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Research Article

Multitarget Search of Swarm Robots in Unknown Complex Environments

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When searching for multiple targets in an unknown complex environment, swarm robots should firstly form a number of subswarms autonomously through a task division model and then each subswarm searches for a target in parallel. Based on the probability response principle and multitarget division strategy, a closed-loop regulation strategy is proposed, which includes target type of member, target response intensity evaluation, and distance to the corresponding individuals. Besides, it is necessary to make robots avoid other robots and convex obstacles with various shapes in the unknown complex environment. By decomposing the multitarget search behavior of swarm robots, a simplified virtual-force model (SVF-Model) is developed for individual robots, and a control method is designed for swarm robots searching for multiple targets (SRSMT-SVF). The simulation results indicate that the proposed method keeps the robot with a good performance of collision avoidance, effectively reducing the collision conflicts among the robots, environment, and individuals.

1. Introduction

Swarm robotics is inspired by the self-organization behavior of social animals such as ants and bees. It aims to make the system consisting of a swarm of simple agents exhibit the desired intelligent behavior with the advantages of robustness, flexibility, and scalability [1]. Then, the system is used to complete more complex tasks by the coordinated control of agents and the interaction between the agents and the environment [2–4].

After years of research and development, the swarm robots system has been successfully applied to complete a large number of collaborative tasks as well as the target search tasks [5–7]. According to the number of targets, the search problem can be divided into single target search problem and multitarget search problem. In terms of single target search, some researchers have focused on the collaborative research among individuals. For example, Ducatelle et al. [8] enhanced the interaction between individual robots by the use of local wireless communication strategies; aiming at the characteristics and limitations of the search space, Dadgar et al. [9] proposed an adaptive particle swarm optimization algorithm for robot control. Hong-qiang et al. [10] abstracted a simplified virtual-force model for swarm robots hunting problem and designed the kinematic control input of the robot based on the model. In addition, some work is also devoted to parameter optimization and system modeling. Doctor et al. [11] extended the particle swarm algorithm to the modeling of the swarm robots system, focusing on the optimization of algorithm parameters. In case of multitarget search task, the situation will be different. The swarm robots must first be divided into several subswarms through the task division strategy and then search for their respective targets collaboratively [12, 13]. According to the target signal strength detected by the robots, a packet

strategy is developed by Derr et al. [14] and then the subswarms cooperatively search for their targets by the particle swarm algorithm principle. However, this approach lacks a subswarm size adjustment mechanism. Zhang et al. [15] proposed a dynamic task division strategy with closed-loop regulation for multitarget search of swarm robots, which considered the coordination of the subswarm. However, this strategy removed some advantageous individual members when adjusting the size of the sub_swarm and did not take into account of some underlying behaviors, such as collision and roaming. Manzoor et al. proposed a multirobot coordination and navigation algorithm for intercepting the long distance targets [16]. In order to improve the communication efficiency during the plan consensus, Kim et al. developed a decentralized multi-UAV task allocation algorithm and a consensus-based binding algorithm for grouping the UAVs based on their task preferences [17]. The multitarget particle swarm optimization is an effective tool for solving multitarget optimization problem [18]. In order to consider practical constraints for the collaborative search of robot swarms, Yang et al. proposed a collaborative search method for robot swarms based on constrained particle swarm optimization [19]. Ibraheem et al. combined the improved fruit fly optimization algorithm and the modified adaptive particle swarm optimization algorithm to design a novel neural network-based fractional PID controller for mobile robots [20].

In view of the above problems, the task allocation in this paper is performed based on the probability principle and target response threshold, and a closed-loop regulation strategy is introduced, including target type, target incentive intensity, and distance to communicating individual, so as to reasonably allocate the level of robot resources. For the collision avoidance problem of robots in an unknown complex environment, the simplified virtual-force analysis model of individual robot is firstly abstracted, and then it is introduced into the subswarm alliance and the roaming individuals. The input strategy of robot motion control is designed accordingly. Furthermore, a roaming searching strategy is designed, which aims to keep different search directions with two nearest neighbors and guarantee the largest search area. Simulation experiments are performed in the environment containing convex obstacles with various shapes, and the results demonstrate that the swarm robots searching for multiple targets based on the proposed simplified virtual-force model (SRSMT-SVF) can reasonably configure the robot resource level and effectively avoid collisions among the internal members of the system and between the system and the environment.

2. Model Construction

2.1. Kinematics Model and Related Functions of Mobile Robots. Considering a swarm robot system with multiple identical autonomous mobile robots, the kinematic equation of individual robot R is as follows:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} \cos\theta(t) & 0 \\ \sin\theta(t) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V(t) \\ \omega(t) \end{bmatrix}, \tag{1}$$

where $V(t)$ and $\omega(t)$ are the linear velocity and angular velocity of the robot, respectively. And, $|V(t)| \le V_m$, $|\omega(t)| \le \omega_m$; V_m and ω_m are the maximum linear velocity and the maximum angular velocity, respectively. The linear acceleration and angular acceleration satisfy $|\dot{V}(t)| \le a_m$ and $|\dot{\omega}(t)| \le \omega_{am}$, respectively, where am and ω_{am} represent the maximum line acceleration and the maximum angular acceleration, respectively.

Definition 1. φ_i and φ_j denote the angles of the directional line l_i and l_j, respectively, and φ_{ij} represents the angle from l_i to l_j [21], which is defined as

$$\varphi_{ij} = \mathrm{dvgl}\left(\varphi_i - \varphi_j\right). \tag{2}$$

The analytical expression of the function dvgl (•) is as follows:

$$\mathrm{dvgl}(x) = x - 2\pi \mathrm{sgn}(x) \cdot \psi(|x| - \pi), \tag{3}$$

where

$$\psi(x) = \begin{cases} 1, & x > 0, \\ 0, & x \le 0. \end{cases} \tag{4}$$

Definition 2. In the search environment, the forcing functions of various objects (e.g., targets, robots, and obstacles) are defined as

$$f_{\mathrm{at}}^{i} = \left\| V_i^{\mathrm{ac}}(t+1) \right\|, \tag{5}$$

$$f_{\mathrm{rr}}(d) = \frac{c}{\left[\left(d/c_r \right)^2 \right]}, \tag{6}$$

$$f_{\mathrm{ro}}(d) = \frac{c}{\left[\left(d/c_s \right)^2 \right]}, \tag{7}$$

where $V_i^{\mathrm{ac}}(t+1)$ is the velocity vector of robots at time $t+1$, f_{at}^{i} indicates the gravitational interaction of the target t acting on the robot r (assuming that the movement of the robot to the target is due to the presence of this gravity), d is the distance between two points, and r is mainly used for routing optimization, and c_r and c_s represent the potential field radius of the robots and obstacles, respectively.

