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Paper:

A Discrete Adaptive Auction-Based Algorithm for Task Assignments of Multi-Robot Systems

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For reasons of production cost and differences in manufacturing dates for mobile robots, individual robots on a robot team have different processing, movement, and detection abilities. To maximize the potential ability of individual robots and minimize overall exploration time in unknown environments, this paper proposes a novel discrete adaptive auction-based algorithm for coordinating multirobot systems (MRSs). A utility calculation scheme that takes into account the dispersion of teammates is presented, followed by an identical performance index formula that converges to a value for measuring differences in exploration efficiency. The performance measure is taken into account in calculating bids for exploration tasks. We compared our results to other exploration strategies by simulation and results show improved exploration time.

Keywords: multi-robot systems (MRSs), discrete adaptive auction-based algorithms, market economy, task assignments

1. Introduction

There are many potential applications for multirobot systems (MRSs), such as exploring and mapping, surveillance, and foraging. Making a MRS of heterogeneous robots exploring an unknown environment efficiently requires a coordinated algorithm. A number of coordinated algorithms have been developed in the last two decades. A representative result proposed early on is a frontier-based strategy for decentralized MRS coordination [1]. In assigning targets to individual robots, the approach considered distances alone. Distance is taken as cost that is one of two factors in arriving at a target cell in frontier-based approaches. To trade off on the cost of arriving at a frontier cell and the utility of the cell, a decision-theoretic approach was proposed [2]. The utility consists of two parts – a constant value for all frontier cells and a reduction value proportional to the detection range of other robots. The second part forces dispersion of all teammates throughout the environment. Target distribution for all teammates is not considered from the view of the scale of the whole environment. Dias et al. summarized achievements of early market-based coordination algorithms [3].

Results were in some cases based on the fact that knowledge about the environment was known *a priori* by individual robots. Dynamic task assignment through a repeated algorithm based on single-item auction was realized [4]. A distinctive feature of this work is its robustness against uncertainties and against robot malfunctions. The cost measure was travel time. It was assumed that all robots possessed constant and equal speeds in the approach. Total tasks and unknown workspace are partitioned into as many clusters of tasks [5] and regions [6, 7] as robots by K-mean clustering algorithms (K-Means). Based on clustering results, the coordination problem was converted to a multitraveling salesmen problem [5]. Total cost consisting of travel cost and idle cost minimization and robot workload balancing were realized by an auction mechanism. The result is limited to static conditions. A K-Means-based coordinated algorithm optimized the online assignment of robots to targets, and kept robots working in separate areas [6]. It efficiently reduces variations in average waiting time in those areas and fulfilled balanced and sustained exploration for each teammate of the MRS. In [7], unknown space was dynamically repartitioned whenever new areas were discovered by the team. A coordinated approach based on a partitioning of an environment *Voronoi* graph generated from occupancy grid maps was proposed [8]. The contribution is that task assignment for robots takes into account the environmental structure.

In contrast to above results, a kind of time-extended coordination – more than one task is assigned to a robot – with intrapath constraints was investigated [9]. Tiered auctions and clustering and opportunistic path planning were utilized in bounded searching of possible schedules and allocations. A genetic algorithm was then adopted to solve the coordinated problem again. Results indicated that the second approach with an enough large population has better quality solutions than the first approach at a cost of greater calculation time.

An optimal task allocation approach via stochastic clustering auction that uses a Markov chain search process along with simulated annealing was proposed [10]. Results showed that team performance slides into the region between global optimal performance and performance associated with random allocation. Mapping and exploration approaches for a heterogeneous MRS were discussed [11], adopting a hierarchical system consisting of manager robots at upper levels and worker robots at lower levels. The two kinds of robots are divided by the calculation power of individual robots. Unfortunately, the approach assumed that processing abilities of individual robots are known in advance. In contrast, the approach proposed in this paper removes the prerequisite. Decentralized coordinated strategies used consensus algorithms to overcome inconsistencies in detected target positions, target classification, and robot position [12]. Work combined consensus and auction algorithms to obtain task allocation solutions robust against both the above inconsistencies across the team and variations in the communication network topology. The decentralized auction approach used a consensus algorithm for conflict resolution without the need for an auctioneer.

