Hybrid Dynamic Mobile Task Allocation and Reallocation Methodology for Distributed Multi-robot Coordination

Guanghui Li, Yusuke Tamura, Min Wu, Atsushi Yamashita and Hajime Asama

***Abstract*—Dynamical mobile task allocation, by which tasks can move randomly before they are assigned robots to execute. For such a new task assignment domain, we propose a hybrid dynamic mobile task allocation and reallocation method that combines our previous proposed dynamical sequential method and global optimal method. Robots bid for tasks and transmit the costs to other robots. Then all robots select tasks from the combinatorial cost table to minimize the objective function. During the next time step, robots continue to select the assigned tasks for which costs are smaller than the set thresholds. Alternatively, robots for which costs exceed the corresponding threshold rebid unassigned tasks and transmit the calculated costs to others. The un-selected robots then re-select unassigned tasks from the combinatorial cost table according to global optimal task allocation method. In this study, the advantages of the proposed approach are demonstrated by comparison with existing task allocation methods. The simulation results demonstrate that a system implementing our method can obtain maximal accomplished efficiency of whole system and minimal executed costs for each individual robot. The negotiation time steps, communication costs and computational times are reduced using the proposed algorithm. Moreover, we believe that our method can extend the previous methods to be suitable for a large-scale distributed multi-robot coordination system.**

***Index Terms*—Dynamical Mobile task allocation, Multi-round negotiation, Global optimization, Body expansion behavior, Distributed multi-robot coordination system**

I. Introduction

SERVICE robots are in a stage of infancy as a new high-technology industry to address needs of society such as labor shortages accompanying the reduction in younger population, and longer lifespan of humans in the coming aged society. 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. Transport robots have been examined in previous studies [1-3]. Results showed that robots can transport pharmaceuticals safely and effectively to a destination. Network robots have been proposed for use as shopping guides, which expand from a single location to multiple locations [4, 5]. Robots can guide a customer to a shopping area when the person reaches the store. 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 human at a shopping mall, museum, or exhibition.

The remainder of this paper is structured as follows. The next section presents a formal definition of the dynamical mobile task assignment problem, along with disadvantages of existing investigated task assignment methods used to resolve the new domain. Section III describes objective functions and notions about body expansion behavior, setting two thresholds for robot decision-making, in addition to our proposed algorithm. Section IV presents a discussion of simulation results. Finally, section V explains the conclusions and outlines future work.

II. Task Description

A. Formal Definition

As described in this paper, the task assignment problem is studied for multiple, fully distributed, initially homogeneous mobile robots. We develop a 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 execute, and because the conditions of these tasks can vary over time, thus we should assign and reassign tasks to robots properly. We allow a set of tasks V_T and robots V_R to be time-dependent (i.e. $V_T(t)$ and $V_R(t)$) and require that the objective functions be minimized/maximized (The method should minimize 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 propose a method combining dynamical sequential and global optimal task allocation and reallocation approach, to resolve new domains of this kind.

B. Related Works and Disadvantages of Existing Methods

Task allocation for a multi-robot coordination system is a widely studied field. Related works have examined task allocation problems such as market-based auctions [6, 7] and

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system auctions tasks for all robots. After bidding for tasks, robots that obtain profits that are largest for the whole system execute these tasks. In other methods, ALLIANCE [8–10] and broadcast local eligibility (BLE) [11] set some thresholds for robots: each robot plans a path from its location to tasks and calculate the costs between robots and tasks. Systems will assign tasks to robots when the corresponding value exceeds the set threshold. Based on these methods, however, once the situations of tasks vary, the system should reassign all tasks to all robots. In other words, the efficiency of these methods is extremely low to address the dynamic mobile task allocation and reallocation problem, it necessitates long computational times for motion planning, cost calculation, and negotiation. Furthermore, neither the BLE nor ALLIANCE method explicitly considers global efficiency. Instead, these methods are satisfied with finding any feasible solution. A notable exception is the work by M. Nanjanath et al. [12], which proposes a method named repeated auction for distributing tasks dynamically among a group of cooperative robots. Tasks that are not yet achieved are re-submitted for bidding every time a task has been completed.

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.

