynamical mobile task allocation problem. The formal definition of this problem is reasonable and efficient dynamically mobile task assignment to multiple robots. For the whole system mission, because the dynamical mobile tasks can change in many ways before assigned robots can execute and because the conditions of these tasks can vary over time, we should assign and reassign tasks to robots properly. We allow a set of tasks T and robots R to be time-dependent (i.e. $T(t)$, $R(t)$) and require that the objective function be minimized/maximized (Task allocation and reallocation method should minimize the objective functions which are cost, energy and others. Conversely, it should maximize the objective functions such as efficiency.) for every instant of time or over the entire history. The definition also includes the online and dynamical domain, from which tasks and robots might be added or removed over time. We previously have proposed a dynamical sequential task allocation and reallocation approach to resolve new domains of this kind [8]. In this research, we mainly focus on studying the influence of setting thresholds on our proposed task allocation and reallocation methodology.

III. Related Works

Task allocation for a multi-robot coordination system is a widely studied field. Related works have examined task allocation problems such as coalition maintenance scheme for dynamic reconfiguration of assigned tasks to obtain optimum allocations in noisy environments during the running time [9]. This framework is used to address different types of failures common in robot systems and solve conflicts in cases of communication and robot failures. Task allocation using particle swarm optimization method is suggested to determine coalitions and sequence for all targets [10]. They employ this algorithm to resolve the problem in a reasonable amount of time. Market-based auction [11, 12] is well known for dealing with task allocation problem, system auctions tasks for all robots. After bidding for tasks, robots that obtain profits that are largest for the whole system execute these tasks. Additionally, they investigate a real time single item allocation method under uncertain and dynamic environment [13]. The initial assigned targets may need to be reallocated during time when the environment is dynamic and/or unknown. Because of market-based auction method could be successful and effective to resolve conventional task allocation domain, large number of researchers improve and study the variation of such method, such as sequential single-item auction [14], distributed sequential auction [15] and decentralized task sequencing method [16]. Therefore, previously, few researchers have addressed the domain of tasks which are dynamical and which move arbitrarily. All existing methods are suitable for tasks for which positions are fixed. For mobile tasks, such methods are inefficient. Furthermore, earlier reports neglect discussion of task reallocation when robots are executing tasks, except for robot malfunction, partial system failure, and communication failure. Actually, for mobile tasks in terms of position change, we should consider not only assigning tasks to robots, but also finding a mode by which robots perform tasks efficiently for the whole coordinated system.

For example, as previously mentioned above, if we only consider homogeneous robots, efficiency of robots to perform tasks depend on time needed by a robot to reach the location of task. This measure depends on the task and robot's position which is a function of time. Therefore, the efficiency for a robot to perform a task varies with time, as a result, robots should select the optimal tasks which the time needed by robots to reach are shortest (i.e., the distance between robots and tasks are shortest.) to perform every time to improve the efficiency for the whole guidance system. As Fig. 2 shown, at T_0, the system assigns *task1* to *robot1*, *task2* to *robot2* and *task3* to *robot3* according to the distances. While at T_1, since changing positions of tasks and robots, the system should reallocate tasks to robots reasonably, because of the values of distance between *robot1* and *task1*, *robot2* and *task2*, *robot3* and *task3* are large than the distance between *robot1* and *task2*, *robot2* and *task3*, *robot3* and *task1*.

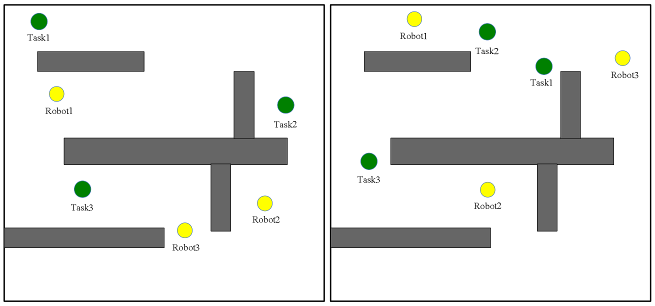


Fig. 2. Dynamical task allocation and reallocation.