From the view of coordination, MRSs may have centralized [2, 10], decentralized [1, 12], distributed [4, 13], or hierarchical [11] architectures. Distributed and decentralized system architectures have no centralized auctioneer, and individual robots bids for tasks and auctions tasks detected independently. To assign unfinished tasks, the auction algorithm is repeated whenever a robot finishes its task [2, 4], or whenever the distance traveled by robots or time elapsed exceeds a given threshold [2]. In the auction-based algorithm developed here, the former mode is adopted to start a new series of auction actions.

This paper is organized as follows. After reviewing the representative results based on market economy for MRS coordination, Section 2 gives an overview of the MRS considered here and discusses the motivation of our research. Section 3 presents a utility calculation scheme. Section 4 covers the main contribution of this paper, i.e., the establishment of an identical performance index for teammates, and the presentation of our discrete adaptive auction-based algorithm based on the performance index. Section 5 gives simulation results, and Section 6 summarizes conclusions.

2. System Overview

Due to limitations on communication bandwidth [13], the limited MRS dealt with here consists of a total of n heterogeneous mobile robots called $R_1,\ldots,R_n$. The MRS explores and maps in an unknown environment. The environment is sparsely occupied by obstacles and is modeled by a grid map. All teammate robots have the same geometrical shapes which occupy a planar cell on the map. Individual robots have no knowledge about the environment except for relative distances from other robots. As exploration progresses, individual robots run a simultaneous localization and mapping (SLAM) algorithm. When the assigned task is finished or when time for the current auction period is over, the algorithm on individual robots builds a local environment model. By interchanging mapping results and map merging, all robots have a common global environment model before each new auction period begins.

Market economy-based approaches are suitable for coordinating heterogeneous MRSs. The essence of the approach is that robots trading tasks and resources to maximize individual profit simultaneously improve team efficiency [3]. An issue arises of differences in the motion speed, processing ability and detection range of the individual robots. The issue is not taken into account when tasks are assigned to each teammate in the literature. Motivated by the above fact, this paper proposes a novel adaptive auction-based strategy for moving target assignment of a team of heterogeneous MRSs.

The main contribution of this paper is a meaningful scheme that takes full advantage of available environment and robot location information for a calculation utility. Conventional methods take the utility for each frontier cell as a constant [2] or as the number of unknown cells that fall within the radius of the frontier [13, 14]. Because the environment is unknown, the number of cells is unknown until a robot arrives at the frontier cell. To prevent duplicating exploration of a local area, the proposed Gaussian function-based utility calculation scheme keeps different robots separated effectively over the whole environment.

It is difficult to describe performance differences in all aspects when exploring. To differentiate the exploration and mapping ability for individual robots and to simplify the corresponding algorithm, a unified performance formula is established and applied to individual robots, so the achievement per time unit of each teammate, i.e., the area explored by each teammate per time unit, is used as the performance index. As exploring progresses, the performance formula converges to a different value that correctly reflects its exploration ability on individual robots. Adaptability means that the performance calculation strategy adapts to performance differences step by step (discrete).

3. Improvement of the Auction Algorithm

In the market economy-based approach, exploration tasks are assigned based on the utility and cost of each frontier cell. The utility of a frontier for R_i takes the form of

$$\begin{aligned}&U_p^i\left(R_i|R_1,\ldots,R_{i-1},R_{i+1},\ldots,R_n\right)\\&\quad=U_{p1}^i+U_{p2}^i\left(R_i|R_1,\ldots,R_{i-1},R_{i+1},\ldots,R_n\right)\quad. \quad (1)\end{aligned}$$

where U_{p1}^i and $U_{p2}^i(\bullet)$ are the first and second parts of the utility of frontier cell c_p $(p=1,\ldots,m)$ $\in C$, where $C=\{c_1,\ldots,c_m\}$ is the set composed of frontier cells that R_i would bid for, i $(i=1,\ldots,n)$ is the index of current robot R_i, c_p may be a frontier cell detected by any robot in the MRS. Contrary to current available methods, the two parts are calculated as described below. First part U_{c1}^i

