A Balanced Heuristic Auction Method for Multi-robot Task Allocation of Intelligent Warehouses

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Abstract: In this paper, the problem of coordinating a team of mobile robots is studied to fulfil a large number of given tasks in an intelligent warehouse system. The system is modeled with unknown task cost and dual goals (i.e., equally allocating the workload as well as minimizing the travel cost). Then a balanced heuristic action method is proposed to achieve the dual goals by improving the classical single-item auction allocation strategy. Simulated experimental results show that the improved heuristic auction method can achieve better performances and has potential for task allocation of intelligent warehouses.

Key Words: multi-robot task allocation; balanced heuristic auction method; intelligent warehouse

1 Introduction

The logistics industry has witnessed rapid development of intelligent warehouses since the 1990s. Recently, autonomous robots are increasingly used to transport materials in warehouses [1, 2] and the complex coordination problem of robots has attracted much attention from related research communities. In this paper, we focus on the task allocation process in which a team of autonomous robots must fulfill a set of orders (tasks) with routes that optimize certain criteria. This problem is also known as a multi-robot task allocation (MRTA) problem.

In general, the approaches to the MRTA problems can be classified as static methods (tasks are known to robots before execution) and dynamic methods (tasks are only made known to robots during execution) [3]. The dynamic method has attracted much attention from researchers, but it can result in suboptimal performance. So we propose an approach which combines both dynamic and static methods by means of Task Pool and Dynamic Task Adjustment. On the other hand, the control structure for the MRTA problems can be divided as the centralized control and the decentralized control. Although some existing methods uses decentralized control and let each robot make all decision autonomously, purely central control in our system is impossible because the decentralized control is less likely to compute and optimize plenty of data efficiently and keep the complex system in a good order. Hence in this paper we adopt a control structure which combines both decentralized and centralized mechanism.

As pointed out in literatures, the MRTA problem is a NP hard problem [4], and we cannot find the optimal solution in polynomial time. Thus, heuristics and approximation algorithms are commonly used. There have already been some methods to deal with this kind of problem. In 1998, Yamauchi presented a greedy strategy [5] to coordinate robots. Each robot chooses the closet task as soon as they finish their previous tasks. However, it is evident from literatures that greedy-type heuristic is only suitable for Euclidean TSP problem, and cannot solve a general TSP problem in the warehouse setting [6]. Gerkey introduced a dynamic task allocation method for groups of autonomous robots [7]. The robots bid on all unallocated targets, and the bids depend on the distance between their last targets and those unallocated targets. Unfortunately, the author does not provide any guarantee on the quality of its method. The combinatorial auction algorithm proposed by Sandholm [8] is considered more efficient because it divides tasks to different clusters according to correlations between tasks, then robots bid on clusters of tasks [9]. In 2005, Lagoudakis used Prim Allocation [10] to produce MSF (minimum spanning forest) of tasks for robots, after that transform the forest to paths by depth-first travel of MSTs (minimum spanning trees). It also has a guarantee of at most twice as large as the optimal total cost. Later, some other literatures [11, 12] improve the depth-first travel process in prim allocation method and better result is obtained.

As a matter of fact, most of the current attempts concentrate on minimizing the travel cost of the robots group but regardless of minimizing the travel time, that is, balancing the individual travel cost of each robot. In that condition, the performance of the whole system is decreased due to the bias using of robots. For example, one robot carries inventory pods from time to time while some others are always idle by contrast. Considering the specific characteristics of our problem: (1) balancing task allocation, (2) the cost of tasks are unknown, (3) large scale and dynamic environment, we propose a Balanced Heuristic Mechanism (BHM) to coordinate autonomous robots and apply this mechanism to traditional Auction We provide three criteria to evaluate the performance of different strategies: Travel Time (TT), Sum Travel Cost(STC) and Balancing Utilization(BU). The simulation results shows that this new mechanism have a better balancing performance compared to the traditional auction allocation method.

