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RESEARCH ARTICLE

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Multi-robot exploration mission planning and stochastic increment replanning for load balance

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Abstract Multi-robot mission planning is composed of assignment allocation and mobile-robot route planning in this paper. Multi-robot exploration missions adopts fuzzy c-mean (FCM) algorithm to allocate, and then, heterogeneous interactive cultural hybrid algorithm (HICHA) is devised for route planning in order to optimize mobile-robot execution path. Meanwhile, we design multi-robot mission replanning mechanism based on the rules system of greedy algorithm for dynamic stochastic increment missions. Finally, extensive simulation experiments were shown that FCM for assignment allocation and HICHA for route planning were efficacious for mobile-robot exploration mission planning. Furthermore, the improved greedy algorithm based on experience rules met dynamic stochastic increment missions replanning requirement for load balance.

Keywords multi-robot, mission planning, heterogeneous interactive cultural hybrid algorithm (HICHA), replanning

1 Introduction

Multi-robot cooperation system has been applied successfully in many domains, especially in unmanned vehicles formation and outer space exploration. Multi-robot system (MRS) can improve the effectiveness, robustness, and reliability of a robotic system [1]. Thus, it is significant and practical to research the issue.

There are many methods for multi-agent assignment allocation. Reference [2] put forward a market mechanism negotiation protocol using extended contract network, and Ref. [3] improved further on its executive efficiency. Reference [4] proposed an improved auction algorithm to deal with large-scale tasks in dynamic environments. Reference [5] used market-based coordination protocols that are limited by its optimality. Reference [6] mapped task assignment problem into minimum spanning tree (MST), but it is hard to load balance. Reference [7] described an almost communicationless and time-limit approach for unmanned aerial vehicles (UAVs) tasks; however, UAVs are all equipped with global position system (GPS) receivers, synchronized clocks, and radars, which are different from our robots. References [8–10] used swarm intelligent algorithm for allocation that showed a new development trend for multi-robot mission planning. In this paper, we utilize an efficient fuzzy c-mean (FCM) allocation algorithm for load balance and min-cost to assign a large scale of tasks. The detailed process is introduced in Sect. 3. Multi-robot route planning also made great progress. Reference [11] brought forward a neural network algorithm to minimize the longest path, but the model parameters are complex. An augmented Lagrangian decomposition [12] and coordination technique are used to minimize the total transportation time. Reference [13] proposed an autonomous decentralized method for multiple automated guided vehicles (AGVs) static route planning. Discrete particle swarm optimization (DPSO) [14] was considered an efficient method to solve route planning problem. Reference [15] realized a kind of DPSO algorithm for traveling salesman problem (TSP); meanwhile, the validation of novel quantum swarm evolutionary algorithm (NQSEA) was verified in Ref. [16]. Those algorithms showed strong evolution features, which proved that particle swarm optimization (PSO) was a feasible method for route planning. Thus, a heterogeneous interactive strategy based on cultural architecture is presented in this paper, and the details can be found in Sect. 4. This paper mainly analyzes exploration mission planning and stochastic increment replanning for load balance.

The rest of the paper is organized as follows: In Sect. 2, we describe an exploration mission planning model. In Sect. 3, multi-robot assignment allocation based on FCM

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algorithm is introduced, and in Sect. 4 we devise a mobile-robot route planning based on heterogeneous interactive cultural hybrid algorithm (HICHA). Robot exploration static and stochastic mission planning simulation and experiment are analyzed in Sect. 5. Finally, some conclusions are stated in Sect. 6.

2 Exploration mission planning descriptions

Definition 1 (Execution time) W_i, $i=1,2,\ldots,n$, and R_j, $j=1,2,\ldots,m$, denote the number of missions and robots, respectively. Here, $|W|=n$ and $|R|=m$. C_e is a nonnegative execution time cost function. Ω is the set of missions, S_k is a missions set of robot k, which is an element of Ω (i.e., $S_k\in\Omega$), and $S_1\cap S_2\cap\cdots\cap S_m=\varnothing$. If task w_i is allocated to robot r_j, then $x_{ij}=1$; otherwise, $x_{ij}=0$. The total task execution time $\mathrm{ET}_k(S_k)$ spent by robot r_k is as follows:

$$\mathrm{ET}_k(S_k)=\sum_{w_i\in S}[C_e(w_i,r_k)x_{ik}], \tag{1}$$

$$C_e(w_i,r_k)=\frac{Q_{w_i}}{v_k}, \tag{2}$$

where Q_{w_i} is the execution total amount of task w_i, and v_k is the execution velocity of robot k.

