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A Comparative Study of Dynamical Sequential and Global Optimal Task Reallocation Methodology for Distributed Multi-robot System

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Abstract – We firstly consider a kind of dynamical mobile task assignment problem, which allows the condition of tasks and robots to be time dependent before assigned robots accomplish the relational tasks. For such new domain, we propose two methods, one is called dynamical sequential task allocation and reallocation, and another is global optimal task allocation and reallocation, for the distributed multi-robot coordination system. The former approach implements multi-round negotiation and body expansion behavior for mobile tasks selection. To utilize body expansion behavior, we set two distance thresholds for robot decision making. The latter method is extended from combinatorial optimization and market-based task allocation. Robots bid tasks and transmit the costs to other robots. Then robots select tasks from the combinatorial cost table based on the objective function. This paper is a comparative study of the mentioned methods above. The simulation results show that minimal executed costs and maximal accomplished efficiency are obtained by global optimal task allocation and reallocation method, while this method consumes numerous communication costs and computation times. Reversely, dynamical sequential task allocation and reallocation is an approximative global optimal assignment approach. Otherwise it expends acceptable communication costs and computation times.

Keywords – Mobile task allocation and reallocation. Body expansion behavior. Multi-round negotiation. Global optimization. Distributed multi-robot system.

1. Introduction

The field of distributed multiple robots coordination system (DMRCS) has received increased attention in recent decades. There are many potential advantages of DMRCS compared with single robot system, such as reducing the complexity of a single robot's structure, and decreasing the total cost to accomplish complicated and large scale tasks, since DMRCS can be used to complete the given tasks more quickly than a single robot, and execute tasks concurrently. The inherent complexity of certain tasks environment may require using multiple robots due to the demanded capability is quite difficulty for a single robot to be resolved. Moreover, multiple robots are assumed to enhance the system robustness and flexibleness by taking advantage of parallelism and redundancy.

However, the number of required communication which utilizes both previous centralized and distributed task allocation approaches is still excessively high requirements, and computational time required to plan an optimal solution is too long, that make the DMRCS unable to keep up with real-time execution demand. Thus, neither communication nor computational time is high undesirable for realistic applications, especially for dynamical mobile tasks that can move randomly before assigned robots execute, and the condition of these tasks could vary over time. The solution which tasks have been assigned to the given robots may not suit for the next solution when the conditions of tasks are changing during time. Therefore, the allocated system should reallocate robots to tasks so as to find the potential optimal solution. For such new dynamical mobile task assignment domain [1], we propose two novel methods for the distributed multi-robot coordination system, that one is dynamical sequential task allocation and reallocation, and another is global optimal task allocation and reallocation. The former method implements multi-round negotiation and body expansion behavior [2] for tasks selection. The latter approach is extended from combinatorial optimization [3] and market-based task allocation method. This paper is a comparative study of the mentioned methods above.

The remainder of this paper is structured as follows. The next section presents a formal definition of dynamical mobile task assignment problem, and the disadvantages of existing investigated task assignment methods which are utilized to resolve the new domain. Section III describes notion about body expansion behavior, setting two thresholds to make decision, and details the two proposed algorithms for DMRCS. Section IV presents the implementation and discusses simulation results. Section V discusses related works of task allocation. Finally, section VI draws conclusions and sketches future work.

2. Task Description

2.1 Formal Definition

In this paper, task assignment problem among multiple, fully distributed, initially homogeneous mobile robots is studied, i.e., we develop two novel task allocation and reallocation methods which can deal with dynamical mobile tasks. The formal definition of this problem is that assume such kind of environment included two kinds of mission, one is initial mission assigns multiple dynamic mobile tasks to robots reasonably and efficiently, another is final mission. The final mission is that robots should

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take the selected tasks to its destinations sequentially.

For the initial mission, due to dynamical mobile tasks can move randomly before assigned robots execute, and the condition of these tasks could vary over time, we should assign and reassign tasks to robots propertly. That is, we allow a set of tasks T and robots R to be time dependent (i.e., *T(t)*, *R(t)*) and require the objective functions be minimized/maximized (The task allocation reallocation method should minimized the objective functions which are cost, energy and others. Reversely, it should maximize the objective functions which are efficiency and so on.) every instant of time or over the entire history, then the definition also covers online and dynamical domain where tasks and robots may be added or removed over time. We propose two methods, which are dynamical sequential and global optimal task allocation and reallocation, to resolve this kind of new domain. While the final mission, when robots move nearby tasks, tasks transmit its destinations to robots, then in each robot global coordinate system, robots find the coordinate of destination, plan the optimal path (e.g., we utilize the particle swarm optimization to motion planning which is proposed in [4]), finally, take tasks to its destinations.