In papers [17, 18], they firstly introduce an algorithm for allocation at mission-time of moving targets to a group of unmanned vehicles. The Hungarian algorithm is implemented to perform optimal task assignment, and then exact path lengths between vehicles and targets are computed from the off-line computed Dijkstra paths. For mobile task allocation of distributed multi-robot coordination system, we previous proposed a method [8]: dynamical sequential task allocation and reallocation which comes closest a repeated auction [19]. This approach implements multi-round negotiation and body expansion behavior for task selection. To implement body expansion behavior, we set two distance thresholds for robot decision-making. Based on the body expansion behavior, one robot can request, accept, and refuse other robots' requests to execute tasks by intention communication. We demonstrated that this method is an approximate global optimal assignment method and expends acceptable communication costs and computational times compared to the existing investigated task assignment methods. However, the setting thresholds: large distance threshold and small distance threshold are assigned as a priori values. Herein, we mainly focus on studying the influence of setting thresholds on our previous method. Various kinds of large and small distance threshold values and their combination are simulated and compared.

IV. PROPOSED ALGORITHM

A. Mathematical Model

As described in paper [8], we consider a homogeneous set of robots. The efficiency with which robots perform mobile tasks depends on the time necessary for robots to reach the task location, which depends on the relative positions of the task and robot. It is a function of time. Therefore, the efficiency with which a robot performs a task varies. For that reason, robots should select optimal tasks for which the time needed by robots to reach is shortest to perform. Doing so for each task improves the overall system efficiency.

The locations of M robots and N mobile tasks are known, as is the cost function D that specifies the cost of moving from one location to another. The objective is to find an allocation of tasks to robots such that the total travel cost is minimized for the whole system. The major criterion for the proposed strategy is to optimize the total travel distance. The model formulated to enhance the mobile task allocation and reallocation is presented below. Let V_R denote the set of robot vertices and V_T denote the set of mobile task vertices.

Minimize

$$\sum_{r\in V_R}\sum_{t\in V_T} D_r x_t^r \quad (1)$$

where $$D_r = \sum_{r\in V_R}\sum_{t\in V_T} D_{rt} \quad (2)$$

subject to the following equations.

$$\sum_{t\in V_T} x_t^r = 1 \qquad \forall r\in V_R \quad (3)$$

$$\sum_{r\in V_R}\sum_{t\in V_T} \pi_{st,t}^r x_t^r = 1 \qquad \forall st\in(0,+\infty) \quad (4)$$

$$x_t^r \in \{0,1\} \qquad \forall r\in V_R, t\in V_T \quad (5)$$

Therein, a binary variable x_t^r denotes whether a robot $r\in V_R$ performs task t selected from all tasks V_T. D_r signifies the distance that robot $r\in V_R$ moves; $\pi_{st,t}^r$ is a binary value showing whether task $t\in V_T$ is executed at time step $st\in(0,+\infty)$.

The objective function, Eq. (1) minimizes the execution cost of the whole distributed multi-robot coordination system. In this case, the system cost is the total travel distance that robots move. The first set of constraints, Eq. (3), specifies that each robot performs exactly one task. The second set of constraints, Eq. (4), specifies that each task is assigned to exactly one robot at each time step.

B. Body Expansion Behavior

Body expansion behavior means that a robot can transmit its own intention and the receiver executes the order, thereby a robot can control others' behavior. This demonstrates an expansion of the robot's degrees of freedom (D.O.F.). Two distance thresholds for robot decision-making are settled to implement body expansion behavior. One is the small distance threshold $\theta 1$, which means that a robot is about to execute the assigned task. Another is the large distance threshold $\theta 2$, which means that robots have a long time to execute the assigned task (Fig. 3).

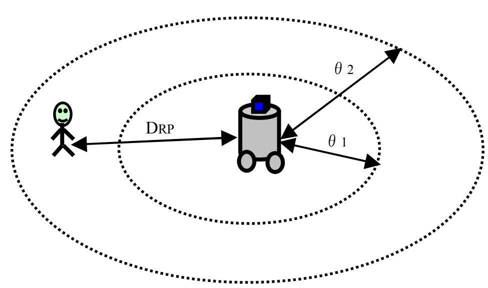


Fig. 3. Distance threshold.

If the distance is greater than $\theta 2$, then a robot can request that other robots execute the assigned task, as shown in Fig. 4. If the distance between $\theta 2$ and $\theta 1$, then robots compare the distance and select the shortest distance task to accomplish. If the distance is less than $\theta 1$, then robots refuse all others' requests. For all robots, three working states exist: 1.

