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OPTIMIZATION OF SWARM ROBOTICS ALGORITHMS

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ABSTRACT

Context. Among the variety of tasks solved by robotics, one can single out a number of those for the solution of which small dimensions of work are desirable and sometimes necessary. To solve such problems, micro-robots with small dimensions are needed, the mass of which allows them to move freely in tight passages, in difficult weather conditions, and remain unnoticed. At the same time, the small dimensions of the microrobot also impose some indirect restrictions; therefore, it is better to use groups of microrobots for the solution of these problems. The efficiency of using groups of microrobots depends on the chosen control strategy and stochastic search algorithms for optimizing the control of a group (swarm) of microrobots.

Objective. The purpose of this work is to consider a group of swarm algorithms (methods) belonging to the class of metaheuristics. The group of these algorithms includes, in particular, the ant colony algorithm, the possibilities of which were investigated to solve the traveling salesman problem, which often arises when developing an algorithm for the behavior of a group of microrobots.

Method. At the first stage of the study, the main groups of parameters were identified that determine the flow and characterize the state at any time of the ant colony algorithm: input, control, disturbance parameters, output parameters. After identifying the main groups of parameters, an algorithm was developed, the advantage of which lies in scalability, as well as guaranteed convergence, which makes it possible to obtain an optimal solution regardless of the dimension of the graph. At the second stage, an algorithm was developed, the code of which was implemented in the Matlab language. Computer experiments were carried out to determine the influence of input, control, output, and disturbance parameters on the convergence of the algorithm. Attention was paid to the main groups of indicators that determine the direction of the method and characterize the state of the swarm of microrobots at a given time. In the computational experiment, the number of ants placed in the nodes of the network, the amount of pheromone, the number of graph nodes were varied, the number of iterations to find the shortest path, and the execution time of the method were determined. The final test of modeling and performance of the method was carried out.

Results. Research has been carried out on the application of the ant algorithm for solving the traveling salesman problem for test graphs with a random arrangement of vertices; for a constant number of vertices and a change in the number of ants, for a constant number of vertices at different values of the coefficient Q; to solve the traveling salesman problem for a constant number of vertices at different values of the pheromone evaporation coefficient p; for a different number of graph vertices. The results showed that ant methods find good traveling salesman routes much faster than clear-cut combinatorial optimization methods. The dependence of the search time and the found optimal route on the values of control parameters are established using the example of test networks for a different number of graph vertices and iterations.

Conclusions. The studies were carried out to make it possible to give recommendations on the application of the ant colony algorithm to control a group (swarm) of microrobots.

KEYWORDS: swarm robotics, ant colony optimization algorithm, salesman problem.

ABREVIATIONS

ACO is a ant colony optimization algorithm.

NOMENCLATURE

I_i is a input parameters;

H_k is a perturbation parameters;

O_z is a output parameters;

C_i is a control parameters;

α is a control parameter;

β is a control parameter;

Q is a control parameter;

p is a control parameter;

m is a number of ants;

n is a number of vertices;

t is a time.

INTRODUCTION

One of the current problems is the natural increase in the complexity of management systems, which, in turn, is determined not only by increasing production productivity, speed of processing operational information, but also the commissioning of increasingly complex distributed technical and technological systems (transport, information, energy, etc.). Effective operation of the latter depends on purposeful activities related to obtaining the best results under appropriate conditions. Ultimately, such activities are reduced to solving the problems of continuous global optimization.

Usually, scientific publications on robotics address issues related to the use of a single robot. Such a robot is equipped with a powerful onboard computer, a large supply of onboard energy, and, as a rule, a significant set

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of working bodies. This configuration leads to an increase in the size and weight of the robot, which in turn significantly limits the possible scope of its application. At the same time, among the variety of tasks that are solved by robotics, we can identify a number of those for which small dimensions of the work are desirable and sometimes necessary. These include the task of reconnaissance of territories and waters in the face of organized enemy resistance, the task of finding victims in debris after natural or man-made disasters, the task of finding and disposing of explosive devices in anti-terrorist operations in dense urban areas, the study of surfaces of other planets and others.

To solve such problems requires micro-robots with small dimensions, the mass of which allows you to move freely in narrow passages, difficult weather conditions, to remain unnoticed. Such works are characterized by lower costs for transportation of the technical complexity of equipment to the place of work. However, the small size of microrobots imposes some restrictions: 1) complicated movement in unprepared space, because relatively small protrusions and depressions on the surface can impede the movement of microrobots; 2) it becomes more difficult to perform tasks on the movement of large bodies (for example, victims in the earthquake zone, or rock samples) by a single microrobot.

The small size of the microrobot also imposes some indirect restrictions: 1) a small stock of onboard energy; 2) small size and power consumption of means of communication lead to limitation of the maximum radius of radio communication; 3) significantly a limited number of available working tools.

These restrictions apply to a single microrobot. Therefore, the obvious solution to these problems may be the use of a group of microrobots that can combine efforts to solve complex problems. Microrobots can help each other to overcome obstacles [13], to transport large bodies together [21]. Information exchange in a group of robots allows expanding the information available to each work about the environment. In this case, some tasks can be distributed between microrobots and run in parallel. For example, while some group work collects environmental data, others collect soil samples.

