A swarm intelligence labour division approach to solving complex area coverage problems of swarm robots

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Abstract: The complex area coverage problem is classical and widespread in the research field of swarm robots. In order to solve the complex area coverage problem with complex nonlinear boundary and special task area (forbidden area or threat area), firstly, the task area is adjusted and grid discretisation. Then, inspired by the labour division phenomenon of typical biological groups such as bee colony and ant colony, the paper analyses the performance characteristics of typical ant colony labour division model (response threshold model) and bee colony labour division model (activation-inhibition model) from the perspectives of individual and environment, individual and individual, and a new swarm intelligence labour division approach (activation-inhibition response threshold algorithm) to solve the complex area coverage problem of swarm robot. Three experiments are carried out to illustrate that the algorithm are endowed with great ability of area coverage and dynamic environment. It can respond to the sudden threat in time and make an efficient response, which has a good practical application prospects.

Keywords: area coverage; swarm robot; swarm intelligence; labour division; response threshold model; activation-inhibition model.

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1 Introduction

Ant colony, birds, fish school, wolf pack, bee colony and other social creatures have simple individual structure and limited intelligence, but they can emerge amazing group intelligent behaviour and adaptive ability to complete complex tasks under the local interaction, group cooperation and self-organisation based on simple rules (Slowik and Kwasnicka, 2018). Enlightened by swarm intelligence, a new field of multi-robot system research named Swarm Robotics mainly studies how a large number of simple single robot interacts with each other and the environment through information interaction and local interaction between robots, so as to generate swarm robots system that are highly adaptable to complex environment and tasks (Chung et al., 2018).

The research fields of swarm robot system mainly focus on path planning problem (Hidalgo-Paniagua et al., 2017), formation control problem (Jia and Li, 2018), target search problem (Yang et al., 2015), area coverage problem (Iftekhar et al., 2019), etc. among which the area coverage problem is the classic and fundamental one (Hassan and Liu, 2017). This technology enable swarm robots system to traverse through some dangerous and complex areas where human beings are hardly to reach. These areas widely exist in the actual application scenarios such as automatic painting for large-scale building, cooperative reconnaissance of multi-UAVs, mine laying and sweeping in field, anti-mine of multi-AUVs, cooperative interception of missile, robot cooperative interception on ground, search and rescue after disaster, cooperative salvage detection of UUV under the water, satellite reconnaissance on high altitude (Cao et al., 2019; Oh et al., 2017), etc.

The area coverage problem can be defined as: taking a mobile robot with a certain detection range of sensors to traverse through the coverage task area, and possibly strive to meet the needs of a short time, less repeated paths and few areas not traversed (Barrientos et al., 2011). There are some shortcomings in the traditional way of taking single robot to detect the coverage of task area, such as parallel coverage, grid coverage, internal spiral coverage and so on (Yao et al., 2019). For example, during the area coverage task, the single robot not only takes a large amount of computation, but also is easy to fall into a local areas, and then repeatedly traverses the same area, instead of completing the subsequent area detection, which result in low and repeated coverage, long time-consuming, and poor completion of the task (Azpurua et al., 2018).

At present, some scholars have studied the algorithm of solving the area coverage problem of swarm robots, and have accumulated some achievements. Peng et al. (2010) puts forwards a distributed rolling optimisation method, in which the calculation will increase exponentially with larger robot scale, the amount of information exchange is heavy and the real-time performance is not good. At the same time, scholars often make use of area division method to solve the area coverage problem of swarm robots (McHdizadc, 2012), the solution is mostly to first decompose the task area into multiple sub areas, and assign each sub area to each robot, and then convert it into a single machine area coverage problem (Galceran and Carreras, 2013). Specifically speaking, the region division method can be divided into two kinds:

1. On robot capability: Chen et al. (2016) raises a task area decomposition method based on task performance and sub area width, which is close to the actual motion characteristics of robot (UAV). This kind of region division method is more complex, and easy to cause repeated coverage, resulting in low coverage efficiency.
2. On graph theory: For example, both Chen et al. (2018) and Pinkam et al. (2017) adopt the Voronoi diagram method to divide the task area. This method is characterised by fast response and timeliness, but it requires high autonomy of robot, and has some uncertainty, which makes the feasibility of decomposition results weak.

Therefore, the main challenge of the area coverage problem is how to design more effective algorithms to enable the swarm robots self-organised and decentralised to cover the task area. It is found that the cooperative search, encirclement and formation of robots are similar to the behaviour of biological groups, which can inspire the intelligent research of biological groups. As we all know, there are a large number of swarm behaviours in nature such as wolf hunting, ant foraging, bird migration, cattle resistance to natural enemy attack (Parpinelli and Lopes, 2011). Among them, labour division is one of the most important characteristics of social creatures such as ant colony, bee colony and wolf pack, and is also the specific mode of cluster intelligence (Wu et al., 2013).

Many studies have also shown that the labour division model possesses well adaptability and self-organisation characteristics. Its remarkable feature is that a large number of biological individuals automatically make decisions according to their own state and environmental stimulation without global information and guidance, so as to realise the individual division within biological groups (such as ant colony and bee colony) and achieve a dynamic balance (Xiao and Wang, 2018; Zhu et al., 2017). On the one hand, the plasticity of the group division of labour makes the biological group adapt to the changes of the environment, highlighting its adaptability; on the other hand, it also makes the biological group survive or complete the vested tasks in the case of disaster or mutation, highlighting its robustness. In Wu et al. (2018), a dynamic ant colony labour division model with the characteristics of multi-task, multi-state, adaptive response threshold and multi-individual response is proposed to solve the dynamic task allocation problem of UAV cluster. In Yan et al. (2013), a region coverage algorithm for swarm robots based on response threshold is proposed, which has the characteristics of self-organisation, distributed control, and certain pioneering. However, the threshold in this algorithm is fixed, which results in the dynamic change of task area and the number of robots due to the change of task. In addition, the target area in regular shape is usually covered by horizontal and vertical scanning, internal and external spiral and other methods. However, for the complex target areas such as the complex non-linear boundary and the internal non-coverage mission area (forbidden area or threat area), the efficiency of the traditional area coverage method is obviously lower, or even can not be completed. Therefore, irregular task areas need to be sorted out and discretised.

To sum up, this paper first adjusts to the area of complex and irregular tasks and discretises the grid. Then, combining the respective advantages of response threshold model of ant colony labour division and activation-inhibition model of bee colony labour division, the activation-inhibition model of bee colony labour division is used to dynamically adjust the threshold value in the response threshold model of ant colony labour division. In this paper, a new swarm intelligence labour division approach (activation-inhibition response threshold algorithm, AIRT) is proposed to solve the complex area coverage problem of swarm robots. Four groups of experiments are carried out to demonstrate the effectiveness of the algorithm and the adaptability of dynamic environment.