is the size of the detectable subset of C_i in case of R_i arriving at c_p. Because coordinates of each frontier are known, the calculation scheme is realizable. Second part $U^i_{p2}(\bullet)$ is the influence resulting from targets or locations of all other robots. If a robot was assigned a target, then the influence imposed on R_i by the robot results from the target, or else influence results from the current location of the robot. $U^i_{p2}(\bullet)$ is represented as two summarizations of Gaussian functions

$$U^i_{p2} = -\sum_{j=1}^{i-1} \exp\left(-\frac{(x^i_p - x^j_t)^2 + (y^i_p - y^j_t)^2}{r_j^2}\right) -\gamma \sum_{l=i+1}^{n} \exp\left(-\frac{\left(x^i_p - x^l_c\right)^2 + \left(y^i_p - y^l_c\right)^2}{r_l^2}\right) \quad (2)$$

where x^j_t and y^j_t are target coordinates of R_j, x^l_c and y^l_c are current position coordinates of R_l, x^i_p and y^i_p are coordinates of frontier cell c_p, r_j and r_l are the detection ranges of R_j and R_l, and γ is a weighting scalar. If the direct path between R_i and R_j or R_l is blocked, then R_j or R_l have no influences on R_i. It is assumed that teammate robots are assigned tasks based on a sequence from R_1 to R_n, when discussing assigning task to R_i,R_j $(j = 1,\ldots,i-1)$ are assigned tasks and R_l $(l = i+1,\ldots,n)$ are not.

The evaluation of c_p for R_i is

$$E^i_p = U^i_p - \rho D^i_p \quad (3)$$

where D^i_p is the distance from the current location of R_i to frontier cell c_p, and ρ is a weighting scalar. R_i submits bids to all available frontiers. It is assumed that the frontier cell

$$p^i_{\max} = \arg\max_{p=1,\ldots,m} E^i_p \quad (4)$$

has the maximal evaluation. After time threshold t_s, if no other robot submits a bid with a bigger evaluation than that of R_i, then the corresponding auctioneer robot auctions frontier cell $p^i_{\max}$ to R_i.

For simplicity, the above coordinated algorithm is called improved auction-based algorithm (IA-A). Compared to conventional auction-based algorithms [1–5, 9, 10, 13], IA-A introduces exponential functions to calculate utility for frontier cells. If and only if argument x converges to infinity, the value of exponential function $\exp(-x)$ converges to zero. Because of this fact, influence spreads over the whole environment and the distribution of all teammate robots is more dispersive.

4. Discrete Adaptive Auction Algorithms

In this section, IA-A is improved further. The amount of utility a robot gained per time unit is defined as efficiency. To emphasize the time factor, the evaluation of frontier cell c_p is designed as the expected efficiency, as

$$\hat{E}^i_p = \frac{U^i_p}{\hat{t}^i_p} \quad (5)$$

where $\hat{t}^i_p = D^i_p / v^i$ is the estimated time for R_i moving from the current location to frontier cell c_p, and v^i is the speed of R_i.

Auction behavior is similar to IA-A in that all robots bid for tasks based on Eq. (5), and the winner is determined by Eq. (4). The algorithm is called efficiency auction-based algorithm (EA-A).

Although EA-A is expected to improve the efficiency of MRSs, performance differences in individual robots is not taken into account. In fact, differences result in different exploration efficiency for individual robots. To further improve the efficiency of such a MRS when coordinated by an auction-based algorithm, the robot with higher performance should conduct more exploration tasks.