2.2. Multitarget Search Strategy. The multitarget search problem in an unknown environment mainly involves two major issues: the construction of the self-organizing task division model and the coordination of the subswarms and individuals. In addition, it entails the planning of some underlying behaviors is entailed, such as collision avoidance, collaborative search, and roaming strategy. In this subsection, the associated mathematical model is established and elaborated [10].

In an unknown complex environment, it is assumed that the ternary set $M = \{R, T, S\}$ includes the swarm robots $R = \{R_i, i = 1, 2, \ldots, m\}$, the search targets $T = \{T_j, j = 1, 2, \ldots, n, n > 1\}$, and the static convex obstacles $S = \{S_k, k = 1, 2, \ldots, o_s\}$. In the global coordinate system XOY, the position of object p, robot, or obstacle, is denoted as $O_p = \{(x_p, y_p) \mid p \in M\}$. c_r, c_s, r_{dec}, and r_{com} represent the radius of individual potential field, the maximum collision avoidance distance, the maximum perceived distance, and the maximum effective corresponding distance, respectively. Generally, $r_{\text{com}} > r_{\text{dec}} > c_r > c_s$. Therefore, the static obstacles that the robot needs to avoid can be expressed as $N^i_{\text{RS}} = \{k \in S\colon \|(x_{R_i} - x_{S_k}) - (y_{R_i} - y_{S_k})\| < c_s\}$, and the individual robot within its potential filed radius and communication range are recorded as

$$\begin{aligned} G^i_{\text{RR}} &= \left\{h \in R\colon \left\|\left(x_{R_i} - x_{R_h}\right) - \left(y_{R_i} - y_{R_h}\right)\right\| < c_r\right\}, \\ C^i_{\text{RR}} &= \left\{t \in R\colon \left\|\left(x_{R_i} - x_{R_t}\right) - \left(y_{R_i} - y_{R_t}\right)\right\| < r_{\text{com}}\right\}. \end{aligned} \tag{8}$$

The perceived target is recorded as

$$N^i_{\text{RT}} = \left\{j \in T\colon \left\|\left(x_{R_i} - x_{T_j}\right) - \left(y_{R_i} - y_{T_j}\right)\right\| < r_{\text{dec}}\right\}. \tag{9}$$

3. Self-Organizing Multitask Division Strategy Based on Target Response

3.1. Target Incentive. The swarm robots system is composed of a large number of individual robots based on multisensor structure in this paper. The robot can perceive changes of its surrounding environment and target signals through various sensors equipped. It is assumed that the target can continuously emit perceivable signals with certain characteristics. Due to the distance difference between target and robot, the target response intensity detected by the robot will also be different. Here, the target response function is used to describe this intensity [22, 23]:

$$I_{ij}(d) = \begin{cases} \dfrac{mP}{d^2} + \eta(\cdot), & d \le d_0, \\ 0, & d > d_0, \end{cases} \tag{10}$$

where P is the constant signal power emitted by the center of the target and I_{ij} is the response intensity of the robot R_i to the target T_j, which is inversely proportional to the square of the distance, d represents the distance between the robot and the target, d_0 is the maximum perceived distance of the robot, and m and $\eta()$ represent the attenuation coefficients of the target signal in the environment and the disturbance of the environment, respectively, and $0 \le m \le 1$.

3.2. Multitask Division Model Based on Response Threshold of the Target. Given a multitarget search task, the swarm robot system needs to be autonomously divided into several subswarms according to the target detection, and then all the subswarms cooperatively search for the corresponding target in parallel [24–26]. The overall search efficiency of the system can be greatly improved. Therefore, the primary task is to solve the multitarget problem by constructing a reasonable and effective task division model. Using the existing task division strategy based on the target response threshold, an internal descending sorting principle is introduced in this paper, which combines the target type, target response intensity, and distance to communicating individuals of subswarms. Besides, a multitask division model with closed-loop regulation is proposed. When performing multitarget search task, each target can be treated as a subtask and each robot can participate in a subtask. It is noted that the multiple robots are allowed to participate in a subtask, while a robot can only execute one subtask. Denote the target response threshold as $I_{\min}$ ($I_{\min} = I(d_0)$). If the response value of the target T_j detected by robot R_i satisfies $I_{ij}(d) > I_{\min}$, T_j will be regard as one of its candidate intentional targets by R_i. Denote $P(i, j)$ as the probability that the robot R_i chooses the target T_j as its own target. $P(i, j)$ can be written as

$$P(i, j) = \frac{I_{ij}(d)^2}{\sum_{k \in \text{intention}_i} I_{ik}(d)^2}, \quad \forall j = \{1, 2, \ldots, n\}, k \in \text{intention}_i, \tag{11}$$

where intention_i ($i = 1, 2, \ldots, m$) is the set of alternative intention targets for robot R_i. Let Randi be a random number uniformly distributed on the interval (0, 1). If $P(i, j) >$ Randi, the robot R_i will choose the target T_j as its own search goal. For an individual robot whose alternative intentional target set is not empty, the detected target response needs to be evaluated and the intent target needs to be determined in the same way.

3.3. Dynamic Closed-Loop and Self-Organizing Task Division Model

3.3.1. Construction of Robot Information Card. In an unknown complex environment, the individual robot can directly detect the target signals through sensors and calculate the target response intensity by equation (10). The directly detectable targets are classified as target I. Meanwhile, the robots can share information such as the target perception through local communication, which expands the cognitive range of individuals. Therefore, the robot can obtain the cognitive information of targets by interacting with other robots within the communication range, and such targets are classified as target II. Obvious, target I has priority over target II. According to the cognitive information acquired by the robot and the state of the robot itself, the structure of individual robot information card is defined as shown in Table 1.

As shown in Table 1, the robot information card includes robot number, search target, task set, target response incentive, communicating individual, distance to the communicating individual, intentional target, and individual state. Since the robot can simultaneously perceive multiple target information and communicate with multiple robots, some elements in the individual robot information card are

Table 1: Examples of the robot information card.

