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A Novel Multi-robot Task Allocation Algorithm under Heterogeneous Capabilities Condition

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Abstract: With the continued development of robotics, robots can perform more and more complex multi-robot tasks. The subtasks decomposed by multi-robot task may be different significantly and member robots in system may be varying on capability models. It is a challenge to most of task allocation algorithms in this context. This paper studied ST-MR-IA task allocation algorithm under heterogeneous capabilities condition. We give the concept of capability heterogeneity; provide a multi-robot task allocation algorithm, whose complexity being simplified by distributed computing and pruning strategy. The effectiveness of this new algorithm is verified in practice.

Key words: Multi-robot task, task allocation, multi-robot system, capability heterogeneity

INTRODUCTION

Cooperative multi-robot systems (MRSs) should benefit from cooperation to achieve a common goal optimally (Parker, 2008). The critical foundation of cooperation is Multi-robot Task Allocation (MRTA), i.e., let tasks be assigned to member robots automatically. Paper (Gerkey and Mataric, 2004) classified MRTA by three axes. The simplest SR-ST-IA problem can be solved in polynomial time. But in most cases MRTA is an NP-hard problem.

Many achievements have been made in research on MRTA problem. Subtask allocation optimization is often overlooked. They presume that either subtasks are similar or reward of coalition is nothing to do with specific tasks assignment. However, with the development of robotics, capability of robots is continuously enhanced. A robot is generally equipped with a variety of sensors and actuator. So it can carry out more and more complex task and work in different application scenarios. In this context, a task's subtasks likely to be different and reward of coalition is probably related with specific tasks assignment. When the ability models of robots are different and subtasks are different, it is a challenge to find the optimal assignment for most of MRTA algorithms.

This study studied the formation of robot coalition and ST-MR-IA task allocation algorithm under heterogeneous capabilities condition. We give the concept of capability heterogeneity. We provide a multi-robot task allocation algorithm, whose complexity being simplified by distributed computing and pruning strategy. The effectiveness of this new algorithm is verified in practice.

RELATIVE WORKS

ALLIANCE (Parker, 1998) is a representative of the behavior-based approach which is the most researched in the multi-robot task allocation problems. Another method modeled allocation decision as a partially observable Markov process (MA-POMDPS) (Seuken and Zilberstein, 2008), whose disadvantage is high time complexity. Jiang *et al.* (2008) proposed a multi-robot task autonomous allocation method based on ACO algorithm. Yu *et al.* (2010) presented a centralized planning approach based on ACO which uses local search strategy to improve the distributional effects of the ant colony algorithm.

The most important method in the multi-robot task allocation is the market-based approach. Dias (2004) presented a framework for distributed control multi-robot systems. MURDOCH is a market-based system proposed by Gerkey and Mataric (2002). Hoplites was proposed by Kalra *et al.* (2005) but there is no global optimal search.

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Vig and Adams (2005) described a framework RACHNA. Vig and Adams (2006) provided a method derived from multi-agent systems. In this method, the complexity of distributed computing is $O(|R|^k)$ and the complexity of centralized computing is $O(|R|^{k+1})$. ASyMTRe and ASyMTRe-D were proposed by Parker and Tang (2006), ASyMTRe is a multi-robot task planning framework combined with the market concept, ASyMTRe-D is a distributed version of ASyMTRe. Their time complexity is $O(|R|!)$. A dynamic task allocation method was proposed by Zu *et al*. (2006) which reduced communication traffic on the basis of shortening task completion time.

PROBLEM DEFINITION

We assume that robots can fully communicate with each other, task is independent, Instantaneous assignment and delay of task will caused cost. Task is independent, i.e., task should be carried out without dependency on other tasks. But a weakly dependency on time should be allowed, especially when a multi-robot task is decomposed into several subtasks.

