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A Regional Necessity Based Multi-agent Target Search Strategy for Post-earthquake Rescue

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Abstract: The damage caused by the earthquake is huge. And the purpose of post-earthquake rescue is to reduce casualties. So it is necessary to improve the efficiency of rescue as much as possible. This paper focuses on multi-agent cooperative target search in the post-earthquake rescue and how to exploit the prior information of post-disaster building to improve the searching efficiency. A regional necessity based searching strategy is proposed which utilizes pre-disaster building information and adapts to dynamic environments. Firstly, the target probability map is estimated according to the distribution information of pre-disaster buildings. Then, the regional necessity map is constructed by integrating the target probability map and the perception of the environment during the search process. Finally, the search strategy is proposed based on the regional necessity map and the particle swarm optimization algorithm. Combining the gradient direction of regional necessity and local optimal velocity, the agent dynamically selects the search direction. By comparing with other search strategies in simulation experiments, the proposed strategy could shorten the searching time and improve the searching efficiency in the small and medium-scale task environment. Meanwhile, the search strategy can adapt to the post-earthquake dynamic environment, which is confirmed by dynamic experiments.

Key Words: multi-agent cooperative target search, post-earthquake rescue, regional necessity, particle swarm optimization

1 Introduction

In recent years, distributed multi-agent systems have been increasingly used in security and emergency management, especially post-disaster search and rescue, where search and rescue path planning is an important issue [1]. The search agent is generally equipped with various sensors (e.g., radar, laser, etc.) and wireless electronic communication equipment. When multiple agents collaborate to search for a target, the agent first fuses the detected environmental information and target information to estimate the target state, and then plans the movement on this basis [2].

This paper mainly focuses on the decision-making step, in the framework of the multi-agent cooperative target search problem in the post-earthquake rescue. The search and rescue work after the earthquake is short of time, and secondary disasters may occur again [3]. The original road was damaged by the earthquake and the road condition was complicated. Therefore, the agent needs to find the optimal search path according to the environment information, in order to find the target to be rescued as soon as possible [4]. At the same time, when the agent plans a path, it also needs to consider constraints such as obstacle avoidance[5], communication maintenance and collision avoidance. At present, various search algorithms have been proposed. According to the motion direction of the agent, they are mainly divided into geometric methods and random methods [6], among which random methods are divided into non-heuristic and heuristic according to whether there is heuristic information [7].

Geometric methods are that the agent conducts an overlay search in the assigned sub-areas based on the set route, such as raster scan or spiral [8]. Random methods are common in animal search patterns. Generally, they are strategies to change the search direction based on biological incentives. There are various intelligent optimization algorithms, including neural networks [9], genetic algorithms, fireflies [10], ant colonies [11], bee swarms and particle swarms [12], etc. Viswanathan et al. verified the most effective flight length of Levy's random search method with the foraging data of insects, mammals and birds. This method belongs to non-heuristic exhaustive coverage and is effective when the target is sparse and completely uniform or randomly distributed [13]. However, after an earthquake, the distribution of targets is usually uneven, with a greater probability of appearing around buildings [14]. The probability of the target appearing in some areas is small, geometric methods and non-heuristic random methods are both less efficient, and the heuristic methods are more suitable for this problem. Ristic et al. discretized the search area into a target occupancy grid graph to plan the path based on consensus [15]. The objective function of heuristic methods is usually determined by prior information and environmental information, including target occurrence probability and environmental cognition. However, these methods cannot adapt to the long-lasting and dynamic post-disaster environment, and easily fall into a local optimum, which makes the agent stay in a sub-optimal area. In order to exploit the prior information before disaster to improve the search efficiency[16], particle swarm algorithm is utilized to solve the problem due to its high efficiency and flexibility in this paper.