2 Problem Formulation

2.1 Problem Statement

The problem concerned in this paper is the task allocation for a team of autonomous guided vehicles (AGVs) in an intelligent warehouse. To characterize the system, some assumptions are described as follows:

- The system is composed of large-scale physical embedded robots;
- Robots are homogenous and tasks are homogenous;
- The environment of the system is known to each robot;
- The robots are self-interested and fulfills their own tasks independently;
- The robots may conflict with each other when fulfilling their tasks and they intercommunicate when close to other vehicles (collision avoidance);
- Time consuming at station is constant for all robots.

For the task allocation problem, we strive to optimize the system in a dual objective function: keep the sum travel cost as low as possible and keep individual travel time as equal as possible, respectively. These two objectives correspond to a balance between time expenses and robot expenses, which both deserve consideration in a concrete physical system. Figure 1 illustrates such a mechanism system in a specific warehouse. Each storage shelf consists of several inventory pods and each pod consists of several resources. By order, a robot lifts and carries a pod at a time along a pre-planned path, deliver it to specific station which is appointed in the order and finally keeps the pod back. The main consideration is how to allocate the tasks to the robots efficiently and equally, with path planning and conflict avoidance proposed.

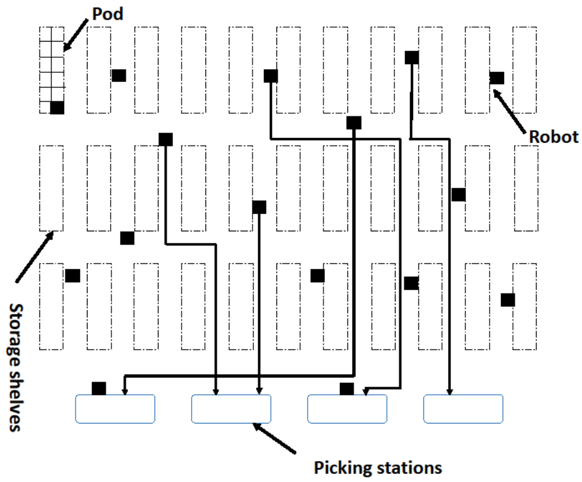


Figure 1. Configuration of a warehouse system

Another point must be taken into account is that traditional task allocation methods are based on the assumption that the cost of each task is known. However, in this problem, the input to the warehouse system is a sequence of orders, from which we only know the location of the task and the specific station which it is supposed to deliver. The cost of each task as well as the travel cost from one location to another is unknown, so it is more challenging and cannot been effectively handled using the existing methods.

2.2 Modelling

The model formulated to solve the balanced multi-robot task allocation problem mentioned above in the warehouse system is shown below.

Let a set of robots $R=\{\mathrm{r}_1,\mathrm{r}_2,\cdots,\mathrm{r}_m\}$ to complete a set of tasks $T=\{\mathrm{t}_1,\mathrm{t}_2,\cdots,\mathrm{t}_n\}$ .The cost of task t_i is w_i , which refers to the travel cost of carrying the inventory pod to the specified station and then delivery it back, ignoring the time cost of collusion avoidance, and $C_{ij}(\mathrm{i},\mathrm{j}\in \mathrm{R}\bigcup \mathrm{T})$ is the travel cost between every two locations (usually from robot to inventory pod assigned in task) .

Suppose r_i have k tasks, $T_i=\{\mathrm{t}_{i1},\mathrm{t}_{i2},\cdots,\mathrm{t}_{ik}\}$ then the sum cost of all the assigned tasks in T_i is expressed as $W(r_i)$ and