Robot	Target set	Task type set	Task incentive set	Communicating individual set	Distance to the communicating individual distance set	Intention target	Individual state
R_1	$\{T_1, T_3\}$	{type I, type I}	{4.3324, 1.7674}	ϕ	ϕ	T_1	1
R_2	$\{T_1, T_3\}$	{type II, type II}	{4.3324, 1.7674}	$\{R_1\}$	231.1376	T_1	1
R_3	ϕ	ϕ	ϕ	ϕ	ϕ	ϕ	0
R_4	$\{T_4\}$	{type I}	{2.3378}	ϕ	ϕ	T_4	1
R_5	$\{T_4\}$	{type II}	{2.3378}	$\{R_4\}$	128.9953	T_4	1
R_1	$\{T_1, T_3\}$	{type I, type I}	{4.3324, 1.7674}	ϕ	ϕ	T_1	1

embodied in the form. If the robot has no the cognition of a certain part, the corresponding remark is expressed as ϕ. The individual state information refers to current search state of the robot, including roaming state (indicated by 0) and collaborative search state (indicated by 1).

3.3.2. Formation of Subswarms. Once the intentional target is determined, the robot will carry out a self-organizing task division on the individual level, aiming to guarantee that the robots with the same intentional target collaboratively perform the local search in the form of subswarm alliance, and then the system can execute the task in parallel. When the subswarm is formed, the subswarm information card is defined as shown in Table 2, which can be used to facilitate the acquisition of information within subswarms and the interaction between the subswarms.

Subswarm information card includes its number, subswarm target, leader, member information, size, recruitment number (recruit number), and optimal records. For the part with noncognition, it is denoted as ϕ. As the external speaker of the subswarm, the leader is the most dominant individual and the target of the nearest robot in the subswarm. In this paper, the upper limit of subswarm size is $N_{\max} = 6$, and M robots can be recruited to a subswarm, where $M = N_{\max} - N$ and $M \leq N_{\max}$. In addition, each subswarm holds its own optimal record table, including the optimal information of its searching target and other I targets (called alternative targets) acquired by the subswarm during the search process. The noncognition part in the table is denoted by "—."

3.3.3. Evaluation of Subswarm Scale and Closed-Loop Regulation. Based on the target response threshold and probability principle, the task division model is established, and a closed-loop adjustment strategy is proposed: when performing task division, the level of robot resource allocation is evaluated for the subswarms that exceed the upper limited size. And, the evaluation results are taken as the negative feedback of the task division model to regulate the migration of some robots between different subswarms.

This strategy can effectively handle the serious imbalance of the resource allocation in the swarm robots system, so that the robot resources are rationally and effectively configured. As shown in Section 3.3.1, the targets are classified as type I and type II, and the priority of type I is higher than that of type II. In order to assess whether the size of the subswarms exceeds the upper limit size, it is necessary to prioritize their internal members. Firstly, the internal members of the subswarms are sorted according to the categories of their targets. The position of members with the target type I is superior to those with the type II target. If the target category is the same, the descending sorting of the members is performed according to the target incentive intensity. For robots with the same type II target, they obtain the target information by communicating with the same neighborhood; if the strength of the target incentive is the same, they can be sorted according to the decline of the distance to the communicating individuals. The details are shown in Table 3.

As shown in Table 3, the task type for R_1, R_5, R_7, and R_8 is type I and the task type for R_2, R_3, R_4, and R_6 is type II. According to the above ranking rules, the dominant position of the robots with type I targets should be higher than that of the individuals with type II targets. In case of the same task target type, the higher the task incentive priority, the higher the dominant position. Hence, R_1 has the greatest advantage in the subswarm. For individuals with the same type II target and the same target incentive, the closer the distance to the communicating robot, the more advantage they have. Therefore, R_2 has an advantage over R_3. Since the upper limit of the subswarm size is set to 6 robots, R_4 and R_6 do not enter the top 6. They will be out of the subswarm and then trigger the punishment mechanism; then, they cannot participate in the task division for a period of time. After the punishment, R_4 and R_6 can still join the subswarm. Via the withdrawing the union and the second-join mechanism, the dynamic migration of several robots between different subswarms is realized and the robot resources can be allocated reasonably.

4. Searching Algorithm

Figure 1 shows the flowchart of multitarget search algorithm for swarm robots in an unknown complex environment.

4.1. Simplified Virtual-Force Model. In the global coordinate system XOY, it is assumed that the robot R_i can sense the local information of the two nearest neighbors p_1 and p_2, which may be individual robots and static convex obstacles, through the sensors. As shown in Figure 2, the coordinate

Table 2: Examples of the subswarm information card.

Numbering	Target	Leader	Members	Task type set	Task incentive	Distance to the target
Sub_1	T_1	R_1	$\{R_1, R_2\}$	{type I, type II}	{4.33, 4.33}	$\{\phi, 231.13\}$
Sub_4	T_4	R_4	$\{R_4, R_5\}$	{type I, type II}	{2.33, 2.33}	$\{\phi, 128.99\}$

Historical optimum records of subswarm								
Number	RecruitNum	Searching target			Alternative target			
		Robots	Task incentive	Optimal position	Target	Robots	Task incentive	Optimal position
2	4	—	—	—	T_3	R_1	1.76	(x_{R_1}, y_{R_1})
2	4	—	—	—	—	—	—	—

Table 3: Robot sorting in subswarm.

Robots	Target type	Signal strength	Communication individuals in the neighborhood	Distance to the communication individuals	Order status
R_1	Type I	10.7483	ϕ	ϕ	1
R_2	Type II	10.7483	R_1	58.7324	5
R_3	Type II	10.7483	R_1	131.0357	6
R_4	Type II	4.7578	R_5	112.5613	7
R_5	Type I	4.7578	ϕ	ϕ	3
R_6	Type II	1.6476	R_8	83.8139	8

position of the robot at time t is R_i (x_i, y_i) and the position vector $\mathbf{d}_{ip1}$, $\mathbf{d}_{ip2}$ are defined as

$$\begin{aligned}\mathbf{d}_{ip1} &= \left(x_{p1} - x_i\right) + i\left(y_{p1} - y_i\right),\\ \mathbf{d}_{ip2} &= \left(x_{p2} - x_i\right) + i\left(y_{p2} - y_i\right).\end{aligned} \tag{12}$$

When moving to p_0 at the speed of $V_{\text{if}}(t+1)$, robot R_i will be subjected to the gravitational effect of p_0 and the repulsive effects of p_1 and p_2, which are denoted as $\mathbf{f}_{\text{ac}}$, $\mathbf{f}_{\text{re1}}$, and $\mathbf{f}_{\text{re2}}$, respectively. The directed angles from $\mathbf{f}_{\text{ac}}$, $\mathbf{f}_{\text{re1}}$, and $\mathbf{f}_{\text{re2}}$ to x-axis positive direction are recorded as γ_{fac}, γ_{fre1}, and γ_{fre2}, respectively. $\mathbf{f}_{\text{rem}}$ is the resultant force of the repulsive force, which is received by the robot in a direction perpendicular to the desired direction of the motion, and $\gamma_{\text{frem}} = \gamma_{\text{fac}} - (\pi/2)$ represents the directed angle from $\mathbf{f}_{\text{rem}}$ to the positive direction of the x-axis. $\mathbf{f}_{R_i}$ is the resultant force of R_i.

