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Implementation of an Auction Algorithm Based Multiple Tasks Allocation Using Mobile Robots

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Abstract: The article uses the ant colony system (ACS) and auction algorithms to solve the path planning and task allocation problems of multiple mobile robots such that the robots can move from different start points to reach to different task points in a collision-free space. Ant colony optimization (ACO) is a new evolvement algorithm that is proposed by Dorigo M., and solves some task allocation and target searching problems. The utilization of the auction algorithm improve the efficiently of the tasks allocation. The article uses three performance functions to compare the cost on the motion displacement and waiting time for mobile robots. In this manner, a near optimal assignment of multiple task points according to a team objective can be obtained using the proposed algorithms. The simulated results present that Ant colony optimization and auction algorithm find the optimization motion path for multiple mobile robots moving to task points from start points in a collision-free environment.

Keywords: ant colony system. auction algorithm. path planning. Task allocation. multiple mobile robots.

I. Introduction

There have been a growing interest in multi-robot coordination research in recent years. Multi-robot cooperation is fundamental and significant in the robotic research fields. With the increasing number of robots in one task team efficiency important and energy consumption reduction research become more important in robots coordination. Compared to single robot, multiple mobile robots can operate to faster task completion, higher quality solutions, as well as increased robustness ability to compensate robot failure [1]. The path planning and task allocation problems of the multiple mobile robots are important research issues. Its task is to find collision-free paths from different start points moving to the different target points in an known or unknown environment with obstacles according to a reasonable algorithm.

Motion control and path planning of the wheel based mobile robots is a currently active area of robot research field. The motion control of multiple mobile robots for path tracking [2], navigation [3,4], wall following [5], task allocation [6] and path planning [7] has been proposed [8]. How to cooperate effectively with multiple robot is a challenge. To overcome the challenge, many cooperation algorithms have been proposed which mainly include behavior-based approach [9], auction algorithm [10], ant colony optimization (ACO) algorithm [11], threshold-based approach [12], particle swarm optimization algorithm (PSO) [13], etc. Especially, ant colony optimization and auction algorithm have received significant attention to be growing in popularity [1], and have been implemented in the article.

Ant Colony Optimization (ACO) is a new computational paradigm to solve the path planning of the task allocation problems in Swarm Intelligent. Ant colony algorithm is proposed by Italian scholars Dorigo M., and simulates the routing behavior of natural ant and the algorithm is a kind of random optimization approach. It solves some difficult problems in the optimization path planning of the mobile robot system using the ability of optimization in the process of ant colony searching food. The algorithm has the following advantages; such as good robustness, distributed computing and easy combined with other methods. Ant colony algorithm can combine auction algorithm easily to reinforce its performance [14]. Jones and Dias developed a coordination mechanism which was applied by pickup teams in the treasure hunt field [15]. Kishimoto and Sturevant use auction algorithm as solution to multiple robots coordination in routing problem in terms of computational complexity [16]. Michael and Kumar et al have implemented to assign dynamically tasks to multiple agents using distributed solution in formation control scenario [17]. Nanjanath and Gini present auction based method for multirobot dynamic coordination to visited different locations in the map [18].

The article is organized as follows: Section II describes the ant colony algorithm and auction algorithm for the mobile robot system, and propose three performance functions to compare the cost of finishing tasl allocation. Section III presents the experimental results on the target research in the known environment using the multiple mobile robots system. Section IV presents brief concluding remarks.

II. Searching algorithm

The ant system algorithm was developed by Marco Dorigo and his colleagues in the 1990s. Ants move in random orientation from the start point. Pheromones are deposited on the ground from the tail as they move around. The ants would choose motion paths based on the amount of pheromones intensity on all possible motion paths from the start point moving to the target point. Subsequent ants are more likely to choose a shorter path with greater pheromone trail intensity. The ant decides the motion path according to transition probability, $p_{i,j}^k$. The transition probability is influenced by the pheromone of the ant:

$$p_{i,j}^k = \frac{(\tau_{i,j})^\alpha (\eta_{i,j})^\beta}{\sum_{l \in N_i^k} (\tau_{i,j})^\alpha (\eta_{i,j})^\beta}, \ if \ \ j \in N_i^k \qquad (1)$$
$$= 0 \qquad if \ \ j \notin N_i^k$$