$$W(\mathrm{r}_i)=\mathrm{w}_{i1}+\mathrm{w}_{i1}+\cdots+w_{ik}\ .$$

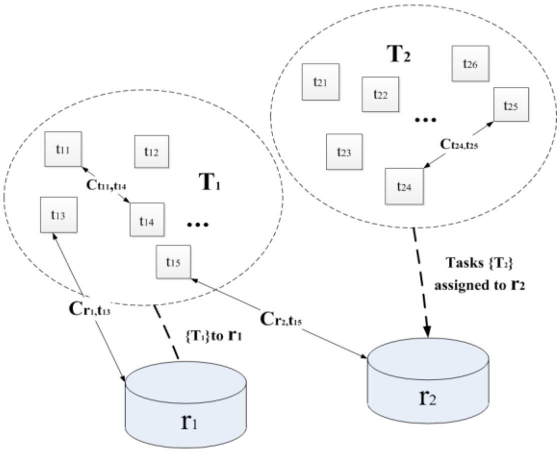


Figure 2. Basic parameters and indices

We rewrites T as $\Gamma = \{T_1, T_2, \cdots, T_m\}$, which means a partition of the set of tasks where task set T_i is allocated to robot r_i. Then, we define the Individual Travel Cost $ITC(r_i, T_i)$, which represents the sum cost for r_i to fulfill its task set T_i and can be calculated as

$$ITC(r_i, T_i) = C_{r_i t_{i1}} + \sum_{j=1}^{k-1} C_{t_{ij} t_{i(j+1)}} + W(r_i) \qquad (1)$$

In Equation (1), $C_{r_i t_{i1}}$ represents the travel cost for r_i to come to its first task t_{i1}, and $\sum_{j=1}^{k-1} C_{t_{ij} t_{i(j+1)}}$ represents the sum travel cost for the rest $k-1$ tasks. $W(r_i)$ represents the sum task cost of all the assigned tasks in T_i.

Our dual goal can be expressed as: $\min_{\Gamma} \max_i ITC(r_i, T_i)$, which can minimize the travel cost as well as balance the individual travel cost of each robot.

Furthermore, we provide three criteria to evaluate the performance of different strategies: Travel Time (TT), equals to the maximum of all the individual robot travel costs; Sum Travel Cost (STC), which reveals the sum travel cost of all robots, evaluate the energy cost and mechanical loss of robots; Balancing Utilization (BU), which assesses balancing condition of task allocation.

$$TT = \max_i ITC(r_i, T_i) \qquad (2)$$

$$STC = \sum_{i=1}^{m} ITC(r_i, T_i) \qquad (3)$$

$$BU = \frac{\min_i ITC(r_i, T_i)}{\max_i ITC(r_i, T_i)} \qquad (4)$$

3 Method

In this section, we first provide the Balanced Heuristic Mechanism (BHM) principles and then we proposed an adapted auction method by introducing the BHM into the traditional auction allocation method.

3.1 Overall System

In our system, the working space of the warehouse can be divided into several grids with inventory storage zones in the middle while stations and workers around. Autonomous robots transport movable inventory pods from storage locations to stations, where workers can pick the items off and pack them up. Then those packages are sent to the customers. In the task allocation process, the controller receives a certain number of tasks from Task Pool, and use certain approach to allocate those tasks to robots. Then, the controller sends sets of tasks to corresponding robots and the robots complete their tasks sequentially by using A star algorithm to plan paths from one place to another, usually from storage locations to stations or in reverse. Moreover, as for the obstacle avoidance, the robot with less tasks left to complete are more likely to give way to the robot with more tasks left by occupying front steps. The whole process is shown as in Figure 3.

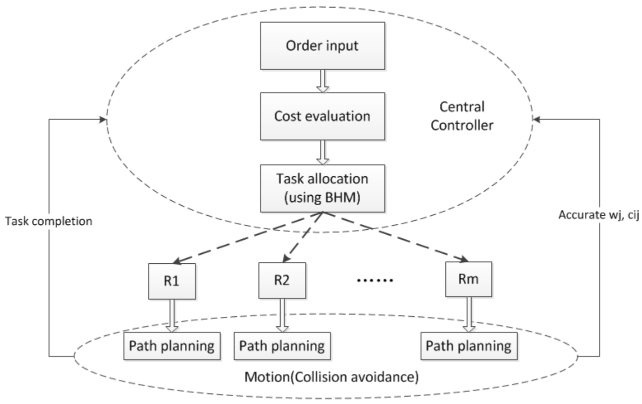


Figure 3. Overall control system configuration.