To implement the above idea, the average area per time unit individual robots explores is taken as performance index $A^i(k)$ of R_i, and

$$A^i(k) = \frac{\sum_{t=1}^{k} \Delta A^i(t)}{\sum_{t=1}^{k} T(t)} \quad (6)$$

where k and t are discrete time variables ($k = 1,\ldots$, $t = 1,\ldots,k$), $\Delta A^i(t)$ is the area of a local environment modeled by R_i in $T(t)$, and $T(t)$ is the time period between two consecutive auction actions at $t-1$ and t. In general,

$$T(t_1) \neq T(t_2) \quad (\forall t_1, t_2 \in \underline{k}). \quad (7)$$

For calculating efficiently, Eq. (6) is converted to an iterative form

$$A^i(k) = \frac{A^i(k-1) + \Delta A^i(k) P^{-1}(k-1)}{1 + T(t) P^{-1}(k-1)} \quad (8)$$

$$P(k) = P(k-1) + T(k) \quad (9)$$

where $A^i(1) = \Delta A^i(1)/T(1)$. The value of $\Delta A^i(t)$ is taken as the number of cells R_i explores in auction period $T(t)$.

Differences in past exploration achievements result in utility differences when these robots bid for the same frontier cell for the current exploration period, so expected utility $\hat{U}^i_c(k|k-1)$ is introduced and taken as proportional to $A^i(k-1)$ by

$$\hat{U}^i_c(k|k-1) = \alpha A^i(k-1) \quad (10)$$

where α is a scalar. To consider $U^i_p(k)$ and $\hat{U}^i_p(k|k-1)$ together when bidding for a frontier cell c_p, let

$$\hat{U}^{ig}_p(k) = U^i_p(k) + \hat{U}^i_p(k|k-1) \quad (11)$$

where $U^i_p(k)$ and $\hat{U}^i_p(k|k-1)$ are the utility and the expected utility as defined in Eqs. (1) and (10). $\hat{U}^{ig}_p(k)$ is defined as a generalized utility function.

Time variable k is omitted below without confusion since evaluating efficiency based on a generalized utility will make MRSs more efficient in exploration than that in EA-A. The algorithm is thus modified into a form that

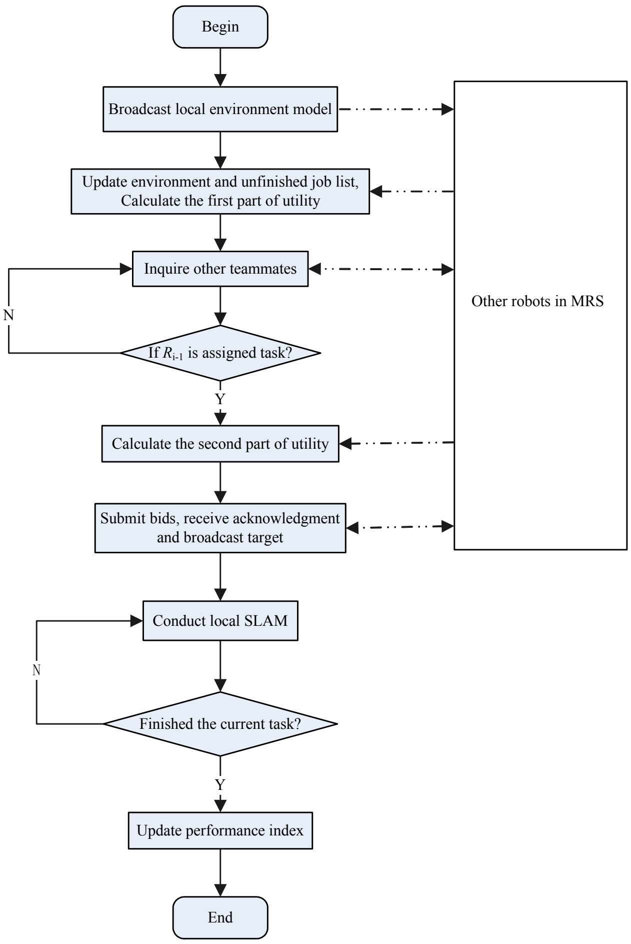

Fig. 1. The flowchart for an auction cycle of DAA-Algorithm.

enables individual robots to bid for tasks based on

$$\hat{E}_p^{ig} = \frac{\hat{U}_p^{ig}}{\hat{t}_p^i} \quad \ldots\ldots\ldots\ldots\ldots \quad (12)$$

where $\hat{t}_p^i$ is estimated time as defined in Eq. (5).