A repeated auction [12] comes closest to our approach. Main differences include our method reallocation tasks for robots in every time step. We mainly specifically examine the dynamical mobile tasks. Moreover, for this study, we use body expansion behavior [13] to reduce the communication costs and computational times when some corresponding values are smaller than the given thresholds. Previously, we proposed two methods: dynamical sequential task allocation and reallocation [14], and named global optimal task allocation and reallocation [15] for a distributed multiple robot coordination system. Simulation results show that minimal executed costs and maximal accomplished efficiency are obtained using the latter method, whereas this method consumes much communication costs and computational time. Another problem is system changes frequently assignment of tasks to robots based on global optimal method which occurs in certain situations. In result that robots always wander between several tasks, this cause the *Total Summation of Completion Times* are extended and waste robot energy. In contrast, the former method is an approximate global optimal assignment method. It expends acceptable communication costs and computational times. However, the fatal shortcoming is that the time which the last task is completed is late, in other words, the *Last Task Completion Time* (i.e. the *Final Completion Time of System*) very close to repeated auction-based method [12]. That means the overall efficiency of distributed multi-robot coordination system is not so particular desirable. Other disadvantages of both proposed algorithms are that they still take so long time for tasks negotiation and robots communication that require certain communication costs and computational times. Therefore, these methods are suitable for small and medium scale multiple robot coordination systems. Herein, we propose a method combining dynamical sequential and global optimal task allocation methods to improve the previous algorithms to overcome the major mentioned disadvantages of those methods. Particularly, the whole system utilizing the hybrid method can obtain minimal executed costs and maximal accomplished efficiency. We believe that this approach can accommodate large-scale multiple robot coordination systems, and to reduce the negotiation time steps, computational times, and communication costs.

III. PROPOSED ALGORITHM

A. Mathematical Model

As described in this paper, we consider a homogeneous set of robots. The efficiency for distributed multiple robots coordination system consists of two important evaluations. One is the *Summation Executed Costs of All Robots* $E_{SECARCost}$ with which robots perform all mobile tasks. $E_{SECARCost}$ depends on the relative positions of the task and robot, in other words it depends on the *Summation Completion Time of All Robots* $T_{SCTARCompletionTime}$ necessary for robots to reach the task location, it is a function of time. Since all tasks can move randomly before they are assigned robots to execute, therefore, $E_{SECARCost}$ and $T_{SCTARCompletionTime}$ which a robot performs a task varies. For that reason, robots should select optimal tasks for which the needed executed costs by robots to reach are least to perform. Doing so for each task improves the overall system efficiency.

Another important evaluation is the time that the last task is completed by robot, we define as *Last Task Completion Time* $T_{LTCTLastCompletionTime}$. As we know that we can declare the entire system is completed only after the last task is finished. In some situations, system consumes very little $E_{SECARCost}$ and $T_{SCTARCompletionTime}$, while $T_{LTCTLastCompletionTime}$ may be large compare with other situations. It means that robots take a long time to execute the last task in these situations, so we say that the time which entire system is completed is later than others, although the $E_{SECARCost}$ and $T_{SCTARCompletionTime}$ are more efficiency. Actually, such situation raises frequently in the coordination system which utilizing dynamical sequential task allocation and reallocation method.

The locations of M robots V_R and N mobile tasks V_T are known, as is the cost function $E_{SIRCIndividualCost,Ri}$ (where $i \in M$)

that specifies the *i-th Summation Individual Robot Cost* when the whole system is completed. $E_{Cost,Ri,t-time}$ specifies the *Cost of i-th Robot* from *t* time step to *t+1* time step. The objective is to find an allocation of tasks to robots such that the total cost $E_{SECARCost}$ is minimized for the whole system. Due to we only consider a homogeneous set of robots and tasks, thus the major criterion for the proposed strategy is to optimize the Total Travelled Distance of All Robots $D_{TTDADistance}$. Accordingly, we can use the *i-th Summation Individual Roobt Distance* $D_{SIRDIndividualDistance,Ri}$ and the *Distance of i-th Robot* $D_{Distance,Ri,t-time}$ from *t* time step to *t+1* time step, to denote $E_{SIRCIndividualCost,Ri}$ and $E_{Cost,Ri,t-time}$, respectively. 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.