At the time step t, the resultant force of the robot R_i represents its actual demand speed, which can be defined as

$$V'_{\text{if}}(t+1) = \mathbf{f}_{R_i} = \mathbf{f}_{\text{ac}} + \mathbf{f}_{\text{rem}} = f_{\text{ac}} e^{j\gamma_{\text{fac}}} + f_{\text{rem}} e^{j\gamma_{\text{frem}}}, \tag{13}$$

where

$$f_{\text{rem}} = \left(f_{\text{re1}}\left(\left\|d_{ip1}\right\|\right) \cdot \cos\left(\text{dvgl}\left(\gamma_{\text{frem}} - \gamma_{\text{fre1}}\right)\right) + f_{\text{re2}}\left(\left\|d_{ip2}\right\|\right) \cdot \cos\left(\text{dvgl}\left(\gamma_{\text{frem}} - \gamma_{\text{fre2}}\right)\right)\right), \tag{14}$$

where $\mathbf{f}_{\text{ac}}$ is the force function calculated by equation (5), acting on the next position of the robot. $f_{\text{re1}}(\|d_{ip1}\|)$ and $f_{re2}(\|d_{ip2}\|)$ are the force functions produced by p_1 and p_2, respectively, which are calculated by equations (6) and (7). $\text{dvgl}(\gamma_{\text{frem}} - \gamma_{\text{fre1}})$ is the deflection angle of $\mathbf{f}_{\text{re1}}$ and $\mathbf{f}_{\text{rem}}$, so is $\text{dvgl}(\gamma_{\text{frem}} - \gamma_{\text{fre2}})$. If $\mathbf{f}_{\text{rem}}$ is directly equivalent to the velocity $V_{\text{ir}}(t+1)$ perpendicular to the direction of the movement at next step, $V_{\text{ir}}(t+1) = \mathbf{f}_{\text{rem}}$, $V'_{\text{if}}(t+1) = V_{\text{if}}(t+1) + V_{\text{ir}}(t+1)$.

4.2. Extended Particle Swarm Optimization. The mathematical expression of the swarm robots system model based on the extended particle swarm algorithm [27, 28] is as follows:

$$\begin{cases} V_{\text{ie}}(t+1) = \omega V_{\text{if}}(t) + c_1 r_1 \left(X^*_{\text{if}}(t) - X_{\text{if}}(t)\right) + c_2 r_2 \left(g(t) - X_{if}(t)\right),\\ V_{\text{if}}(t+1) = V_{\text{if}}(t) + \left(V_{\text{ie}}(t+1) - V_{\text{if}}(t)\right) \times \alpha,\\ X_{\text{if}}(t+1) = X_{\text{if}}(t) + V_{\text{if}}(t+1) \times \lambda, \end{cases} \tag{15}$$

where $X_{\text{if}}(t)$ and $V_{\text{if}}(t)$ denote the position and velocity of robot R_i at time step t, respectively, and $V_{\text{ie}}(t+1)$ is the desired speed of the robot at next time step, c_1 and c_2 are the learning factors (usually defined as cognitive coefficient and social coefficient), $r_1, r_2 \in [0, 1]$ are random values, and ω is the inertia weight. The experience of robot R_i in terms of its own