The winner cell is determined as expressed in Eq. (4). The algorithm is called discrete adaptive auction-based algorithm (DAA-A). It is an iterative procedure and behaves similar to a sequential single item auction-based algorithm. In the algorithm, each teammate plays roles of bidder and auctioneer. **Fig. 1** shows the role of R_i acting as a bidder in an auction period. R_i acts as an auctioneer receiving bids submitted by other teammates and itself to frontiers it detected, and assigned a frontier to a robot with maximal efficiency utility. All teammates are assigned tasks based on an order from R_1 to R_n. Progress goes on until all teammates have finished bidding for tasks. The next round of auction actions is triggered by a signal sent by the robot that finished its assigned task first.

To enable all unassigned tasks to the chance of being auctioned, an unassigned job list is constructed composed of all unexplored frontier cells detected by all teammate robots during the last exploration period. The list is maintained at the same status for all robots based on the newest global environment model before a new auction. Unfin-

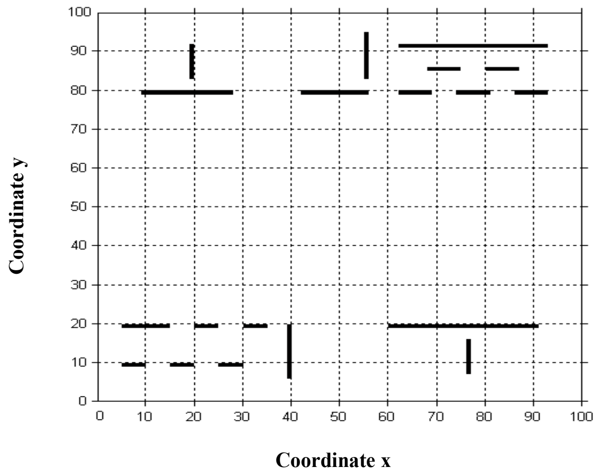

Fig. 2. The simulated environment.

ished tasks in the list and frontiers detected currently are combined and auctioned for all teammates as soon as a teammate robot has finished its assigned task. In other words, unfinished tasks are reauctioned in the next cycle.

Note that Eq. (12) reflects all aspects of robot performance for exploration. In detail, influence resulting from speed v^i is included through $\hat{t}_p^i$, and influence resulting from processing ability, detection range, etc., is included through $\hat{U}_p^{ig}$.

5. Simulation

A MRS considered in our simulation consists of 4 robots with different processing ability, speed, and detection ranges. Individual robot speeds are 3, 4, 3, and 2. Detection ranges of individual robots are 4, 8, 3, and 4. Among the four teammate robots, R_2 has the fastest speed and the largest detection range. When exploration tasks are assigned by the algorithm developed in this paper, R_2 must complete the highest proportion of tasks. R_1 and R_3 move at the same speed and the detection range of R_1 is larger than that of R_3. R_1 should complete more tasks than R_3. R_1 and R_4 have the same detection range and R_1 is faster than R_4. R_1 should complete more tasks than R_4. A communication link with infinite bandwidth is assumed to be ideal.

To demonstrate the effectiveness of our algorithm, much computer simulation is conducted for the environment in **Fig. 2**. The environment is a square 100 by 100 cells. Our algorithms are simulated in MATLAB.

To get comparative results, all utilities in DAA-A, EA-A, and IA-A are calculated using Eqs. (1) and (2). A case simulation in which 4 teammate robots initially located at (97, 36), (5, 76), (89, 29) and (25, 93) is given through **Figs. 3** and **4**. **Fig. 3** shows trajectories for 4 teammates and **Fig. 4** the time when 95% of the environment was explored by the MRS coordinated by the three algorithms.