2.2 Disadvantages of Existing Methods

Previously, few researchers have done the new domain about tasks which are dynamical and move randomly. All existing methods are suitable for the tasks which positions are fixed, while for the mobile tasks, these methods are inefficient. And they don't discuss the task reallocation during robots are executing tasks, except the robot malfunction, communication failure and partial system failure. Actually, for mobile tasks in terms of position change, we should consider not only assign the tasks to robots successfully, but also robots perform tasks efficiently for whole coordination system.

Except for, none of previous approaches explicitly address the problem of minimizing communication, time of path planning, computational time and computational memory. For example, market-based auction methods [5, 6], ALLIANCE [7-9] and BLE [10] need each robot plan the path from location of itself to each task, calculate the distances between robots and tasks, when the positions of tasks change. Once the situation of tasks and robots vary, system should auction these tasks for all robots. After bidding tasks, robots which obtained profits are largest for the whole system execute these tasks. In other words, the efficiency of these methods is very low to deal with the dynamical mobile task allocation and reallocation problem, it takes a long computational time to motion planning, distance calculation and tasks negotiation. Both BLE and ALLIANCE methods don't explicitly consider global efficiency, while these methods are satisfied with finding any feasible solution. A notable exception is the work by M. Nanjanath et al. [11], where they propose a method of repeated auction for distributed tasks dynamically among a group of cooperative robots. Tasks not yet achieved are re-submitted for bids every time a task has been completed. The repeated auction comes closest to our approach. Main differences include our proposed system reallocation tasks for robots every time step, and we mainly contrite on the dynamical mobile task. Moreover, in this paper we utilize body expansion behavior to reduce the communication and computational time when the distance between robot and task is large than a given threshold.

3. The Proposed Algorithm

3.1 Mathematical Model

In this paper, we consider only homogeneous robots, the efficiency which robots to perform the mobile tasks depend on time needed by robots to reach the location of tasks. This measure depends on the mobile 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 to perform every time to improve the efficiency for the whole system.

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

Minimize:

$$\sum_{r\in V_R}\sum_{t\in V_T} D_r x_t^r \tag{1}$$

Where: $$D_r = \sum_{r\in V_R}\sum_{t\in V_T} D_{rt} \tag{2}$$

Subject to:

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

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

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

Where a binary variable x_t^r indicates whether a robot $r\in V_R$ performs a task t which selected from all tasks V_T. D_r is the distance which robot $r\in V_R$ moved, and $\pi_{st,t}^r$ is a binary value that represents whether task $t\in V_T$ executed at the time step $st\in(0,+\infty)$.

The objective function, Eq. (1) minimizes execution cost of the whole distributed multi-robot coordination system. In this case, the system cost is the total distance which robots moved. The first set of constrains, 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.

3.2 Body Expansion Behavior

Body expansion behavior [2] means that one robot can transmit its own intention and the receiver executes the order, thus the robot is capable of controlling the other's behavior. In addition this demonstrates the expansion of the robot's degree of freedom (D.O.F.).

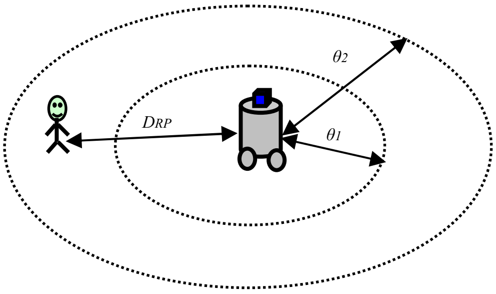


Fig. 1. Distance threshold

Two distance thresholds for decision making are settled to implement body expansion behavior. One is the small distance threshold $\theta 1$, means that robot is about to take the assigned task to its destination. Another is the large distance threshold $\theta 2$, means that robot have a certain time to execute the assigned task (Fig. 1). If the distance is more than $\theta 2$, robot can request other robots to execute the task, if the distance between $\theta 2$ and $\theta 1$, robot compares the distance and select the shorter distance task to execute, and if the distance is less than $\theta 1$, then robot refuses all requests from other robots.