The structure of this paper is organised as follows: Section 2 describes the complex area coverage of swarm robots in detail; Section 3 analyses the principle and characteristics of two labour division models, response threshold model and activation-inhibition model, which are the interaction between individuals and environment and the interaction between individuals, and then proposes a new swarm intelligence labour division approach; Section 4 carries out three groups of experiments (non-threat area coverage, established threat area coverage, and sudden threat area coverage) to illustrate the effectiveness of the proposed algorithm; Section 5 draws conclusion and look forwards to its prospect.

2 Description of complex area coverage problems of swarm robots

2.1 Sorting and discretisation of complex areas

In reality, the working environment of swarm robots is relatively complex. The working map of swarm robots will face a large number of complex, nonlinear and irregular boundary areas. The following steps are used to organise the area before grid discretisation:

1 the complex boundary area is approximated to the polygon area according to the discretisation granularity

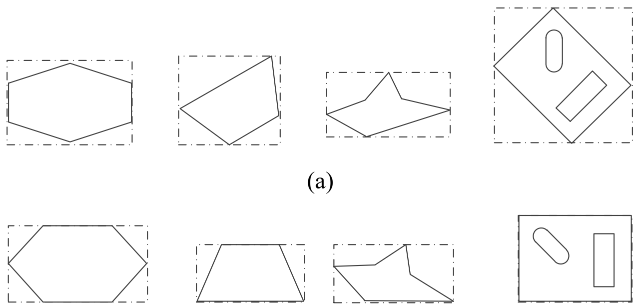
2 the Graham algorithm is used to solve the minimum convex hull of the polygon area, and the width of the area is calculated (Graham, 1972)

3 the minimum area bounding rectangle (MABR) with discrete granularity approaching polygon region is obtained, and the region coordinates are transformed

4 the grid discretisation is carried out after sorting. As shown in Figure 1, it should be noted that the method of minimum bounding rectangle (MBR) used to be adopted will enlarge the search range of swarm robots, increase energy consumption and reduce coverage efficiency.

Due to the simple implementation and great ability in expression, the grid method is used for the discrete modelling of regional map. Putting the area after sorting in the rectangular coordinate system, and the task area is divided into several grids with fixed size, and each grid is assigned a value. Among them, the forbidden area is assigned as 0, the dangerous area is assigned as δ_i (δ_i is the threat coefficient of dangerous area i), and the safe driving area is assigned as 1, where the number of area grid i is carried out according to the formula $i = (m - 1) \cdot M + n$, here m and n are the row number and column number of the grid where the area grid is located, and M is the number of grid columns. Then the grid model and assignment matrix of the task area after sorting are shown in Figure 2.

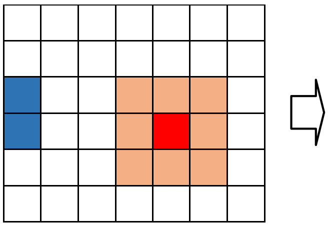
Figure 1 Comparison of (a) MBR (b) MABR in polygon area



(a)

(b)

Figure 2 Grid model and assignment matrix of task area after sorting (see online version for colours)



$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & \delta_{18} & \delta_{19} & \delta_{20} & 1 \\ 0 & 1 & 1 & \delta_{25} & \delta_{26} & \delta_{27} & 1 \\ 1 & 1 & 1 & \delta_{32} & \delta_{33} & \delta_{34} & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

2.2 *Description of area coverage problems*

The area coverage problem can be defined as a triples $\langle E, R, T\rangle$, where E represents the task area model established by grid method, including safe driving area, obstacle forbidden area and danger area with different threat coefficients; R is the attribute set of swarm robots, including the number, state and behaviour, and each robot R_i has certain external information perception and the interaction ability; T is the goal or task that the swarm robot should reach. Boolean functions *In* and *Vi* are introduced here. $In(p)$ indicates whether the area p is within the coverage or not, and $Vi(p)$ indicates whether the area p is accessed. Then the task target T covered by the traverse-through trip can be expressed as:

$$\forall p\left(p \in E \wedge p \notin O\right) Sat.Vi(p) = TRUE \tag{1}$$

After the covered task target is completed, all areas have been visited. That is, before a certain time t, all grids have been visited, then formula (1) is true.

Besides, considering the mobile path of the robot and the traverse-through coverage, the trajectory $Tr(R_i)$ is defined as the number set of all the areas passed by robot i, then the set of all the areas passed by the robot is shown as follows:

$$\sum_{i=1}^{n} Tr\left(R_i\right) = set\left(A_c\right) \tag{2}$$

where $set(A_c)$ represents a number set of all coverage areas and n is the number of robots.

The area coverage problem of swarm robots aims to explore the best traverse-through path for the algorithm to solve the best traversal path problem, so that the solution can meet the following five indexes, that is, the low average coverage number, short time-consuming, small total coverage length, high coverage rate and few number of loss robots. The description in detail is listed as follows.

1 Time consuming T: The time required for a swarm robot to complete an area coverage task. In this paper, it represents the largest steps of a single robot within the swarm robots.

2 Total coverage length L: Refers to the sum of the distance that the group robot runs to complete the area coverage task.

3 Coverage rate C: The ratio of the area covered by swarm robots to the area of all tasks.

4 Number of lost robots S_num: The number of robots that are eliminated while passing through the threat area.

In addition, the following two situations are considered:

1 the forbidden area and dangerous area have been determined after the early reconnaissance

2 the sudden danger during the area coverage operation.

The former considers the conventional coverage ability of the region coverage algorithm, the latter tests the algorithm's dynamic response performance and the ability to respond to sudden threats in the context of dynamic tasks.

3 Analysis on the principle and model of the intelligent labour division

3.1 *Introduction to swarm intelligence labour division*

The swarm intelligence labour division generally exists in social group animals. For example, the lead wolf is in charge of command, the detective wolf in charge of search and reconnaissance, and the fierce wolf in charge of encircling and killing (Li and Wu, 2016); the queen and male ant are in charge of mating and reproduction, the soldier ant in charge of protecting the nest, and the worker ant in charge of collecting and storing food; the queen bee is in charge of reproduction, and other bees are classified into different jobs such as nursing, nesting or foraging in terms of insect ages.

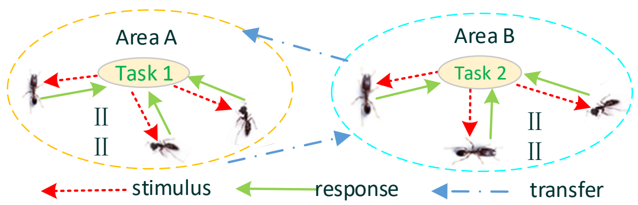
The most remarkable feature of swarm intelligence labour division is that the individual behaviour flexibility without central control produces the plasticity of group labour division (Robinson, 1992), that is, the number of individuals who perform different tasks in the group will adjust dynamically with the environment, and this adjusted labour division just meets the requirements of the group for each task, and can always achieve flexible task distribution. These dynamic self-organisation characteristics of swarm intelligence labour division are very suitable for dynamic disturbance and highly complex practical problems.