3.2 Balanced Heuristic Mechanism

Considering the dual goals that minimizing the travel cost as well as balancing the individual travel cost of each robot, a heuristic function is given in Equation (5) for guiding the task allocation process.

$$C(\mathrm{r}_i, \mathrm{t}_j) = \alpha \times \mathrm{dist}(\mathrm{r}_i, \mathrm{t}_j) + (1-\alpha) \times CW(\mathrm{r}_i) \quad (5)$$

$C(\mathrm{r}_i, \mathrm{t}_j)$ describes the cost (considering both time and distance) for robot r_i to finish task ti. $dist(\mathrm{r}_i, \mathrm{t}_j)$ is the travel cost from robot r_i to task t_j, and $CW(\mathrm{r}_i)$ is the current value of $W(r_i)$.

More specifically, as both the task cost and the travel cost from one location to another is unknown. We need to evaluate w_i (the cost of each task) and C_{ij} (the travel cost from one task to another) before task allocation. Using a standard implementation of A* algorithm, a simple but highly effective path planning algorithm, we get the estimated value of w_i and C_{ij}. Whenever a robot fulfills a task or move from one location to another in real environment, the more accurate w_i and C_{ij} value is shared with the central controller and the original estimated value stored in the controller is replaced. Then the follow-on allocation process is in the light of new information.

BHM awards tasks to be assigned to robot who has the lowest $C(\mathrm{r}_i, \mathrm{t}_j)$. This heuristic mechanism does not compel an actual commitment. Instead, by introducing a parameter α, targets are more inclined to be assigned to the nearby robot with fewer allocated tasks. In practice, an effective value of α can be estimated with a value 0.7~0.9 according to different physical situation.

At the beginning stage, as the value of $W(\mathrm{r}_i)$ is quite small, this mechanism has little effect. Thus the performance of the system has no significant difference from the traditional method that merely focus on minimizing the total travel distance. However, as the process of allocation, the role of $(1-\alpha)\times \mathrm{W}(\mathrm{r}_i)$ begins to kick in efficiently by sharing the workload with those who have fewer assigned task. From a global view, the method can obtain an approximately optimal result both considering total travel cost and the balance of the work load among the group of robots. A sample illustration of this heuristic mechanism is given in Figure 4 ($\alpha = 0.8$).

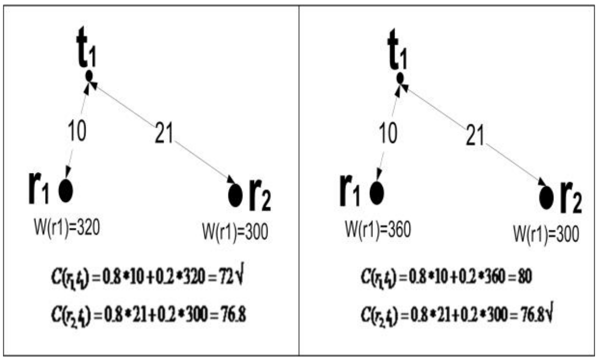


Figure 4. Example of balanced heuristic mechanism

3.3 Balanced Heuristic Auction Method for Task Allocation

A classic seal-bid single-round single-item auction process proceeds in four steps: task announcement, metric evaluation, bid submission, and close of auction (determine the winning bids and notifies the winning robot).

We introduce the BHM into the second step in order to strengthen the balancing performance of auction. Traditionally, the metric is usually defined as a function to the optimistic travel cost for visiting the target from the current position [7]. In our method, the metric evaluation is defined by $C(\mathrm{r}_i, \mathrm{t}_j)$ rather than the optimistic travel distance between r_i and t_j.

$$\mathrm{C}(\mathrm{r}_i, \mathrm{t}_j) = \alpha \times \mathrm{dist}(\mathrm{r}_i, \mathrm{t}_j) + (1\text{-}\alpha) \times CW(\mathrm{r}_i),\ \mathrm{t}_j \in \mathrm{TR} \quad (6)$$

$dist(\mathrm{r}_i, \mathrm{t}_j)$: the distance between the bid target task t_j and r_i's current position computed by A star.