3.3 Dynamical Sequential Task Allocation and Reallocation Algorithm

Assume that all robots are homogeneous robots with the same speed, function, and structure, and can communicate with each other using radio frequency broadcast. One robot is allocated only single task one time, executes only single task and take the assigned task to its destination.

The tasks are randomly distributed in the environment, and can move anywhere with variable speed before robots reach around them. Each task does not know its destination where it is unless under the robot helping. And all tasks are waiting for being taken in the priority queue under the principle of "First In First Executed". Robots always execute the relative most priority tasks regardless other tasks move around. We propose a novel mobile task allocation method, called dynamical sequential task allocation and reallocation which can reallocate the mobile tasks to robots according to the shortest distance. In the environment, $ri \in V_R\{r1, r2, \cdots, rn\}$ denotes the i th robot, $tj \in V_T\{t1, t2, \cdots, tm\}$ denotes the j th task, The $Dritj$ denotes the utilizable distance from ri to tj, and m $\geq$ n. Assumption that tasks $tj \in V_T\{t1, t2, \cdots, tm\}$ are distributed in the environment randomly, and can move anywhere, all tasks need robots take them to their destinations due to these tasks don't know the path to their destinations. In the initial state, the working statuses of all robots are free-robot, and wait for executing tasks.

Tasks broadcast the request information include task IDs and coordinates to all robots every time pulse. In the initial time step, there are two times round negotiation and selection for each robot. For the first time round, all robots receive request information from tasks, then plan paths to all tasks, and calculate the distances between all tasks in the robot's global map of environment. Robots are priority according to the robots index, the priority of robot which index is small is larger than the priority of robot which index is large. From robot $r1$ to robot rn sequentially select tasks to perform according to the given distance thresholds, that is if there are distances which between robots and tasks are less than the small distance threshold θ1, the robot selects the task to perform which distance is smallest. Otherwise, Robot does not select any task, and requests other robots to execute these tasks. Then all robots declare the information to other robots. When all robots have finished the first time selecting, then the remaining un-selection robots choose the rest un-assigned tasks again sequentially in the second time round.

For the second time negotiation, based on the priority of that the smaller robot index firstly does the task selection process, the later robot index should receives the all task selection information from the former robots then can carry out the task selection process, the remaining un-selection robot sequentially selects the un-assigned task which distance is shortest in the un-assigned tasks to perform, even though the distance between them is more the large distance threshold $\theta 2$.

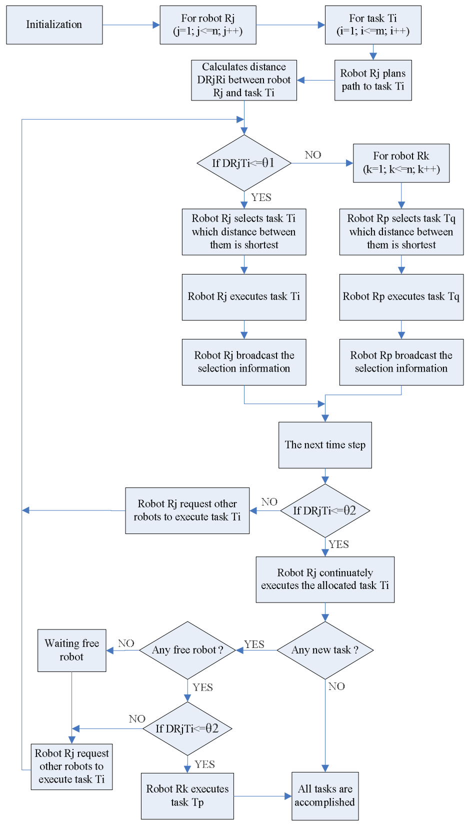


Fig. 2. Dynamical sequential task allocation

Due to the dynamical mobile tasks that move randomly before the assigned robots to reach around and execute them, the condition of these tasks could vary over time, the distances between robots and the corresponding assigned tasks may vary. The DMRCS should reallocate tasks to robots every seconds time based on utilizing body expansion behavior during the implemental period, in order to improve the efficiency of which robots execute tasks for whole system. If the distance between robot and corresponding assigned task is more thanθ2, then robot request other robots to execute this task and broadcasts the information to all other robots. For the other robots which from r_1 to r_n sequentially, if the distance between robot and task which assigned in the latest time step is less than$\theta 2$, the working state of robot change to busy-robot and refuse any requests from other robot. Otherwise, robot selects task which distance is shorter and broadcasts the task selection information to other robots. The other robots can make a decision on accepting/refusing the request according its calculated distance and the received task selection information. If all other robots refuse the task, the robot should continue select the task to perform despite the distance is more $\theta 2$. Note that robot also request other robot to execute the assigned task when robot is failure. At the next time step, robots continue move toward the assigned tasks which are allocated in the latest time step before the system assigns the new task to robot. The entire of our proposed novel dynamical sequential task allocation and reallocation method is shown in Fig. 2.