Free-robot, the robot has not been assigned task; 2. *Half-free-robot*, the robot has been assigned task but is not executing the task, or the distance is less than *θ2*, but more than *θ1*; 3. *Busy-robot*, a robot is executing task, or the distance is less than *θ1*. When robots find remaining un-guided tasks and free-robots exist in the environment, then the robot can request that the free-robot guide the remaining un-guided tasks.

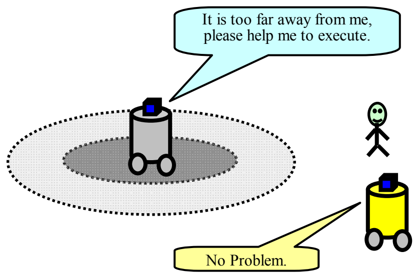


Fig. 4. Body expansion behavior.

C. Proposed Algorithm

We assume that all robots are homogeneous robots with identical speed, function, and structure. They can mutually communicate using radio broadcasts. One robot is allocated only a single task for each time step.

The tasks are randomly distributed in the environment. They can move anywhere with various speed before robots can execute them. All tasks are waiting for execution under the priority queue of 'First-In First-Executed'. Robots always execute the relative highest priority tasks irrespective of other tasks move around. In the environment, $ri \in V_R\{r1, r2, \cdots, rn\}$ denotes the *i*th robot, and $tj \in V_T\{t1, t2, \cdots, tm\}$ denotes the *j*th task. The $Dritj$ denotes the utilizable distance from ri to tj, and *m≥n*. Each task $tj \in V_T\{t1, t2, \cdots, tm\}$ should be executed by a robot only once. At each time step, one robot is assigned to a single task. In initialization, the working status of all robots is free: robots wait for tasks to execute.

Tasks broadcast request information including task IDs and coordinates to all robots at every time step. In the initial time step, there are twice-round negotiation and selection for each robot. For the first-round, all robots receive request, then plan paths and calculate distances among all tasks in the robots' global map. Robots are priority according to the robot ID, the priority of robot which ID is small is larger than priority of robot which ID is large. Robots, from robot $r1$ to robot rn sequentially, select tasks to perform according to the given distance thresholds. That is if there are distances smaller than *θ1*, robot selects the task to perform which distance is smallest. Otherwise, robot does not select any tasks, and requests other robots to execute these tasks. When all robots have finished the first-round selection, the un-selected robots re-select all unassigned tasks again sequentially in the second-round.

For the second-round negotiation, based on the priority of that the smaller ID robot firstly re-select task, the later ID robot should receive task selection information from the former ID robots then can carry out task re-selection, the remaining un-selected robots sequentially select un-assigned tasks to perform, even though the distances between them are greater than *θ2*.

Due to mobile tasks can move randomly before the assigned robots execute them, condition of these tasks could vary over time, thereby distances between robots and corresponding assigned tasks may vary. The system should reallocate tasks to robots every time step by utilizing body expansion behavior during the running time, so as to improve the efficiency of which robots execute tasks for whole system. If the distance among robot and corresponding assigned task is greater than *θ2*, then robot will request other robots to execute this task and broadcast information to others. Other robots from $r1$ to rn sequentially, if the distance between this robot and the corresponding last assigned task is smaller than *θ1*, the working state of the robot changes to busy-robot and refuses all requests. Otherwise, the robot executes and broadcasts information to others. If all others refuse this task, the robot should continue select it despite the distance is greater *θ2*. Note that robot also can request others to execute the assigned task when the robot is failure. The next time step, robots continue move toward the last assigned tasks before system assigns new tasks to robots. The entire of our proposed novel method is shown in Fig. 5.