Particle swarm algorithm is a representative swarm intelligence algorithm. The algorithm is more flexible and can adapt to a variety of environments. It greatly improves

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the search efficiency and facilitates the smooth execution of the subsequent rescue missions, so it has been widely used in the field of target search. Youssefi et al. proposed a new decentralized and asynchronous robot search algorithm based on PSO in a distributed manner, which finds targets in a complex maze environment. Its fitness function is the inverse Euclidean distance to the target, which greatly reduces the communication frequency required between agents [17]. However, when this method is applied to the post-earthquake environment, the environmental changes caused by aftershocks are not considered. Relying on the PSO algorithm, Saadaoui et al. proposed a distributed target search model based on the local subgroup structure (LoPSO). According to the map information searched by the agent, the uncertainty of the target motion is fully considered when constructing the target probability map [18]. Based on these studies, this paper estimates the distribution probability of the target according to the pre-disaster information. Use it as heuristic information for particle swarm optimization. Moreover, this paper fully considers the perception of the environment during the agent search process. It adapts better to the dynamic surrounding environment.

This paper studies the multi-agent path planning problem, under the background of targets rescue after disasters. To improve search efficiency and reduce rescue time, in this paper, the prior information of population density and building distribution before disaster is exploited as heuristic conditions for agent cooperative search. Meanwhile, the unstable factors of post-disaster environment are also considered. Firstly, construct the prior target probability map of the post-disaster area. Then, the target probability and the environmental information detected by the agent combine, forming the regional necessity. The regional necessity based searching strategy is proposed. The agent optimizes the search path according to the regional necessity. The simulation results verify that the proposed method has higher search efficiency than other traditional methods in small and medium-scale task scenarios, and it can adapt to dynamic complex environment.

2 Problem Formulation

The searching task studied in this paper is that multi-agent with sensors executing rescuing task after an earthquake in the 2-D area. Searching targets are trapped people on the edge of the buildings after the earthquake. The real location is unknown. But the prior probability of the location can be generated based on the original building information and population density in the area.

2.1 Description of Target Distribution Probability

The area of interest can be taken as a rectangular region uniformly divided into $G = G_x \times G_y$ grids or cells. During the search process, there are some obstacles such as building ruins after the earthquake, which the agents must avoid. Each grid is attached with a sign $G_{ij}(i \in \{1,2,...,x\}, j \in \{1,2,...,y\})$ to indicate whether it is occupied by obstacles ($G_{ij} = 1$) or empty ($G_{ij} = 0$). If the agents haven't found the grid, the grid is unknown ($G_{ij} = -1$). In this paper, the constraint of obstacle avoidance always dominates the highest priority.

The prior knowledge is expressed in the form of the target probability map. Specifically, each grid G_{ij} is attached with a value $w_{ij} \in [0,1]$ denoting the prior probability that the target exists in this grid, and (i, j) represents the grid position of the i -th row and the j -th column. w_{ij} represents the probability that the target will appear at the location. It decays according to the Euclidean distance along the edge of the obstacle (see Fig. 1). The maximum attenuation distance is R_0. The influence of obstacle $r_q(x_q, y_q)$ follows the two-dimensional Gaussian distribution:

$$w_{ij} = \frac{1}{2\pi R_0^2}\exp[-\frac{1}{2}(\frac{(i-x_q)^2}{R_0^2}+\frac{(j-y_q)^2}{R_0^2})] \tag{1}$$

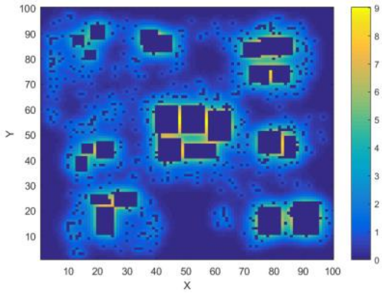

Fig. 1: The target probability

In Fig. 1, the shade of color indicates the size of w_{ij}. The area of yellow is the point with the higher probability of the target appearing, and the area of blue is the point with the smaller probability (among them, most of the dark blue rectangular areas are buildings).