The need to use a large number of different work tools requires the use of a heterogeneous group, ie a group consisting of robots of different designs (for example, the Swarmanoid project [6]). At first glance, it seems that the advantages of using a group of microrobots compared to using a single robot, which is equipped with a sufficient number of functional elements, are not obvious. But do not forget that when used in groups, microrobots retain all the above advantages of small robots: primarily the ability to move in confined spaces, lightweight, and size. Group use of microrobots reduces the risk of task failure because damage to one or more group microrobots in the general case (especially in swarm and collective management strategies, discussed later in the article) does not disrupt the task, although it reduces the effectiveness of the group. At the same time, damage to individual units of a single robot can lead to disruption of work, and attempts to duplicate the most important functional units of the robot lead to increased weight, size, cost of work, but does not increase efficiency (even reduces due to large size and weight).

The effectiveness of the use of groups of microrobots depends on the chosen control strategy. Scholars usually distinguish between centralized and decentralized management strategies [3]. In centralized management strategies, there is some central control device, which has access to information about the state of all robots in the group and the environment. The control device assesses the current situation and decides on the actions of the group’s robots [24]. The central control device can be located outside the group (for example, on the operator’s control panel), or onboard one of the robots of the group. In the latter case, talk about centralized control with a master device. Centralized management strategies show good results with a small number of robots in a group. As the group size increases, the load on the communication channel and the computing means of the control device increase. One way out is to apply hierarchical control strategies in which a group of robots is divided into subgroups, each with its leader (usually a group of robots), and subgroup leaders are controlled by a central control device onboard one of the robots or outside the group. Hierarchical management strategies complicate the nature of communications between the work of the group, resulting in serious requirements for onboard communication equipment. Obstacles in the communication channel have an extremely negative impact on the work of the group in centralized management strategies. In addition, the failure of a robot that performs the functions of managing a group or subgroup leads to serious problems – the connection with all the work under its control is lost.

Decentralized management strategies for groups of robots include collective, team, and swarm management strategies. In a collective management strategy, each robot in the group receives information from all other robots in the group and transmits the information they collect about the environment and their condition to the communication channel so that this information is available to all other robots in the group. Thus, the information exchange in the group of robots in collective management is carried out on the principle of “everyone with everyone”. Due to this, each robot can independently assess the current situation and decide on the need for further action. Collective management strategies allow the team to maintain performance in the event of failure of one or more robots of the group. The load on the communication channel increases in direct proportion to the increase in the number of groups of robots. The load on the onboard computing devices of robots is also increasing because they need to process the received contact information.

The upper limit of the allowable group size in collective management methods is on average higher than in centralized ones, but the scaling of these methods

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leaves much to be desired. In cohesive control strategies, there is no dedicated communication channel for the exchange of information between robots, each robot collects information about the environment independently and also independently decides on their next steps to contribute to the group task. Lack of communication between group work in team management strategies allows you to successfully solve only those tasks that can be easily divided into independent unrelated subtasks. The main advantage of cluster control strategies is scalability: as the number of robots increases, the computational complexity of control tasks does not increase, which allows the use of cluster strategies to control very large groups of microrobots.

Thus, the objective of the article is to study the optimization possibilities of swarm robotics algorithms.

The object of research is the ant colony optimization algorithm.

The subject of the research is the use of the ant colony optimization algorithm for solving the traveling salesman problem.

1 PROBLEM STATEMENT

Let the list of input variables be specified: 1) m is a number of ants; 2) n is a number of vertices; 3) α, β, Q and p – control parameters. The task at the time was to determine the effect of input, control, perturbation parameters on the convergence and time performance of the ant colony algorithm (ACO) when solving the traveling salesman problem (TSP). List of output variables: 1) t is a time; 2) the number of iterations to find the optimal solution; 3) the length of the best way (tour). Limitations: number of iterations of the algorithm 300; the coordinates of the vertices were taken in the range from 0 to 100; the number of vertices varied from 20 to 200; number of ants from 5 to 400.

2 REVIEW OF THE LITERATURE

At the end of the twentieth century, stochastic search engine optimization algorithms became the most popular in solving swarm control problems. This article focuses on the group of swarm algorithms (methods) that belong to the class of metaheuristics. The group of these algorithms includes: 1) the ant colony algorithm; 2) bee algorithm; 3) particle swarm algorithm; 4) stochastic diffusion algorithm; 5) cuckoo algorithm; 6) bacterial optimization algorithm; 7) gravity search algorithm; 8) algorithm of water drops [18].

In these algorithms, individuals that are part of the swarm (ants, bees, bacteria, etc.), in practice, are implemented in the form of software agents. The general scheme of swarm algorithms is based on the following stages: 1) in the field of search in a certain way creates some initial approximations to the desired solution – the initialization of the population of agents; 2) with the help of some set of migration operators (specific tactics for each of the swarm algorithms) agents move in the search area so that, in the end, approach the desired extremum of the objective function; 3) check the condition of the end of iterations. If the last condition is met, the calculations are completed. In this case, the best of the found positions of the agents is taken as an approximate solution. If the condition is not met – Return to stage 2. Widespread practical application in the class of metaheuristics has acquired algorithms of the ant colony, which allow finding approximate solutions to search problems on graphs for polynomial time.