When a task t is fulfilled, the corresponding robot will receive a utility value $u(t)\in R_0^+$. Meanwhile, every action a robot executed caused cost $c(r, a)\in R_0^+$ which depended both on action a and current environment state. The sum of cost of all of actions executed for the task is:

$$C(r,t)=\sum_{a\in ap(t)} c(r,a) \tag{1}$$

where, ap(t) is an action plan of robot r to complete task t. Let the utility value u(t) minus the cost C(r, t), we get the net gain of robot to complete task t:

$$g(r, t) = u(t)-C(r, t) \tag{2}$$

A robot pursuits to maximize net gain value when execute task. Value of g(r, t) will be added to $g_{r,t}$ which will be used to compute the performance of robot.

For a specific task, we need an index to enable making comparison of performance between different multi-robot systems or different operating phase of a same multi-robot system. This index should be independent of the number or type of tasks. We choose $q_{r,t}$ to play this role, obtained from the following equation:

$$q(r,t)=\frac{g_{r,t}}{u_{r,t}} \tag{3}$$

Where:

$$u_{r,t}=\sum_{i=1}^{m_a} u(t_i)$$

$$g_{r,t}=\sum_{i=1}^{m_c} (u(t_i)-C(r,t_i))$$

m_c is number of tasks that have finished, m_a is number of all of tasks including finished and executing. It is obvious that $m_c \le m_a$.

The optimal task allocation solution ψ^* should be found to maximize Eq. 3:

$$\psi^* = \underset{?}{\operatorname{argmax}}\, q(\psi,t) \tag{4}$$

It is harder to find ψ^* if a task is a multi-robot task, i.e. this task will be decomposed to several subtasks and executed by more than one robot. Let $tp(t_j) = <t_{j1}, t_{j2},\dots, t_{jv}>$ be a task plan. $tp(t_i)$ is tuple of subtasks of t_j, where t_{jl} is subtask of t_j, $1\le l\le v$. Any task t, if it satisfy $|tp(t)|\ge 2$, is a multi-robot task. It is more complex for optimal solution searching when ability models of robots in a system are different.

CAPACITY HETEROGENEITY OF MULTI-ROBOT SYSTEM

Let $k\in K$ be a function of special capacity k_r of robot. K is set of all capacity function of robot:

$$k=\frac{n_s(k)}{n_s(k)+n_f(k)} \tag{5}$$

where, $n_s(k)\in N$ is times of successful action who using k_r, $n_f(k)\in N$ is times of failed action who using k_r, $k\in[0,1]$. Each robot $r\in R$ owns a capacity set:

$$K_r = \{k_r^1, k_r^2, \cdots, k_r^l\} \tag{6}$$

Value of k indicates the reliability of robot. Generally we just need a Boolean value to represent whether robot has corresponding capacity. So, k will be obtained by:

$$k\in K_r = \begin{cases} \text{true}, \text{if } k(r)>\delta \\ \text{false, else.} \end{cases} \tag{7}$$

Robot r owns capacity k_r if the value of k(r) is greater than the threshold $\delta\in[0,1]$.

Given two robots r_i, r_j with their capacity set K_{r_i} and K_{r_j}, we call the degree of difference between K_{r_i} and K_{r_j} capacity heterogeneity which can be defined by capacity redundancy:

$$h(r_i, r_j) = 1 - \frac{2|K_{r_i} \cap K_{r_j}|}{|K_{r_i}| + |K_{r_j}|} \tag{8}$$

where, $h(r_i, r_j) \in [0,1]$.

The capacity heterogeneity of a multi-robot system is:

$$h(R) = \frac{2}{|R||R-1|} \sum_{i=1}^{|R|-1} \sum_{j=i+1}^{|R|} \left(1 - \frac{2|K_{r_i} \cap K_{r_j}|}{|K_{r_i}| + |K_{r_j}|}\right) \tag{9}$$

If all of robots in system have same capacity, then h = 0, else if their capacity is different from each other, then h = 0.

Heterogeneity provides a measure of functional diversity within a multi-robot system.

A NEW MRTA ALGORITHM CONSIDERED HETEROGENEITY

In this section, we will discuss a novel MRTA algorithm. The organization of multi-robot system is shown in Fig. 1. There is a system agent be responsible for interactive with coalitions and manager. Some robots will form a coalition to execute a task. There is a coalition agent for each coalition. The coalition will be dissolved at the end of task.