2.2 Agent Movement Capability Model

The agents are equipped with sensors that can collect the local environmental information. The agents also need to plan the search path online. Therefore, the position of agents A^t_{pos} can be represented by the two-dimensional form. The agent occupies a grid, and its movement direction v^t can be selected in 8 surrounding directions φ:

$$\begin{cases} A^{t+1}_{pos} = A^t_{pos} + v^{t+1} \\ v^{t+1} = v^t + \varphi \\ \varphi = \{0°,45°,90°,135°,180°,225°,275°,315°\} \end{cases} \tag{2}$$

As shown in Fig. 2, with the agent as the center, its detection range is a red circle with a radius r of 4, and its movable direction is a beige square:

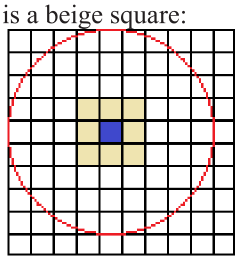

Fig. 2: Agent detection and motion schematic

The agent can connect with the others. They will exchange their map information, if they are within the communication range R :

$$A_{ownmap_i} = A_{ownmap_j}, if \left| A_{pos_i}^t - A_{pos_j}^t \right| \le 2R \quad (3)$$

2.3 Target Searching Model

The goal of multi-agent cooperative target search is to find all n targets in the shortest time. At the same time, the influence of the environment on the movement is considered in the search process. The objective function is:

$$\min F = \min T_{\max} \quad (4)$$

$$s.t. A_{pos_i}^t \ne A_{pos_j}^t \quad (5)$$

$$| A_{pos_i}^{t+1} - A_{pos_i}^t | = 1 \quad (6)$$

where $T_{\max}$ is the maximum time taken to explore the target. The agent moves 1 grid per unit time. Because the agent has a constant speed, this formula can be converted into a comparison of path lengths.

3 Regional Necessity Based Target Search Strategy

Traditional heuristic algorithms such as the greedy method or RHC are utilized to find the search paths based on the short-term evaluation, but they ignore the long-term reward in the future. This paper constructs a model based on the degree of regional necessity to globally represent the complex scene after the disaster, and then selects the optimal path on this basis.

3.1 Regional Necessity

We define $U_{ij}^t \in [0,1]$ as the degree of understanding of the grid (i, j), which means that if it is completely known, $U_{ij} = 0$, otherwise $U_{ij} = 1$. At the time t_0, the grid (i, j) is searched, G_{ij} changes from -1 to others, and $U_{ij} = 0$. As time goes by, the unknown degree of (i, j) will increase:

$$U_{ij}^t = \begin{cases} 1 - \varepsilon(t - t_0), t \le t_0 \,\&\, G_{ij} = -1 \\ 1 - e^{\sigma(t_0 - t)}, t > t_0 \end{cases} \quad (7)$$

where $\varepsilon(t - t_0)$ is the step function, and σ is the coefficient of variation of U_{ij}.

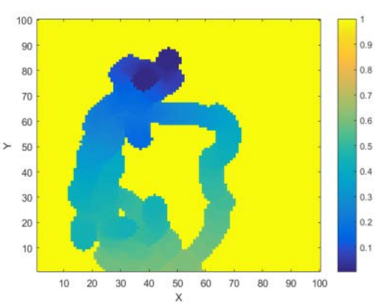

Fig. 3: The unknown degree map of an agent

In Fig. 3, we can see the unknown degree map of an agent in the search process. Yellow represents the area that is completely unknown to the agent, and the dark blue area represents that the agent has just completed the detection and its map information is completely known. As the blue level becomes lighter, that is, the longer the time until the agent's search is completed, the less the agent knows about the map information of the area.

Considering the probability of the target and the unknown degree of the area, we use regional necessity $U_{w_{ij}}^t \in [0,1]$ to indicate the necessity of searching. When $U_{w_{ij}}^t = 1$, the necessity of searching is 100%:

$$U_{w_{ij}}^t = U_{ij}^t * w_{ij} \quad (8)$$

3.2 Path Selection

The agent uses the particle swarm optimization method to select its own route. This means that the speed at the next moment v^{t+1} depends on the local speed D_{local} and the global speed D_{gobal} according to the previous moment v^t :

$$v^{t+1} = w \times v^t + c_1 r_1 \times D_{local} + c_2 r_2 \times D_{gobal} \quad (9)$$

where w is the weight coefficient and r_1, r_2 are uniform random numbers.

According to (2), we know that the agent has a rotation angle limit. Comparing the angle between v^{t+1} and the fixed feasible directions, the closest direction is selected as v^{t+1}.

Since the agent does not know the global information of the map, it is difficult to select its local velocity D_{local} and global velocity D_{gobal}. In this paper, the agent refers to the regional necessity information when selecting D_{local} and D_{gobal}, so that the time to complete the task is greatly shortened.