Swarm intelligence methods [5] are used to solve many practical problems of Swarmanoid [10], can be used to control large groups of robots, which led to the emergence of a separate direction Swarm Robotics [1]. Each robot in the group interacts only with some neighboring robots that fall within the range of visibility, which is limited by the range of its telecommunications devices (or artificially limited). Each robot independently decides on further actions based on simple local rules (simple rules, local rules). The work is available information about the environment, which he collected himself, as well as information about the environment and the state of some of the robots of the group, which was passed to him by neighboring works. The robot transmits the collected information about the environment, as well as about its state to the communication channel. This information becomes available to those robots in the field of view of which this robot falls (in the case of the same radii of the field of view – it's neighboring work). Thanks to this approach, works receive more information about the environment than with team management strategies, and the information available to them relates to the environment, ie the most relevant. This preserves the scaling – increasing the number of groups does not increase the load on onboard computers.

Methods of swarm intelligence open wide opportunities for the development of microrobots of mass use, allowing the successful use of large groups of microrobots. A reasonable question arises: why swarms of microrobots are still not found in practice, and the achievements of swarm robotics are limited to several experimental projects (Swarm-bot [16], Swarmanoid [6], I-SWARM [18]) and some theoretical works.

One of the obvious obstacles to the development of swarm robotics is the fact that the objects of control in it are numerous groups of microrobots, which implies the presence of inexpensive mass production of microrobots. Technologies of such products are based on the most modern technical achievements. Progress in the field of microelectronics, mechatronics, and nanotechnology gives reason to hope that soon mass production of microrobots will be not only possible but also economically feasible.

The second obstacle is the lack of general theory and approaches in the creation and development of swarm management methods in groups of robots. Currently, much of the research is devoted to the use of natural analogs of swarm intelligence methods to solve technical problems: ants [2], bees [11], flocks of birds and shoals of fish [14], immune systems [19], [8]) became prototypes for creating various methods of swarm intelligence.

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Here, individuals who are part of the swarm (ants, bees, immune bodies), in practice, are implemented in the form of software agents. The general scheme of swarm algorithms is based on the following steps.

1) In the field of search in one way or another creates some initial approximations to the desired solution – the initialization of the population of agents.

2) With the help of some set of migration operators (specific tactics for each of the swarm algorithms), the agents move in the search area so that, in the end, they approach the desired extremum of the target function.

3) Check the condition of the end of iterations. If this condition is true, the calculations are completed. In this case, the best of the found positions of the agents is taken as an approximate solution. If the condition is incorrect – return to step 2.

Differences in the tasks and capabilities of natural and technical systems make it difficult to find and adapt natural algorithms to solve technical problems. Some studies are carried out to create artificial methods of swarm intelligence, which are designed solely to solve practical problems. Unfortunately, the lack of a unified approach complicates these studies. Each new task is solved every time almost "from scratch".

Danielli A. Lima [12] propose an inverted ant cellular automata (IACA) model for swarm robots performing the surveillance task. A new distributed coordination strategy is described, which was designed with cellular automata-based modeling and using a repulsive pheromone-based search.

David Payton [15] describe how a robot swarm can become a distributed computing mesh embedded within the environment, while simultaneously acting as a physical embodiment of the user interface. With this simple peer-to-peer messaging scheme, many coordinated activities can be accomplished without centralized control.

An inverted ant cellular automata model called IACA-DI is proposed for the coordination of a swarm of robots performing the surveillance task [20]. The swarm communicates indirectly through the repulsive pheromone, which is available as neighborhood information. The pheromone is deposited at each time step by each robot over its neighborhood.

Schroeder [17] propose a control law for efficient area coverage and pop-up threat detection by a robot swarm inspired by the dynamical behavior of ant colonies foraging for food. They are performance metrics that evaluate area coverage in terms of characteristics such as rate, completeness, and frequency of coverage are developed.

The design of robot swarms inspired by self-organization in social insect groups is currently an active research area with a diverse portfolio of potential applications. Deshpande [3] propose a control law for efficient area coverage by a robot swarm in a 2D spatial domain, inspired by the unique dynamical characteristics of ant foraging.

Dimidov [4] analyze the efficiency of random walk patterns for a swarm of Kilobots searching a static target in two different environmental conditions entailing a bounded or open space. They study the search efficiency and the ability to spread information within the swarm through numerical simulations and real robot experiments.

Fricke [8] use a robot swarm to evaluate the effectiveness of a Lévy search strategy and map the relationship between search parameters and target configurations. They show that the fractal dimension of the Lévy search, which optimizes search efficiency, depends strongly on the distribution of targets but only weakly on the number of agents involved in the search.

Using computer simulations, Fujisawa [9] that the Lévy walk-like searching strategy can maximize the group foraging efficiency of the swarm robots using pheromone trails (mimicking ant group foraging), as well as maximize individual searching area.

Efremov [7] reviewed approaches to a swarm of simple robot behavior design for solving the more complex problem of foraging.

3 MATERIALS AND METHODS

In the given work the generalized algorithm of the organization of swarm interaction based on the dynamic behavior of a colony of ants is offered. The indicators of the effectiveness of the method of covering the territory based on virtual pheromones are considered (Fig. 1).