Generally speaking, there are two classic modes of swarm intelligence labour division (Mersch, 2016). One is the labour division of interaction between individuals and the environment, which is represented by the morphological and behavioural diversity of ant colony, i.e., individual tasks are related to their body shape, and the internal mechanism is stimulation response mechanism. Each task in the environment has a stimulus value. Ants have a threshold corresponding to it according to their own shape and ability. When the stimulus of tasks in the environment exceeds the threshold, the probability of ant response increases, otherwise it decreases. One is the division of labour between individuals, which is represented by the multiple patterns of time behaviour of bee colony, that is, the tasks performed by individuals are related to their physiological age. In short, bees undertake different tasks of feeding, storage and foraging paralleling to their life cycles. Its internal mechanism is activation-inhibition mechanism. The activator (juvenile hormone promotes bee growth) and inhibitor (suppresses bee growth) of honeybee in colony jointly determine whether the behaviour development of honeybee accelerate or remain normal speed, and honeybee is delayed or reversed, so as to maintain the dynamic distribution balance of honeybee population in different tasks.

3.2 *Interaction between individual and environment – response threshold model*

The typical labour division of interaction between individuals and environment is ant colony labour division, and its internal mechanism is stimulus responding mechanism, which can be described as: the task environment space of some ant colonies is separated, that is, different tasks appear in corresponding regions (Pamminger et al., 2014), as shown in Figure 3, A and B represent two different regions, corresponding to two different tasks.

Figure 3 The interaction between individual and environment (see online version for colours)



Ants in region A can sense the stimulation of task 1. According to the intensity of the stimulus, ants will decide whether to execute task 1 or switch to region B. When ants appear in the corresponding area of a specific task, they will perceive the task stimulus correspondingly. According to different task stimuli, there is a threshold in ants, and the performance of ants is related to its internal threshold and external task stimuli. When the stimulation of external tasks increases, the ant population will respond and increase the number of ants executing the task. When the task is executed, the stimulation degree of the task will decrease, and the threshold value of the individual ant will be adjusted.

Therefore, the difference of threshold value of many ants in ant colony and the difference of response of each ant to the task stimulus caused by the task demand of ant colony finally form the unique mode of colony intelligent labour division. Based on the unique mode of ant colony intelligent labour division, the fixed response threshold model (FRTM) established by scholars is a highly abstract model of ant colony cooperative labour division, which is the most classic and basic model of ant colony labour division. The basic idea of the model is that each ant has a response threshold corresponding to a task in line with its own ability. The difference of response threshold of ants can reflect the actual difference of their behaviour response, or the different ways of detecting the stimulation of related tasks. In the environment where ants live, there is stimulation for every task. When the stimulus intensity of a task exceeds the response threshold of an ant, the ant begins to engage in the task. When the ants who perform a specific task quit, the stimulus intensity corresponding to the task will continue to increase to a certain limit, so as to stimulate other ants to perform the task. The mathematical description of the FRTM model is as follows.

1 Environmental stimulus value is a variable of time

   Ants are stimulated by the environment, and the stimulation corresponds to the task one by one. The strength of the stimulation determines whether ants respond to the task or not.

$$s(t+1) = s(t) + \delta - \varphi \cdot n_{act} \tag{3}$$

   In the above formula, t is a discrete-time variable, $s(t)$ represents the environmental stimulus value at time t, δ indicates the increment of stimulus in each period, φ is the task completion amount of a single individual in each period, and n_{act} refers to the number of individuals participating in the task in that period.

2 Responses of inactive individuals to environmental stimuli

   In FTRM, the state of an individual is $ST_i = 0$ or $ST_i = 1$, that is, the active state of the participating task or quitting task. The emergence of task will trigger the environment to give individual stimulation, and the individual will decide whether to participate in the task according to its response threshold. The specific probability is:

$$P(ST_i = 0 \rightarrow ST_i = 1) = \frac{s^n}{s^n + \theta_i^n} \tag{4}$$

   where n is the constant controlling the curve shape of threshold function, it generally takes 2 (Yasuda et al., 2014).

3 The probability of quitting task for active individual

   For each time period T, the individual i participating in the task will quit with a certain probability:

$$P(ST_i = 1 \rightarrow ST_i = 0) = p, \tag{5}$$

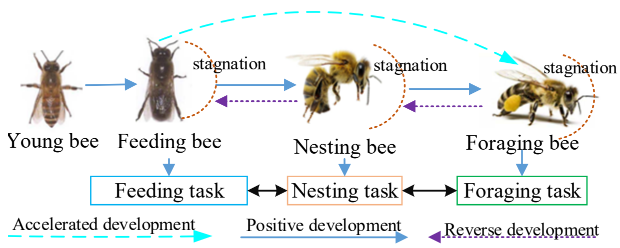
To simplify the model, P is a general constant. In addition, $P(ST_i = 0 \rightarrow ST_i = 1)$ and $P(ST_i = 1 \rightarrow ST_i = 0)$ are independent of each other.

FTRM is suitable for some labour division phenomena in nature, which can form an efficient response to external task stimulation. What is more, due to its simple structure and accessible realisation, it is widely adopted (Pang et al., 2019). However, FTRM also has some defects, its individual response threshold is a single fixed value preset by one person, which remains unchanged in the whole process. Some scholars have conducted a few research, they introduced more factors such as individual learning and forgetting ability (Theraulaz et al., 1998), competition (Merkle and Middendorf., 2004), and individual spatial heterogeneity distribution (Richardson et al., 2011). Although these improvements adjust the individual response threshold to a certain extent, they are still based on experience; Although they can reflect individual differences, they are not fully reflected in the same individual's time-domain differences, and cannot adapt to the dynamic task allocation and the reality of problem in area coverage.

3.3 *Interaction between individuals – activation-inhibition model*

The typical swarm intelligence labour division of interaction among individuals is bee colony labour division. Its internal mechanism is the activating inhibition mechanism. It can be described as follows: the activator and inhibitor jointly determine the individual behaviour development of honeybee, and they have a coupling relationship, that is, the content of activator and inhibitor in the older honeybee is more than that in the younger one (Huang and Robinson, 1992). Juvenile hormone is considered to be an activator of honeybee to promote the positive development of individuals. The labour division of bees in a colony is related to their behaviour development. Generally speaking, young bees can develop into feeding bees to perform feeding tasks in a relatively safe nest, and then develop into nesting bees to perform the task of building a nest in and near the honeycomb, and further develop into foraging bees to search for food and honey in the more dangerous wild distance. The above description is shown in Figure 4.

Figure 4 The diagram of interaction among individuals (see online version for colours)



When the individual indirectly perceives the task demand, the individual interacts with its peers, and inhibitors will be transmitted in the process of interaction, which will hinder the growth of juvenile hormone and honeybee behaviour. For example, when the number of foraging bees decreases, the individual interaction reduces, the inhibitor weakens, and the activator increases, so as to accelerate the development of bees in the hive into foraging bees; otherwise, when the number of foraging bees is large, the individual interaction increases, and the inhibitor strengthens, so as to promote the delayed development of honeybees in the hive, and even some foraging bees will return to the hive (Kuszewska and Woyciechowski, 2013). Therefore, according to the needs of bee colony, bee can accelerate, delay or even reverse its behaviour development.