The objective functions are to minimize:

$$E_{SECARCost} = \sum_{Ri \in V_R} E_{SIRCIndividualCost,Ri} = \sum_{Ri \in V_R} D_{SIRCIndividualCost,Ri} \tag{1}$$

where $D_{SIRDIndividualDistance,Ri} = \sum_{Ri \in V_R} \sum_{st} D_{Distance,Ri,t-time} x_{Tj}^{Ri}$

$$\forall st \in (0,+\infty),\ j \in N \tag{2}$$

$$T_{SCTARCompletionTime} = \sum_{Ri \in V_R} \sum_{st} T_{TimeStep,Ri} x_{Tj}^{Ri} \tag{3}$$

$$T_{LTCTLastCompletionTime} \tag{4}$$

subject to the following equations.

$$x_{Tj}^{Ri} = \begin{cases} 1 & Ri \quad selects \quad Tj \\ 0 & Others \end{cases} \tag{5}$$

$$\sum_{Tj \in V_T, Ri \in V_R} x_{Tj}^{Ri} \le M \tag{6}$$

$$x_{Tj}^{Ri} \in \{0,1\} \qquad \forall Ri \in V_R, Tj \in V_T \tag{7}$$

$$\pi_{t-time,Tj}^{Ri} x_{Tj}^{Ri} = \begin{cases} 1 & Ri \quad selects \quad Tj \\ 0 & Others \end{cases} \tag{8}$$

$$\sum_{Ri \in V_R} \sum_{Tj \in V_T} \pi_{st,Tj}^{Ri} x_{Tj}^{Ri} \le N \tag{9}$$

Therein, a binary variable x_{Tj}^{Ri} denotes whether a robot $Ri \in V_R$ performs task Tj selected from all tasks V_T. $T_{TimeStep,Ri}$ signifies the number of time steps that robot $Ri \in V_R$ selects task $Tj \in V_T$; $\pi_{t-time,Tj}^{Ri}$ and $\pi_{st,Tj}^{Ri}$ are a binary value showing whether task $Tj \in V_T$ is executed at time step $t - time$ and all the time steps, respectively.

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 travelled distance that robots move. Eq. (4) minimizes the completed time of last task, which is to minimize the time to finish whole system. The first set of constraints, Eq. (5), specifies that each robot performs exactly one task. The second set of constraints, Eq. (8), 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.).

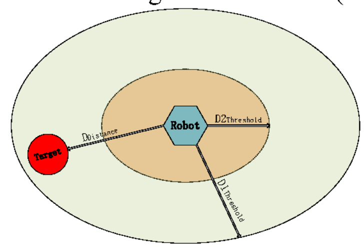


Fig. 1. Distance threshold.

Two distance thresholds for robot decision-making are settled to implement body expansion behavior. One is the small distance threshold $D1_{Threshold}$, which means that a robot is about to execute the assigned task. Another is the large distance threshold $D2_{Threshold}$, which means that robots have a long time to execute the assigned task (Fig. 1). If the distance is greater than $D2_{Threshold}$, then a robot can request that other robots execute the assigned task. If the distance between $D2_{Threshold}$ and $D1_{Threshold}$, then robots compare the distance and select the shortest distance task to accomplish. If the distance is less than $D1_{Threshold}$, 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 $D2_{Threshold}$, but more than $D1_{Threshold}$; 3. *Busy-robot*, a robot is executing task, or the distance is less than $D1_{Threshold}$. 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.

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, $Ri \in V_R\{r1, r2, \cdots, rM\}$ denotes the *i*-th robot, and $Tj \in V_T\{t1, t2, \cdots, tN\}$ denotes the *j*-th task. The D_{ritj} denotes the utilizable distance from Ri to Tj, and *N≥M*. Each task $Tj \in V_T\{t1, t2, \cdots, tN\}$ 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, all robots receive request information from tasks, then plan paths and calculate distances among all tasks in the robots' global map. Each robot transmits the calculated distances to other robots. For each robot, a combinatorial cost table is made after collecting all the bidding from others. Then a task to execute is selected based on the objective function. The objective function to be minimized executed costs and maximized accomplished efficiency for the whole system. The objective of this method is to reduce the total time for executed tasks for the entire system. That is the global optimal allocation method, the algorithm of which is as follows.

