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A Step-by-Step Algorithm for Finding the Optimal Strategy for the Behavior of a Group of Robots

Abstract

The solution of the multi-criteria problem, which includes the distribution of objectives, the planning of trajectories and the optimization of energy consumption, is considered in the realization of the collective interaction of robots. It is proposed to use a genetic algorithm according to the chosen conditions (constraints) and optimality criteria to find the best strategy for group behavior. The considerable difficulty in choosing how to control a team of autonomous mobile robots represents the distribution of tasks among agents that operate under conditions of parametric and information uncertainty, possess "modest" hardware, power and functionality. Therefore, the implementation of a multi-stage search for an optimal solution requires a specialized approach that takes into account the whole range of dynamic parameters, allowing for real-time target correction and degradation of robots until they fail. The basis of the proposed neurogenetic algorithm is a new algorithm for calculating the fitness function, in which the results of the neural network method of trajectory planning for a group of robots are used, as well as information about the initial charge of the batteries of robotic agents of the collective, the energy consumption of each agent and the preliminary estimation of the energy required by some agent to perform the individual tasks available to it. In order to ensure an acceptable performance of the algorithm and given the high dynamism of the external environment, it was decided to limit the search for solutions to only one step (the next working beat of the collective). The paper presents the results of the simulation of the task of finding the optimal behavior of robots, the algorithm of calculation of the specialized fitness function and the options of step-by-step search of the global strategy of distribution of tasks, which make it possible to increase the efficiency of the use of the team of robots due to the guaranteed production of the result while minimizing the total time of completion of all the tasks, as well as to increase the working time of the team due to the correct energy consumption.

Keywords: *strategy of group behavior, robot collective, neurogenetic algorithm, fitness function, problem distribution*

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Алгоритм пошагового поиска оптимальной стратегии группового поведения роботов[1]

Рассматривается решение многокритериальной задачи, включающее распределение целей, планирование траекторий и оптимизацию расхода энергии, при реализации коллективного взаимодействия роботов. Для поиска оптимальной стратегии группового поведения предлагается использовать генетический алгоритм в соответствии с выбранными условиями (ограничениями) и критериями оптимальности.

[1]Работа поддержана в рамках госзадания №0246-2018-007.э

Существенную сложность при выборе способов управления группой автономных мобильных роботов представляет распределение задач между агентами, которые действуют в условиях параметрической и информационной неопределенностей, обладают "скромными" аппаратными, энергетическими и функциональными возможностями. Поэтому реализация многопараметрического поиска оптимального решения требует специализированного подхода, учитывающего весь комплекс динамических параметров, допускающего коррекцию целей в реальном масштабе времени и деградацию роботов вплоть до их выхода из строя.

Основой предлагаемого нейрогенетического алгоритма является новый алгоритм расчета фитнесс-функции, в котором используются результаты нейросетевого метода планирования траекторий для группы роботов, а также информация о начальном заряде батарей роботов — агентов коллектива, энергопотреблении каждого агента и предварительная оценка энергозатрат, необходимых агенту на выполнение доступных ему отдельных заданий. Для обеспечения приемлемой производительности алгоритма и с учетом высокого динамизма внешнего окружения было принято решение ограничиться поиском решений только на один шаг (следующий рабочий такт коллектива). В работе приводятся результаты моделирования задачи поиска оптимальной стратегии поведения роботов, алгоритм расчета специализированной фитнесс-функции и варианты пошагового поиска глобальной стратегии распределения заданий, которые позволяют повысить эффективность использования коллектива роботов за счет гарантированного получения результат при минимизации суммарного времени выполнения всех поставленных заданий, а также увеличить время работы коллектива за счет корректного расхода энергии.

Ключевые слова: *стратегия группового поведения, коллектив роботов, нейрогенетический алгоритм, фитнесс-функция, распределение задач*

Introduction

The current target areas for mobile robotic systems are modern production lines, environmental monitoring, handling and storage, inspection and investigation of hard-to-reach/hazardous environments, threatening human life, etc.