When system agent received a task, it will select a coalition agent, who can be a robot or a software agent in network, who will publish the task and form a new coalition. Algorithm 1 and 2 descript this new multi-robot task allocation algorithm.

Firstly, at step 1 and 2 of algorithm 1, coalition agent will decompose the multi-robot task t_{mr} received from system agent to ST-SR-IA subtasks set t_{sr} = tp(t_{mr}). Coalition agent announces subtasks set via the form of bidding to all member robots in system, including constraints set of capability χ_{t_j} for each subtask $t_j \in T_{sr}$ and utility value u(t_j).

Next, the member robots received will evaluate the subtasks using algorithm 2. They get the net gain of each task using Eq. 2, choose the most suitable one. For robot r, the subtask with the highest net gain value will be chosen. If there is more than one subtask have highest net gain, choose the one have best performance value q_{r,t_j} for robot r. If still there is more than one suitable subtask, then select one randomly.

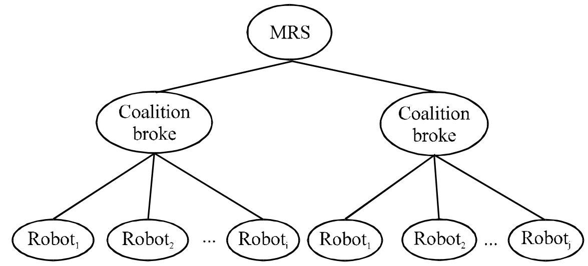

Fig. 1: Organization of UMRS

Algorithm 1: Procedure of coalition agent task allocation

1 Let $T_{sr} \leftarrow$ tp(t), round = 0
2 Announce (T_{sr})
3 Wait and receive bids
4 For each tj $\in T_{sr}$
if only one bidder r then
add (tj, r, g, q) to R_c
Remove t_j from T_{sr}
Else if more than one bidders for t_j then
Choose suitable robot using Eq. 2, 10
Add (t_j, r, g, q) to R_c
Remove t_j from T_{sr}
Else
Do nothing.
End if
End for
5 If empty (T_{sr}) or round>length(T_{sr}) then
goto step 7
Else
round++
goto step 2
end if
6 Using GA to select optimal assignment based on above assignment result R_c
7 End

At step 3 of algorithm 2, robot r submit bidding information to coalition agent, with information set of subtasks which can be done by robot r $B_r = \{b_1, b_2, \ldots b_n\}$, where $b_i = (r, t_j, g(r, t_i), q_{r, ti})$.

Coalition agent waits for receiving bidding information B_r from member robots. These bidding information forms the biddings set $B_r = \{B_{r1}, B_{r2}, \ldots B_{rm}\}$. At step 4 of algorithm 1, for each subtask t_j coalition agent will screen bidders preliminarily. In addition to consider net gain to complete t_j, the performance of robot r for task and the change of heterogeneity of coalition if r joined into coalition is considered. The lower of heterogeneity means more redundant capability. When execute task, if one robot failed, coalition can find another one to take over its task as great as possible. This evaluation reference to equation as follow:

$$I = q(r, t) + \lambda(1 - h(R)) \tag{10}$$

where, I is a evaluation of bidder r for task t. λ is a discount factor, $\lambda \in [0,1]$. The value of λ reflect how important capability heterogeneity in evaluation.

At step 5 of algorithm 1, coalition agent will obtain a suboptimal allocation solution R_c using Eq. 2, 10. This solution can be a reference for adjusting individual fitness in next step. It will need only one loop to get allocation solution in the best case while $|T_{sr}|!$ loops in the worst case.

Next step, coalition agent need to choose a most suitable robot for each subtask of T from their candidates set R_t which is a NP hard problem. We try machine learning methods to obtain the optimal solution. The Genetic algorithm (GA) is one of most suitable methods.