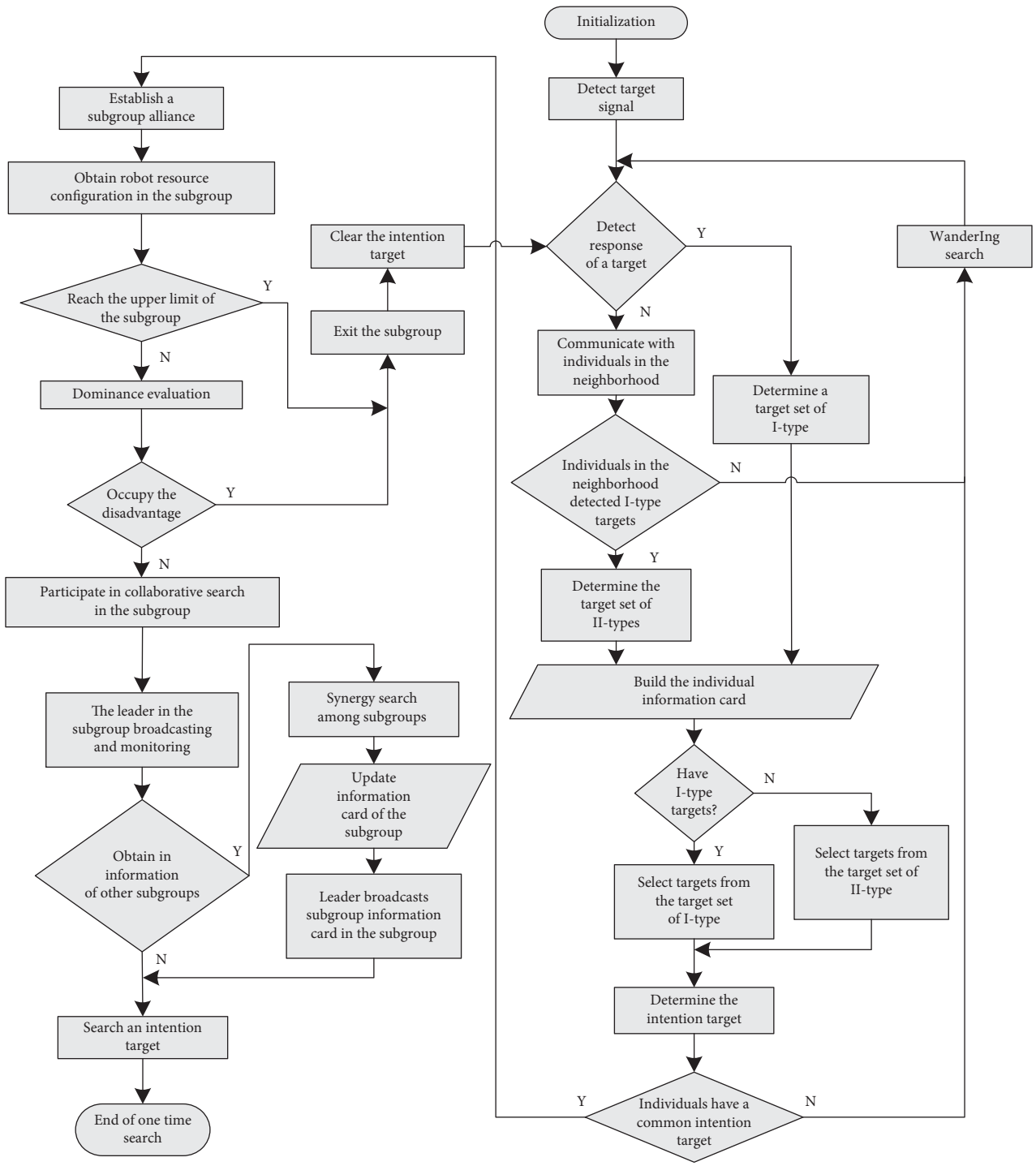

Figure 1: Flowchart of swarm robots search for multitarget in unknown complex environments.

best position thus far are recorded as $X^*_{\text{if}}(t)$, and the position of the best robot in the entire system is denoted as $g(t)$. α is introduced to represent the motion of inertia, and λ is a stride control factor for the embodiment of consequent control.

4.3. Controlling Input of Individual Robot. Based on the simplified virtual-force model (SVF-model) and extended particle swarm optimization (PSO) algorithm, a control input strategy of individual robots is developed in this paper. The actual demand speed and direction of robot R_i are denoted as $V'_{\text{if}}(t+1)$ and $\theta'_{\text{if}}(t+1)$, respectively, and d is the distance to the nearest object. c_m is the maximum collision avoidance distance, indicating that the robot has began to enhance avoiding. According to the different states of the robot R_i, the motive control input is presented as follows.

If R_i is in the roaming state, the motive control input can be written as

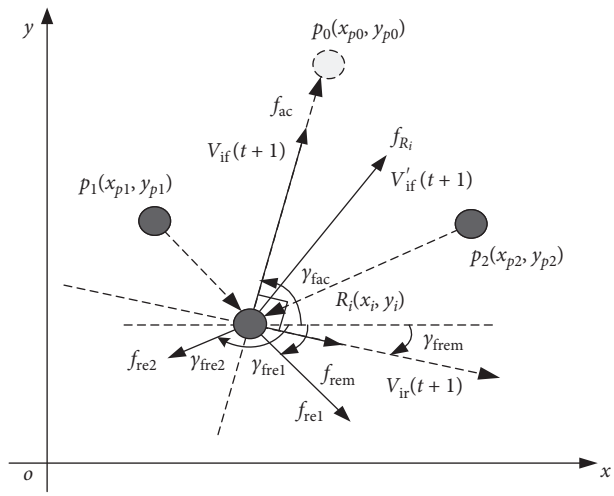

Figure 2: Simplified virtual-force model.

$$\left\{ V'_{if}(t+1) = \left[V_m + V_{ir}(t+1)\right](d \le c_m) + V_m(d > c_m), \theta'_{if}(t+1) = \text{angle}\left(V'_{if}(t+1)\right), \right. \tag{16}$$

where $V_{ir}(t+1)$ is determined by the program in Figure 2 and V_m is the maximum running speed of the robots. Besides, a strategy is designed for the roaming individual: keep driving at the maximum speed and the direction of the robot should be different from its two neighbors, so as to maintain the maximum search area with its two neighbors.

If R_i is in a cooperative search state, the motive control input can be written as

$$\left\{ V'_{if}(t+1) = \left[V_{if}(t+1) + V_{ir}(t+1)\right](d \le c_m) + \left[V_{if}(t+1)\right](d > c_m), \theta'_{if}(t+1) = \text{angle}\left(V'_{if}(t+1)\right), \right. \tag{17}$$

where $V_{if}(t+1)$ is calculated by equation (15).

4.4. Steps of Search Algorithm. According to the model of multitarget search problem in Section 2 and the individual motion input equations in equations (16) and (17), Figure 3 shows the steps of multitarget search algorithm for swarm robots based on the simplified virtual-force model in an unknown complex environment.

5. Simulation

In order to verify the performance of the proposed method, the search experiment of 7 targets is performed on the swarm robots with different sizes ranging from 30 to 80 in steps of 10 in the same search environment. At the same time, the trajectory of the swarm robots with a size of 30 is recorded, and the collision avoidance performance and search performance are analyzed. The system parameters are summarized in Table 4.

5.1. Simulation Results. Here, a simulation experiment is conducted on the swarm robot system. The proposed SRSMT-SVF method and the extended particle swarm optimization algorithm (EPSO) [11] are employed to solve the randomness of the algorithm, and the two strategies with different sizes are repeated 30 times in the same search environment, respectively. Figure 4 compares the average time of the two tasks.

In order to verity the collision avoidance performance and search performance of the proposed algorithm, the simulation results of a swarm robot system with a population size of 30 are recorded. As shown in Figure 4, the black solid line represents the edges of various convex obstacles in the environment; the solid circle represents the targets to be searched; the individual robot is represented by a hollow circle, and the corresponding number is its serial number. Moreover, the motion direction of the robot is also specified, and the subswarm concluded during the search is denoted as Sub_T, where T represents the number of the targets. The members of subswarms are joined by a straight line, and the other unconnected individuals indicate that they are in a roaming state.

As shown in Figure 5(a), the swarm robots are initialized in the rectangular region of 20~80 units, and all robots are in a roaming state at the beginning of the search task. In the case of $T = 69$, after completing the self-organizing task division on the subswarm level, individuals numbered 22, 7, 19, 29, and 3 have successfully formed Sub_1 as shown in Figure 5(b). Accordingly, the search status of the subswarm members change from the roaming state to the cooperative state, while other individuals fail to form a subswarm and continue to search using the roaming strategy.