Note that trajectories in **Fig. 3(a)** are neat and regular and all robots are separated adequately. **Table 1** shows

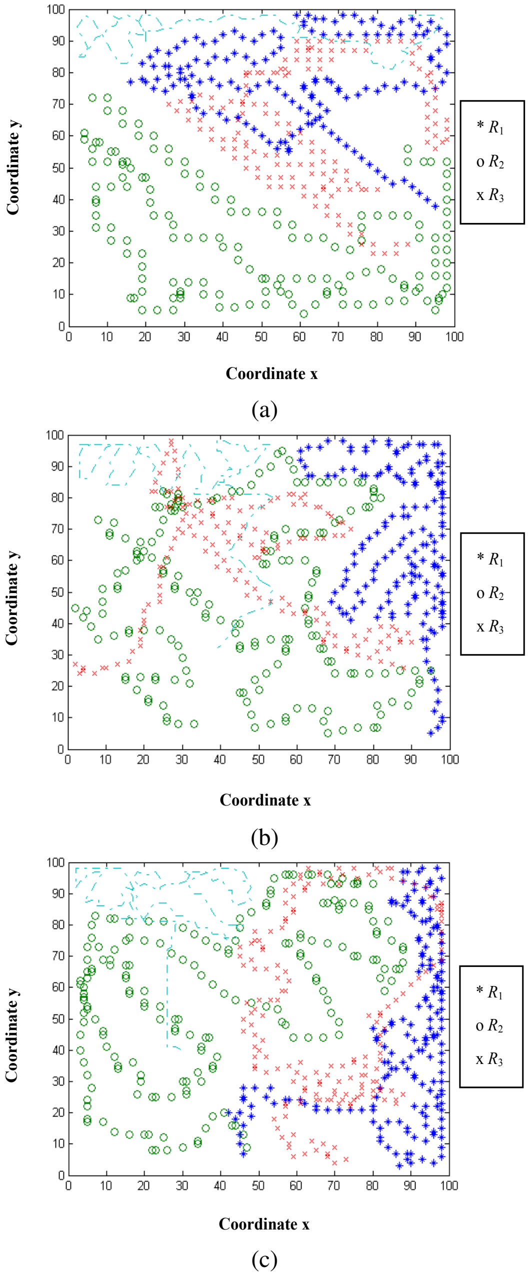

Fig. 3. Trajectories for all teammates under coordination of (a) DAA-A, (b) EA-A, and (c) IA-A, respectively.

intersection numbers (*in*) on trajectories and trajectory lengths of 4 robots for the three algorithms. Note that the *in* of R_2 for DAA-A has the least number among *in*s for the three algorithms. The sum of the individual *in* for DAA-A is also the least. There is no significant difference in trajectory length (*tl*) for all robots. The above fact results in trajectories in **Figs. 3(b)** and **(c)** being anomalistic and disordered compared to those in **Fig. 3(a)**. Most importantly, the percentage of overlap regions explored by the MRS in coordination of DAA-A is the lowest and the other two cases are intermediate and highest. For displaying sharp trajectories in **Fig. 3**, obstacles in the environment are hidden temporarily.

As shown in **Fig. 4**, DAA-A improved exploration efficiency relatively well. The three algorithms in ascending order of exploration time are DAA-A, EA-A, and IA-A. It has been shown that robot behavior does not change no matter how many times simulation is repeated for the same initial conditions.

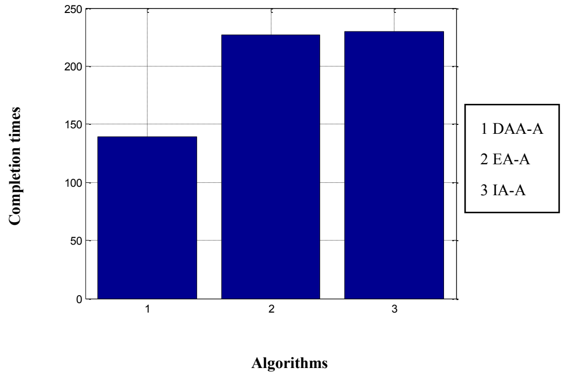

Fig. 4. Completion times vs. algorithms.