We use symbolic coding method for chromosome encoding. The length of chromosome for each individual is $|T|$. In fact, each individual represents an allocation solution. The ids of genes in a chromosome are corresponding with subtasks. The values of genes are corresponding with robots. $R \in R_t$. The objective function is:

$$F(R_t, t) = \sum_{t_i \in T, r \in R_t} g(r, t_i) \cdot I_{r, t_i} \tag{11}$$

Algorithm 1 computes the fitness of each individual based on sum of net gains of robots chosen for all subtasks in set T_{sr}. To make individual who represent an allocation R'_c better than R_c have more chance appear in next generation, we try to adjust its fitness using Eq. 12:

$$\text{Fitn}'(R'_c, t) = \gamma(R'_c, t) \tag{12}$$

where, γ is a factor, $\gamma \geq 1$.

Algorithm 2: Procedure of member robot evaluating subtasks

1. Receive (T_{sr})
2. For each $t_j \in T_{sr}$
   Obtain $g(r, t_j)$ using Eq. 1, 2
   Obtain $q(r, t_j)$
   end for
3. Choose the task with the maximum $g(r, t)$, submit it with set B_r to task agent
4. End

Whether allowing a robot undertaking more than one task simultaneously will lead to different allocation solution and result. If this situation is not allowed, the fitness of individuals of each generation population should be adjusted. In practice, when the number of robots is less than the number of subtasks, it has to allow one robot undertaking multiple subtasks. This brings in new problems. When the member robots bid for subtasks, they evaluate subtasks based on their current state. When one robot undertakes multiple subtasks, what it costs will probably deviate from its original estimation, i.e. its actual net gain is too little even negative. To take full advantage of distributed parallel execution of the system, it is necessary to make subtasks distribute in robots evenly. We use Eq. 13 achieving this objective:

$$\text{Fitn}'(R_t, t) = (e^{1-|T_r|})\text{Fitn}(R_t, t) \tag{13}$$

where, $|T_r|$ is the max number of subtasks a robot allowed to receive.

Finally,algorithm 1 outputs the best individual which be converted to phenotype, i.e., the optimal allocation result we want. The robot coalition is formed based on R_i. The coalition agent will notice every robot who belong to R_t. If algorithm 1 does not output anything, it means that the system cannot complete the task.

EXPERIMENT AND ANALYSIS

We apply the new MRTA algorithm to transformer substation inspection robot system. The indoor inspection experiments were carried out. It needs to check the status of equipment in substation. Compared with the letting a robot integrates all sensors S needed in inspection, multi-robot system is a better solution. Member robots in MRS equipped with a subset of S are easier to design and implementation, making MRS have adequate redundancy and thus more robust.

Member robots used are shown in Fig. 2. They are inspection robot cei-I, improved version of Voyager-II and III. The capacity set of cei-I is $k_{cei\text{-}1} = \{k_{move}, k_{local}, k_{obj}, k_{spk}, k_{ti}, k_{sound}\}$, Voyager-II $k_{voyager} = \{k_{move}, k_{local}, k_{obj}, k_{spk}, k_{ti}, k_{sound}\}$ Voyager III $k_{voyager} = \{k_{move}, k_{local}, k_{obj}, k_{spk}, k_{ti}, k_{sound}\}$, where, k_{move} is ability of movement, k_{loc} is ability of localization, k_{obj} is ability of object detection, k_{spk} is ability of spark detection, k_{ti} is ability of thermal Imaging, k_{sound} is ability of sound sensing. The capacity heterogeneity of this MRS is 0.061.

Member robots use dead reckoning and magnetic navigation as the main navigation technology. There is a raster map of workplace in each robot, shown as Fig. 3. The thin lines are magnetic stripes underground which will guide robots moving on right routine. The points of A, B, C, D are four charging dock for robots. The robots will go back to their charging dock when they are free. There are some cross symbol in Fig. 3, they are RFID stored their own information about coordinates which can help robots position themselves precisely.

When two robots meet, they use the method of traffic rules to avoid collision. When it closes to a device, the robot extracts the features of the device using SURF algorithm and matches with features of target stored in system, as shown in Fig. 4 shown. If the matching is successful, the robot can obtain the relative position with the target. The working scene of robots is shown in Fig. 5.