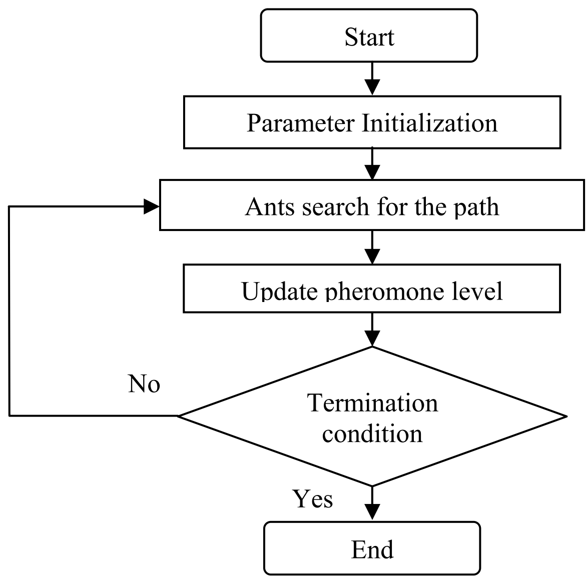

Figure 1 – Flow chart of ant colony optimization algorithm

The authors of this study propose to consider the process of the behavior of a swarm of agents in such a way as to obtain the selection of the main groups of parameters that determine its course and characterize the state at any time. This approach is used to solve optimization problems, for example, in the field of chemistry. According to this approach, it is possible to

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select the following groups of parameters for the behavior of an ant colony.

1) Input parameters $I_i, i \in \overline{1,m}$. The values of this group of parameters can be measured, but they cannot be influenced. When solving the salesman's problem, this group should include quantitative characteristics of the search area (for example, dimension and weights of the adjacency matrix).

2) Control parameters $C_i, j \in \overline{1,r}$. These parameters should be considered as variables that can be directly influenced to control the process itself. Such adjustable parameters for solving the salesman's problem can be, for example, the initial values of the parameters α, β, *Q*, *p*, and *m*.

3) Perturbation parameters $H_k, k \in \overline{1,e}$. The values of these variables change over time randomly. As a rule, the values of the perturbation parameters are not available for measurement. For the salesman's task, these parameters can be the characteristic of the "desire" of the agent η_{ij}, the amount of pheromone τ_{ij}, etc.

4) Output parameters $O_z, z \in \overline{1,n}$. For these variables, the values are determined by the mode of the swarm behavior. These parameters describe the state of the process resulting from the total action of input, control parameters, and perturbation parameters. The initial parameters can be considered the number of iterations that are performed to find the solution, the proximity of the found solution to the optimal, etc.

4 EXPERIMENTS

After identifying the main groups of parameters that determine the course and characterize the state at any time of the ant colony algorithm (ant colony optimization algorithm), computational experiments were performed to influence the input, control, perturbation parameters, output parameters on the convergence of the algorithm. The advantage of the algorithm is its scalability, as well as guaranteed convergence, which allows you to get the optimal solution regardless of the dimension of the graph. The only drawback is that the convergence rate of the algorithm is unknown.

In the experiments, the number of ants placed in the nodes of the network varied: 1–5, 10, 30, 50. During the random experiments, different network topologies were generated, and the number of iterations at which the optimal cycle was achieved was recorded.

Table 1 shows the dependence of the search time and the optimal route found on the example of randomly generated test graphs shown in Figure 2 with the number of iterations 300. The coordinates of the vertices of the graphs were generated using the function Randi ():

x=randi(100,1,20);

y=randi(100,1,20);

Table 1 shows the dependence of the search time and the optimal route found on the values of the control parameters on the example of the test networks shown in Fig. 2.

Table 2 shows the dependence of the search time and the optimal route found on the number of ants on the example of a graph with the number of vertices 20 with the number of iterations 300. The coordinates of the vertices of the graph were chosen arbitrarily:

x=[82 91 10 19 63 15 28 55 96 87 15 98 96 49 80 14 42 92 89 43];

y=[6 30 85 19 68 16 75 39 66 79 71 3 27 4 9 83 68 21 95 3];

According to the results obtained, the following conclusions can be drawn:

1) with a constant number of vertices *n* and a change in the number of ants m and iterations t, time costs change according to the estimate of time complexity $Q\ (m \cdot t \cdot n^2)$;

Table 1 – Application of the ant algorithm for solving the salesman problem for test graphs with a random arrangement of vertices

№ networks	Number of ants	*p*	α	β	*Q*	Number of vertices	Number of iterations to find the optimal solution	Result	Time, s
1	40	0.1	1	1	1	20	104	385.6315	22.847178
2	40	0.1	1	1	1	20	29	340.9843	22.458717
3	40	0.1	1	1	1	20	272	405.6638	22.755844
4	40	0.1	1	1	1	20	136	376.4947	22.737581
5	40	0.1	1	1	1	20	246	384.7575	22.546910
6	40	0.1	1	1	1	20	91	336.088	22.494738
7	40	0.1	1	1	1	20	230	342.5689	22.420198
8	40	0.1	1	1	1	20	239	368.5756	22.860189
9	40	0.1	1	1	1	20	162	325.4138	22.602328
10	40	0.1	1	1	1	20	75	347.0352	23.463464
11	40	0.1	1	1	1	20	230	366.0119	22.635822
12	40	0.1	1	1	1	20	37	385.2827	22.472831
13	40	0.1	1	1	1	20	24	291.521	22.500305
14	40	0.1	1	1	1	20	232	448.2383	22.488642
15	40	0.1	1	1	1	20	93	414.5459	22.417555