Based on the above activation-inhibition mechanism, Naug and Gadagkar (1999) established a computational simulation model. Each individual in the colony contains an activator A (activator) and two inhibitors (inhibitor) I_1 and I_2. The activator can promote the development of honeybee. I_1 is an internal inhibitor of honeybee, which will not hinder the development of honeybee itself, but will inhibit the behaviour development of other individuals in the process of individual interaction. I_2 is an external inhibitor obtained by individuals in interaction, which will hinder their own behaviour development. Finally, the relative level of activator A / (aI_1 + I_2) and inhibitor A determines whether honeybee behaviour development is accelerated, delayed or reversed at normal speed.

Referring to the work of Beshers et al. (2001), and considering that activation-inhibition itself is an interactive process with time-varying uncertainty, self-study performance and high adaptability to external systems, the activation-inhibition labour division model (AILD) of bee colony labour division is given as follow (Hu, 2019).

$$x(t+1) = f\left(x(t),\, y(t)\right), \tag{6}$$

where the state variable x is the physiological age of honeybee; the auxiliary variable y is the inhibition effect of honeybee colony through the interaction between individuals; the mapping f (x, y) is a function of the activation-inhibition relationship between x and y, which determines whether the physiological age of honeybee increases, decreases or remains unchanged through the activation-inhibition ratio. The principle of activation-inhibition is to control the physiological age of honeybee by the ratio of activator, internal inhibitor and external inhibitor (hereinafter referred to as activation-inhibition ratio). The details are shown as follows:

$$k_i = A_i \Big/ \left(aI_1 + \sum_{j=1, j\neq i}^{n} I_2 \right) \tag{7}$$

where k_i is the activation-inhibition ratio, A_i is the activator, I_1 is the internal inhibitor and I_2 is the external inhibitor.

$$f\left(x(t),\, y(t)\right) = \begin{cases} x(t) + y(t), & k_i > d_{higher} \\ x(t) - y(t), & k_i < d_{lower} \\ x(t), & d_{lower} \le k_i \le d_{higher} \end{cases} \tag{8}$$

$$y(t)=\begin{cases} e(k_i-d_{higher}), & k_i>d_{higher} \\ e(d_{lower}-k_i), & k_i<d_{lower} \\ y(t-1), & d_{lower}\le k_i\le d_{higher} \end{cases} \tag{9}$$

where k_i is the activator-inhibitor ratio, d_{higher} and d_{lower} are the upper and lower thresholds of activation-inhibition ratio, $x(t)$ is the individual physiological age, $y(t)$ is the auxiliary variable quantity. When $k_i > d_{higher}$, the individual physiological age increased, and the variable quantity was positive correlation; when $k_i < d_{higher}$, the individual physiological age decreased, and the variable quantity was negative correlation; when $d_{lower} \le k_i \le d_{higher}$, the individual physiological age remained unchanged, and the variable quantity remained stable.

From the above formula, if the number of foraging bees suddenly decreases at time t, the total inhibitor content of the whole colony will decrease, and the activator and inhibitor content of individual i will not change. According to equation (7), the activator-inhibitor ratio of individual i increases at $t + 1$. According to formulas (8) and (9), the physiological age of individual i will increase at the time of $t + 1$. In conclusion, the activator-inhibitor ratio of individual I increase, then it will accelerate the transformation to foraging bee. In the same way, if the number of foraging bees is too large at t time, the interaction between individuals will increase, and the total content of external inhibitors of the whole colony will increase. It can be seen from the above formula that the activator-inhibitor ratio of individual i decreases at $t + 1$. The development of individual i is inhibited, and the transformation speed from the safe nest to the dangerous one slow down, and even makes the foraging bee become the nesting bee or the feeding bee returning to the nest to perform tasks. It is not difficult to find that the colony is in a dynamic equilibrium state under the action of stimulating and restraining the division of labour. However, in essence, the response of individuals to tasks in the activation-inhibition model is indirect perception, and the interaction between individuals and peers belongs to the swarm intelligence labour division of individual-individual interaction.

3.4 AIRT algorithm

Based on the above analysis, it can be considered to combine the response threshold model and the activation-inhibition model. The former endows with better perception and response to external environment and task stimulation, and the latter with high-efficiency collaboration between individuals. The specific idea is to dynamically adjust the threshold value of the ant colony labour division model by the interaction between individuals in colony labour division, and shape the AIRT algorithm. The specific formula is:

$$P(i,j)=T_{\theta_i}(s_j)=\frac{s_j^2}{\sum_{k=1}^{m}s_k^2+\theta_i^2+w},\ s_j\ge 0, \theta_i\ge 0 \tag{10}$$

where s_j is the stimulus of cell j, θ_i is the response threshold of robot i, s_k is the stimulus of adjacent cell i_0 where robot i is located, m is the number of adjacent cells, and $T_{\theta_i}(s_j)$ is the probability $P(i, j)$ that robot i performs the task of moving to cell j. Obviously, the probability that the robot will stay in place is:

$$P(i,i_0)=1-\sum_{k=1}^{m}T_{\theta_i}(s_j) \tag{11}$$

Here, it should be noted that the confidence matrix Q of the grid obtained in Subsection 2.1, for cells in the dangerous area, its task stimulus is a negative correlation function of threat coefficient, that is, the greater the threat coefficient, the smaller the task stimulus. For cells in the obstacle area, the task stimulus is 0.

In formula (11), the response threshold of robot i changes with time passing by, as shown in the following formula:

$$\theta_i(t+1)=\theta_i(t)+\sigma_i \tag{12}$$

$$\sigma_i=\begin{cases} e(d_{lower}-k_i), & k_i<d_{lower} \\ e(k_i-d_{higher}), & k_i>d_{higher} \\ \sigma_{i-1}, & d_{lower}<k_i<d_{higher} \end{cases} \tag{13}$$

$$k_i=\frac{A_i}{\sum_{j=1,j\ne i}^{n}I_2(j)} \tag{14}$$

where θ is the response threshold of individual i, σ_i is the variable quantity of threshold, k_i is the activation-inhibition ratio, A_i is the activator of individual i, I_2 is the inhibitor of other individuals interacting with individual i, d_{higher} is the upper threshold and d_{lower} is the lower threshold.

Robots can communicate with surrounding robots. When there are fewer robots around, the individual's external inhibitors will be reduced, and so do the individual's response threshold and external inhibitors. At the same time, the individual will stand little chance of staying in place when the individual's response threshold is reduced. This way of adjusting the response threshold in terms of the number of surrounding robots can increase the efficiency of the robot, avoiding unnecessary work in the case of saturation for the surrounding robots, which not only increase congestion, but also reduce the efficiency.

Specifically, the AIRT algorithm dynamically adjust the individual response threshold by activator-inhibitor ratio as follows.

1 When $k_i < d_{lower}$, it shows that there are more robots around robot i, and the response threshold of robot i increases, as shown in equation (15). The smaller the k_i is, the larger the response threshold is, the robot i is more likely to stay in place, thus reducing congestion and invalid mobile coverage;

$$\theta_i=\theta_i+\psi(k_i) \tag{15}$$

where d_{lower} is the lower threshold value and $\psi(k_i)$ is the negative correlation function of k_i.