Definition 2 (Traveling time) d_{ij} is the distance from task i to task j, and C_t is a nonnegative traveling time cost function. $C_t(w_{S_j},r_j)$ denotes the time cost of robot r_j visiting mission subset S_j. Then, the traveling time of robot r_k, $\mathrm{TT}_k(S_k)$, equals

$$\mathrm{TT}_k(S_k)=C_t(w_{S_k},r_k). \tag{3}$$

Traveling time is proportional to the distance

$$C_t(w_{S_k},r_k)=\sum_{i=1}^{|S_k|}\sum_{j=1}^{|S_k|}\frac{d_{ij}}{v_k}y_{ij}, \tag{4}$$

where v_k is the traveling velocity of robot k. If robot k visits edge (i,j), then $y_{ij}=1$, else, $y_{ij}=0$. The general constraint conditions of Eq. (4) are as follows:

$$\sum_{i=1}^{|S_k|}y_{ij}=1,\ j=1,2,\ldots,|S_k|, \tag{5}$$

$$\sum_{j=1}^{|S_k|}y_{ij}=1,\ i=1,2,\ldots,|S_k|, \tag{6}$$

$$y_{ij}\in\{0,1\},\ \forall(i,j)\in E. \tag{7}$$

The total completion time $T_k(S_k)$ spent by r_k robot includes the executing time and the traveling time,

$$T_k(S_k)=\mathrm{ET}_k(S_k)+\mathrm{TT}_k(S_k). \tag{8}$$

Then, the task planning performance evaluation can be defined as

$$\min_T\max_S\ (T_1(S_1),T_2(S_2),\ldots,T_k(S_k)).$$

Min-max total time cost is

$$T(\Omega)=\min\left\{\max_{1\leqslant k\leqslant m}[\mathrm{ET}_k(\Omega)+\min\mathrm{TT}_k(\Omega)]\right\}. \tag{9}$$

3 Fuzzy c-mean descriptions for multi-robot assignment allocation

FCM is a fuzzy decision method [17], which is an effective approach to allocate roughly. Unlabeled mission space $X=[x_1,x_2,\ldots,x_n]\subset\mathbb{R}^2$, $\{u_{ik}\}$ can be arrayed as a $p\times n$ matrix $U=[u_{ik}]$. Here, u_{ik} is the membership of x_k for fuzzy subset of robot i, allocation centers $C=[c_1,c_2,\ldots,c_m]$, $c_i\in\mathbb{R}^2$. FCM divides n vectors x_k, $k=1,2,\ldots,n$, into p subsets. The fuzzy membership value is at [0,1], and the sum is 1:

$$\sum_{i=1}^{p}u_{ij}=1,\ \forall j=1,2,\ldots,n. \tag{10}$$

The objective function is defined by $J(U,C)$ as follows:

$$J(U,c_1,c_2,\ldots,c_p)=\sum_{i=1}^{p}J_i=\sum_{i=1}^{p}\sum_{j=1}^{n}u_{ij}^m d_{ij}^2, \tag{11}$$

$$\text{s.t.}\ \begin{cases}0\leqslant u_{ik}\leqslant 1, & 1\leqslant i\leqslant p, 1\leqslant k\leqslant n,\\ \sum_{i=1}^{p}u_{ik}=1, & \forall k=1,2,\ldots,n,\\ 0<\sum_{k=1}^{n}u_{ik}<n, & \forall i=1,2,\ldots,p,\\ 1\leqslant m<\infty,\end{cases} \tag{12}$$

where $u_{ik}\in[0,1]$, c_i denotes the ith allocation center, and $m\in[1,\infty)$ is weighting exponent. Reconstruct a new objective function as follows:

$$\begin{aligned}&\bar{J}(U,c_1,c_2,\ldots,c_p,\lambda_1,\lambda_2,\ldots,\lambda_n)\\&=J(U,c_1,c_2,\ldots,c_p)+\sum_{j=1}^{n}\lambda_j\left(\sum_{i=1}^{p}u_{ij}-1\right)\\&=\sum_{i=1}^{p}\sum_{j=1}^{n}u_{ij}^m d_{ij}^2+\sum_{j=1}^{n}\lambda_j\left(\sum_{i=1}^{p}u_{ij}-1\right),\end{aligned} \tag{13}$$