Take the agent as the center and the detection radius r as the side length. Calculate the sum of regional necessity U_w along each feasible direction, and take the unit vector of the direction with the largest regional necessity as the local motion direction D_{local} :

$$deta\_U_w = \begin{cases} 0, \exists G(l) = 1 \\ \sum_l U_w, else \end{cases} \quad (10)$$

$$D_{local} = \max deta\_U_w \quad (11)$$

In this paper, the area with the regional necessity $U_w \ge \delta$ is defined as the key search area. We use the k-means method to cluster the regional necessity in the map into n key points of the area. Among them, P_q is the basis for dividing the area:

$$P_q = \left\{ P_q \in U_{w_{ij}} \middle| P_q \ge \delta \right\} (q = 1, 2, ..., n) \quad (12)$$

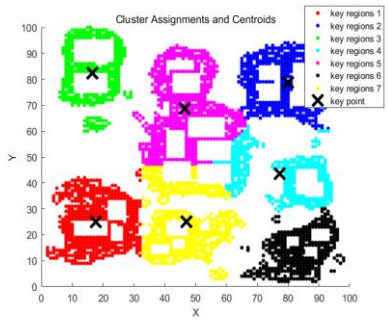

Fig. 4: Clustering regions

In Fig. 4, the map is clustered into 7 key regions according to the regional necessity. The black cross is the center point of the cluster, and the seven regions with different colors indicate that the regional necessity is higher than the threshold δ , and it is clustered into the same key region.

The agent measures the distance to the area P_q by the distance from the key point. The agent selects the area with the greatest degree of regional necessity and the closest distance as the target area, and the key point of the target area is selected as the global optimum.

$$goalpoint = \max \frac{P_q}{l_q} \tag{13}$$

$$D_{gobal} = \frac{A^t_{pos_i} - goalpoint}{\left\| A^t_{pos_i} - goalpoint \right\|} \tag{14}$$

If two agents are in the range r and their speed directions are the same, reselect the global target for the rear agent and calculate the speed. If the final calculated speed is an infeasible direction, use the A-star algorithm to jump out of the dead zone.

The detailed process of the search strategy is as follows:

Search strategy

Initialize map information $r_q(x_q, y_q)$;

Calculate w_{ij} according to (1);

Initialize the agent perception map U_{ij} and position $A^t_{pos_i}$;

While (presence of undiscovered target)
{
update regional necessity U_w according to (8);
calculate the local motion direction D_{local} according to (10), (11);
calculate the local motion direction D_{gobal} according to (13), (14);
calculate v^{t+1} according to (9);
if ($\left| A^t_{pos_i} - A^t_{pos_j} \right| \le 2R$)
  $A_{ownmap_i} = A_{ownmap_j}$;
  if (($\left| A^t_{posi} - A^t_{pos\,j} \right| \le r$) & ($v_i^{t+1} = v_j^t$))
    reselect goalpoint;
    update D_{gobal} according to (14);
    update v^{t+1} according to (9);
  end if
end if
Update $A^{t+1}_{pos_i}$ according to (2);
Update U_{ij} according to (7);
}

4 Post-earthquake Scenario Simulation Experiment and Analysis

In order to demonstrate the effectiveness of the search strategy, some simulation experiments are performed in MATLAB.

The simulation environment is a 100*100 grid space. The search radius of agents $r = 4$, and the communication radius of agents $R = 15$. Environmental obstacles randomly generate small obstacles around the building based on the pre-disaster map. Except for the number of targets and the environmental boundary, the agent only knows the pre-disaster map information. During the task, the agent plans and selects the path online in real time. The agent's initial position is at the boundary of the environment, and the target position is randomly set. The moving direction of the agent is the surrounding 8 grids.

The first work verifies the high efficiency by comparing the results of the detection using different methods. The second work carried out dynamic verification experiments to observe whether the search algorithm has stability under dynamic emergencies.

4.1 Experiment of Post-earthquake Search

After the disaster occurs, all agents start from the same place. If the search is completed, the search completion time will be counted. Taking the maximum search completion time as the evaluation metric. And the time will be calculated after 25 experiments.