Fig. 2: Member robots

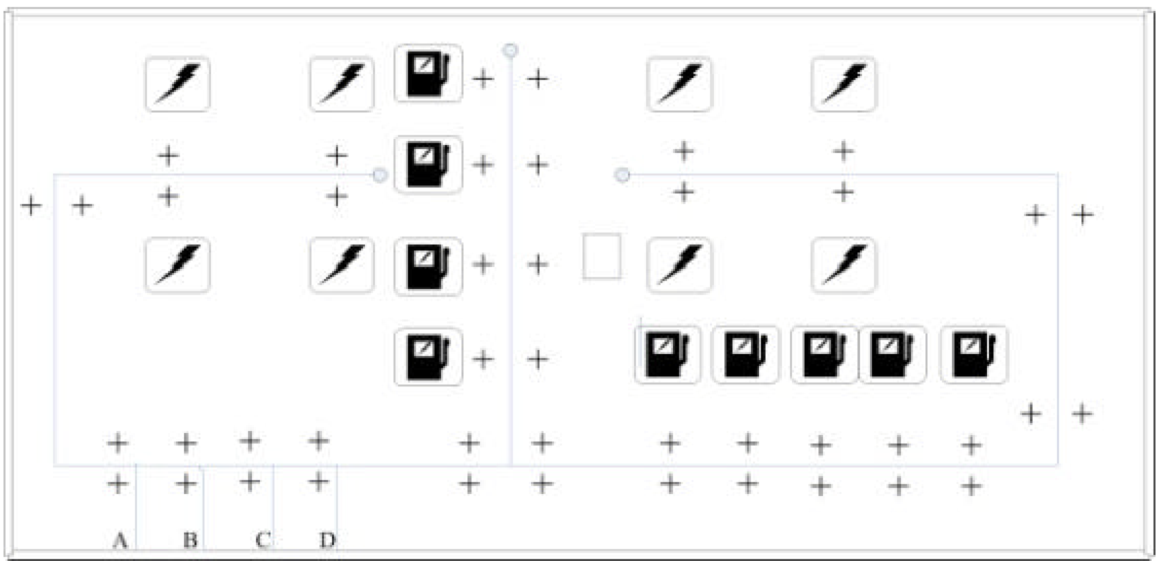

Fig. 3: Schematic diagram of workplace

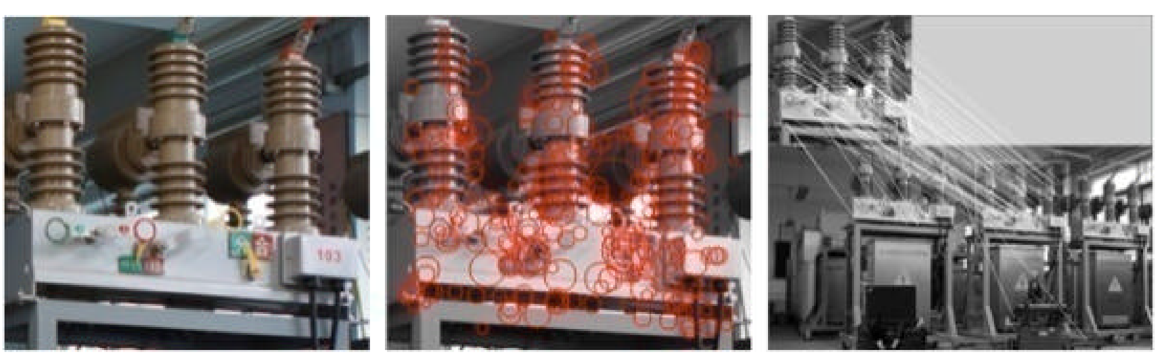

Fig. 4: Matching target based on SURF

Fig. 5: Working scene of robots

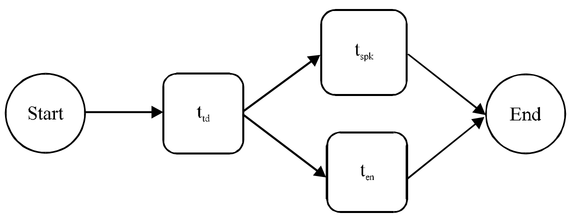

Fig. 6: Dependencies among tasks

Currently, The MRS provide three type of inspection, they are thermal distribution td, electric spark spk and noise of device dn. Task t_{td} needs a robot satisfy the capability constraint $\chi_{t_{td}} = k_{move} \wedge k_{loc} \wedge k_{obj} \wedge k_{ti}$, task t_{spk} needs $\chi_{t_{spk}} = k_{move} \wedge k_{loc} \wedge k_{obj} \wedge k_{spk}$, task t_{dn} needs $\chi_{t_{dn}} = k_{move} \wedge k_{loc} \wedge k_{obj} \wedge k_{sound}$. Dependencies among tasks are shown in Fig. 6.

We subdivide inspection task of a device, i.e. each item detection of a device is seen as a subtask. Then, as shown in Fig. 3, to detect the 17 devices, there are 51 subtasks. This solution is flexible and customizable.

Coalition agent launches the bidding process. The value of utility computed using Eq. 14:

$$u(t) = \alpha(\frac{\max(l)}{v} + \text{time}(op_t)) \tag{14}$$

where, l is the distance between a point on magnetic stripes and target device. max(l) is the maximum distance. v is average velocity of robots, time(op_t) is the time need to take to complete the detection operation op_t. α is a discount factor, if utility is only depend on time, then $\alpha = 1$.

The cost a robot to executed subtask t is computed using Eq. 15:

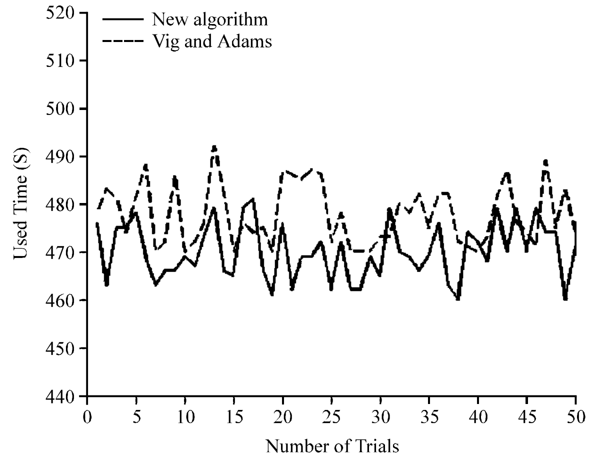

Fig. 7: Comparison of time taken of completing task