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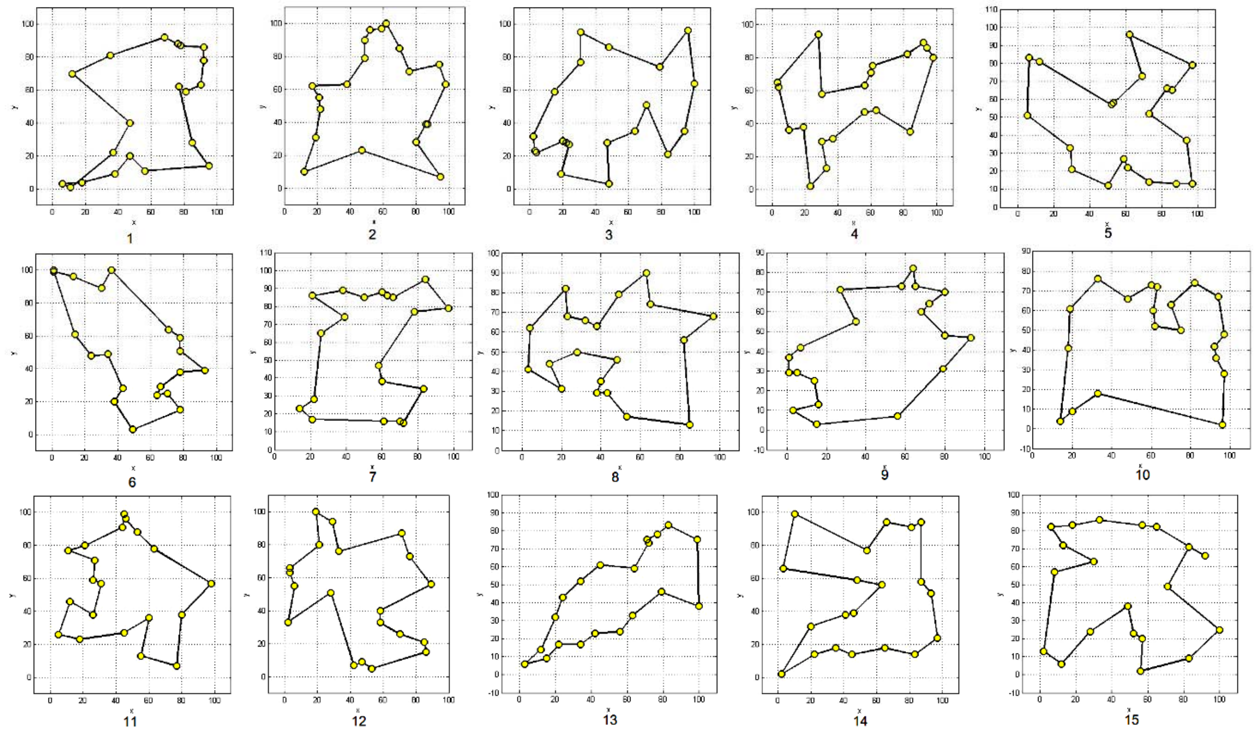

Figure 2 – Graphs to table 1

Table 2 – Application of the ant algorithm to solve the salesman problem for a constant number of vertices and change the number of ants

№ networks	Number of ants	*p*	α	β	*Q*	Number of vertices	Number of iterations to find the optimal solution	Result	Time, s
1	5	0.1	1	1	1	20	232	395.5417	15.992249
2	10	0.1	1	1	1	20	75	400.1229	14.405423
3	15	0.1	1	1	1	20	235	400.6502	16.202756
4	20	0.1	1	1	1	20	187	396.1515	16.977871
5	25	0.1	1	1	1	20	261	395.5417	19.182736
6	30	0.1	1	1	1	20	137	395.5417	23.441613
7	35	0.1	1	1	1	20	157	395.5417	25.109654
8	40	0.1	1	1	1	20	106	395.5417	26.945276
9	60	0.1	1	1	1	20	185	395.5417	33.179504
10	80	0.1	1	1	1	20	62	395.5417	43.445270
11	100	0.1	1	1	1	20	99	395.5417	47.043559
12	150	0.1	1	1	1	20	153	395.5417	62.791894
13	200	0.1	1	1	1	20	94	395.5417	80.507522
14	300	0.1	1	1	1	20	21	395.5417	113.99703
15	400	0.1	1	1	1	20	53	395.5417	143.40482

2) changing the parameter m affects the time cost, but does not guarantee a better result. This is due to the probabilistic approach to the choice of peaks by ants.

The values of the control parameter Q are selected in the same order as the length of the optimal route. Q depends on the length of the path to the destination: the shorter the path, the greater should be the value of Q: $1 \le Q \le 10000$.

A computational experiment showed (Table 3) that changing the control factor Q does not have a significant effect on finding the optimal solution.

Parameters α and β set the weight of the pheromone trace and visibility when choosing a route. They vary within $0 \le \alpha \le 5$; $1 \le \beta \le 5$. The computational experiment allowed us to identify the optimal combinations of parameters used in the ant colony algorithm (Table 4).

In case of unsuccessful selection of parameters, the following situations may occur:

1. Large values of the parameter α, at which ants enter a dead-end without finding solutions.

2. At small values of the α-parameter, ants can find the path from the starting point to the end, but this path is not optimal.