The left side of the Eq. (1) represents the transition probability in which ant k will traverse from point i to point j. The numerator on the right side of the equation consists of a product of two terms, $(\tau_{i,j})^\alpha$ represents the intensity of the pheromone trail between points i and j with a corresponding weight value of α. On the other hand, $(\eta_{i,j})^\beta$ represents the heuristic information between points i and j with corresponding weight value of β. $\eta_{i,j} = 1/d_{i,j}$, while $d_{i,j}$ is the distance between points i and j. N_i^k is point i's feasible neighbourhood at the ant k. The denominator on the right side of the equation is a summation of the products of the pheromone intensity and heuristic information for all possible moving paths [19].

The pheromone value evaporates on all paths by a constant factor, and adds pheromone on the paths. Pheromone evaporation is implemented by Eq. (2). The parameter $\rho(0 < \rho \le 1)$ is used to avoid unlimited accumulation of the pheromone. Where $\Delta\tau_{i,j}^k$ is the amount of pheromone for the ant k depositing on the motion paths it has visited? It is defined as follows:

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \sum_{k=1}^{m} \Delta\tau_{i,j}^k, \forall (i,j) \in L \qquad (2)$$

$$\Delta\tau_{i,j}^k = \begin{cases} 1/C^k, \text{if path } (i,j) \text{ belongs to } T^k; \\ \quad 0, \text{ otherwise}; \end{cases} \qquad (3)$$

Where C^k, the length of the tour T^k that is build by the ant k moving to the target point successfully, and is computed as the sum of the lengths of the paths belonging to T^k, or $\Delta\tau_{i,j}^k = 0$.

Auction algorithm solves the tasks allocation problem using a fleet of mobile robots, and is classified single-item auctions and combinatorial auctions. The single-item auction parallel contains single-item auction and sequential single-item auction. We use sequential single-item auction in the paper, and assign the mobile robots moving to the formation position using ant colony algorithm. A formal definition of the auction algorithm is given a number of tasks $t_1, t_2, ..., t_m$, and subtasks are, $T = \{T_1, T_2, ..., T_N\}$. A subtask T_i is a set that contains some tasks that is bided and completed by the robot R_i. Then how to decide the optimal allocation methods between robots and subtasks so that the pattern formation task is achieved efficiently? A fleet of robot set is defined $R = \{R_1, R_2, ..., R_N\}$. A function $TD(R_i, t_j)$ that specifies the cost of executing task t_j by the robot R_i, and find the assignment that allocation one task per robot to minimize the global cost defined as $\sum_{i=1}^{J} TD(R_i, t_j)$, where task j is assigned to the robot i.

$TD(R_i, T_i)$ specifies the cost of executing subtasks T_i by the robot R_i. $TW(R_i, T_i)$ is defined the waiting time cost of the robot R_i to execute subtasks T_i. We have three performance function to compare the efficiently for the team robots executing tasks allocation. There have MINSUM, MINMAX and MINAVE functions. The MINSUM function is the displacement summation of the total paths for team robots executing all subtasks to be minimized. The MINMAX function is the maximum displacement of the robot R_i that has been finished the subtask to be minimized. The MINAVE function is the average cost of the waiting time for all robots to be minimized. These functions can be represented as follows:

$$MINSUM : \min_T \sum_{i=1}^{N} TD(R_i, T_i) \qquad (4)$$

$$MINMAX : \min_T \max_i TD(R_i, T_i) \qquad (5)$$

$$MINAVE : \min_T \frac{1}{m} \sum_{i=1}^{N} TW(R_i, T_i) \qquad (6)$$

III. Experimental results

We implement the simulation results on the known map of Yunlin University of Science & Technology Electrical Engineering Department in order to verify the effectiveness of the ant colony algorithm and auction algorithm using the multiple mobile robots. The map is shown in Fig.1, and contains 64 nodes (black rectangles). The mobile robot can moves on the path between node and node. We use four ants (mobile robots) to search the twelve different task points from different start points. We compare the cost of the performance functions (MINSUM, MINMAX and MINAVE) to find target points. In the map, we use black point to represent the mobile robot (R_1, R_2, R_3 and R_4), and the black rectangle represent the task points. The motion paths of four mobile robots are presented by variety color lines. The mobile robots are the same speed in the simulation experiment, and waiting time is proportion to the displacement of mobile robots.