2 When $k_i > d_{higher}$, it shows that there are fewer robots around robot i, and the response threshold of robot i decreases, as shown in equation (16). The larger the k_i is, the greater the response threshold will reduce, the more likely the robot i will move to other regions, thus accelerating the mobile coverage.

$$\theta_i = \theta_i - \phi(k_i) \tag{16}$$

where d_{higher} is the upper threshold value, $\phi(k_i)$ is the positive correlation function of k_i.

3 When $d_{lower} < k_i < d_{higher}$, the response threshold of robot i remained unchanged.

To sum up, the specific steps to solve the complex area coverage problems by utilising the AIRT algorithm are achieved as follows.

Step 1 Sort out and grid the complex task area by the methods described in Subsection 2.1.

Step 2 Set parameters of robots' number R, cell quantity of stimulus s and so forth.

Step 3 The robot is randomly distributed in the task area and starts to perform the area coverage task.

Step 4 Detect the current position of robot i.

Step 5 Adjust the stimulation amount of the current cell of robot i by using the formula $s_i(t + 1) = s_i(t) \cdot \alpha$.

Step 6 Adjust the current cell threshold of robot i by formulae (15) and (16).

Step 7 Detect the stimulus of the cell near the current position of robot i.

Step 8 Calculate the response function T by formulae (10), (12), (13) and (14).

Step 9 Consider the response function value calculated as the probability, determining the moving direction of robot i and move to the next cell.

Step 10 If there is still a unit cell that is not covered by the robot, then turn to step 4.

Step 11 Calculate the output average coverage times, total coverage length and area coverage rate.

4 Simulation experiments and analysis

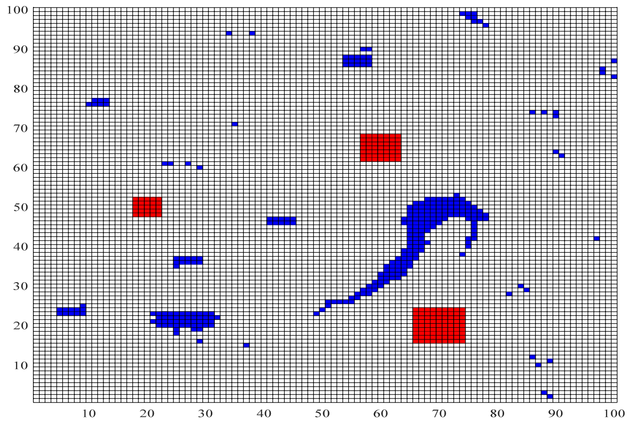
4.1 Experiment environment and parameter setting

In order to verify the effectiveness of AIRT algorithm in solving the complex area coverage problem, in the experiment, the confidence matrix and grid map of the area are obtained after sorting and gridding a actual military map. Set the initial cell stimulation amount of the passable area as 100, multiply the stimulation amount by 0.1 each time it is covered, the lower threshold value d_{lower} is 0.4, the upper threshold value d_{higher} is 0.6. The initial positions of swarm robots are a random cell in grid. The grid schematic diagram of the coverage map is shown in Figure 5.

As shown in Figure 5(a), a military map is introduced into the experiment, and then it is sorted into a grid map with area of 100 × 100, which is shown in Figure 5(b). The white square refers to the accessible area; The blue one stands for the restricted area, and the red one is dangerous area. The threat areas are respectively (20, 50), (70, 20), (60, 65), the threat radius is respectively 2, 4 and 3, and the threat coefficients of the threat areas are correspondingly 0.2, 0.05 and 0.1.

Figure 5 Schematic diagram of grid map corresponding to actual map at a certain time during the execution of area coverage, (a) map of an actual task (b) grid map to be covered (see online version for colours)

(a)



(b)

4.2 Area coverage without threat

In order to verify the effectiveness of the algorithm mentioned above, this paper proposes the AIRT, the random coverage algorithm (RCA) and the response threshold algorithm (RTA) to cover the map of swarm robots. To be specific, for the same area coverage problem, it sets the number of different groups of robots (2–10 robots respectively). In order to fully highlight the excellent performance of AIRT algorithm, the stopping conditions of RCA algorithm and RTA algorithm are taken as twice the step length when AIRT algorithm reaches 100% coverage.

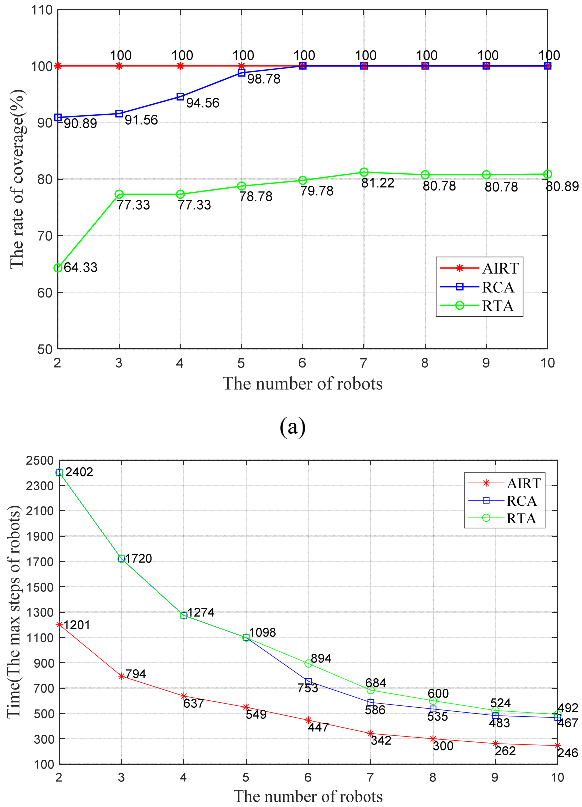
That is, RCA algorithm and RTA algorithm have twice the time of AIRT algorithm proposed in this paper to carry out area coverage. In the experiment, each group of experiments were repeated 10 times to take the average value, and finally the results of each index were counted. The average coverage times, coverage time (the most steps of robot within the swarm robots), total coverage length and coverage rate are analysed. The experimental results are shown in Table 1, the coverage map is a kind of grid map with area of 30 × 30. In order to display the results intuitively, Figure 6 draws three algorithms of the coverage time (total running step length) and coverage ratio of three algorithms.