$CW(\mathrm{r}_i)$: current value of $W(r_i)$.

For instance, if the bidder r_i has already wined three rounds in the former auction process, and has three tasks at hand t_{i1}, t_{i2}, t_{i3}, the current position of r_i is the position of its last task t_{i3}. So in the next round, the bid value of r_i for t_j:

$$C(r_i, t_j) = \alpha \times \mathrm{dist}(r_i, t_j) + (1-\alpha) \times CW(r_i) \quad ,$$

where $CW(\mathrm{r}_i) = w_{i1} + w_{i2} + w_{i3}$.

4 Experimental Results and Analysis

4.1 Experimental Settings

As shown in Figure 5, there are 4×12 shelves in the simulation interface and each storage shelf consists of 6 inventory pods. We introduce the idea of processing in batches into the process using a Task Pool to store the dynamic entry-orders and send specific number (for example: 200) of orders from Task Pool to controller when the last batch of tasks have been finished. Then the Auction and BHM based Auction method is respectively used for allocating the orders. When the task allocating process is finished, the controller will send the allocated tasks to the corresponding robot, and robots begin to work on their tasks (using the A star algorithm to calculate the path and the less-task-prior mechanism to avoid collision).

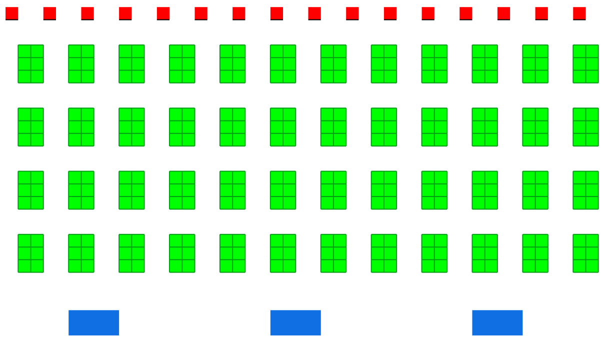
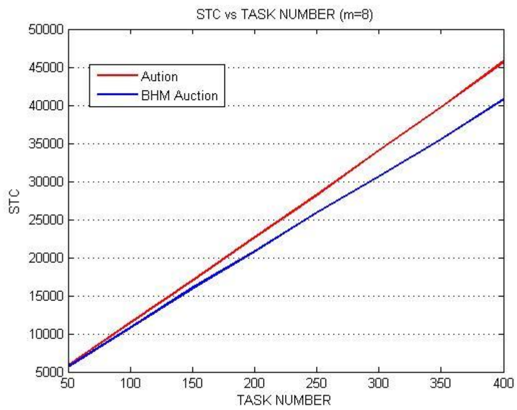


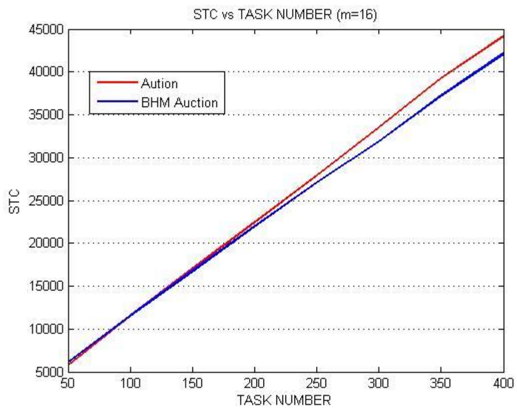
Fig.5 The simulation interface

4.2Results

In this part, we use three criteria to evaluate the performance of the two methods: Sum Travel Cost (STC), Travel Time (TT), Balancing Utilization (BU). First we compare the Auction method with BHM based Auction method under different task number and robot number respectively. We do each experiment for 20 times and take the average. The results are shown in Table.1 and Table.2. Moreover, we study the effluence of variable α to our system performance.