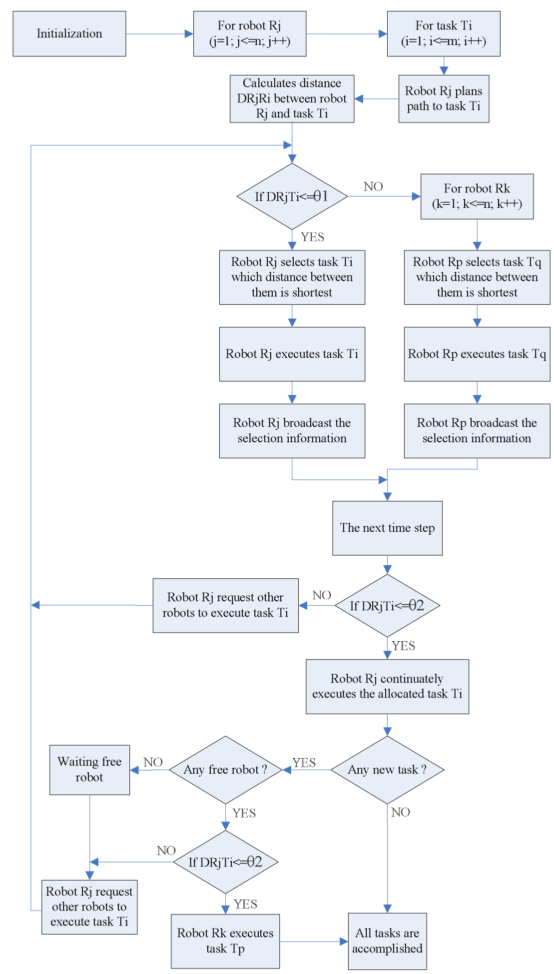


Fig. 5. Dynamical sequential task allocation.

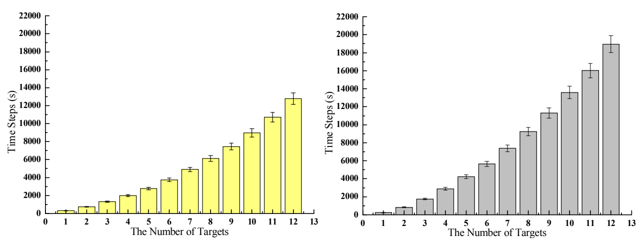
V. Simulation and Results

A. Simulation Environment Setting

The simulation environment without obstacles is built up with the setting of 400 × 400 m^2. At the initial time step, five tasks and three robots are distributed randomly in the environment. A robot accomplishes a task when the robot captures the task. For the whole system, three robots should execute 12 tasks. During the simulation, tasks move with variable speed over time, although the robot speed is a constant of 0.76 m/s. We have demonstrated the validity and efficiency of our approach through various experiments compare with repeated auction method in the same situation [8]. In this paper, we mainly focus on studying the influence of setting thresholds on our method. Various kinds of large and small distance threshold values and their combination are simulated.

B. Simulation Results

The simulation results depicted in Fig. 6 are the consumed time steps during which robots accomplish all 12 tasks. We simulate each situation 20 times. Therefore, the consumed times shown in the figure are the average of 20 simulations. As the figure shows, it is apparent that the consumed time steps using dynamical sequential task allocation are much smaller than using the repeated auction method. Moreover, the more tasks that are executed, the greater the reduced consumed time steps are. Consequently, the whole system can obtain maximal accomplished efficiency and minimal executed costs based on our method.

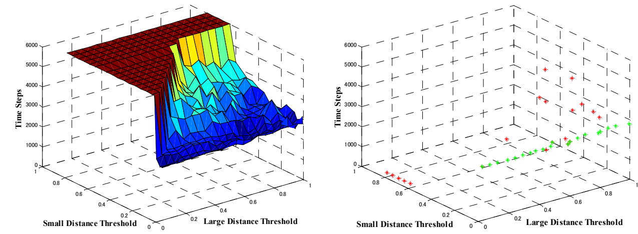


(a) Dynamical sequential task allocation and reallocation (b) Repeated auction method

Fig. 6. The consumed time steps.

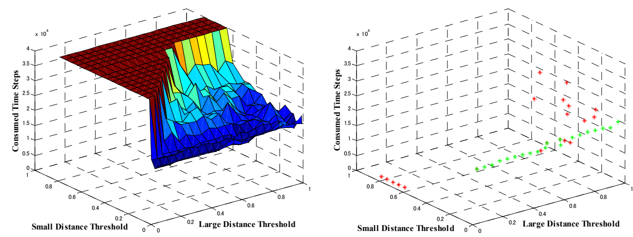
C. Performance Comparison

Results show that an important strength of our method is the ability to address changing conditions efficiently. The method does not rely on the initial task allocation. It can perform task reallocation according to variable solutions. Therefore, the distributed multi-robot coordination system is highly robust to changes in the environment, including robot malfunction. Consequently, the method presented in this paper enables a robot to address a dynamical environment in an opportunistic and adaptive manner. Figure 7(a)-11(a) presents the results of completed time steps, the consumed time steps, computational times, communication costs and number of changing assigned times under various kinds of large and small distance threshold values and their combination. From the figures we can see that values of setting large distance and small distance thresholds are great influence on performances of dynamical sequential task allocation and reallocation method. Especially, those performance parameters including completed time steps, the total consumed time steps, computational times and communication costs, fluctuation obviously when the values of large and small distance threshold are large.