Table 1 Simulation results of map coverage of swarm robots with area of 30 × 30

Robot number	*Algorithms name*	*Average coverage times*	*Coverage time*	*Total coverage length*	*Coverage rate*
2	AIRT	2.6100	1,201	2,349	100%
	RCA	4.0189	2,402	3,617	64.33%
	RTA	4.3489	2,402	3,914	90.89%
3	AIRT	2.8189	860	2,537	100%
	RCA	4.3211	1,720	3,889	73.67%
	RTA	4.2544	1,720	3,829	91.56%
4	AIRT	2.6711	637	2,404	100%
	RCA	4.2456	1,274	3,821	77.33%
	RTA	4.0822	1,274	3,674	94.56%
5	AIRT	2.8589	549	2,573	100%
	RCA	4.6022	1,098	4,142	78.78%
	RTA	4.6022	1,098	4,189	98.78%
6	AIRT	2.9578	447	2,662	100%
	RCA	4.4856	894	4,037	79.78%
	RTA	4.4200	753	3,978	100%
7	AIRT	2.5167	342	2,265	100%
	RCA	4.006	684	3,600	81.22%
	RTA	4.2644	586	3,838	100%
8	AIRT	2.5867	300	2,328	100%
	RCA	3.9622	600	3,566	80.78%
	RTA	4.0811	535	3,673	100%
9	AIRT	2.6022	262	2,342	100%
	RCA	3.9533	524	3,558	80.78%
	RTA	4.6144	483	4,153	100%
10	AIRT	2.6256	246	2,363	100%
	RCA	4.0622	492	3,656	80.89%
	RTA	4.4122	467	3,971	100%

As shown in Table 1 and Figure 6, the coverage rate of AIRT algorithm is 100%, it is clear that combining the swarm intelligence labour division of individual and environment interaction (response threshold model) and that of individual and individual interaction (activation-inhibition model), the algorithm proposed can ensure 100% coverage of tasks, avoiding regional omission, and correspond to the actual situation such as full coverage reconnaissance without dead spots and blind areas for UAV. The RCA algorithm cannot achieve 100% coverage until the number of robots is increased to 30 in the subsequent experiments. It can be seen that the coverage of uncoordinated swarm robots is inefficient. While the RTA algorithm cannot achieve 100% coverage until the number of swarm robots is increased to six robots.

Figure 6 Schematic diagram of grid map corresponding, (a) the coverage rate with the number of robots (b) time-consuming with the number of robots (see online version for colours)



(a)

(b)

Then, in the whole process of increasing the number of robots from 2 to 10, the average number of coverage of AIRT algorithm fluctuates from 2 to 3, and that of RTA algorithm and RCA algorithm fluctuates from 4 to 5. On the one hand, the average number of coverage of AIRT algorithm remains stable with the change of the number of robots. On the other hand, the less average number of coverage also indicates this method calculation can achieve the cooperation between swarm robots and effectively reduce unnecessary repeated coverage.

Secondly, from the perspective of coverage time, with the increasing number of robots, the overall coverage time of these three algorithms shows a downward trend. For the AIRT algorithm, especially when the number of robots is 2–4, the number of robots increases and the coverage time decreases significantly. However, when the number of robots increases to 6, the decrease of coverage time tends to be gentle, and the reduction effect of coverage time caused by the number of robots is not obvious. The other two algorithms are more than twice the time consuming. On the one hand, it shows that the AIRT algorithm can achieve efficient cooperation among machines, thus effectively reducing the coverage time and completing the coverage task with high efficiency. On the other hand, it also shows that for a limited task area, although increasing robots can shorten the overall coverage time, the benefits of continuously increasing the number of robots have a decreasing trend. That is to say, there is a compromise between the best number of robots in the allowable range, and in reality, too many robots in the limited area may also cause traffic congestion, which will reduce the efficiency of overall coverage time while completing task area;

Thirdly, in terms of the total coverage length, the overall change trend of the total coverage length of AIRT algorithm does not grow at an explosive speed, and it is almost half of the other two algorithms. Even if the RTA algorithm achieves 100% coverage when the number of robots is greater than or equal to 6, the time required by the RTA algorithm is still nearly twice that of AIRT algorithm. It further demonstrates that the algorithm can reduce the repetitive coverage, the total coverage length and the efficient area coverage.

This section focuses on the effectiveness of the AIRT algorithm to deal with the general non-threat area coverage problem. However, in the real battlefield, swarm robots, such as UAVs, are often threatened by the ground air defence fire in the enemy's war zone while performing area coverage reconnaissance tasks, and unmanned boats and unmanned ships are also attacked by enemy ships while performing sea area search tasks.

4.3 Coverage problem of known threat areas

This section introduced threat which has been detected. For instance, in actual combats, satellites or high-altitude UAVs are adopted to detect and analyse the dangerous area and its threat to us. That is to say, the problem studied in this section is to investigate the ability of the algorithm to deal with the complex area coverage problems including the no-fly zone and danger area, on the premise that the threat coefficient δ_i and danger area *i* have been detected clearly in advance. Given that a certain square *i* in the map has a certain threat coefficient δ_i, then all areas within the given threat radius belong to the threat area. If the UAV passes through a certain threat area and the probability of being shot down (i.e., the threat coefficient of this area) is δ_i in multiple UAV reconnaissance application scenarios, the survival probability of the UAV is considered to be $1 - \delta_i$. If the survival probability expectation $P \leq (1 - \delta_i)$ of the UAV is required, the UAV can try to pass through the threat area. Therefore, unlike obstacles or no-fly/travel zones, robots can pass through threat zones, but the risk value will increase cumulatively.

In the specific test, the number of robots is 5–50. When the robot carries out area coverage operation without knowing location of the threat area. But for the AIRT algorithm and RTA algorithm, when a robot covers the threat area, each time it is covered, the quantity of stimulus multiplies $0.01 * P_w$ where P_w is the threat coefficient, and the survival probability of the robot is $1 - P_w$. When the limit value of survival probability is $P = 0.5$, if the cumulative risk of a robot is greater than 0.5, it is considered that the robot is killed, and listed in the ranks of loss robots. The coverage time is the most steps of single robot within the swarm robots.

Table 2 Simulation results of area coverage of given threat area with the number of swarm robots

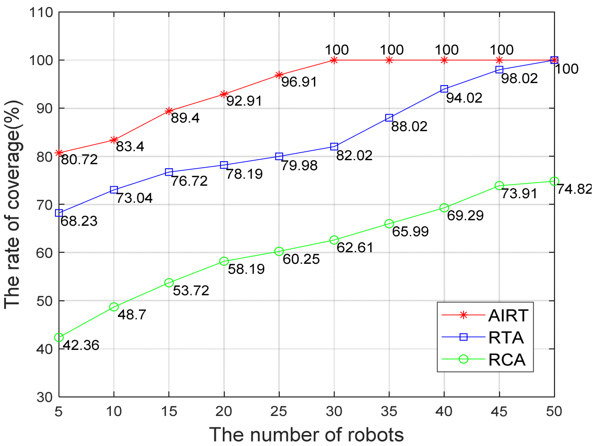
Robot number	*Algorithm*	*Coverage time*	*Total coverage length*	*Loss robot number*	*Coverage rate*
5	AIRT	9,920	29,172	5	80.72%
	RCA	10,000	59,803	5	42.36%
	RTA	10,000	37,439	5	68.23%
10	AIRT	8,646	33,457	10	83.40%
	RCA	10,000	97,524	10	48.70%
	RTA	10,000	67,448	10	73.04%
15	AIRT	7,132	49,957	15	89.40%
	RCA	10,000	172,394	15	53.72%
	RTA	10,000	112,394	15	76.72%
20	AIRT	6,834	50,892	20	92.91%
	RCA	10,000	196,348	20	58.19%
	RTA	10,000	149,968	20	78.19%
25	AIRT	4,289	69,957	22	96.91%
	RCA	10,000	226,348	25	60.25%
	RTA	10,000	187,181	25	79.98%
30	AIRT	3,862	78,932	22	100%
	RCA	10,000	254,980	30	62.61%
	RTA	10,000	224,980	26	82.02%
35	AIRT	3,389	92,230	22	100%
	RCA	10,000	284,980	35	65.99%
	RTA	10,000	244,754	28	88.02%
40	AIRT	3,029	100,239	22	100%
	RCA	10,000	300,068	36	69.29%
	RTA	10,000	268,911	29	94.02%
45	AIRT	2,679	105,837	22	100%
	RCA	10,000	336,811	38	73.91%
	RTA	10,000	283,728	29	98.02%
50	AIRT	2,290	110,922	22	100%
	RCA	10,000	360,914	46	74.82%
	RTA	7,191	289,927	30	100%