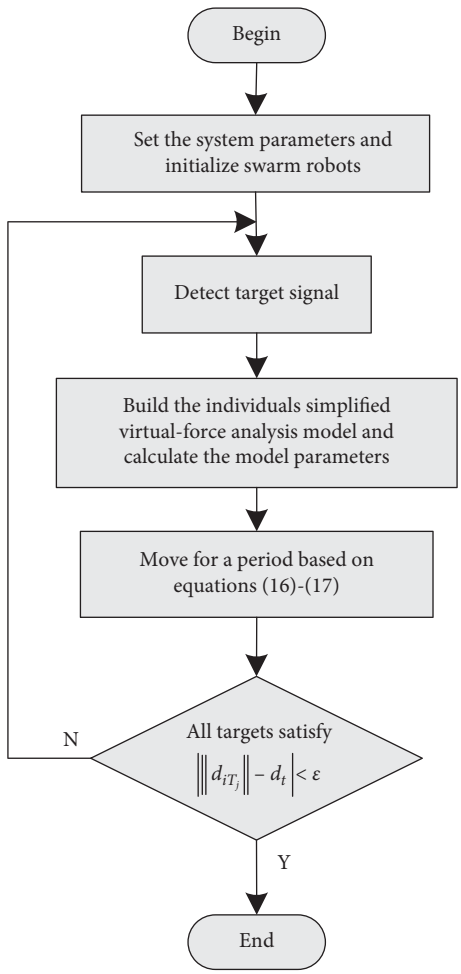

Figure 3: Flowchart of the swarm robots searching algorithm.

Table 4: Parameter settings of the swarm robot system.

Parameter	Value
Searching area	1000 unit × 1000 unit
Number of robots, N_{ro}	30~80
Number of targets, N_{ob}	7
Maximum movement speed of the robot, V_m	5 unit/sec
Maximum radius detecting target, d_0	100 unit
Maximum communication radius, r_{com}	300 unit
Target signal energy, P	10^5
Target signal propagation attenuation coefficient, m	0.1
Response threshold, I_{min}	1
Inertia link, α	0.1
Stride control factor, λ	0.3
Target arrival threshold, d_t	5 units
Virtual-force function coefficient, c	3.9

In the process of searching for target 1, other roaming robots still need to perform the self-organization task division according to the detecting situation of the targets. Moreover, the individuals targeting the same target will form subswarms and search in parallel, greatly improving the search efficiency. In the case of $T = 91$, the individuals numbered 18, 8, 26, 27, 16, and 28 form Sub_3, which searches in parallel with Sub_1, and the details are shown in Figure 5(c).

Figure 5(d) shows the case with $T = 106$, the members of Sub_1 declare that the target has successfully reached, and their status changes to the roaming state correspondingly. Then, the subswarm is disbanded. In addition, the robot numbered 19 can successfully avoid the triangle convex obstacles in the environment.

In the case of $T = 135$, the Sub_3 has successfully searched for target 3, and its search process is shown in Figure 5(e). It can be seen that the members can successfully avoid the polygonal shape of convex obstacles in the environment. When $T = 338$, individuals numbered 21, 7, 19, 22, and 30 form Sub 5 and reach the last target 5. The search process is shown in Figure 5(f). So far, all the targets in the environment have been successfully searched.

5.2. Result Analysis. Observing the entire search process of the swarm robots, it can be seen that the proposed multitask division model with closed-loop regulation strategy can greatly improve the configuration level of robots resource. Meanwhile, the size of subswarm is guaranteed to be within

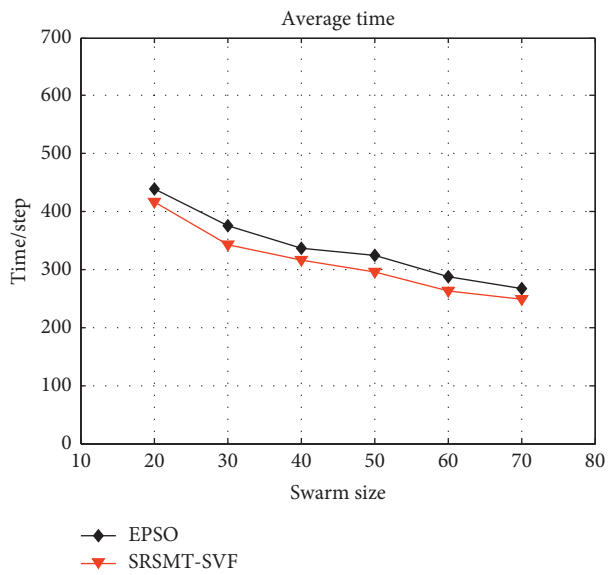

Figure 4: The comparison of average searching times between SRSMT-SVF and EPSO.