3.4 Global Optimal Task Allocation and Reallocation Algorithm

Global optimal task allocation and reallocation method is extended from combinatorial optimization [3] and market-based task allocation method [12]. It is proved that combinatorial optimization can obtain the global optimal assignment. In addition, market-based task allocation is a simple and valid method for complicated assignment. Robots bid tasks and communicate costs with other robots. For each robot, makes a combinatorial cost table after congregating all the bidding from others, then selects task to execute based on objective function at every time step. The objective function which is to be minimized executed costs and maximized accomplished efficiency for the whole system. The objective of this method is to reduce the total tasks executed time for the entire system. The algorithm of global optimal allocation and reallocation approach is shown in Fig. 3.

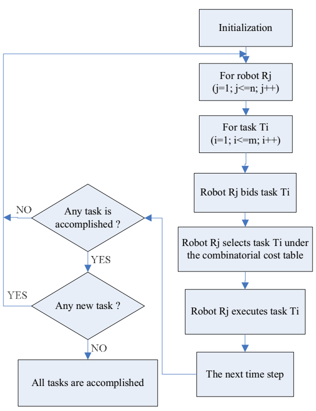


Fig. 3. Global optimal task allocation and reallocation

4. Simulation and Results

4.1 Simulation Environment Setting

To compare the validity and efficiency of the proposed two approaches, a variety of experiments are carried out by computational simulation. The simulation environment without obstacles is built up with the setting of 400*400m^2. At the initial time step, three tasks and three robots are randomly distributed in the environment. Then at time step = 500, 800 and 850, the fourth, fifth and sixth tasks move in the simulation environment. During the simulation tasks move with the variable speed over time which are shown in Fig. 4, while the speed of robot is constant which is 0.76m/s. The small distance threshold $\theta 1$ is 4m. The large distance threshold $\theta 2$ is 40m.

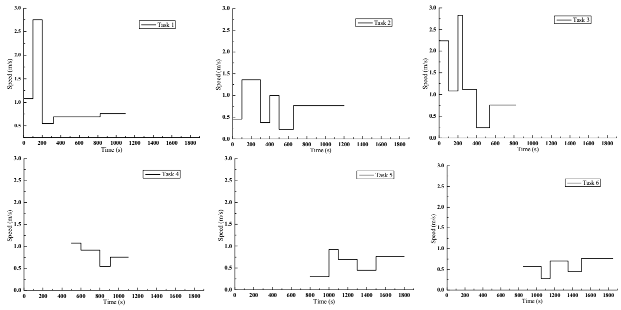
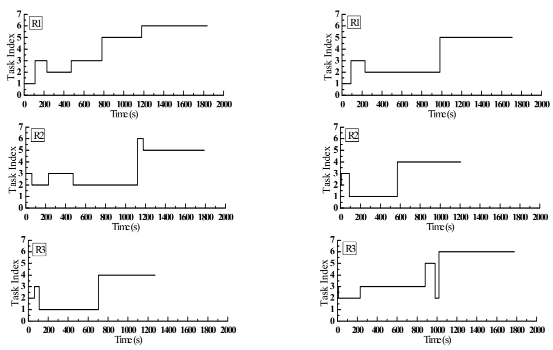