In Table 2, it is necessary to explain that the overall coverage refers to the coverage calculated after removing the number of squares occupied by the forbidden area. In this paper, AIRT, RCA and RTA are used to cover the area of swarm robots. The stopping conditions of each algorithm are as follows:

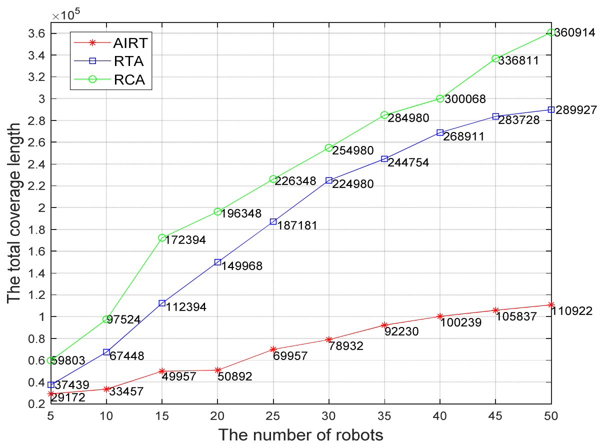
1 the robot is exhausted
2 the overall coverage rate reaches 100%
3 the covering time (the most steps of the robot) reaches the maximum limit value 10,000.

At the same time, the priority of area coverage is set, that is to say, in order to complete the task of area coverage (including threat area), the robot can be lost at any cost. Since the total number of squares is 10,000, the relationship between the average coverage times and the total coverage length is a multiple of the total number of squares, so only the coverage time, the total coverage length, the number of loss robots and the overall coverage are examined here. Table 2 shows the experimental results of the number of robots increasing from 5 to 50, and the coverage rate and the total coverage length are drawn as shown in Figure 7.

Figure 7 Comparison of map coverage simulation results of swarm robots, (a) the coverage rate with the number of robots (b) the total coverage length with the number of robots (see online version for colours)



(a)



(b)

The simulation results show that with the increasing number of robots the coverage of AIRT algorithm, RTA algorithm and RCA algorithm increases from 80.72%, 68.23% and 42.36% to 100%, 77.82% and 100%, respectively. It can be seen that increasing the number of robots is a more effective method to improve the coverage rate, which is suitable for every method. But compared with Tables 1 and 2, we can see from the coverage rate alone, although RCA algorithm can improve the coverage rate to 100% by increasing the number of robots in the non-threat area. However, it is obviously not applicable to the complex areas with threat areas and forbidden areas. In Figure 7(a), it can be seen that although the number of robots increases, the coverage obtained by RCA algorithm does not increase in the same proportion, but take a trend of slowing down. It shows that it is tough to improve the coverage simply relying on the number of robots and people, and the coverage algorithm and strategy must be changed.

In Table 2, due to the blindness of RCA algorithm in covering operations, the number of robot losses increases despite the increase of the size of swarm robots. During the implementation of AIRT algorithm and RTA algorithm, when the threat area is detected, the stimulation amount of this area is multiplied by 0.01 each time it is covered, which can effectively reduce the probability of other robots entering the covered threat area again.

At the same time, in order to pursue higher coverage, both the AIRT algorithm and the RTA algorithm are at the expense of robots, but the difference is that the AIRT algorithm effectively takes into account the relationship between environmental task stimulation and individual response threshold, as well as the relationship between individuals, so that the robots cooperate with each other. When a robot detects the threat area, it adjusts the stimulation value between groups, preventing other robots from entering the dangerous area again, so it can effectively improve the area coverage efficiency. The RTA algorithm only considers the task's response to individual stimulation and robot's individual, and ignores the interaction between swarm robots, so it has the problem of repeated coverage of dangerous areas. Therefore, the number of lost robots is relatively large.

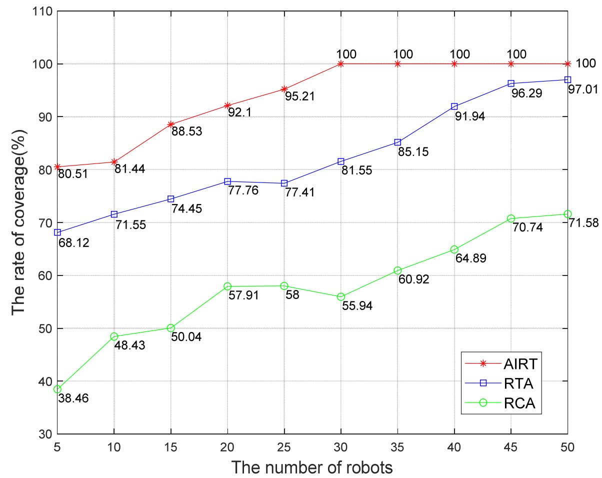
As shown in Figure 7(b), the total coverage length of swarm robots also increases with the number of robots. The difference is that the AIRT algorithm not only effectively realises the coordination between task stimulation and individual response threshold, but also takes into account the distribution of swarm robots in regional coverage. This way of adjusting response threshold-based the number of surrounding robots can increase the service efficiency of robots, to avoid the surrounding robot in the case of saturation, do some useless work, not only increase congestion, but also reduce efficiency. Thus, it can be seen that the total coverage length of AIRT algorithm is relatively short, which is 1/2 to 1/3 of the other two algorithms. Furthermore, it proves that the implementation of AIRT algorithm with better perception of task stimulation and efficient cooperation between swarm robots can reduce the repeated coverage of swarm robots, shorten the total coverage length and achieve efficient area coverage.