The most effective use of mobile robots in these domains is when they are used collectively when they come together to solve a single target. However, the following issues of group management related to the organization of the collective interaction of robots arise:

1) Distribution goals and tasks to robots, taking into account the nature of the objectives, functionality and environment of each robot;

2) The planning of the trajectories and the allocation of subspaces for each robot, taking into account possible conflicts in operation;

3) Optimization of energy consumption of individual robots when moving through working space and performing functional tasks in order to increase the efficiency of work of the whole team.

Therefore, the problem of group control of mobile robots with the definition of a multi-criteria problem, which includes the distribution of objectives, planning and optimization of energy consumption, is topical. Analysis of current research has shown that insufficient attention has been paid to group control of robots with integrated performance optimization at both the strategic, tactical and energy levels. Quite often, research offers its own method of solving only a private problem, which is usually either not applicable or requires considerable refinement in solving a complex problem. Consider in more detail some of the methods of solving private problems encountered in group control of mobile robots.

Among the many publications on task distribution are: centralized distribution algorithms [1, 2], multi-agent RTS control algorithms under uncertainty, using neural networks [3], fuzzy logic [4] and dynamic programming algorithms [5], augmented and virtual reality technology [6], potential fields [7], cognitive adaptive method [8]. In some cases, heterogeneous groups of robots act as distribution algorithms target and treat the problem as a complex combinatorial problem [9, 10]. In addition, methods of relaxation of Lagrange [11] and ant algorithms [12] are often used. It should be noted that a large part of the algorithms presented in the above-mentioned publications are designed to solve target allocation problems in a particular case where the number of robots in the working space corresponds to the number of objectives.

The problem of planning optimal routes for mobile robots, which is closely related to operational planning, has been addressed in numerous studies, but as a separate application. Currently known solutions can be divided into two main classes — precision and approximation [13]. Among the latter are various ways of implementing intelligent planning algorithms constructed using neural networks, fuzzy or genetic algorithms (GA) [14]. Intelligent methods show the best results in solving planning problems that are difficult to implement on-board computing systems of mobile robots using classical breakthrough or potential algorithms.

Optimization of energy consumption in the collective use of robots and trajectories/movements of individual robots has been repeatedly raised by researchers [15—20]. Most often, energy efficiency improvements were achieved through hardware modifications: the use of adjustable speed drives and special software with the emulation of a mobile robot in a virtual model based on analytical data and working in real time [15] or the application of parallel elastic elements to reduce energy consumption in a two-legged walking robot Sandia [16].

Interesting approach in work [17] where the algorithm of optimization of energy consumption in the swarm of feeding robots is presented, which implements rules of adaptation of robots based on information about environment and quality of communication. Reduction of electrical consumption and minimization of energy consumption are achieved in a group of robots by using a computer cluster, on which the software code is realized for rapid calculation of movement of robots in a group, simulation of movements in a labyrinth [18, 19]. Variants of evolutionary algorithms for optimizing the energy consumption of a group of robots during their movement and information exchange are also known [20].

According to the results of the survey, at present, there is no uniform method for the group control of the mobile robot team to solve the problems of target distribution, route planning and energy optimization as a single complex task. As the number of robots and the complexity of the task assigned to the team increase exponentially, the time to make decisions grows. Therefore, it is important to develop non-resource-based planning and control algorithms that take into account the specific capabilities of mobile robot on-board computing systems.

This work proposes a strategy for control a heterogeneous group of mobile robots with optimal performance parameters at strategic, tactical and energy levels.

Setting the goal of optimizing a group behavior of robots

A working field of size $N \times M$, containing n robots and m tasks, coordinates of robots (x_i, y_i, $i \in [1, n]$), location coordinates of tasks ($x^*_j, y^*_j, j \in [1, m]$) is considered. The goal of the team of robots is to perform tasks located in the field. Some field cells have an identifier for the incoming tasks ($\mathbf{V}_j$ vector). Robots have a class identifier (F_i), with only one robot and/or one task in a single field cell.