Table 1: Comparison of average value of maximum fitness A:B

	|T|		
|R|	6	30	50
5	0.8987:1.9696	0.8196:1.9760	0.8024:1.9819
6	1.2859:1.9665	0.7983:1.9536	0.8071:1.9730
7	1.3104:1.9674	0.7953:1.9626	0.7842:1.9704
8	1.3947:1.9693	0.1224:1.9679	0.8042:1.9626

$$c(r,t) = \alpha(\frac{l(r,d)}{v} + \text{time}(op_t)) \tag{15}$$

where, l(r, d) is the actual distance between robot and target device.

Member robots evaluate subtasks and submit bids reference to algorithm 2. Coalition agent completes the task allocation process using algorithm 1. Since cei-1 can execute noise detection and thermal distribution detection of devices, it bids for the task that to detect the nearest device which lead to 3 times bidding, sent 9 times message.

When the member robots assigned subtasks are ready, coalition agent will issue command of start. Coalition agent start subtasks t_{td} firstly. After received completion messages from robots, it will start t_{spk}. t_{en}. This process is managed by coalition agent.

Table 1 showed the comparison of average value of maximum fitness. A is the average value of maximum fitness after algorithm 1 used Eq. 13 while B is the value before uses Eq. 13. It can be found that after handled the average value of maximum fitness is less than before which means there are multiple subtasks assigned to a same robot. This can make subtasks distribute among robots evenly.

We studied a particular inspection task can be decomposed into 17 subtasks. Figure 7 showed the comparison of time used to complete task by our new algorithm and Vig and Adams. After 50 times execution, it is obvious that the new algorithm taken less time than Vig and Adams.