1. *All tasks broadcast the request information including task IDs Tj and the coordinates to each robot Ri.*

2. *All robots do the following steps simultaneously:*

For Ri (i=1, i<=M, i++)

i. *Robot Ri Plans the path for the first n tasks.*

ii. *Calculate distance DRiTj between robot Ri and the first n tasks Tj.*

iii. *Robot Ri transmits all distances DRiTj to other robots.*

3. *All robots Ri receive distances DRiTj from other robots.*

4. *Each Ri produces combinatorial distance table based on DRiTj.*

5. *Each Ri simultaneously selects a task from the combinatorial distance table to minimize the objective function:*

$$E_{SECARCost} = \sum_{Ri \in V_R} E_{SIRCIndividualCost,Ri} = \sum_{Ri \in V_R} D_{SIRCIndividualCost,Ri} .$$

67. *All robots move to the selected tasks according to the planned paths.*

In the next time step, the system conducts body expansion behavior. Each robot plans a path and calculates the distance to the corresponding last assigned task. For all robots from $R1$ to Rm sequentially, if the distance is greater than $D2_{Threshold}$, then the robot requests that other robots execute and broadcast information to others. Otherwise, the working state of the robot changes to half-free-robot and refuses all requests. Robots for which the distance exceeds the set threshold rebid all unassigned tasks and transmit calculated costs to others. The un-selected robots re-select unassigned tasks from the combinatorial cost table using global optimal task allocation. The algorithm of body expansion behavior is as follows.

1. *Renew time step.*

2. *All robots compare the distances DRiTj between robots and the selected tasks with a large/small distance threshold.*

If $D_{RiTj} <= D2_{Threshold}$.

If $D_{RiTj} <= D1_{Threshold}$.

Then i. *Robot Ri executes the allocated task Tj.*

ii. *Robot Ri broadcasts the execution information to other robots.*

iii. *Robot Ri changes state to Busy-robot.*

iv. *If Robot Ri completes task Tj.*

Then *Robot Ri changes state to a Free-robot.*

Else *Return to 1.*

Else i. *Robot Ri continues to select the allocated task Tj.*

ii. *Ri broadcasts the selection information to other robots.*

iii. *Robot Ri changes state to Half-free-robot.*

iv. *Return to 1.*

Else i. *Robot Rt requests that other robots execute task Tj.*

ii. *Collect all information about robots and tasks for which distances DRiTj>=* $D2_{Threshold}$.

iii. *Return to global optimal task allocation.*

IV. Simulation and Results

A. Simulation Environment Setting

To demonstrate the validity and efficiency of our approach, various experiments are conducted through computer simulation. 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. The small distance threshold $D1_{Threshold}$ is 4 m. The large distance threshold $D2_{Threshold}$ is 40 m. To compare our approach, we simulate a kind of general method market-based repeated auction, dynamical sequential task allocation and global optimal task allocation in the same situation.

B. Simulation Results

The simulation results depicted in Fig. 2 are the consumed time steps during which robots accomplish all tasks. As the figure shows, it is apparent that the consumed time steps using dynamical sequential, global optimal and hybrid dynamic method are almost identical, but much smaller than using the repeated auction method. Moreover, the more tasks that are executed, the greater the reduced consumed time steps are. Furthermore, the average consumed time steps using hybrid dynamic mobile method are between the dynamical sequential and global optimal method. Consequently, the whole system can obtain maximal accomplished efficiency and minimal executed costs based on our method.

Figure 3 displays the assigned status of robots that implement the methods described above in each time step. Results show conditions in which a robot assigns tasks during the simulation. As the figure shows, it is apparent that robots often change the tasks to perform according to the distance order, but not as frequently as we expect. In contrast to the consumed time steps, the reassigned tasks using the repeated auction method are fewer than other three methods. Similarly, the proposed method a little more frequently reallocates tasks to robots than dynamical sequential method, but far less than global optimal method. That also proved that the proposed method can prevent robots always wandering between several tasks and changing frequently allocation of tasks to robots in all simulation situations. Therefore, the hybrid dynamic task allocation and reallocation method saves more robot energy and reduces the *Total Summation of Completion Times*.