Robots are divided into classes that uniquely define the group of tasks it can perform, the energy consumption of the robot in different modes, and the speed of movement. There are three modes/states of the robot: sleep (waiting for the task), movement, and implementation of the task, each with its own energy consumption (for the i-robot — W_i^{SL}, W_i^{MV}, W_i^{WR} respectively). Each robot has an initial charge (P_i^R).

Tasks are divided into several classes. Each class has its own energy consumption (W_j^{WR}) — the energy that the robot must use to complete a given class of task. A robot can perform the same or a lower class task, but only if it has enough energy to execute it.

Given the above characteristics and constraints, it is necessary to synthesize an algorithm to find the optimal distribution of tasks among available robots, while minimizing the energy and time spent.

The optimality criteria used are:

1) total energy consumption:
$\phi_1(\bar{z}) = W_\Sigma(\bar{z}) \to \min\limits_{\bar{z} \in \mathbf{Z}}$;

2) implementation time of all tasks:
$\phi_2(\bar{z}) = t_{\max}(\bar{z}) \to \min\limits_{\bar{z} \in \mathbf{Z}}$;

3) a number tasks in a queue:
$\phi_3(\bar{z}) = N_{\text{out}}(\bar{z}) \to \min\limits_{\bar{z} \in \mathbf{Z}}$.

Here $\bar{z}$ is a vector of problem numbers, each element of which z_i, $i = \overline{1, n}$ defines the problem for the i-robot in the next step. The domain of valid $\bar{z}$ vector values forms a set $\mathbf{Z}$.

The three-criteria problem is to choose the optimal distribution of tasks among available robots: to find the values of variable parameters $\bar{z}$, which within the limit fulfill all the above conditions 1)—3). The vector optimality criterion $\mathbf{J}(\phi_1(\bar{z}), \phi_2(\bar{z}), \phi_3(\bar{z}))$ is defined on the set $\mathbf{Z}$, and the value of each of the private optimality criteria must be minimized $\phi_i(\bar{z})$, $i = \overline{1, n}$:

$$J : \min_{\bar{z} \in Z}(\phi_1(\bar{z}), \phi_2(\bar{z}), \phi_3(\bar{z})).$$

To find a solution, it is proposed to use GA according to the listed conditions (limitations) and optimum criteria. At the same time, the synthesis of GA and the coding of the decision are carried out according to the method presented in other authors' papers, where the applicability of GA for solving such a class of problems is proved [21] and the best results according to two criteria are obtained [22] but the motion trajectory module worked autonomously.

The main changes have been made in the algorithm for forming a fitness function for GA with parallel operation of the neural network system of trajectory planning, which makes it possible to obtain optimal routes for each of the evaluated workplans, So the synthesized algorithm can be considered a class of hybrid, neurogenetic.

The search for the optimal strategy is carried out for the multi-criteria task on one step in time (discrete), taking into account the energy consumption, the trajectory of the robots' motion and the time to complete the tasks. The optimal distribution of tasks is determined by the initial charge of the battery, the energy consumption of each robot and the energy spent on individual tasks. To plan trajecto-