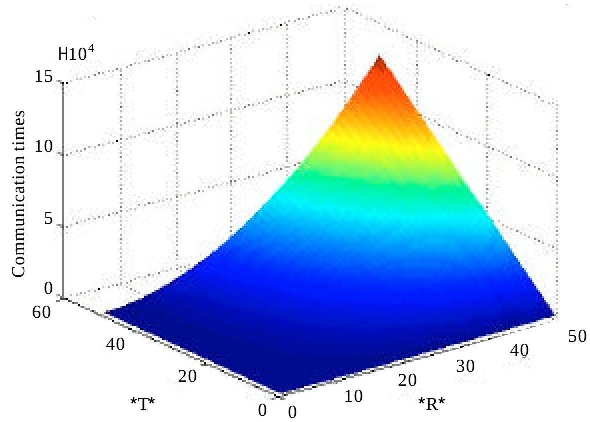

Fig. 8: Communication times vs. No. of robots and subtasks

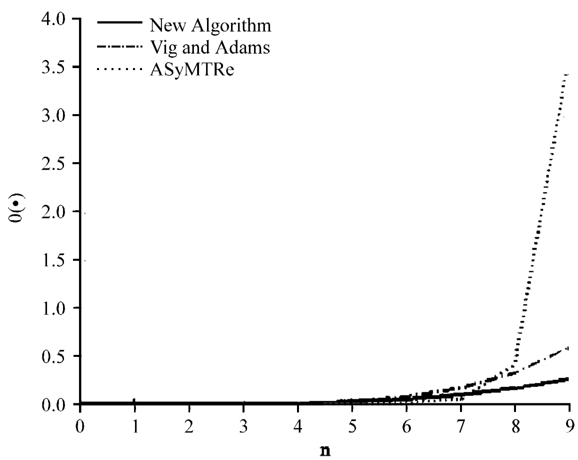

Fig. 9: Comparison of compute complexity A

Table 2: Communication times

Message type	SR task	MR task
Announce	$\|R\|$	$\frac{(\|T\|+1)\|T\|}{2}\|R\|$
Bid	$\|R\|$	$\frac{(\|T\|+1)\|T\|}{2}\|R\|$
Assign	$\|R\|$	$\|R\|$
Confirm	$\|R\|$	$\|R\|$
Total	$4\|R\|$	$(\|T\|+1)\|T\|+2\|R\|$

To verify the performance of the new algorithm when robots and subtasks increased, we put some virtual robots and subtasks in the network. Figure 8 showed the relationship among communication times, number of robots and subtasks. The communication times is proportional to the latter two as shown in Table 2, where $|R|$ is the number of robots in coalition, $|T|$ is the number of subtasks in task T.

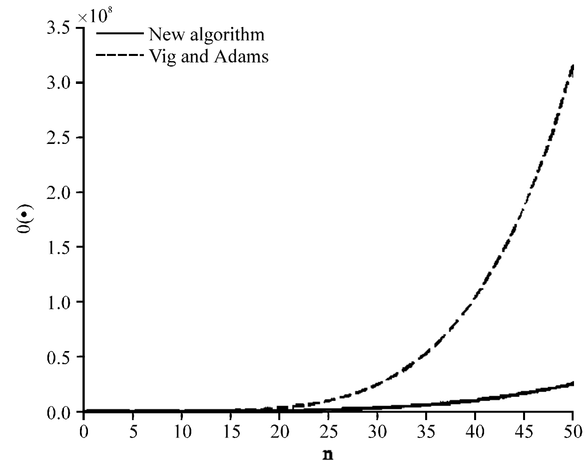

Fig. 10: Comparison of compute complexity B

The step 2 of algorithm 1 uses GA to obtain option solution. The compute complex of algorithm 1 is $O(n^4)$ which is increased since to fitness of each individual needs to be post processed, where $n = \max(|T|, m, n)$, m is the value of iteration times, n is number of individuals in population.

In algorithm 2, the evaluation of each member whether suitable to complete each task is optimized by distributed computing. In this process, the complexity of the algorithm is reduced via pruning strategy. The complexity of algorithm 2 is $O(n^2)$, where $n = \max(|R|, |T|)$.