where λ_j, $j=1,2,\ldots,n$, are the Lagrange multipliers. The distance between the ith allocation center and the kth mission point is defined as follows:

$$d_{ik}^2 = \|x_k - c_i\|_A = (x_k - c_i)^T A (x_k - c_i), \tag{14}$$

where A is symmetric positive definite matrix. If A is a unit matrix, then Eq. (14) is transformed into Euclidean distance. u_{ik} and c_i is updated as follows:

$$u_{ik} = \begin{cases} \dfrac{1}{\sum\limits_{j=1}^{p} \left(\dfrac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}}, \text{ if } I_k = \varnothing, \\ 0, \qquad \forall i \in I_k \text{ and } \sum\limits_{i \in I_k} u_{ik} = 1, \text{ if } I_k \neq \varnothing, \end{cases} \tag{15}$$

$$c_i = \frac{\sum\limits_{k=1}^{n} u_{ik}^m x_k}{\sum\limits_{k=1}^{n} u_{ik}^m}. \tag{16}$$

For $\forall k$, define set I_k and $\overline{I_k}$ as

$$I_k = \{i | 1 \leqslant i \leqslant p, d_{ik} = 0\},$$

$$\overline{I_k} = [1,2,...,p] - I_k.$$

The steps of FCM iteration optimization are as follows:

Step 1 Initialize membership matrix U, which must meet Eq. (12). Given the allocation kind number p (here, it is equal to robot number), set iteration threshold $\varepsilon > 0$, and the max-iteration number MAX_NUM.

Step 2 Update new allocation center $C^{(i+1)}$ by Eq. (16).

Step 3 Compute Eq. (11), if its difference with last calculation time is less than ε, then break to end, and put out the fuzzy membership matrix U and allocation center C.

Step 4 Update new membership matrix $U^{(i)}$ with Eq. (15), and go to Step 2.

FCM depends on initial centers, which cannot ensure converge to the best value each time. Thus, we need to run FCM multiple times.

4 Mobile-robot route planning based on HICHA

HICHA is composed of upper ceiling knowledge evolutionary space, bottom ceiling population space, and a customer interactive estimation unit. The architecture of HICHA is shown in Fig. 1.

We define three kinds of rules, which are population space evolution rules, knowledge space evolution rules, and interactive interface operation rules. HICHA first initializes population space using good point set in order to make particles swarm uniform distribution in feasible region. Second, novel evolution model and particle

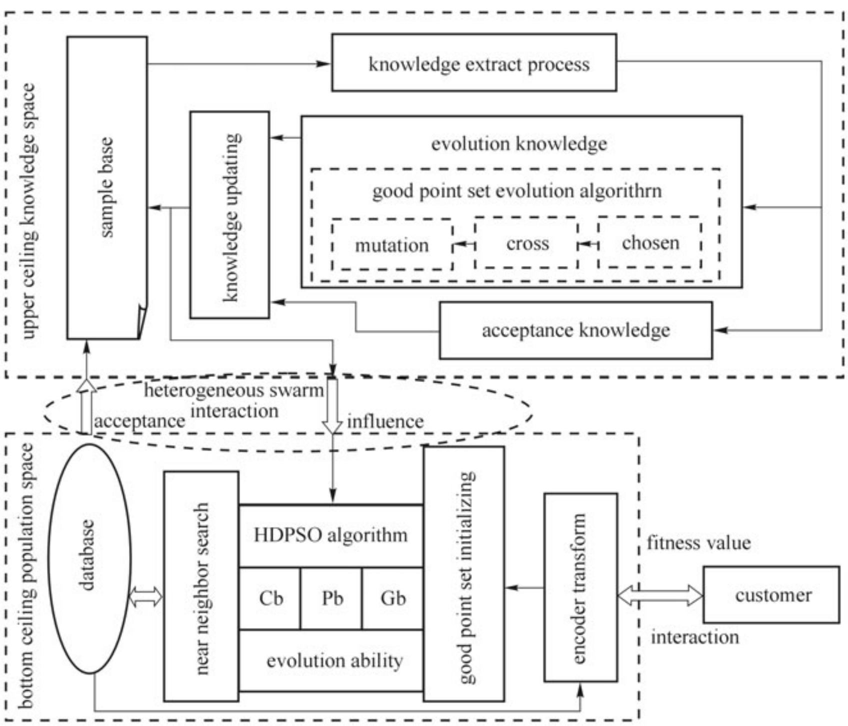

Fig. 1 HICHA system architecture frame graph

evolution ability indexes are redefined, which increase particles swarm diversity and improve algorithm stability. Third, near neighbor local search strategy is introduced to enhance search capability. The detailed information can be referred to Ref. [18].