I. Auction v.s. BHM Auction





m=8	Auction Method			BHM Auction Method		
task number	STC	TT	BU	STC	TT	BU
50	5813	1215	29.70%	5658	789	77.26%
100	11443	2286	41.55%	10764	1440	87.92%
150	16968	2963	53.23%	15962	2069	91.87%
200	22625	3703	55.41%	20774	2654	94.75%
250	28187	4328	61.05%	25897	3296	96.07%
300	34041	5120	65.28%	30673	3875	97.16%
350	39749	5914	67.98%	35491	4484	97.46%
400	45702	6669	72.38%	40743	5127	97.80%

Table.1 Simulation result (m=8)

m=16	Auction Method			BHM Auction Method		
task number	STC	TT	BU	STC	TT	BU
50	5750	992	22.18%	6101	478	58.37%
100	11521	1659	21.40%	11500	800	78.50%
150	16998	2387	22.83%	16730	1124	84.79%
200	22367	3109	22.87%	21941	1437	89.35%
250	27877	3956	22.22%	27077	1754	91.33%
300	33548	4533	24.22%	31865	2066	92.45%
350	39266	5091	23.90%	37197	2385	93.84%
400	44181	6328	23.10%	42107	2696	93.95%

Table.2 Simulation result (m=16)

As is shown in Figure 5, BHM Auction Method show significant superior in the achieving the goal of the system, minimizing the TT(shrink by more than half). This is because by introducing the balanced heuristic mechanism, robots can efficiently share the workload. We can see from the BU vs TASK NUMBER that, the value of BU in BHM Auction method is around 90% and, with the increasing of task number the value keeps increasing. However, the traditional Auction Method has a pool balancing performance with a BU value around 20%, which indicates a severe bias using of robots. In that condition, one robot carries inventory pods from time to time while some others are always idle by contrast, which results in larger system time cost.