The overall compute complexity of the algorithm we provide is $O(n^4)$ while ASyMTRe-D is $O(|R!|)$. Vig and Adams algorithm is $O(|R|^k)$, where, k is the maximum size of coalition. The comparisons of compute complex of the three algorithms are shown in Fig. 9 and 10. The complex of the new algorithm is lower than the other algorithms even $k \leq 5$. When the value of n increases, the advantage of the new algorithm is particularly obvious. When $n \geq 10$, the complex of ASyMTRe-D is too high to show in one figure with others. Figure 10 is another comparison between the new algorithm and Vig and Adams algorithm when $0 \leq n \leq 50$.

It is not enough only using net gain to analyze the effectiveness of a MRTA algorithm, because the net gains of different tasks are not comparable. The net gains need to be normalized using Eq. 16:

$$q'(T) = \frac{\sum_{r=\varphi(t), t\in T} g(r,t)}{\sum_{t\in T} u(t)} \tag{16}$$

where, T is the set of subtasks that MRTA task decomposed. $R = \varphi(t)$ is a mapping $T \rightarrow Z$ which represent

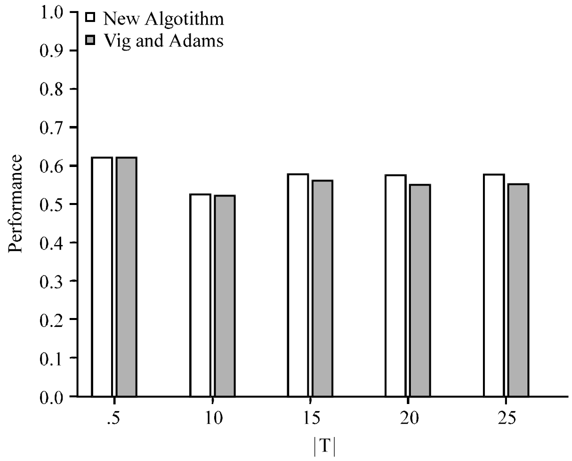

Fig. 11: Performance comparison of algorithms when number of subtasks changed

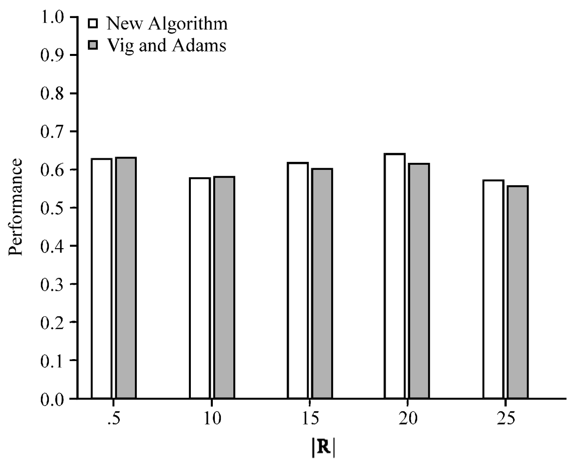

Fig. 12: Performance comparison of algorithms when No. of robots changed

a specific subtask assignment. $q' \in (-\infty, 1)$, $q' = 0$, means that the cost of coalition completing the MRTA task is equals to value of utility and net gain is 0. If the utility and cost are computed using Eq. 15 and 16, the value of q' closer to 1 means the quicker of task being completed.

Figure 11 is performance comparison of algorithms when number of subtasks changed while Fig. 12 is performance comparison of algorithms when number of robots changed. It can be found that the new algorithm has a great advantage not only on performance but also on allocation speed when number of robots or subtasks reaches a certain size.

CONCLUSION

This study studied the formation of robot coalition and ST-MR-IA task allocation algorithm under heterogeneous capabilities condition. We give the concept of capability heterogeneity. We provide a new multi-robot task allocation algorithm, whose complexity being simplified by distributed computing and pruning strategy. The total compute complex is $O(n^4)$. The relationship of communication times with number of robots and subtasks is $(|T|+1)|T|+2|R|$. The effectiveness of this new algorithm is verified in practice.

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