5 Experiment and analysis

We use mobile robots of central south-2 (MORCS-2) team as the experiment platform, as shown in Fig. 2.

5.1 HICHA advantages verification for a mobile-robot route planning

We compare HICHA with traditional genetic algorithm (GA) and particle swarm optimization based algorithm (PSOBA) [19] in order to verify the validity of HICHA. Figures 3 and 4 are the robot route planning evolution curves for eil101 and tsp225. It shows that the convergence of HICHA is better than GA and PSOBA; meanwhile, the solution quality of HICHA is superior to the others.

5.2 Exploration missions planning experiment

We choose different kinds of standard data from traveling salesman problem library (TSPLIB) as mission map (http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsp/index.html, 1995/2008), as shown in Table 1. Ψ represents the number of allocation or executive mission for each robot. D is each robot visiting route length. They are both important parameters for computing time cost. Bold data closely relate to fitness, and it can gain max-min time cost, for example, aiming to eil51 map for three robots, $R1$ time cost is

$$16 \times 10 + \frac{147.863}{10} = 174.7863,$$

$R2$ time cost is 195.6942, $R3$ time cost is 185.2083, and the maximal time cost value is 195.6942 of $R2$, marked with the data in Table 1 with bold font. We also discover that the time cost for the same mission map is decreasing with the number of robot increasing; meanwhile, the time cost is rising with mission number rising up when the robot number is unchanged, as shown in Fig. 5. Figure 6 reveals the results of static known exploration missions planning.