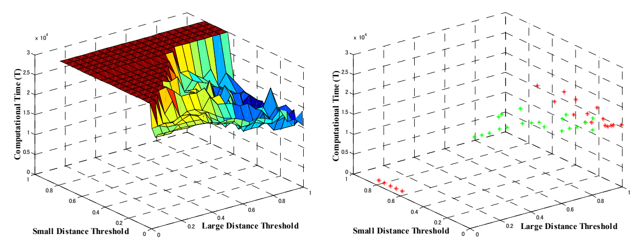
(a) (b)

Fig. 7. Completed time steps



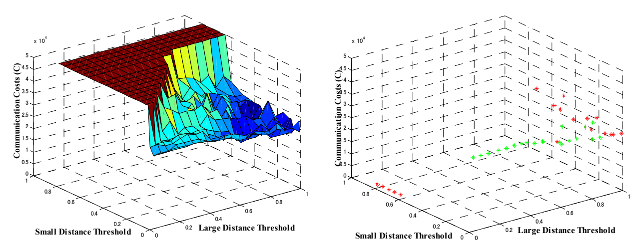
(a) (b)

Fig. 8. Total consumed time steps



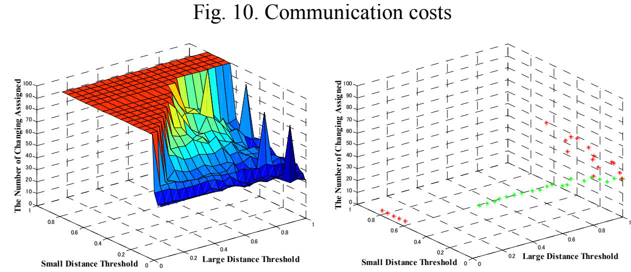
(a) (b)

Fig. 9. Computational times



(a) (b)

Fig. 10. Communication costs



(a) (b)

Fig. 11. The number of changing assigned

The simulation results also suggest that it is better to allocate large and small distance threshold to a relatively small value according to environment area, the large distance threshold is about one-tenth of environment's length and width, the small distance threshold is below half of the large distance threshold, respectively. Interestingly, if the large distance threshold $\theta 2$ is settled as constant, while vary the small distance threshold $\theta 1$. The optimal values of completed time steps, total consumed time steps, computational times, communication costs and number of changing assigned times are appeared when small distance threshold is small, as Fig. 7(b)-11(b) shown which presented by green points. Reversely, if $\theta 1$ is settled as constant, while change $\theta 2$. The optimal values of performance are appeared when large distance threshold is great, which presented in Fig. 7(b)-11(b) by red points. We believe that the results are very significant for us to choose and adjust the values of thresholds to adapt different environment scale.

VI. Conclusion

Dynamical mobile task allocation, by which tasks can move randomly before they are assigned robots to execute, is the condition in which tasks and robots are allowed to be time-dependent before assigned robots to accomplish the relational tasks. We previous proposed a dynamical sequential task allocation and reallocation method to resolve this new mobile task assignment domain. It was demonstrated that our method improved the efficiency for the whole multi-robot coordination system to accomplish all tasks compared to the existing investigated task assignment methods. In this study, we researched the influence of setting thresholds on our dynamical sequential task allocation and reallocation method. Various kinds of large distance threshold and small distance threshold values and their combination were simulated. The simulation results suggested that it is better to assign both large and small distance threshold to a relatively small value according to environment area, the large distance threshold is about one-tenth of environment's length and width, the small distance threshold is below half of large distance threshold, respectively. The results are very significant for us to choose and adjust the values of thresholds so as to adapt different environment scale.

In future works, we will implement reinforcement learning for mobile task allocation and reallocation system to optimize values of large and small distance threshold according various kinds of environment scales, and employ our approach to real museum guide-robot system.

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