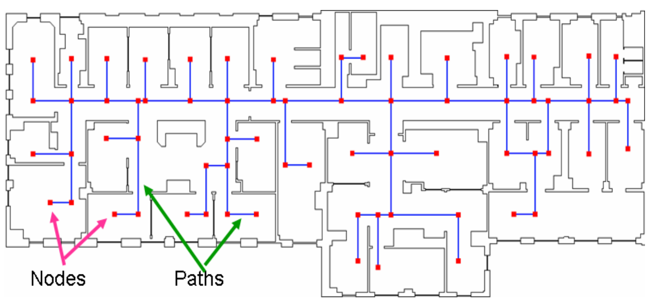


Fig. 1 The map of task allocation for four mobile robots

In the simulation results, we use four mobile robots assign twelve task points from different start points, and use three performance functions to compare the cost. We can list the cost of the performance functions in Table 1, Table 2 and Table 3. We can see the total displacement of the MINSUN function to be minimum, and has long waiting time to be shown in Table 1. The time of each mobile robot moves to each node to be listed in Table 4. We can see the cost of MINSUM to be equal to the total time of Table 4 (R_2). The value is 58.2.

Table 1. The cost of MINSUM

	MINSUM	MINAVE
R1	19	36
R2	58.2	175
R3	8	8
R4	27	40.5
Cost	112.2	259.5

Table 2. The cost of MINMAX

	MINMAX	MINAVE
R1	37	91
R2	35.2	68.6
R3	23.5	49.5
R4	32	54
Cost	127.7	263.1

Table 3. The cost of MINAVE

	MINSUM	MINAVE
R1	19	36
R2	35.2	68.6
R3	20	28
R4	42	87.5
Cost	116.2	220.1

Table 4. The time of each node for MINSUM

R1				*R2*				*R3*				*R4*			
Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time
2	6	4	4	65	66	4	4	18	22	2	2	30	31	4	4
6	10	3	7	66	63	2.2	6.2	22	21	4	6	31	32	0.5	4.5
10	13	3	10	63	62	4	10.2	21	26	2	8	32	33	5	9.5
13	14	3	13	62	63	4	14.2					33	32	5	14.5
14	15	6	19	63	60	4	18.2					32	31	0.5	15
				60	61	4	22.2					31	24	5	20
				61	58	1	23.2					24	20	3	23
				58	54	2.8	26					20	19	4	2
				54	53	4	30								
				53	49	5.2	35.2								
				49	44	5	40.2								
				44	45	4	44.2								
				45	37	4	48.2								
				37	45	4	52.2								
				45	46	5	57.2								
				46	41	1	58.2								