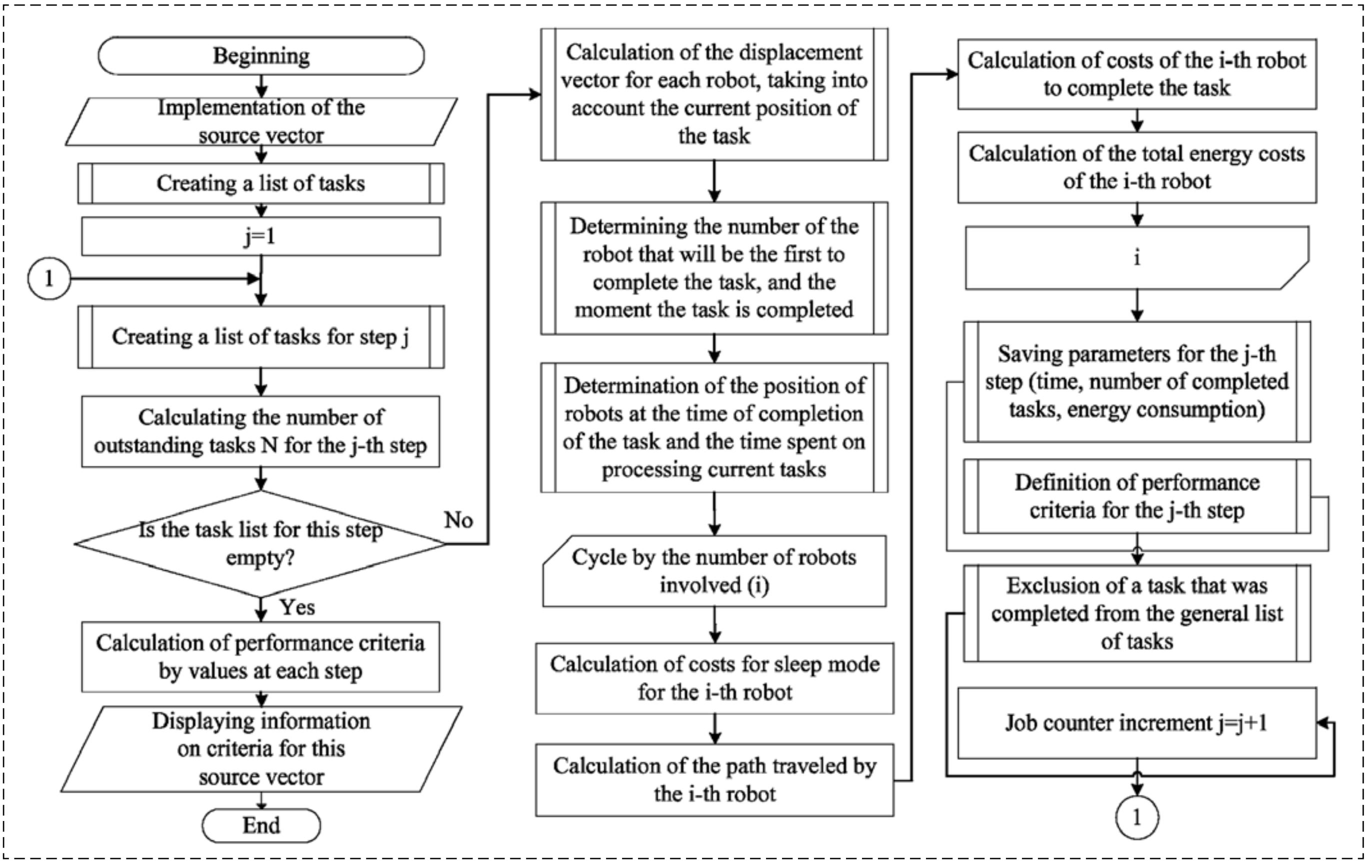

Fig. 1. Basic fitness function algorithm

ries of motion, a neural network algorithm is used to find the optimal set of paths of the whole group of robots from starting points to target coordinates (problems) [23]. The GA is used as the basic approach for solving the multi-criteria problem. Each mode of operation and class of operation (problem) is characterised by their level of energy consumption, so the use of GA makes it possible to solve a multi-criteria optimization problem taking into account the integral criterion of efficiency, taking into account also the hardware realizable possibility of energy redistribution between robots. The classical search for such solutions relates to the multi-criteria optimization problem, so the main purpose of the synthesized algorithm is to find a minimum on a set of allowable combinations of the distribution and the use of the GA with the chosen conditions and optimality criteria will allow for an acceptable time for on-board computing systems to obtain a problem distribution close to optimal in parallel with the search for energy-efficient trajectories.

The following algorithm has been synthesized to calculate the fitness function:

1. Chromosome decoding. Genes are decrypted into problem numbers for each robot.
2. Compute the trajectory of robots to chromosome-encoded targets using a neural network algorithm.
3. Calculates the parameter W_Σ for the estimated task combination.
4. Calculate the time taken by robots to complete assigned tasks. Select the maximum time.
5. Calculates the parameter N_{out} for the estimated problem combination as the difference between the number of all tasks m and the number of non-zero elements in the vector $\bar{z}$.
6. Output of the derived fitness function vector for the individual in question $\bar{z}$.