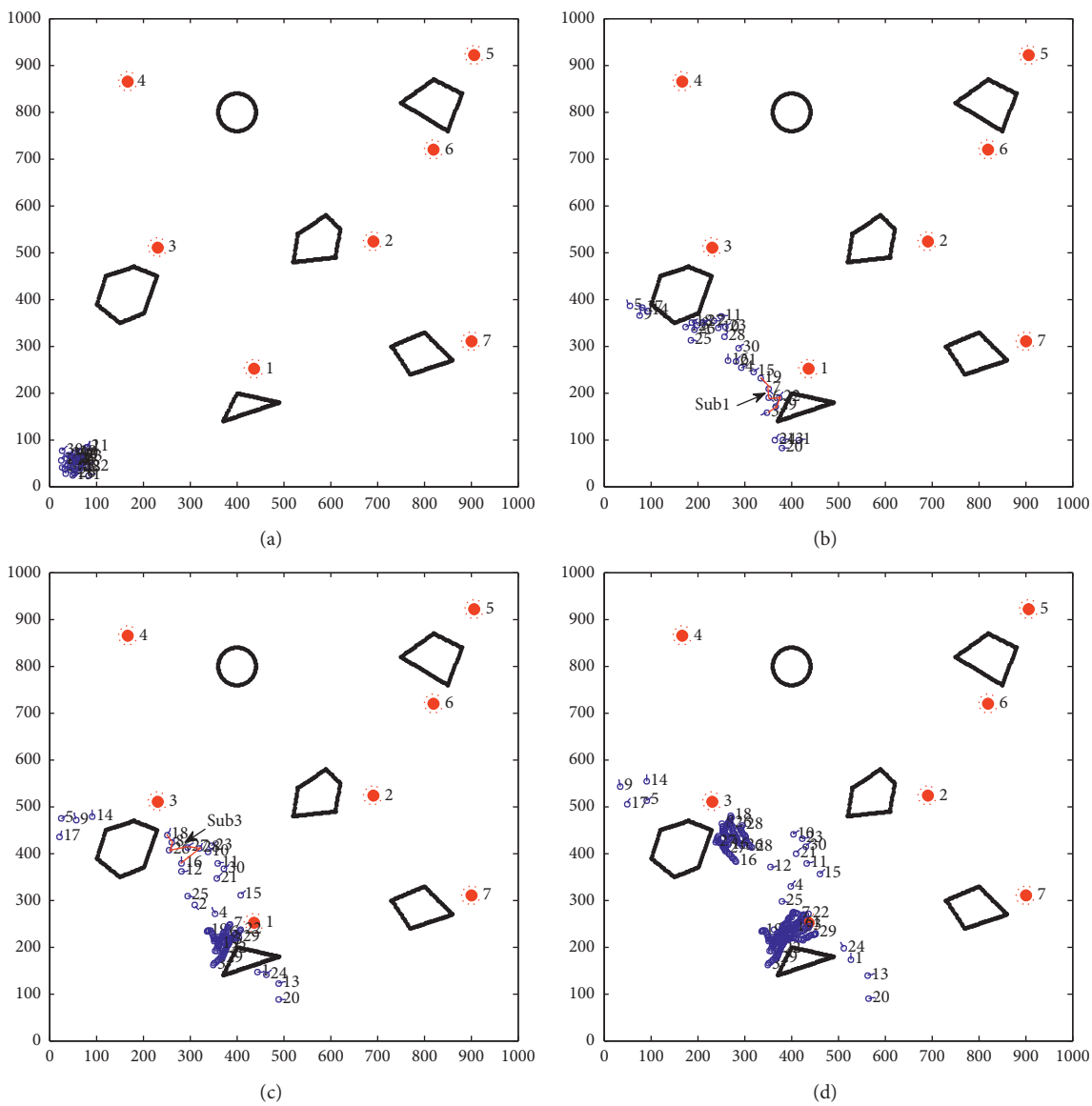

Figure 5: Continued.

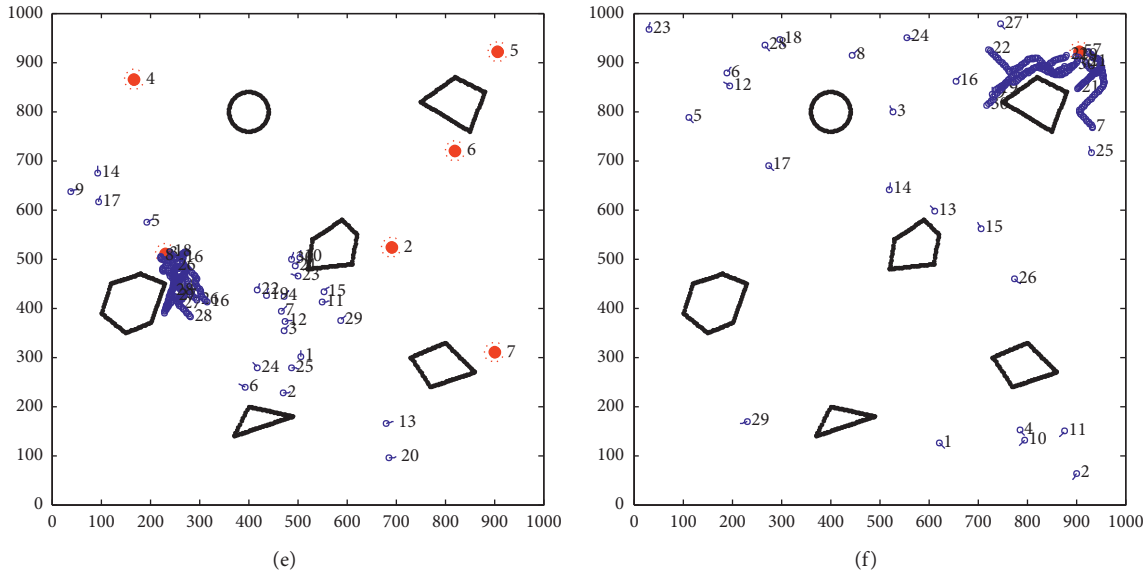

Figure 5: Swarm robots for multitarget search in unknown environments with convex obstacles. (a) $T = 0$, (b) $T = 69$, (c) $T = 91$, (d) $T = 106$, (e) $T = 135$, (f) $T = 338$.