Fig. 2 MORCS-2 mobile robots team

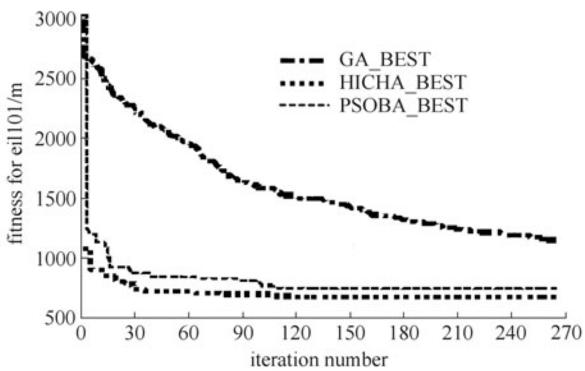

Fig. 3 Evolution curves of HICHA, GA, and PSOBA for eil101

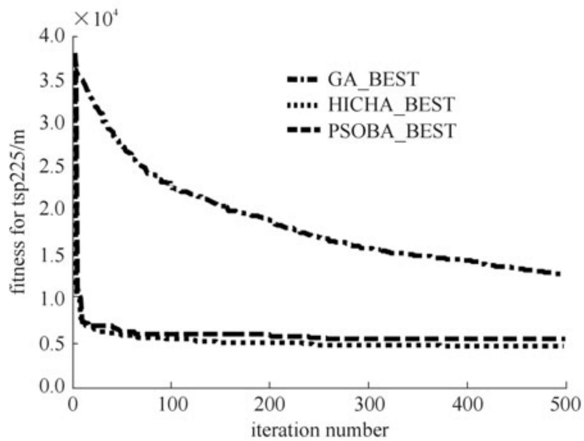

Fig. 4 Evolution curves of HICHA, GA, and PSOBA for tsp225

Table 1 Multi-robot mission planning results for different TSPLIB

	problem	robot number		$R1$	$R2$	$R3$	$R4$	$R5$	fitness	traveling velocity	execution time
FCM + HICHA	eil51	3 robots	Ψ	16	**18**	17	—	—	195.694	10	10
			D	147.863	**156.942**	152.083	—	—			
		4 robots	Ψ	**14**	13	13	11	—	152.600		
			D	**125.998**	121.296	114.925	97.709	—			
		5 robots	Ψ	10	11	8	**12**	10	130.055		
			D	97.825	90.231	88.671	**100.549**	92.594			
	eil76	3 robots	Ψ	24	**28**	24	—	—	302.158	10	10
			D	175.358	**221.578**	183.355	—	—			
		4 robots	Ψ	18	18	18	**22**	—	235.168		
			D	154.439	137.443	132.675	**151.679**	—			
		5 robots	Ψ	**18**	16	15	11	16	191.998		
			D	**119.983**	125.908	115.533	96.801	146.478			
	eil101	3 robots	Ψ	**38**	32	31	—	—	402.321	10	10
			D	**223.206**	209.972	240.094	—	—			
		4 robots	Ψ	20	27	**34**	20	—	359.272		
			D	163.873	185.426	**192.721**	138.130	—			
		5 robots	Ψ	19	19	19	**30**	14	316.051		
			D	159.9582	116.277	126.692	**160.510**	118.960			
	kroB100	3 robots	Ψ	30	32	**38**	—	—	450.574	100	10
			D	7712.298	8433.243	**7057.388**	—	—			
		4 robots	Ψ	**27**	21	26	26	—	339.465		
			D	**6946.543**	4273.182	6090.733	7301.108	—			
		5 robots	Ψ	17	15	20	**24**	24	**304.8735**		
			D	4507.353	4881.395	3887.999	**6487.350**	4994.951			
	kroB150	3 robots	Ψ	50	**58**	42	—	—	**692.911**	100	10
			D	8774.995	**11291.10**	8602.267	—	—			
		4 robots	Ψ	38	35	30	**47**	—	**549.355**		
			D	7133.406	7760.342	5677.615	**7935.498**	—			
		5 robots	Ψ	35	28	**36**	24	27	**429.014**		
			D	6440.832	5564.241	**6901.426**	5153.072	5121.520			

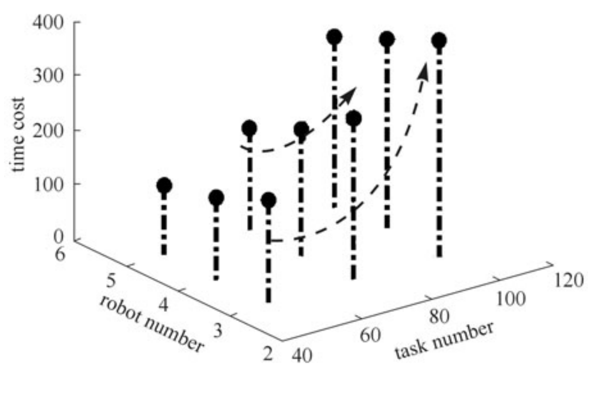

Fig. 5 Relationship between time cost, robot number, and task number

5.3 Dynamic stochastic increment missions replanning mechanism

We consider new generation points as dynamic stochastic increment missions. When a new incremental task happens, we must allocate the stochastic task to a robot as soon as possible, which is called traveling route replanning. Greedy algorithm is usually utilized for this replanning. Furthermore, we devise an improved greedy strategy for robot route replanning in this paper. If a robot has the heaviest load beforehand, we cannot reallocate more tasks to it. At this time, membership function is defined according to the distance between stochastic task and robot position, which is an essential evaluation criterion. When a stochastic task happens, greedy algorithm is first used to allocate, then the load balance fitness function is computed. If the discrepancies of the