Fig.4. The speed of tasks

4.2 Simulation Results

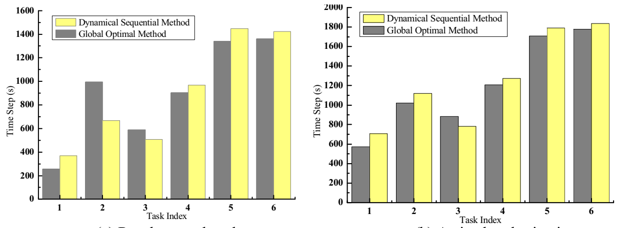
Figure 5 is the selected situations of robots that utilize the above mentioned approaches in every time step. We employ Fig. 5(a) which is the figures about dynamical sequential method to illustrate. Global optimal method is similar like Fig. 5(a). At T=62, 110, 230, 475 and 1179, tasks are reallocated to robots because of distances between them are vary. At T=371, robot r_3 arrive at t_1 and will take t_1 to destination D1. In such situation, r_3 will refuse all requirements from other robots, since distance is short than$\theta 1$, T=507, 667, 969, 1422 and 1448 are the same as T=371. t_4 walks into the environment at T=500(The same as T=800 and 850 are distributed into the environment). t_4 will move randomly with the un-assigned state, due to each robot can assign to only single task to guide each time, until there is a free-robot that like T=705, t_1 has arrived at D1 under the r_3 guiding, in the next time robot will check whether there is un-assigned task. Robot will assign to the un-assigned task if there is a un-assigned task in the environment like T=705, 1120, 1273 and 1789, or like the situation that robot will move freely due to there is no un-assigned task (as T=782).



(a) Dynamical sequential method (b) Global optimal method

Fig.5. The selected situation

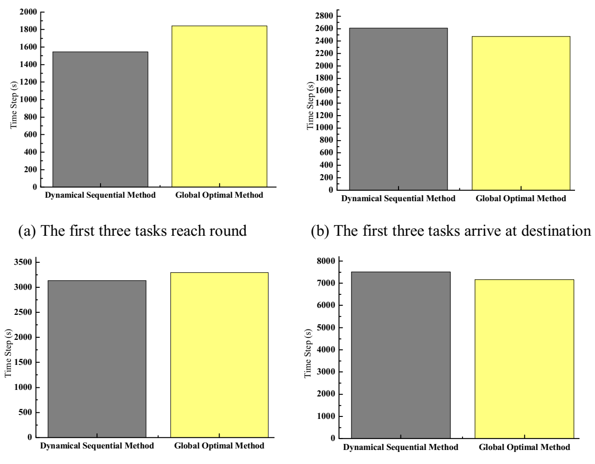
Results show that the condition which robot assigns which task during the simulation time. From the figure, we can see that robots often changed the task to perform according to the shorter distance, but not as frequently as we expected. Figure 6 shows the time steps which robots reach around tasks and take tasks to the destinations.



(a) Reach around tasks
(b) Arrived at destinations

Fig.6. The executed time step

Figure 7 shows the total costed time steps that robots reach around the first three tasks and all tasks, and take the first three tasks and all tasks to their destinations. Simulation results show that the total number of time steps for robots reach around tasks is 3134 by utilizing dynamical sequential method, while for the first three tasks it only needs 1545 time steps. The total time steps which robots take the first three tasks and all tasks to the destination are 2607 and 7505. Similarity, for global optimal approach, the total number of time steps for robots reach around tasks is 3293, while for the first three tasks it only needs 1840 time steps. The total time steps which robots take the first three tasks and all tasks to the destination are 2472 and 7165. From Fig. 7 we can see that the costed time steps which under dynamical sequential method for robots reach around the first three tasks and guide the first three tasks to their destinations are the least than global optimal method, due to the positions of these tasks could vary over time. While for accomplishing the all six tasks, the costed time steps by utilizing global optimal method are the least than dynamical sequential method. Because of dynamical sequential method is an approximative global optimal allocation approach, which is a suboptimal allocation approach.



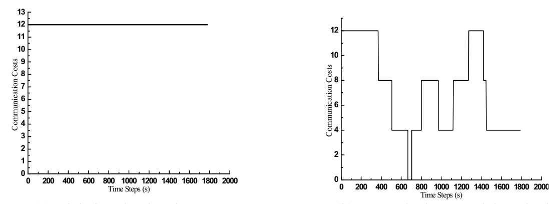
(a) The first three tasks reach round
(b) The first three tasks arrive at destination
(c) All tasks reach round
(d) All tasks arrive at destination

Fig.7. The total costed time step

4.3 Communication Costs and Computation Times

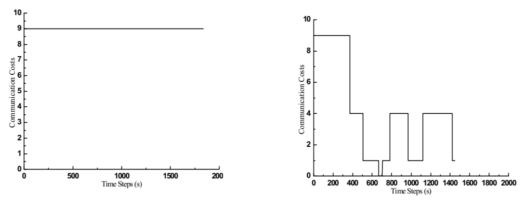
One of the greatest strengths of our task allocation and reallocation methods is their ability to deal efficiently and successfully with the changing conditions. Since our approaches do not rely on the initial task allocation and it can task reallocation according to the variable solutions, the DMRCS is highly robust to change with the environment, including malfunctioning robots. Thus, the presented methods in this paper allow robots to deal with dynamical environments in an opportunistic and adaptive manner. The communication costs and computation times by using global optimal method are $2*N*(N-1)*T$ and $N*N*T*T_0$, where N is the number of robots, T is the number of time steps and T_0 is the time for calculating the distance from one robot to one task. The communication costs and computation times of dynamical sequential method vary dependent time, because of implementing body expansion behavior for robots to select tasks.