4.4 *Coverage of sudden threat areas*

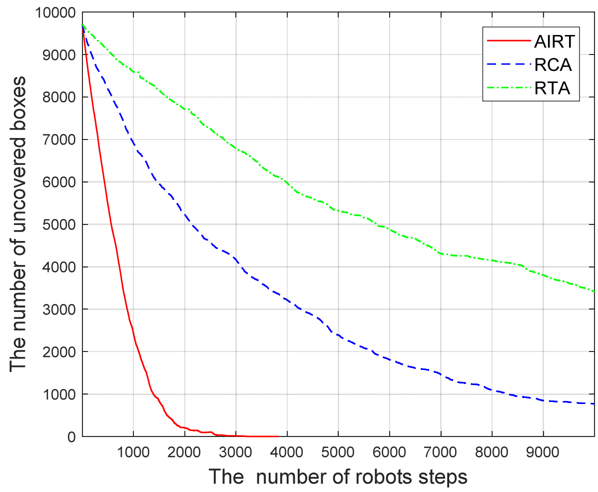
In Subsection 4.3, the effectiveness of the algorithm proposed in dealing with fixed threat area coverage is investigated. But the real battlefield may be more complex, for many threats do not exist at the beginning, but suddenly appear at some time. For example, when the UAV cluster is performing reconnaissance tasks, the air defence firepower in some areas of the enemy cannot be detected when the radar is turned off, and it needs to be turned on to be found. Moreover, the threat coefficient and threat area in the enemy area are unknown in advance, but suddenly appear in the process of group robot performing area coverage. In this case, the conventional swarm intelligence optimisation algorithm needs to restart and recalculate the best route and task allocation scheme. The AIRT algorithm proposed in this paper is based on the local interaction rules between individuals, which is pretty suitable for the dynamic battlefield environment. In the grid map of 100 × 100 mentioned above, not only the given threat area and no-fly area are set, but also two sudden threats are set in the process of the robot's coverage task. When the robot steps are 1,000 and 2,000 respectively, the threat radius of the two sudden threats is 2, and the threat coefficient of the threat area is 0.2, which mainly investigate the adaptability of the algorithm to the dynamic environment. Figure 8(a) draws the results of the simulation statistical coverage. At the same time, due to the similar regularities, only the map coverage process is given as shown in Figure 8(b) when the number of swarm robots is 40.

As shown in Figure 8(a), through the analysis of simulation results, it can be seen that, similar to the established threat area, the coverage rate of each algorithm is growing as a whole in the process of increasing the number of robots from 5 to 50, and the total coverage length augments with the increasing number of robots. The difference is that more robots need to be consumed to cover the threat area due to the sudden threat. Compared with AIRT algorithm, the coverage of RTA and RCA algorithm decreased more after the introduction of burst threat. At the same time, due to the random introduction of the sudden threat shown in Figure 8(a), the emergency response of RCA algorithm is poor, resulting in the unstable performance of its coverage. As shown in the Figure 8(a), when the number of robots increases from 25 to 30, the coverage is not increased but decreased. At the same time, compared with the RTA algorithm, the performance of the threshold algorithm of activator suppression response proposed has not been greatly affected. At last, the algorithm still achieves 100% coverage in more than 30 robots, which shows that the algorithm can adapt well to the sudden threat. This is mainly because the proposed intelligent labour division approach uses the activation-inhibition model of bee colony labour division to dynamically adjust the threshold value in the response threshold model of ant colony labour division, which better combines the respective advantages of the response threshold model of ant colony labour division and the activation-inhibition model of bee colony labour division. On the one hand, it makes the proposed method superior to the traditional centralised method. Without central control guidance and global information, it can automatically make decisions according to the state and environmental stimulation of robots, and then realise the individual division of labour within the robot swarm, and achieve a dynamic balance, with good adaptability and self-organisation characteristics; on the other hand, when encountering sudden threaten, due to the dynamic adjustment mechanism of the threshold, the proposed swarm intelligence labour division model makes the task behaviour of the robots have better flexibility, so that the robot swarm can adapt to the sudden threat and still complete the established coverage task, highlighting its robustness.

Figure 8 Comparison of simulation results of map coverage of swarm robots, (a) coverage rate with the number of robots (b) process chart of group robot map coverage (see online version for colours)



(a)



(b)

In Figure 8(b), the abscissa is the time required for the group robot to perform the area coverage task, it shows in this paper the steps of the single robot with the most steps in the group robot. The ordinate is the number of the remaining grids not covered except the forbidden area. As can be seen from Figure 8(b), on the one hand, the algorithm mentioned in this paper combines the advantages of the response threshold model of ant colony labour division and the activation-inhibition model of bee colony labour division respectively, which makes the coverage efficiency of swarm robots higher, and it spends few time in covering the most areas, and completes all area except that of the forbidden one when the robot executed more than 3,800 steps, coverage rate reaches 100%.

In addition, both RCA and RTA algorithms failed to complete all coverage tasks within 10,000 steps, achieving 64.89% and 91.94% respectively. Moreover, it can also be seen from the map coverage work process chart of swarm robots that RTA algorithm and AIRT algorithm based on topo-interaction rules have better response to sudden threat areas. When the robot steps reach 1,000 and 2,000, there is no obvious situation of process stagnation or rate sudden decline shown by RCA algorithm. After the emergence of the sudden threat target, the swarm intelligence labour division of activation-inhibition response method proposed can still respond quickly, adjust in time according to the battlefield situation, and enable the robots to take covering action arrangement that is conducive to the overall situation, which again illustrate the great adaptability of the algorithm proposed to the sudden threat, and it is of great practical significance.

5 Conclusions and prospects

The coverage problem of complex areas is a classic problem in the field of swarm robots, which is widely used in military, people's livelihood and other fields. Firstly, aiming at the complex target area, such as the complex nonlinear boundary and the threat task area, the task area is adjusted and the grid is discretised. Then, from the perspectives of the relationship between individual and environment, individual and the other individual, combined with the advantages of the response threshold model of ant colony division of labour and the activation-inhibition model of bee colony division of labour, the threshold value in the response threshold model of ant colony labour division is adjusted dynamically by the activation-inhibition model of bee colony labour division, and a new swarm intelligence labour division approach is put forward to solve the complex area coverage problem of swarm robots. Three groups of experiments are carried out, including coverage problem of non-threat area, coverage problem of established threat area and coverage problem of sudden threat area. In the last two experiments, threat region threat coefficient is introduced. When a robot is threatened to a certain upper limit, it is regarded as the eliminated robot, which is different from the constant number of robots in the conventional model and algorithm, which has been working all the time. It increases the practical adaptability of solving area coverage problem. Three groups of experiments show that the proposed swarm intelligence labour division algorithm has good ability to solve area coverage and dynamic environment adaptability, and can respond effectively to sudden threats, and has good adaptability and practical application prospects.

However, this research is not perfect, and can be further studied, for example:

1 The algorithm is abstracted from the interaction between individual and environment, individual and individual, which only needs local perception and interaction and makes swarm robots more adaptable to dynamic environment without prior knowledge and global communication. However, in practical application, robot communication and movement constraints in dynamic environment also need to be considered.

2 By the characteristics of battlefield confrontation environment, it is necessary to give more research on other area coverage issues, such as complex area coverage problems with repair bases (supply and maintenance points) and threat areas at the same time.

3 The algorithm has good universal applicability, and can expand the feasible application range of the algorithm in the later stage, such as forest fire coverage monitoring, UAV task allocation, nuclear and biochemical detection, disaster area search and rescue, anti-terrorism explosives search and other issues.

Acknowledgements

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