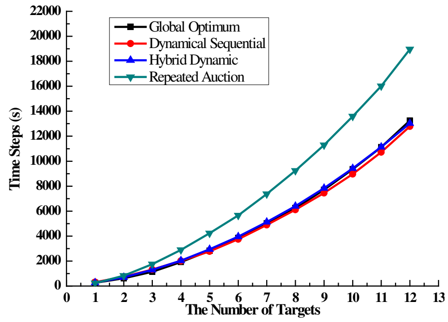
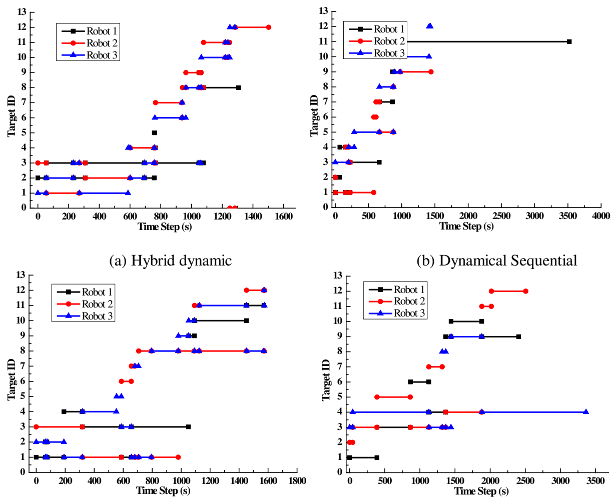


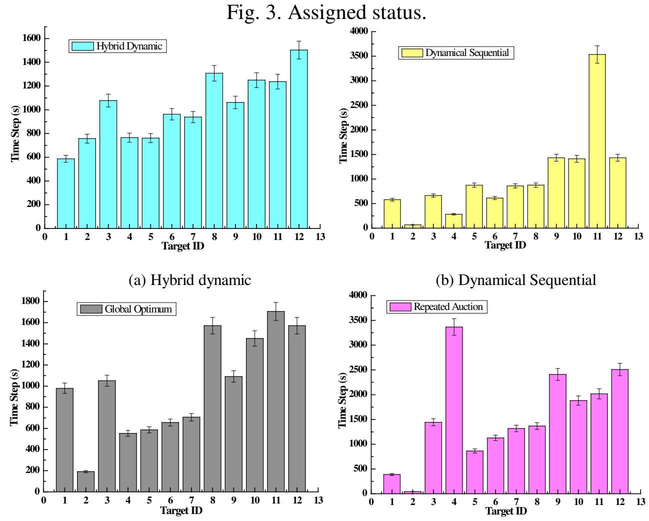
Fig. 2. Total consumed time steps.



(a) Hybrid dynamic (b) Dynamical Sequential

(c) Global optimum (d) Repeated auction

Fig. 3. Assigned status.



(a) Hybrid dynamic (b) Dynamical Sequential

(c) Global optimum (d) Repeated auction

Fig. 4. Consumed time steps for each task.

The necessary time steps during which each task is accomplished by a robot are presented in Fig. 4. As mentioned above, the *Final Completion Time of System* based on both dynamical sequential and marked-based repeated auction method is very later than hybrid dynamic and global optimal method, for example, the *Final Completion Time of System* are 1521 and 1736 using hybrid dynamic and global optimal method, respectively. Whereas for dynamical sequential and repeated auction task allocation method, the *Final Completion Time of System* are 3472 and 3633, respectively. The results show that the *Final Completion Time of System* which implemented dynamical sequential method is even more than repeated auction method in those situations. Thus the overall efficiency of distributed multi-robot coordination system by our algorithm is very desirable.

C. *Communication Costs and Computational Times*

An important strength of our task allocation and reallocation method is the ability to address changing conditions efficiently. Our 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. Communication costs and computational times using the four methods presented in Table I and Table II, where M represents 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. Communication costs and computation times of hybrid dynamic mobile task allocation and dynamical sequential task allocation method vary according to time because of implementation of body expansion behavior for robots to select tasks.