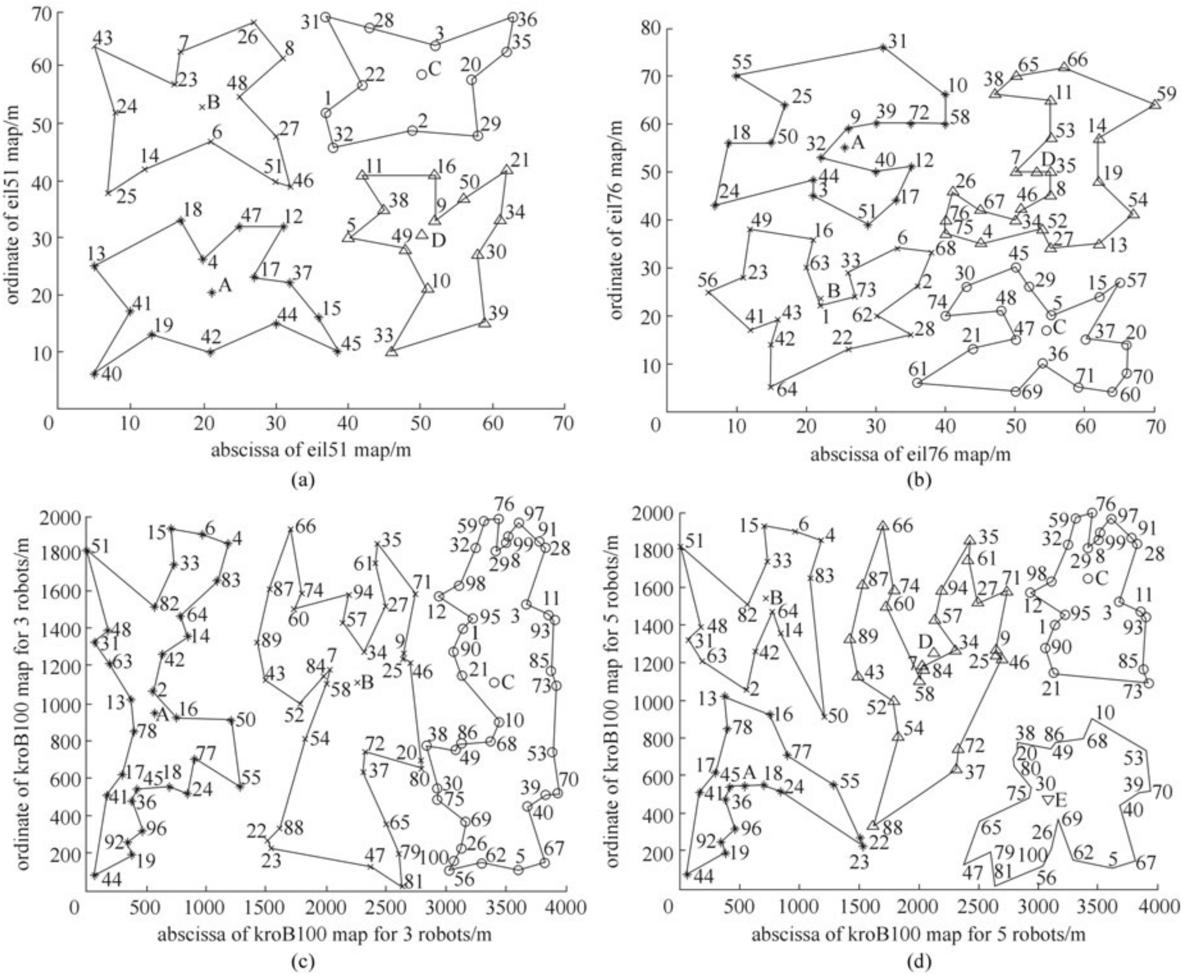

Fig. 6 Results of static known exploration missions planning. (a) Mission planning result for eil51 map and 4 robots; (b) mission planning result for eil76 map and 4 robots; (c) mission planning result for kroB100 map and 3 robots; (d) mission planning result for kroB100 map and 5 robots

heaviest load robot fitness and the least load fitness are less than a threshold, then the balance-load requirement is satisfied; else, we need reallocate according to membership function. We reallocate some of the heaviest load robot missions to the second maximal membership robot. If it also cannot meet the balance-load satisfaction, we take some missions to the third maximal membership robot. Moreover, it is analogized like this, until replanning result satisfies balance-load requirement.

We improve those strategies to greedy FCM algorithm and discover that the fitness function value is better than greedy algorithm; meanwhile, the time cost does not increase. The principle of reallocation mission is the load balance. In Figs. 7 and 8, we can learn that the improved reallocating mechanism is not the shortest path allocation but is a load balance allocation. "⊙" indicates dynamic stochastic increment missions, and the linkage lines denote multi-robot visiting route. Table 2 shows that the cost of improving strategies for FCM is less. For example, the cost of improved algorithm for eil76 add 10 increment missions and 4 robots is 235.924, but greedy algorithm is 256.068, thus, we can save lots of time cost.

6 Summaries and prospect

FCM is a classic allocation algorithm that has a broaden application. Meanwhile, HICHA can be also used to another combination optimization, for example, vehicle scheduling, network routing, very large scale integration (VLSI) layout, and so on. It is significant to modify greedy FCM algorithm for load-balance and minimizing maximal time cost. Dynamic mission planning is a difficult issue, and this paper is only a new attempt. The multi-robot mission reallocation and replanning are also close with the robot fault detection and diagnosis that is also a significant research field, and we will study those problems comprehensively in the future.