The algorithm of the developed fitness function, taking into account the characteristics of the type of GA used, as well as the problem itself in the form of a flowchart, is shown in Fig. 1.

Finding the best one-step strategy for robots

In order to prove the functionality and efficiency of the neurogenetic algorithm, computer simulations are conducted on the generated set of variants of the distribution of robots and problems in the working field. Two variants of the simulated situations are shown below, the same for the baseline is only the size of operating field 10x10.

Example 1. One step strategy. There is a group of three robots that needs to do six tasks. The robots are located in the cells of the working field with coordinates: {6,2} a robot of Class 3, {4,10} — Class 1 and {1,7} — Class 2; the energy reserve is equal to 40 units. The tasks are located on the working field with coordinates 1, 2 and 6 — {8,3}, {1,6} and {2,7}, the task 2 of Class 3 — {5,4}, the tasks 3 of Class 4 and 5 — {4,9} and {2,10}. The energy consumption of the robots is given in table 1. The time required to complete the tasks is: for the robot of class 1, {3,–,–}; for the robot of class 2, {5,4,–}; for the robot of class 3, {5,7,2}.

The location of the robots and tasks in the working field is shown in Fig. 2.

The results of the one-step task distribution simulation are presented in table 2.

The minimum number of outstanding tasks is three, which is determined by the difference between the number of robots and the number of tasks (6-3).

	1	2	3	4	5	6	7	8	9	10
1										
2						$P_1^{(3)}$				
3								$T_1^{(1)}$		
4					$T_3^{(2)}$					
5										
6	$T_2^{(1)}$									
7	$P_3^{(2)}$	$T_6^{(1)}$								
8										
9				$T_4^{(3)}$						
10		$T_5^{(3)}$		$P_2^{(1)}$						

Fig. 2. Location of robots and tasks in the workfield

Table 1

Robot energy consumption

Robot class	W^{SL}, en. unit	k^{MV}, unit/unit of length	M_v, unit of length/unit of time	Task class	W^{WR}, en. unit
1	2,1	0,7	100	1	3,2
2	1,1	1,2	200	2	2,8
3	1,7	0,9	150	3	5,8

Table 2

Decisions received

Decison, №	Robot, №			W_Σ, en. unit	t_{max}, unit of time	N_{out}
	1	2	3			
1	0	0	0	0	0	6
2	0	0	2	3,68	2,0	5
3	3	0	2	8,16	12,4	4
4	1	0	2	8,36	10,9	4
5	3	6	2	12,74	19,8	3

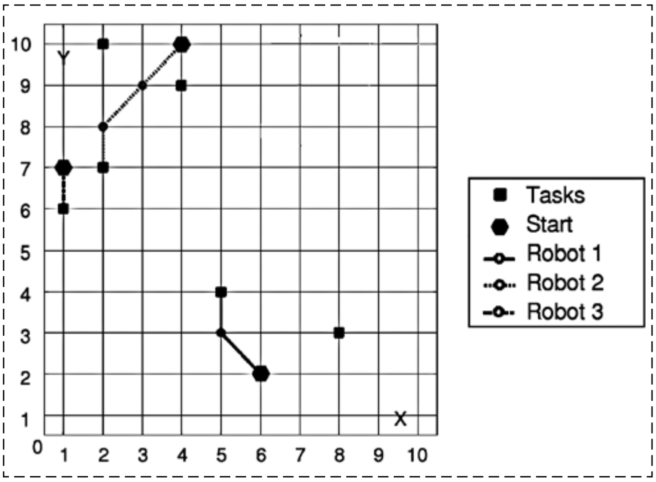

Fig. 3. The path travelled by robots for solution 5 (example 1)