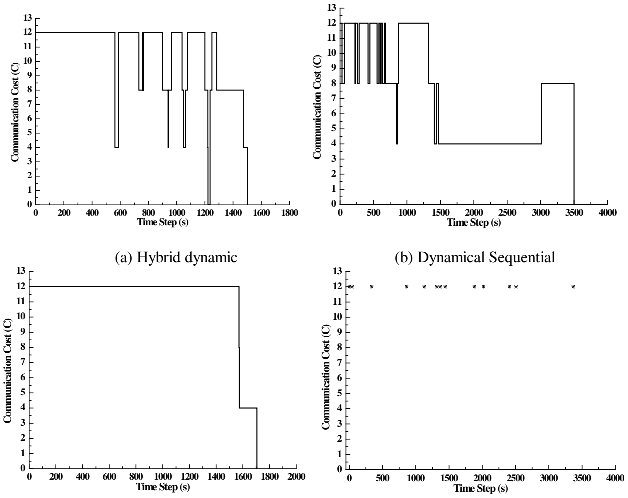
TABLE I COMMUNICATION COSTS

Hybrid Dynamic	Dynamical Sequential	Global Optimal	Repeated Auction
Variable	Variable	$2*M*(M-1)*T$	$2*M*(M-1)*(N-M+1)$

TABLE II COMPUTATION TIMES

Hybrid Dynamic	Dynamical Sequential	Global Optimal	Repeated Auction
Variable	Variable	$M*M*T*T_0$	$M*M*T_0+(N-M)*T_0$

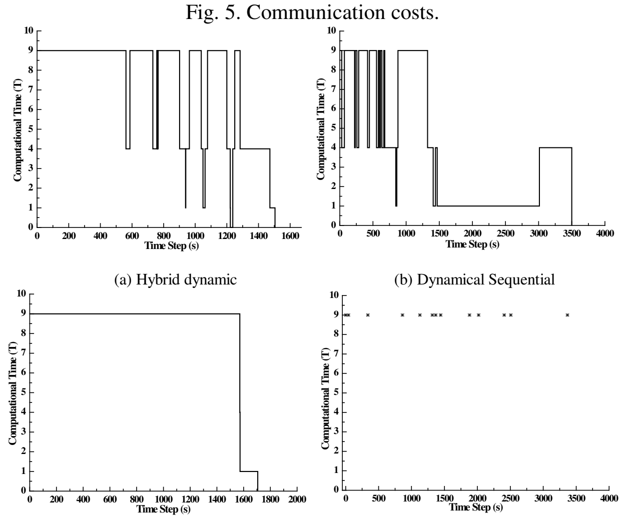
Figure 5 and 6 portray communication costs and computation times for the simulated example. Results show that the global optimal method entails higher communication costs and computation times. For the hybrid dynamic and dynamical sequential method, if the distance is less than $D2_{Threshold}$, then the robot only plans path to the assigned task. Thereby it is more conducive to reduction of the numerous computational times to calculate the distance for the entire system. Because the communication costs are task-selection information between robots, communication costs are also greatly diminished. Communication costs and computational times based on hybrid dynamic are intermediate between the global optimal and dynamic sequential task allocation method. However, the repeated auction method is the least because the communication costs and computational times only occur when a task is achieved.



(a) Hybrid dynamic (b) Dynamical Sequential

(c) Global optimum (d) Repeated auction

Fig. 5. Communication costs.



(a) Hybrid dynamic (b) Dynamical Sequential

(c) Global optimum (d) Repeated auction

Fig. 6. Computational iterations.

Actually, based on the global optimal task allocation method, all robots plan paths, calculate distances, conduct negotiations, and perform task selection simultaneously. Consequently, the negotiation times of the whole system are less than the dynamical sequential under which robots select tasks sequentially, which requires overly long negotiation times for the whole system, especially when the robots are extremely numerous. While using global optimal, each time step, robots calculate distances to all tasks and communicate mutually, so the computational times of each robot and communication costs are much greater than under dynamical sequential because communication only occurs with the un-selected robots. Fortunately, the proposed hybrid method combines both methods, which implements their advantages. Therefore, probably the proposed method can improve all these performances and can be suitable for a large-scale distributed multi-robot system.

V. CONCLUSION

A hybrid dynamic mobile task allocation and reallocation method was developed in this study to resolve a new mobile task allocation domain. The proposed algorithm combines our previously proposed methods: dynamical sequential method and global optimal method. The advantages of the proposed approach are demonstrated in comparison with existing task allocation methods. The simulation results demonstrate that the whole system can obtain maximal accomplished efficiency and minimal executed costs based on our method. The negotiation times, communication costs and computational times are lower when using the proposed algorithm. Moreover, we can extend the previous methods to be very suitable for a large-scale distributed multiple robot coordination system. In future works, we will implement our approach to real robots and optimize the given distance thresholds according to the scale of the environment and the number of robots.

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