To show their effectiveness and generality, our three algorithms and a conventional auction-based algorithm (TA-A) [10] are compared for two cases of different initial locations of teammates. Each case consists of 20 trials for each algorithm. In each trial of the first case, initial locations for all teammates are generated randomly. In each trial of the second case, an initial location generated randomly for a robot is imported to the other three robots. All four algorithms have the same initial location. For convenience, the two cases are called random initialization and uniformly random initialization case. **Tables 2** and **3** show initial coordinates and corresponding exploration times of the four algorithms. To show the level of difference in exploration times between DAA-A and other algorithms from the view of statistics, exploration time data for each algorithm is taken as a sample for statistical testing. Sample means and unbiased estimators of variations in the four algorithms under two initial cases are shown in **Table 4**. Based on the above data, paired two-sample t-tests are applied to test the null hypothesis in each initialization case.

Test statistics for significance level $\alpha = 0.05$ for the two cases are shown in **Tables 5** and **6**. The null hypothesis implies that the means of populations from which the two samples were taken are equal. If the null hypothesis is rejected, then exploration times are different. In the 6 tests listed in **Tables 5** and **6**, the null hypothesis is rejected for all tests, indicating that improvement resulting from DAA-A are evident.

Percentages of average areas that individual robots explore are summarized in **Table 7**. A_i $(i = 1, \ldots, 4)$ is the percentage of average unknown area explored by R_i. A_2 is clearly the largest among the four percentage variables for each algorithm. A_1, A_3, and A_4 in DAA-A are the largest among corresponding variables of the three algorithms. For each algorithm, percentages of areas explored by individual robots have the relationship described at the beginning of this section. DAA-A improved efficiency most

Table 1. Intersection numbers (*in*) on trajectories and trajectory lengths (*tl*).

Algorithms	R_1		R_2		R_3		R_4		Team	
	in	*tl*	*in*	*tl*	*in*	*tl*	*in*	*tl*	*in*	*tl*
DAA-A	11	321.0	4	439.9	22	294.3	11	199.4	48	1254.6
EA-A	2	300.5	44	433.0	58	308.5	28	199.4	132	1241.3
IA-A	42	318.7	35	471.5	53	331.5	16	201.4	146	1323.1

Table 2. Exploration times for four algorithms – random initialization case.

No.	Initial coordinates	Exploration times			
		DAA-A	EA-A	IA-A	TA-A
1.	(88,74),(14,1),(89,20),(30,66)	173	217	179	207
2.	(61,2),(2,19),(59,6),(37,63)	137	207	188	167
3.	(27,25),(87,23),(80,91),(23,24)	163	184	234	164
4.	(72,51),(78,49),(19,70),(98,81)	163	186	239	185
5.	(5,57),(70,96),(75,74),(43,63)	151	207	205	166
6.	(68,5),(36,50),(43,56),(62,11)	159	258	176	173
7.	(33,48),(60,16),(83,96),(60,3)	174	178	237	209
8.	(95,64),(25,35),(19,49),(41,46)	159	237	245	232
9.	(72,57),(46,45),(9,44),(37,30)	130	196	195	159
10.	(97,36),(5,76),(89,29),(25,93)	139	227	230	154
11.	(41,82),(87,2),(73,85),(73,96)	165	176	195	185
12.	(84,18),(51,45),(33,38),(89,76)	171	170	239	218
13.	(10,64),(44,7),(37,25),(93,63)	179	210	188	195
14.	(82,13),(88,51),(96,12),(5,38)	157	203	221	177
15.	(95,26),(51,64),(40,49),(75,13)	152	210	212	189
16.	(84,88),(70,76),(97,40),(13,72)	141	198	208	185
17.	(56,70),(29,99),(22,50),(43,52)	144	216	240	167
18.	(1,66),(72,28),(26,71),(78,99)	140	206	200	215
19.	(13,94),(70,85),(21,46),(8,85)	159	181	202	179
20.	(5,1),(76,60),(95,82),(56,98)	156	201	234	160

Table 3. Exploration times of four algorithms – uniformly random initialization case.