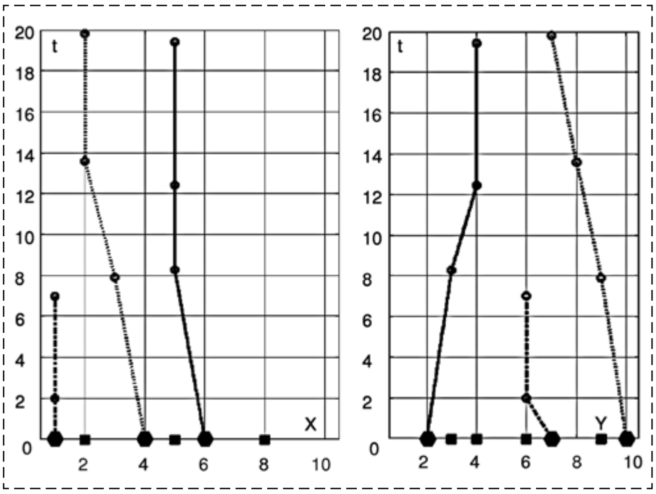

Fig. 4. Movement dynamics of robots for solution 5 (example 1)

Fig. 3 and Fig. 4 show the trajectories of the robots and the velocity (dynamics) of movement on the working field for the fifth solution — the solution with the maximum number of completed tasks.

Step-by-step search for a global assignment strategy

Since the initial task is to find a distribution strategy for all tasks, we use the resulting algorithm to find a common strategy for the behavior of the robots in achieving the goal. We will find the optimal solution for assigning tasks to each of the next steps until all the tasks have been completed to do this. Step refers to the time from the starting point to the end of the task to be solved.

According to the original assignment, the task is removed after its completion, which leads to a change in the structure of the task: one of the tasks is eliminated, and the robot performing it is ready to proceed to the next.

Therefore, after the task has been completed by the robot, it is necessary to restart the optimal strategy algorithm for the next step. Due to the discreteness of the field and the specificity of the task, the following points should be taken into account when switching to the following iteration of optimization:

1) a robot which, at the time of restart, is located at an intermediate point (moves between the grid nodes) is considered to be in the nearest traversed node;

2) the implemented task is considered complete (removed from the list of tasks) and transparent (not an obstacle) to robots;

3) one of the best three-criteria solutions must be chosen.

To select optimal solutions from the group, either an integral criterion is used or a command is expected from the decision maker. In order to automate the calculations, the choice of the final decision will be made on the basis of the following criteria:

— select a solution with a minimum execution time among the decisions with a minimum number of unresolved tasks;

— if two solutions meet this condition, the one that uses less energy is selected.

This rule may vary depending on the global tasks.

We note that the algorithm is repeated with the original population obtained by the decision in the previous step.

The proposed algorithm also takes into account the situation where a robot can be removed from a task. That is, if a robot has started a task, and the results of calculating the next step show that it is more efficient to redirect it to another task, it stops doing the task. At the same time, the time required to complete a task is reduced by the time that the robot has already spent on it.

Example 2. The complete problem is solved, i.e. the robots have to complete all the tasks on the working field and there are static obstacles (black areas in Fig. 5).

The solution in the form of trajectories and displacement dynamics is presented in Fig. 6 and Fig. 7. The total time of the task was 62.1 units of time and the robots spend part of

	1	2	3	4	5	6	7	8	9	10
1										
2						$P_1^{(3)}$				
3								$T_1^{(1)}$		
4					$T_3^{(2)}$					
5										
6	$T_2^{(1)}$									
7	$P_3^{(2)}$	$T_6^{(1)}$								
8										
9				$T_4^{(3)}$						
10		$T_5^{(3)}$		$P_2^{(1)}$						

Fig. 5. Location of robots, tasks and obstacles in the field of work for example 2