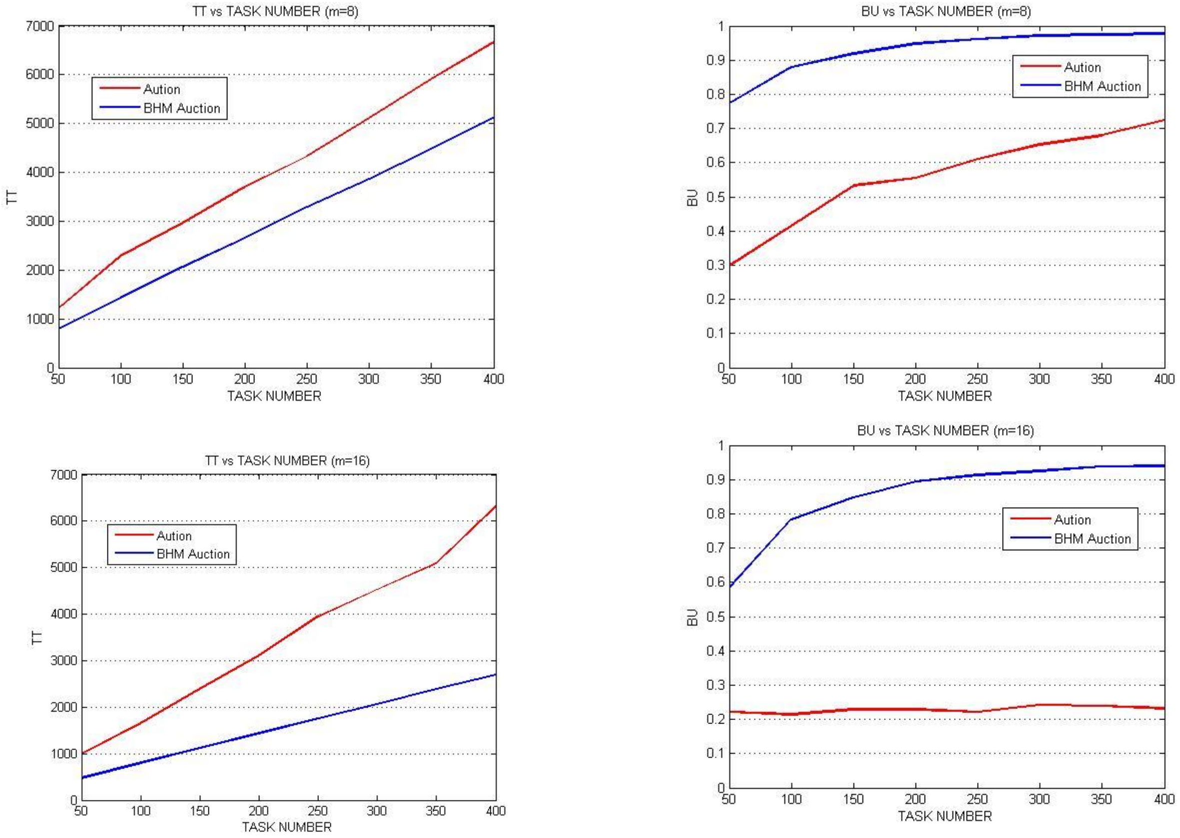
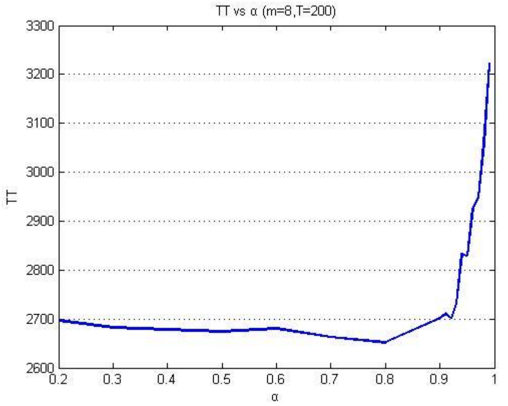
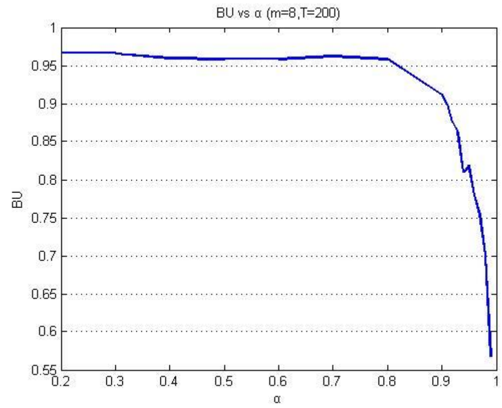


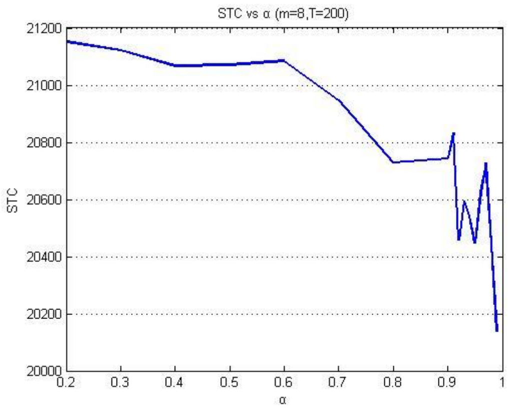
Fig.5 performance of Auction Method and BHM Auction Method when m=8 or m=16

II. The variance of STC, TT according to α (m=8, task number=200)

We further study the effluence of variable α to our system performance and we find that when α values between 0.7 and 0.8, our system works in the most efficient condition, at this point, the value of TT is minimal.







5 Conclusions

In this paper, an improved balanced heuristic auction method is proposed the multi-robot task allocation problem in an intelligent warehouse. To evaluate the performance of the proposed method, three criteria are adopted, namely, Travel Time (TT), Sum Travel Cost (STC) and Balancing Utilization (BU). Then we compare existing single-item auction performances with BHM-based auction method under those criteria. The simulation results show the success of the proposed method and further analysis also demonstrate the characteristics of BHM in details. Our future work will focus on more applications of BHM to other task allocation problems.

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