Figure 8 and figure 9 show the communication costs and computation times for the simulated example. The results show that global optimal method could be faster to complete all tasks for the whole system than dynamical sequential method, but need more communication costs and computation times. Reversely, for the dynamical sequential method , if the distance between robot and task is less than the large distance thresholdθ2, robot only plan the path to the assigned task, thus it is more conducive to reduce the numerous computational time to calculate the distances from robots to tasks for the entire system. Since the communication costs between robots are task selection information, communication is greatly decreased.



(a) Global optimal assignment
(b) Dynamical sequential method

Fig.8. The communication costs



(a) Global optimal assignment
(b) Dynamical sequential method

Fig.9. The computation times

5. The Related Works

Task allocation for MRCS is a widely studied field. It can be broadly classified into two classes: one is centralized planner based systems, planners are often based on auction mechanisms in which robots bid for tasks, e.g. Gerkey's MURDOCH [13]. As [14] proposes a method for team-task allocation in a multiple robots transportation system, since such kind of systems are that agents and tasks are still fixed, in addition capabilities and resources do not depend on time, while in real world application it is not very useful. Another problem is the systems which rely on individual robots to make individual task allocation decision without considering other team member and the optimization of whole system. Empirical results of an auction based algorithm for dynamic allocation of tasks to robots is proposed by [11]. In their researches, they propose a method of repeated auction for distributed tasks dynamically among a group of cooperative robots. The distinctive feature of this algorithm is its robustness to uncertainties and to robot malfunctions that happen during task execution.

Another kind of method is distributed task assignment, e.g. Asama et al. develop an autonomous and decentralized robot system called ACTRESS to address the issues of communication, task assignment, and path planning among heterogeneous robotic agents [15, 16]. This approach revolves primarily around a negotiation framework which allows robots to recruit help when needed. A distributed multi-robot cooperation framework for real time task achievement is proposed in [17, 18]. The framework integrates a distributed task allocation scheme, coordination mechanisms and precaution routines for multi-robot team execution. When initial assignments of tasks may become inefficient during real time execution due to the real world issues such as failures, and these allocations are subject to change if efficiency is a high concern, reallocations are needed and should be performed in a distributed fashion. They propose an online dynamic task allocation system for reallocation to achieve a team goal that can respond to and recover from real time contingencies. [19] presents a reasonable system that enables a group of heterogeneous robots to form coalitions to accomplish a multi-robot task using tightly coupled sensor sharing. The advantages of this new approach are that it enables robots to synthesize new task solutions using fundamentally different combinations of sensors and effectors for different coalition compositions, and provides a general mechanism for sharing sensory information across network robots. However, all the mentioned above mainly concern the computational performance, and tasks are fixed location, they do not mention the dynamical mobile tasks and method of such task reassignment.

6. Conclusion

The DMRCS based on the methods of dynamic sequential and global optimal task reallocation are developed in this paper. We propose two novel methods which can reallocate tasks to robots for dynamical mobile task assignment problem according to shortest travelled distance. The dynamic sequential method is based on multi-round negotiation and body expansion behavior. Global optimal approach is extended from combinatorial optimization and market-based task allocation. In this paper, we compare the accomplished efficiency, communication costs and computational times between the two methods. The simulation results show that the minimal executed costs and maximal accomplished efficiency are obtained by global optimal method, while consumes numerous communication costs and computational times. Reversely, dynamical sequential method is an approximation global optimal assignment approach, and expends acceptable communication costs and computational times.

The disadvantages of both algorithms are still take long time to negotiation and communication, and need certain communication costs and computational times. Moreover, dynamical sequential method is an approximative global optimal allocation method that is a suboptimal allocation approach. Therefore, it is very suitable for small/medial scale distributed multi-robot coordination system. In the future work, we will improve the novel proposed algorithms for the large scale multi-robot coordination system and implement our approaches to real robot system, such as employing our methods for guidance service system which using multiple robots guide customers in shopping mall, museum and exhibition.

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