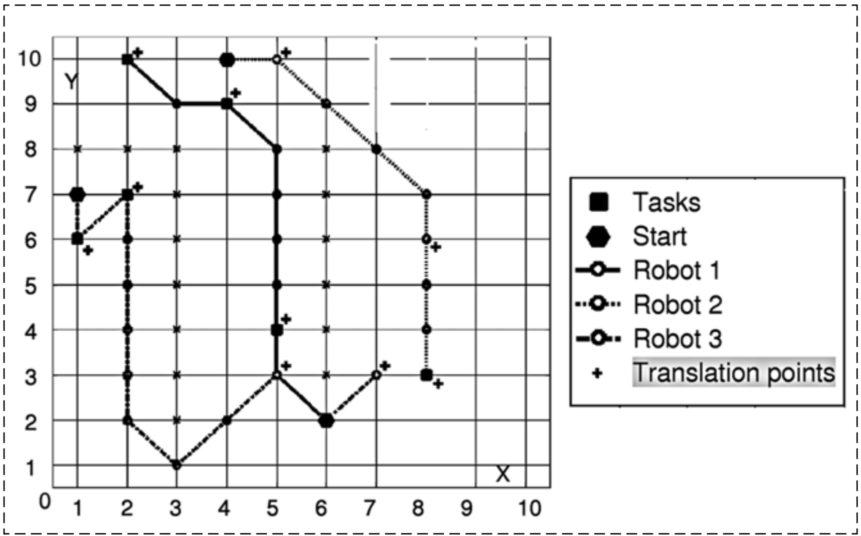

Fig. 6. Trajectories of robots for example 2

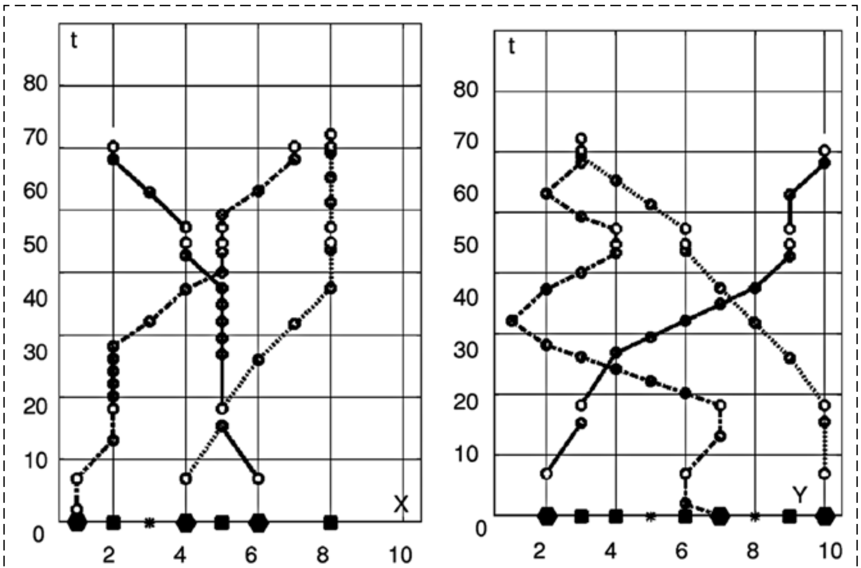

Fig. 7. Dynamics of robots for example 2

their time doing roadblocks. We note that despite the obstacles, the algorithm allows the robots to be reallocated according to the respective tasks with the required efficiency.

This is a consequence of the introduction of the following specific actions into the algorithm for finding the optimal strategy:

1. In the next step robot coordinates shall be rounded to the nearest cell (to be achieved by reducing the grid size);

2. The solution obtained for each of the steps modifies the task list (the list contains only the remaining tasks) for the robots.

A further modification of the proposed approach consists in improving the strategy algorithm by 2—5 steps forward for each time frame, which will allow for a deeper analysis of the initial and intermediate states and a more efficient solution to the problem as a whole but it would require a lot of computing resources.

Conclusion

The work synthesizes the algorithm of step-by-step search of optimal behavior of the group of robots. The proposed algorithm is based on: a three-parameter adaptability function, the GA, a neural network algorithm for finding disjoint pathways for a group of robots and an algorithm for step-by-step solving of a common problem.

Using the developed algorithm, different source data generated strategies for a group of robots that minimized the sum of task time. Similarly, solutions can be obtained by minimizing the total energy consumption of a group of robots or maximizing the number of tasks completed in a limited time.

As part of further work, it is planned to implement the algorithm of finding the optimal strategy with several steps missing.

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