No.	Initial coordinates	Exploration times			
		DAA-A	EA-A	IA-A	TA-A
1.	(95,23) ×4	156	201	183	246
2.	(46,51) ×4	186	215	208	269
3.	(92,74) ×4	172	210	225	258
4.	(41,89) ×4	144	200	179	265
5.	(20,60) ×4	167	172	206	274
6.	(45,93) ×4	196	179	197	271
7.	(20,67) ×4	181	225	205	281
8.	(83,50) ×4	171	244	241	284
9.	(19,68) ×4	162	250	199	277
10.	(38,86) ×4	159	209	199	288
11.	(82,64) ×4	192	179	252	292
12.	(34,53) ×4	144	187	208	298
13.	(37,40) ×4	187	221	195	258
14.	(79,96) ×4	202	188	209	250
15.	(27,25) ×4	152	161	207	260
16.	(30,66) ×4	184	205	196	272
17.	(58,42) ×4	173	200	238	241
18.	(58,76) ×4	177	205	193	268
19.	(78,68) ×4	187	187	225	274
20.	(60,5) ×4	198	215	197	245

Table 4. Statistical parameters of robot team for two cases.

Algorithms	Random initialization case		Uniformly random initialization case	
	Mean	Var.	Mean	Var
DAA-A	155.6	187.5	174.5	307.5
EA-A	203.4	469.1	202.7	511.2
IA-A	213.4	511.4	208.1	364.5
TA-A	184.3	490.5	268.6	253.3

on the grounds that each teammate runs on an efficient trajectory, as shown by **Fig. 3** and **Table 1**. Overlap regions explored by any two teammates in the MRS are reduced. To save space, all robot trajectories for the two cases are omitted. It was found from **Table 4** that only DAA-A saves exploration time compared to TA-A for random initialization cases. All three algorithms save on exploration times compared to TA-A for uniformly random initialization cases, however, because all 4 robots are located together initially. The calculation scheme of the second part utility takes a role in the second case. In the first case, all robots are separated initially and the scheme takes fewer roles.

Table 5. Paired two-sample t-test for exploration time data in **Table 2**.

t-test	A = DAA-A		
	B = EA-A	B = IA-A	B = TA-A
t_{AB}	−8.3424	−9.7691	−4.9291
$d.f._{AB}$	32.0973	31.2822	31.6741
Null hypothesis	Rejected	Rejected	Rejected

Table 6. Paired two-sample t-test for exploration time data in **Table 3**.

t-test	A = DAA-A		
	B = EA-A	B = IA-A	B = TA-A
t_{AB}	−4.3997	−5.7964	−17.7605
$d.f._{AB}$	35.7856	37.7287	37.6482
Null hypothesis	Rejected	Rejected	Rejected

Table 7. Comparison of four algorithms in explored areas (percentages).

Algorithms	Random initialization case				Uniformly random initialization case			
	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4
DAA-A	10.43	77.32	4.99	7.26	10.17	77.53	4.98	7.32
EA-A	8.95	79.82	4.83	6.39	9.12	79.71	4.77	6.40
IA-A	8.97	80.02	4.89	6.12	8.87	80.41	4.65	6.07
TA-A	10.63	76.98	5.03	7.36	10.53	77.21	5.68	6.58

6. Conclusions

A novel discrete adaptive auction-based algorithm for coordination of MRS has been proposed based on a performance measure for individual robots calculated iteratively by an identical formula. Without initial knowledge about performance differences between individual robots, the performance index converges to a different value that expresses performance correctly. In cases in which some robots degrade performance or malfunction, the performance index reflects this fact in DAA-A. Our coordinated algorithm brings out the best in individual robots for exploration, so the efficiency of exploration for MRS is improved.

Improvement was realized at the cost of distances traveled by individual robots being different. A potential disadvantage is that the robot traveling the longest distance may consume its energy first. Time for calculating bids and communication are not considered. Future work will be to extend the approach to make it suitable for dynamic environments.

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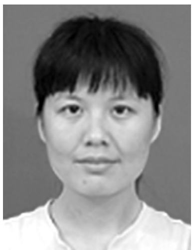

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