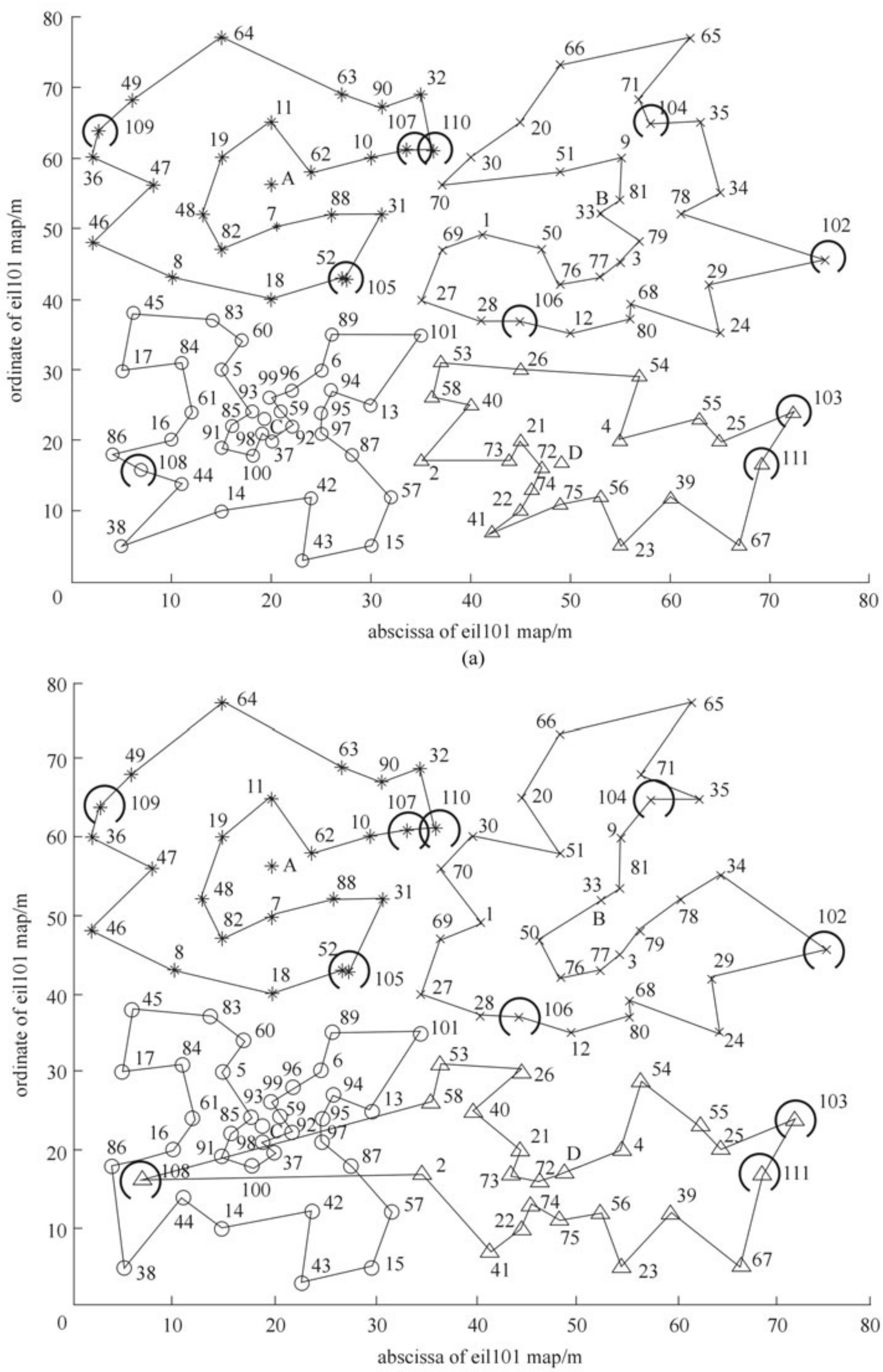

Fig. 7 Dynamic stochastic increment missions reallocating and replanning results for eil101 with 4 robots. (a) Reallocating result for eil101 with 4 robots; (b) improved reallocating mechanism result for eil101 with 4 robots