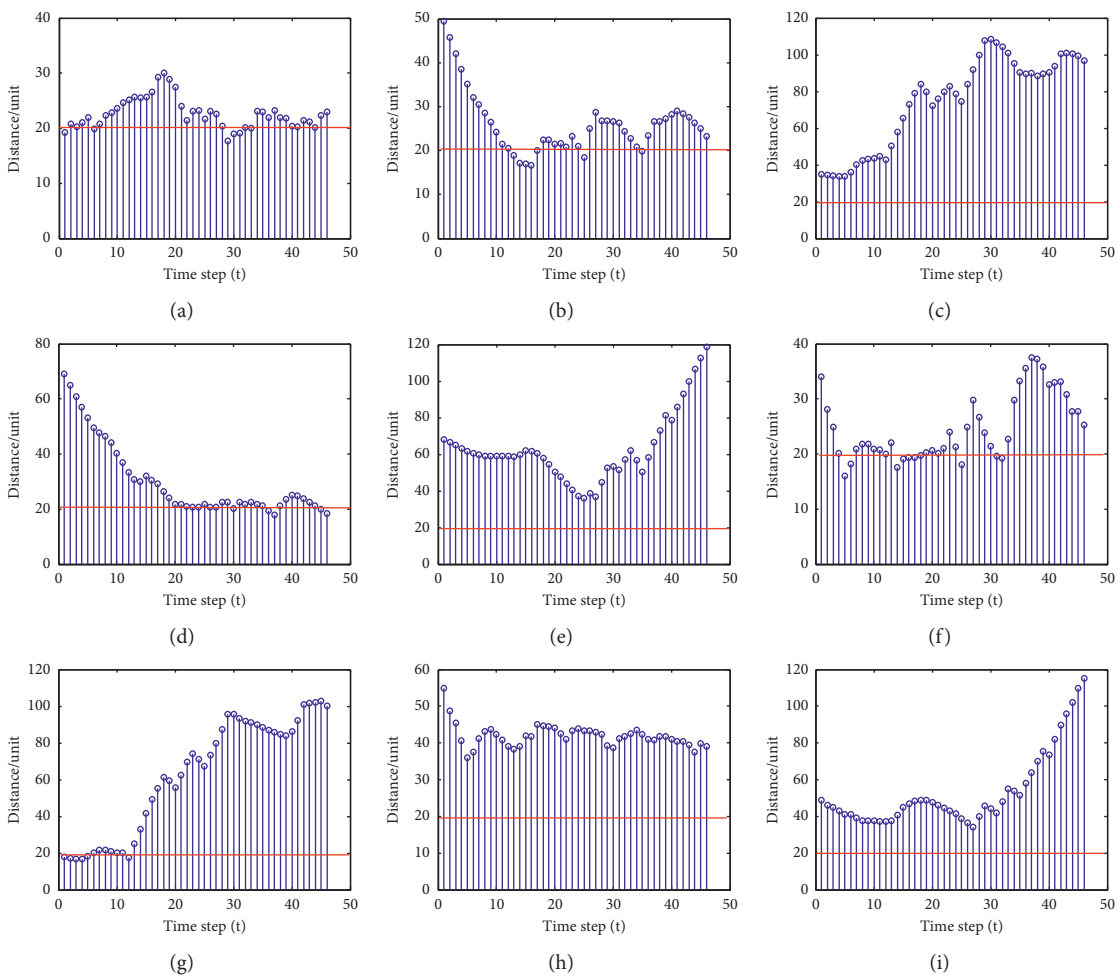

Figure 6: Continued.

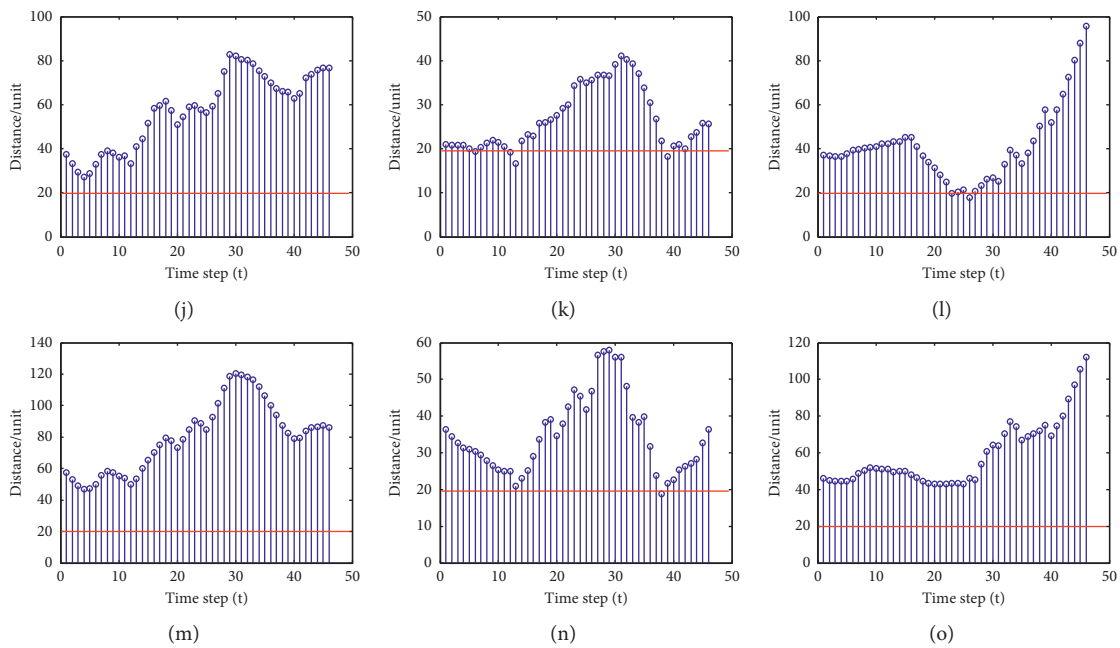

Figure 6: Performance of distance deviation between subswarm Sub_3 members. (a) d_{12}, (b) d_{13}, (c) d_{14}, (d) d_{15}, (e) d_{16}, (f) d_{23}, (g) d_{24}, (h) d_{25}, (i) d_{26}, (j) d_{34}, (k) d_{35}, (l) d_{36}, (m) d_{45}, (n) d_{46}, (o) d_{56}.

the upper limit. The simulation results indicate that the size of the formed subswarm does not exceed the upper limit in the search process. As shown in Figures 5(d)–5(f), via the collision avoidance strategy and the simplified virtual-force model, the individual robot can successfully avoid convex obstacles with various shapes in the environment during the search process. In order to check the collision avoidance between robots, Sub_3 subswam is taken as an example to analyze the distance between the two members in the entire search process, as shown in Figure 5. Sub_3 includes individuals numbered 18, 8, 26, 27, 16, and 28, which are referred to as 1, 2, 3, 4, 5, and 6 for convenience. The distance from the robot m to the robot n is recorded as d_{mn}. For example, d_{12} represents the distance from the robot 18 to the robot 8.

As shown in Figure 6, during the entire collaborative search process, the members of Sub_3 can maintain the maximum collision avoidance distance (safety distance) above 20. When the distance between individuals is less than the maximum collision avoidance distance, individual can quickly adjust to a safe distance. The inspection of the d46 deviation analysis indicates that, when $t = 23$ and $t = 38$, if the distance between the robots is less than or equal to 20, it can be quickly adjusted to a safe distance at the next moment. The simulation results demonstrate that the individual control input based on the simplified virtual-force model can make the robot strictly keep a safe distance from other objects (individual robots or obstacles) in the environment in the process, and the system can successfully search for all targets.

6. Conclusion

This paper aims to handle the issue of multitarget search of swarm robots in an unknown complex environment, and its emphasis is put on the task allocation model and individual collision avoidance. Based on the probability principle and target response threshold, the closed-loop regulation strategy with subswarm scale evaluation is introduced into the allocation model. After a subswarm is successfully established, the members are sorted according to the target type, target response intensity, and distance to the communicating individual. The lower-level members will withdraw from the subswarm and participate in the search of other subswarms, so that some robots can migrate between different subswarms and the robot resources can be reasonably configured. For the problem of robot collision avoidance, a simplified virtual-force model is established in this paper, whereby the motion control method of the robot is designed. Since the individual only needs to consider the information of two neighbors, reasonable motion input can be provided to effectively avoid collision with various convex obstacles and other individuals. Therefore, to a certain extent, the complexity of calculation and various collisions of the system are reduced.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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