The algorithm in this paper (UPSO) is compared with the ant colony algorithm based on regional necessity (UACO) and the particle swarm algorithm based on unknown degree (LUDS-H)[19].

Table 1: Parameter Table

Algorithm	Parameter	Definition	Value
UPSO	w	Inertia weight	0.8
	c_1	Acceleration factor	2
	c_2	Acceleration factor	2
UACO	α	Heuristic factor	1
	β	Heuristic factor	7
	ρ	Pheromone volatilization rate	0.3
	Q	Pheromone Enhancement Coefficient	1
	$\max\_gen$	Number of iterations	100
	M	Number of ants	50
LUDS-H	r_1	Inertia weight	0.8
	r_2	Acceleration factor	2
	r_3	Acceleration factor	2

The ant colony algorithm is that the ants choose their own path according to the strength of the pheromone. The ant colony algorithm based on regional necessity combines the regional necessity with the pheromone enhancement and volatilization. Because it is an unknown map, during each iteration, the ants will choose their own direction according to the roulette wheel.

The particle swarm algorithm based on unknown degree selects the path based only on the degree of information mastery of the map, without considering the heuristic target distribution probability information, and the rest of the speed update is consistent with the algorithm of this subject.

The parameter settings are shown in Table 1. After experimental verification, the parameters shown in Table 1 are all selected parameters that are most suitable for this experimental environment.

The initialization result of the search task is shown in Fig. 5. The orange point is the starting position of the agent, and the red point is the position of the task point that needs to be discovered.

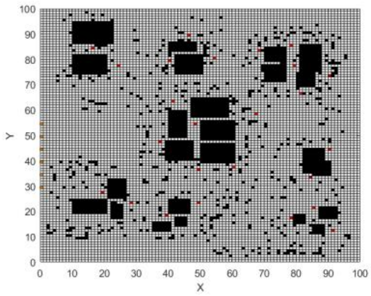

Fig. 5: Initialization

The search result is shown in Fig. 6. The colored lines are the agents' search path, and the orange area is the area searched by the agent. In Fig. 6, agents start from the adjacent points on the same side of the map, and search in the direction of dense buildings in the map. The searched area is the area not searched by other agents, and the phenomenon of repeated searches is relatively small. But inevitably, due to the limited range of inter-agent communication, agents will pass through places that other agents have already passed.

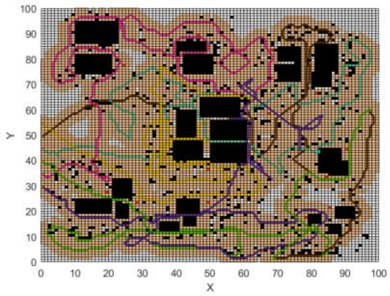

Fig. 6: Final state-UPSO

The maximum time average number of search completions is shown in Table 2.

Table 2: Experimental Results

Number of tasks	Number of agents	UPSO(s)	UACO(s)	LUDS-H(s)
10	6	**564.32**	799	938
25	6	**714.67**	911.33	938
35	6	**859.58**	912	936
50	6	**904.33**	1006	1100

The search strategy based on regional necessity is higher than the search strategy based on unknown degree under different task scales, and the difference is more obvious in the case of small-scale tasks.

From the perspective of algorithm analysis, particle swarm algorithm is more suitable for search tasks in complex unknown environment than ant colony algorithm. Because the ant colony algorithm is a probabilistic algorithm, and it is more dependent on the global feasible path situation. Therefore, in the context of this problem, the search efficiency of particle swarm optimization is higher. As the task size increases, the performance difference between particle swarm algorithm and ant colony algorithm decreases.

In general, in the context of small-scale tasks, the search strategy and algorithm performance of the particle swarm algorithm based on the regional necessity are better than those of other strategies and algorithms. As the scale of the task increases, the difference decreases, but it still maintains certain advantages, which proves its effectiveness.

4.2 Dynamic Capability Verification Experiment under Aftershock

In the post-earthquake environment, secondary disasters such as aftershocks often occur, causing buildings in some areas to collapse again. At this time, the environmental information changes, and the agent becomes unknown to the area again. At the same time, the agent may be destroyed in this area, the original task information will also disappear, and the area needs to be searched again by other agents.