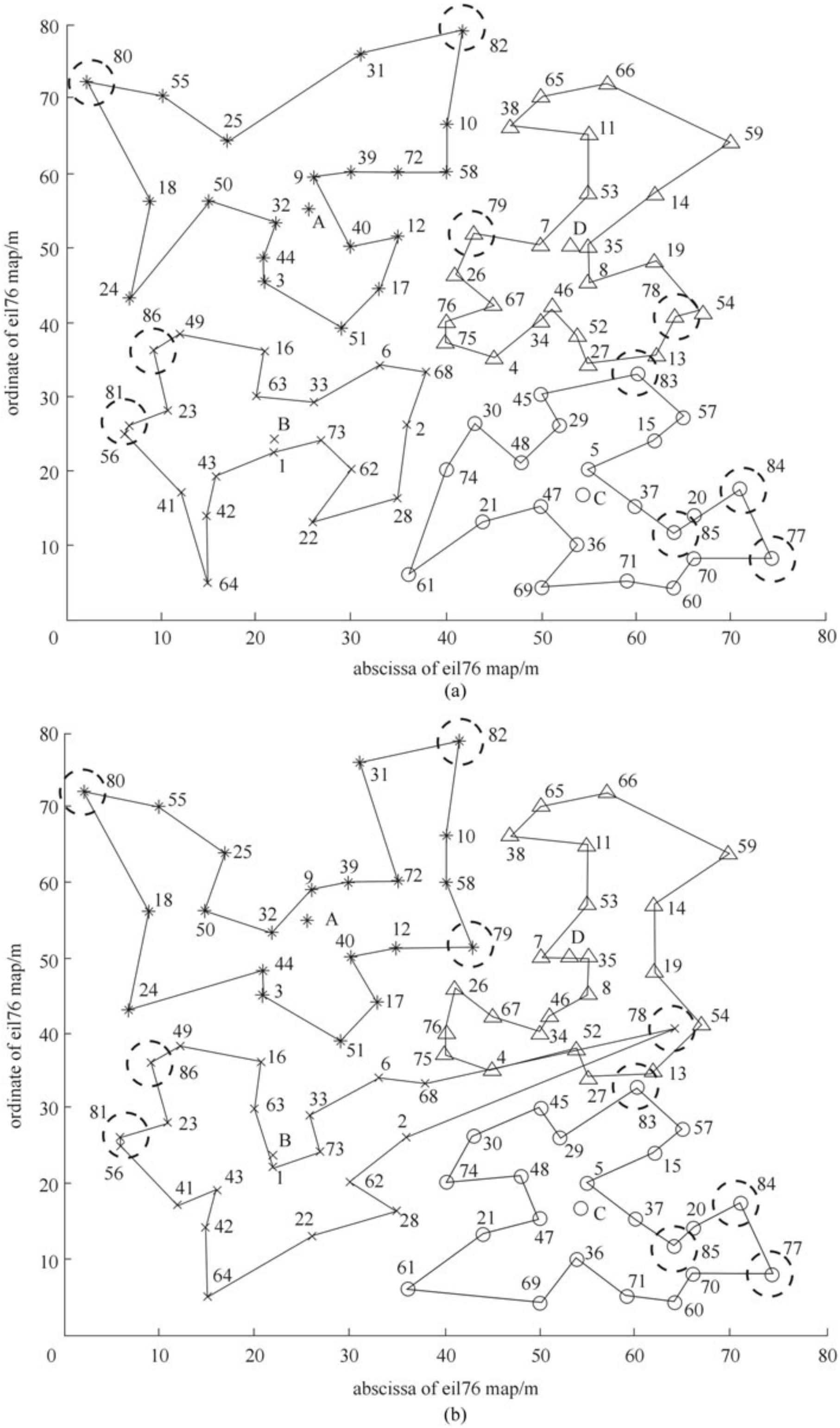

Fig. 8 Dynamic stochastic increment missions reallocating and replanning results for eil76 with 4 robots. (a) Reallocating result for eil76 with 4 robots; (b) improved reallocating mechanism result for eil76 with 4 robots

Table 2 Dynamic stochastic increment missions reallocating and replanning results comparison

problem	robot parameters	*R*1	*R*2	*R*3	*R*4	fitness
eil76-10 increment missions with 4 robots (improved reallocating algorithm)	number of executive mission	21	21	**22**	22	235.924
	visiting route length	189.406	191.110	**159.242**	151.679	
eil76-10 increment missions with 4 robots (greedy FCM algorithm)	number of executive mission	20	20	22	**24**	256.068
	visiting route length	179.695	141.239	158.969	**160.679**	
eil101-10 increment missions with 4 robots (improved reallocating algorithm)	number of executive mission	24	30	**34**	23	359.385
	visiting route length	167.476	203.061	**192.721**	204.314	
eil101-10 increment missions with 4 robots (greedy FCM algorithm)	number of executive mission	24	30	**35**	22	369.385
	visiting route length	167.476	203.061	**193.850**	153.5851	

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