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Table 3 – Application of the ant algorithm for solving the salesman problem for a constant number of vertices at different values of the coefficient *Q*

№ networks	Number of ants	*p*	α	β	*Q*	Number of vertices	Number of iterations to find the optimal solution	Result	Time, s
1	40	0.1	1	1	1	20	152	395.5417	25.516824
2	40	0.1	1	1	650	20	88	395.5417	22.386155
3	40	0.1	1	1	1300	20	139	395.5417	22.359020
4	40	0.1	1	1	2000	20	246	396.1515	22.053672
5	40	0.1	1	1	2600	20	195	395.5417	22.323921
6	40	0.1	1	1	3250	20	202	395.5417	22.714128
7	40	0.1	1	1	4000	20	34	395.5417	23.427087
8	40	0.1	1	1	4600	20	50	396.1515	22.297267
9	40	0.1	1	1	5250	20	207	395.5417	22.361742
10	40	0.1	1	1	6000	20	136	395.5417	22.536203
11	40	0.1	1	1	6650	20	106	395.5417	22.382881
12	40	0.1	1	1	7300	20	163	395.5417	22.254868
13	40	0.1	1	1	8000	20	84	395.5417	22.217386
14	40	0.1	1	1	9000	20	23	395.5417	22.793634
15	40	0.1	1	1	10000	20	296	395.5417	23.697207

3. In the third case, it is possible to find the optimal solution (Table 4).

Table 4 – The optimal set of α and β parameters

α parameter	β parameter
0.5	0.5
5.0	5.0
1.0	1.0

5 RESULTS

The results obtained in the process of the computational experiment can be explained as follows: the parameter α allows taking into account the experience of previous generations of ants, while β is focused only on the path length. Only with the right combination of parameter values is it possible to find the optimal route.

Initial experiments with the ant colony algorithm found that ants come to a decision quickly and spend little time exploring alternative pathways. To force ants to do more research and to prevent premature convergence, the pheromone on the links is allowed to "evaporate" in each iteration of the algorithm before they increase based on the newly constructed pathways (2). The evaporation coefficient of pheromone p varies within $0.1 \le p \le 0.99$. The constant p determines the rate at which pheromones evaporate, causing ants to "forget" about previous decisions. In other words, p determines the degree of influence of the search history. For large values of p, the pheromone evaporates rapidly, while small values of p lead to a slowing of the evaporation rate (Table 5). The more pheromones evaporate, the more random the search becomes, which improves intelligence. For $p = 1$, the search is completely random.

In the calculation process, the execution time of the algorithm was recorded depending on the number of vertices of the graph (Table 6, Fig. 3). A number of iterations 500.

Analysis of the obtained time characteristics of the route calculation shows that as the number of vertices in the graph increases, the time required to find the route increases (Fig. 4).

Table 5 – Application of the ant algorithm for solving the salesman problem for a constant number of vertices at different values of the pheromone evaporation coefficient *p*

№ networks	Number of ants	*p*	α	β	*Q*	Number of vertices	Number of iterations to find the optimal solution	Result	Time, s
1	40	0.10	1	1	1	20	96	395.5417	22.665959
2	40	0.16	1	1	1	20	80	395.5417	22.389597
3	40	0.22	1	1	1	20	69	395.5417	22.574964
4	40	0.28	1	1	1	20	216	395.5417	22.288871
5	40	0.34	1	1	1	20	42	398.6139	22.282747
6	40	0.40	1	1	1	20	19	395.5417	22.303454
7	40	0.46	1	1	1	20	186	400.1162	22.171169
8	40	0.52	1	1	1	20	43	395.5417	22.197507
9	40	0.57	1	1	1	20	102	395.5417	22.340538
10	40	0.63	1	1	1	20	265	395.5417	22.165415
11	40	0.69	1	1	1	20	241	395.5417	22.264250
12	40	0.75	1	1	1	20	54	397.184	22.521302
13	40	0.81	1	1	1	20	147	398.474	22.347847
14	40	0.87	1	1	1	20	243	395.5417	22.887289
15	40	0.99	1	1	1	20	86	395.5417	22.227174

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Table 6 – Application of the ant algorithm for solving the salesman problem for different numbers of graph vertices

№ networks	Number of ants	p	α	β	Q	Number of vertices	Number of iterations to find the optimal solution	Result	Time, s
1	40	0.1	1	1	1	20	158	361.2807	25.662532
2	40	0.1	1	1	1	33	173	443.1308	29.997125
3	40	0.1	1	1	1	46	257	602.3146	39.447256
4	40	0.1	1	1	1	59	299	647.2844	45.851241
5	40	0.1	1	1	1	71	76	798.1173	52.468550
6	40	0.1	1	1	1	84	289	830.3252	63.123333
7	40	0.1	1	1	1	97	264	910.8729	69.387167
8	40	0.1	1	1	1	110	290	982.5124	78.692760
9	40	0.1	1	1	1	123	299	1064.4672	89.291780
10	40	0.1	1	1	1	136	267	1105.5601	99.569191
11	40	0.1	1	1	1	149	296	1196.1199	116.750170
12	40	0.1	1	1	1	161	214	1255.0331	129.761123
13	40	0.1	1	1	1	174	276	1262.4144	139.675033
14	40	0.1	1	1	1	187	266	1344.9961	154.827335
15	40	0.1	1	1	1	200	298	1515.7214	168.314706