In this section, experiments are set up to verify the dynamic performance of the algorithm and observe whether the agent can respond timely and effectively according to the algorithm. The agent motion model is shown in section 2.2. By changing the location of aftershocks and the number of new tasks, five experimental scenarios are set as shown in Table 3.

Table 3: Aftershock Scenarios

Scenarios	1	2	3	4	5
Aftershock area	$x \in [15, 42]$ $y \in [2, 30]$			$x \in [30, 60]$ $y \in [40, 70]$	$x \in [10, 40]$ $y \in [60, 90]$
New tasks	6	8	10	10	10
Original tasks	25				
Agents number	6				
Map size	100*100				
Starting position	Approach point				

The number of experiments for each algorithm is 25 times. The results are shown in Fig.7.

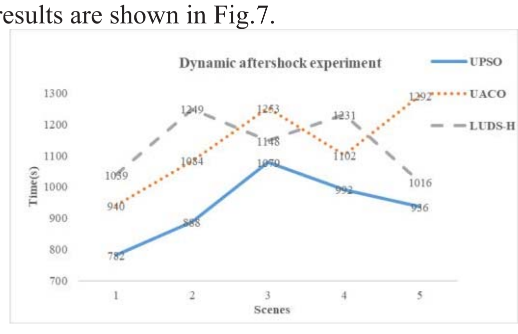

Fig. 7: Dynamic aftershock experiment

In Fig.7, the horizontal axis is 5 scenes, the vertical axis is the search time required for each scene. When the number of new tasks increases, the search time required by each algorithm gradually increases. Among them, UPSO outperforms the others in each scenario. When the aftershock area changes, it has less impact on the search time and is mainly related to its location. Locations close to the agent's search point are shorter.

Fig. 8 is the map of unknown degrees before and after aftershock. The yellow area has the largest unknown degree, and the blue area is the area detected by the agent. We can see that a yellow area is added to the blue area after the occurrence of an emergency. Fig. 9 shows the change of the agents' search path before and after aftershocks. After the aftershock occurs, the regional necessity of the aftershock area becomes larger, and the possibility of the agent to explore this area increases, and it tends to search for this area.

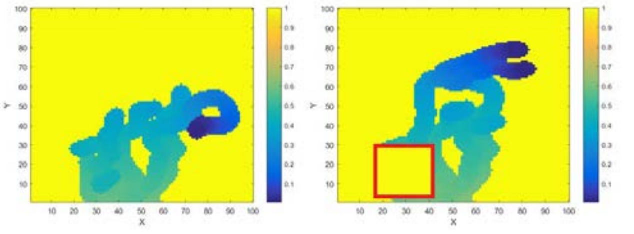

Fig. 8: Unknown map before and after aftershock (the red box is the aftershock area)

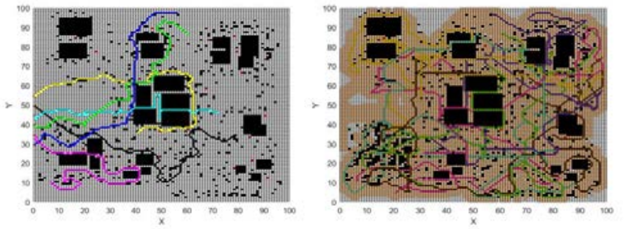

Fig. 9: Agent path before and after aftershock

By changing the location of aftershocks and the number of new tasks, the effectiveness of the particle swarm algorithm based on regional necessity can be verified in a complex dynamic environment.

5 Conclusion

The environment of post-disaster is dynamic and unknown. The main idea is to improve search efficiency. This paper proposes a target search strategy based on regional necessity, which combines the target distribution probability and the perception of the environment. The gradient of the regional necessity is utilized to integrate local optimal points and global optimal points based on the particle swarm optimization. The search strategy based on regional necessity can decrease the search time and improve the efficiency confirmed by the comparative experiments, especially in the small and medium-scale task environment. At the same time, it is verified that the search strategy can be effectively applied to dynamic environments through experiments such as aftershock simulation. In future work, the strategy will be considered to improve the search efficiency in large-scale environment.

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