Table 5. The time of each node for MINMAX

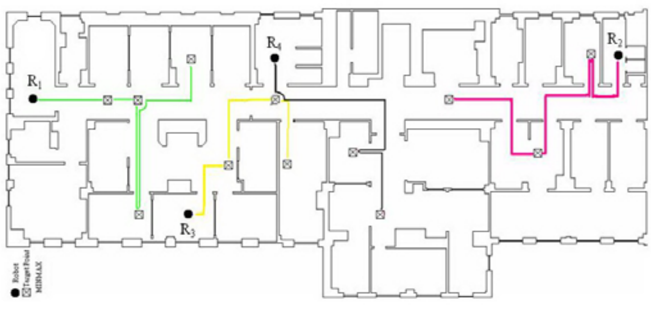
R1				*R2*				*R3*				*R4*			
Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time
2	6	4	4	65	66	4	4	18	22	2	2	30	31	4	4
6	10	3	7	66	63	2.2	6.2	22	21	4	6	31	32	0.5	4.5
10	13	3	10	63	62	4	10.2	21	26	2	8	32	36	5	9.5
13	14	3	13	62	63	4	14.2	26	25	2	10	36	44	4.5	14
14	15	6	19	63	60	4	18.2	25	24	3	13	44	45	4	18
15	14	6	25	60	61	4	22.2	24	31	5	18	45	37	4	22
14	13	3	28	61	58	1	23.2	31	32	0.5	18.5	37	45	4	26
13	17	1	29	58	54	2.8	26	32	33	5	23.5	45	46	5	31
17	20	4	33	54	53	4	30					46	41	1	32
20	19	4	37	53	49	5.2	35.2								

In the Table 2, we can see the four mobile robots that have been finished the tasks allocation to be faster. The time of each mobile robot moves to each node to be listed in Table 5. We can see the cost of MINSUM to be equal to the total time of Table 2 (R_1). The value is 37. The MINAVE value is long time, too. The time of each mobile robot moves to each node to be listed in Table 6. We can see the cost of MINSUM to be equal to the total time of Table 3 (R_3). The value is 20.

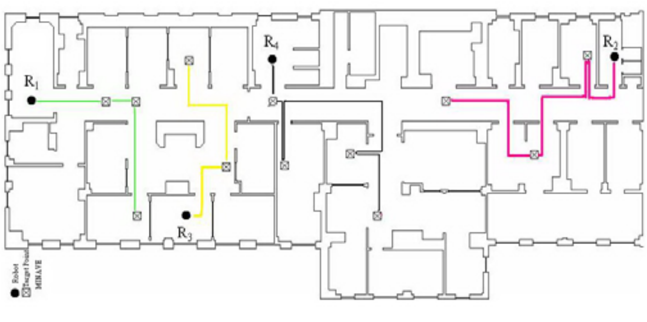
Table 6. The time of each node for MINAVE

R1				*R2*				*R3*				*R4*			
Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time	Start Node	End Node	Node time	Total Time
2	6	4	4	65	66	4	4	18	22	2	2	30	31	4	4
6	10	3	7	66	63	2.2	6.2	22	21	4	6	31	32	0.5	4.5
10	13	3	10	63	62	4	10.2	21	26	2	8	32	33	5	9.5
13	14	3	13	62	63	4	14.2	26	25	2	10	33	32	5	14.5
14	15	6	19	63	60	4	18.2	25	24	3	13	32	36	5	19.5
				60	61	4	22.2	24	20	3	16	36	44	4.5	24
				61	58	1	23.2	20	19	4	20	44	45	4	28
				58	54	2.8	26					45	37	4	32
				54	53	4	30					37	45	4	36
				53	49	5.2	35.2					45	46	5	41
												46	41	1	42

(a) The motion paths of MINSUM function



(b) The motion paths of MINMAX function



(c) The motion paths of MINAVE function
Fig. 2 The experiment results of task allocation

Finally, we make the minimum of the waiting time of four mobile robots to allocate twelve task points, and the average value of MINAVE function is minimum to be shown in Table 3. In the three cases, the motion paths of four mobile robots according to the variety performance functions to be shown in Fig. 2. We can see the displacement of the mobile robot R_2 is bigger than the others to be shown in Fig 2 (a). We reduce the displacement of the robot R_2, and allocate some task to the others using the MINMAX function to be shown in Fig. 2 (b). Fig. 2 (c) is the motion paths of four mobile robots on the MINAVE function.

IV. Conclusion

The article presents the path planning and task allocation problems of mobile robots using ant colony algorithm and auction algorithm. It solves the shorter paths of the mobile robots to allocate all task points. We have been implemented variety performance functions to compare the cost for finishing task allocation, and implement the simulation results using the proposed algorithms on the known map. In future, we want to implement the different task allocation using a fleet of robots, and use mobile robots to present the scenario on the platform.

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