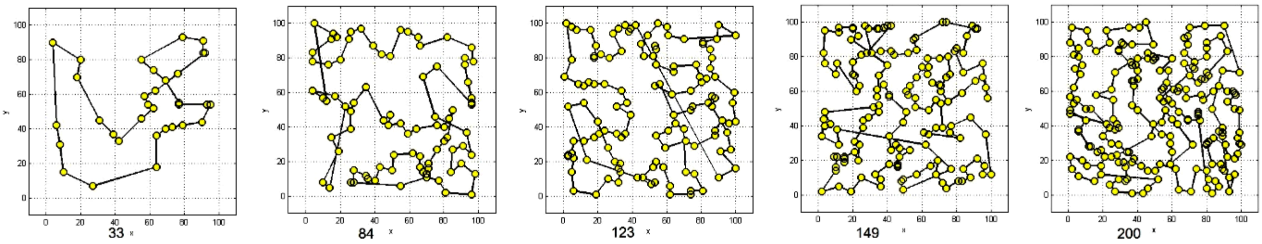

Figure 3 – Some graphs to table 6: with 33, 84, 123, 149, and 200 vertices

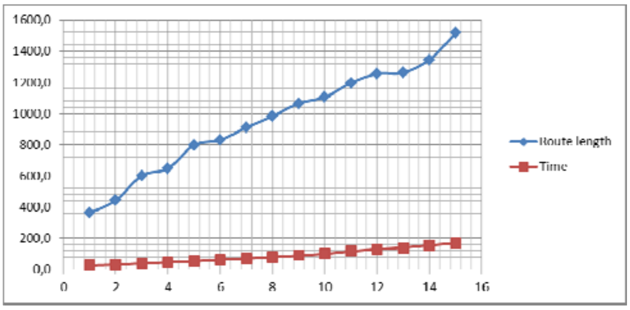

Figure 4 – Dependence of the time of the ant algorithm and the length of the found route on the number of vertices in the graph at 300 iterations

6 DISCUSSION

The study identified the main groups of parameters that determine the course and characterize the state at any time of the ant colony algorithm and performed computational experiments to influence the input, control, perturbation parameters, output parameters on the convergence of the algorithm.

Ant algorithms are an example of an adequate mathematical model of ant colony activity, which is suitable for creating computer methods for the probabilistic solution of some combinatorial problems.

The basic idea behind the ant colony algorithm is to use a positive feedback mechanism to help find the best approximate solution to complex optimization problems.

The efficiency of ant algorithms increases with an increasing dimension of the optimization problem. Ant algorithms provide solutions to other combinatorial problems no worse than general metaheuristic optimization technologies and some problem-oriented methods. All this allows us to recommend the use of ant algorithms to solve complex combinatorial optimization problems and their application, in particular, to the optimization of group robotics algorithms.

The paper investigates the application of the ant algorithm for solving the salesman problem for test graphs with a random arrangement of vertices; for a constant number of vertices and a change in the number of ants, for a constant number of vertices at different values of the coefficient Q; to solve the problem of the salesman for a constant number of vertices at different values of the evaporation coefficient of the pheromone p; for different numbers of graph vertices. The analysis of the obtained time characteristics of the route calculation was also performed. The computational experiment allowed us to identify the optimal combinations of parameters used in the ant colony algorithm.

It is known that most likely it will not be possible to construct an exact polynomial algorithm for the traveling salesman problem. Apparently, these simply do not exist. Therefore, it is necessary either to go beyond the scope of polynomial algorithms, or to seek approximate solutions to the problem. But the ant colony optimization algorithm approach may not be simpler than the exact solution of the problem. This algorithm can be applied to a relatively small number of ants and graph vertices.

Ant Colony Optimization (ACO) refers to metaheuristics, that is, in general algorithms that can be applied to almost any discrete optimization problem. All metaheuristics are iterative procedures, and for many of them asymptotic convergence of the best found solution to the global optimum has been established.

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The ACO idea is an attempt to imitate the behavior of ants that have almost no sight and are guided by the smell left by their predecessors. It should be noted that ACO is not the optimal method for solving this problem. In the future, it is necessary to continue to work on optimizing algorithms used in swarm robotics.

CONCLUSIONS

The article shows how to implement the components of the self-organization of ants in the algorithm for solving discrete optimization problems in the example of the salesman problem.

The scientific novelty of the research lies in the fact that the dependence of the search time and the found optimal route on the values of control parameters is established using the example of test networks for a different number of graph vertices and iterations.

The ant colony optimization algorithm was further developed.

The practical value is that the stated variant of the description of the process of behavior is supposed to be extended to the whole group of swarm algorithms.

Prospects for further research are that the received description of processes is planned to be used for further researches – statement and carrying out computational experiments for parametric optimization of swarm algorithms, which are used for management of a swarm of robots.

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ОПТИМІЗАЦІЯ АЛГОРИТМІВ ГРУПОВОЇ РОБОТОТЕХНІКИ

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АНОТАЦІЯ

Актуальність. Серед різноманіття завдань, які вирішуються робототехнікою, можна виділити цілий ряд таких, для вирішення яких невеликі габарити робота бажані, а часом і необхідні. Для вирішення подібних завдань необхідні мікророботи з малими габаритами, маса яких дозволяє безперешкодно переміщатися у тісних проходах, складних погодних умовах, залишатися непоміченими. Водночас, малі габарити мікроробота накладають також і ряд непрямих обмежень, що зумовлює застовування для означених завдань групи мікророботів. Ефективність застосування груп мікророботів залежить від обраної стратегії управління і стохастичних пошукових алгоритмів оптимізації управління групою (роєм) мікророботів.

Мета. Метою данної роботи є розгляд групи ройових алгоритмів (методів), які відносяться до класу метаеврістік. До групи означених алгоритмів відноситься, зокрема, алгоритм мурашиної колонії, можливості якого досліджувалися для розв'язування задачі комівояжера, яка часто постає при розробці алгоритму поведінки групи мікророботів.

Метод. На першому етапі дослідження було виділено основні групи параметрів, які визначають перебіг і характеризують стан в будь-який момент часу алгоритму мурашиної колонії: вхідні, керуючи, параметри збурення, вихідні. Після виділення основних груп параметрів було розроблено алгоритм, перевага якого полягає в масштабованості, а також гарантованій збіжності, що дозволяє отримати оптимальний розв'язок незалежно від розмірності графа. На другому етапі ророблений алгоритм ACO (ant colony optimization algorithm) було реалізовано на мові Matlab. Були проведені комп'ютерні експерименти з метою визначення впливу вхідних, керуючих, вихідних і параметрів збурення на збіжність алгоритму. Було приділено увагу основним групам показників, які визначають напрямок способу і характеризують стан рою мікророботів у даний момент часу. В обчислювальному експерименті варіювалася кількість мурах, що розміщуються у вузлах мережі, місткість феромона, чисельність вузлів графа, визначалася чисельність ітерацій для розшуку найменшого шляху та час виконання методу. Проведено тест підсумків моделювання та продуктивності методу.

Результати. Проведено дослідження застосування мурашиного алгоритму для розв'язування задачі комівояжера для тестових графів з випадковим розташуванням вершин; для постійної кількості вершин і зміні кількості мурах, для постійної кількості вершин при різних значеннях коефіцієнта Q; для розв'язування задачі комівояжера для постійної кількості вершин при різних значеннях коефіцієнта випаровування феромону p; для різної кількості вершин графа. Результати показали, що мурашині способи знаходять хороші маршрути комівояжера значно швидше, ніж чіткі методи комбінаторної оптимізації. Встановлено залежності часу пошуку і знайденого оптимального маршруту від значень керуючих параметрів на прикладі тестових мереж для різної кількості вершин графа та ітерацій.

Висновки. Проведені дослідження дозволяють дати рекомендації щодо застосування алгоритму мурашиної колонії ACO (ant colony optimization algorithm) для управління групою (роєм) мікророботів.

КЛЮЧОВІ СЛОВА: рой роботів, алгоритм мурашиної колонії, задача комівояжера.

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ОПТИМИЗАЦИЯ АЛГОРИТМОВ ГРУППОВОЙ РАБОТОТЕХНИКИ

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АННОТАЦИЯ

Актуальность. Среди многообразия задач, решаемых робототехникой, можно выделить целый ряд таких, для решения которых небольшие габариты работа желательны, а подчас и необходимы. Для решения подобных задач необходимы микророботы с малыми габаритами, масса которых позволяет беспрепятственно перемещаться в тесных проходах, в сложных погодных условиях и оставаться незамеченными. В то же время малые габариты микроробота накладывают также и ряд косвенных ограничений, поэтому к применению для решения указанных задач лучше использовать группы микророботов. Эффективность применения групп микророботов зависит от выбранной стратегии управления и стохастических поисковых алгоритмов оптимизации управления группой (роем) микророботов.

Цель. Целью данной работы является рассмотрение группы роевых алгоритмов (методов), относящихся к классу метаэвристик. К группе этих алгоритмов относится, в частности, алгоритм муравьиной колонии, возможности которого исследовались для решения задачи коммивояжера, часто возникающей при разработке алгоритма поведения группы микророботов.

Метод. На первом этапе исследования были выделены основные группы параметров, определяющих течение и характеризующие состояние в любой момент времени алгоритма муравьиной колонии: входящие, управляющие, параметры возмущения, выходные параметры. После выделения основных групп параметров был разработан алгоритм, преимущество которого заключается в масштабируемости, а также гарантированной сходимости, позволяющей получить оптимальное решение независимо от размерности графа. На втором этапе разработан алгоритм, код которого был реализован на языке Matlab. Были

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проведены компьютерные эксперименты с целью определения влияния входных, управляющих, выходных и параметров возмущения на сходимость алгоритма. Было уделено внимание основным группам показателей, определяющих направление способа и характеризующих состояние роя микророботов в данный момент времени. В вычислительном эксперименте варьировалось количество муравьев, размещаемых в узлах сети, количество феромона, число узлов графа, определялось количество итераций для поиска кратчайшего пути и время выполнения метода. Проведен итоговый тест моделирования и производительности метода.

Результаты. Проведены исследования применения муравьиного алгоритма для решения задачи коммивояжера для тестовых графов со случайным расположением вершин; для постоянного количества вершин и изменения количества муравьев, для постоянного количества вершин при разных значениях коэффициента Q; для решения задачи коммивояжера для постоянного количества вершин при разных значениях коэффициента испарения феромона p; для разного количества вершин графа. Результаты показали, что муравьиные способы находят хорошие маршруты коммивояжера гораздо быстрее, чем четкие методы комбинаторной оптимизации. Установлена зависимость времени поиска и найденного оптимального маршрута от значений управляющих параметров на примере тестовых сетей для разного количества вершин графа и итераций.

Выводы. Проведенные исследования позволяют дать рекомендации по применению алгоритма муравьиной колонии для управления группой (роем) микророботов.

КЛЮЧЕВЫЕ СЛОВА: рой роботов, алгоритм муравьиной колонии, задача коммивояжера.

ЛІТЕРАТУРА / ЛИТЕРАТУРА

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