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METAHEURISTIC METHOD FOR SEARCHING QUASI-OPTIMAL ROUTE BASED ON THE ANT ALGORITHM AND ANNEALING SIMULATION

Today, for intelligent computer systems of general and special purpose, the task of finding the optimal route is actual. Currently, there is a problem of lack of efficiency of methods for finding the quasi-optimal route. The object of the research is the process of solving optimization problems of finding a route. The subject of the research is a method for finding a quasi-optimal route based on metaheuristics. The current work increases the efficiency of searching for a quasi-optimal route using a metaheuristic method based on the ant algorithm. To achieve this goal, the work was created a method based on the ant algorithm and simulated annealing for the traveling salesman problem, was formulated the problem of the shortest path in the world of tiles, was developed a method based on the ant algorithm and simulated annealing for the problem of the shortest path in the world of tiles. Advantages of the proposed methods include the following. First, for calculating the probability of an ant moving from the current vertex to other vertices at the initial iterations, the random pheromone level plays the main role, which makes it possible to implement a random search, and at the final iterations, the normalized previous pheromone level plays the main role, which makes it possible to implement directed search. This is ensured by the use of simulated annealing and increases the accuracy of finding a quasi-optimal route. Second, for calculating the change in the pheromone level at the initial iterations, the pheromone increment plays the main role, which ensures the breadth of the search, and at the final iterations, the previous pheromone level plays the main role, which ensures the convergence of the method. This is ensured by the use of simulated annealing and increases the accuracy of finding a quasi-optimal route. Third, the modification of the ant algorithm by calculating the length of the edges based on the Chebyshev distance, placing all ants in the initial vertex, checking for a dead-end, checking that the target vertex has been reached, and using Moore's neighborhood allows solving problems of the shortest path in the world of tiles. The performed numerical study made it possible to evaluate both methods (for the first method, the root-mean-square error was 0.04, and for the second method it was 0.03). The proposed methods make it possible to expand the area of application of metaheuristics based on the ant algorithm, which is confirmed by its adaptation for the specified optimization problems and contributes to an increase in the efficiency of intelligent computer systems for general and special purposes. The prospects for future research are the study of the proposed methods for a wide class of artificial intelligence problems.

Keywords: metaheuristics; optimal route search; ant algorithm; simulated annealing; traveling salesman problem; shortest path problem in the world of tiles; pheromone level; Moore's neighborhood.

1. Introduction

1.1. Motivation

Today, there is an urgent task in developing methods aimed at solving the problems of finding the optimal route, which are used in intelligent computer systems for general and special purposes.

Optimization methods that find an exact solution are highly computationally complex. Optimization methods that find an approximate solution through directed search have a high probability of hitting a local extremum. Methods of random search do not guarantee convergence. According to this, the problem of insufficient efficiency of optimization methods arises, which needs to be solved.

Metaheuristics (or modern heuristics) [1-3] are used to accelerate the finding of a quasi-optimal route and to reduce the probability of hitting a local extremum. Metaheuristics expands the capabilities of heuristics by combining heuristic methods based on a high-level strategy [4-6]. The most promising metaheuristics include agent-based metaheuristics, which show the best results when searching for a quasi-optimal route [7-8].

1.2. Current state

Existing metaheuristics have one or more of the following advantages:

- the convergence rate is higher than in global (for example, enumeration) methods due to the operator of reproduction and crossing over [9];

- the breadth of the search for a solution is greater than in local (for example, gradient) algorithms due to the mutation operator [10].

Existing metaheuristics have one or more of the following disadvantages:

– the convergence of the method is not guaranteed [9];

– there is only an abstract description of the method or the description of the method is focused on solving only a certain problem [10];

– the influence of the iteration number on the process of finding a solution is not taken into account [11];

– there is no possibility to use non-binary potential solutions [12];

– insufficient accuracy of the method [13];

– there is no possibility to solve the problems of conditional optimization [14];

– the procedure for determining parameter values is not automated [15].

According to this, the problem of constructing effective metaheuristic optimization methods arises.

One of the popular metaheuristics is the ant algorithm proposed by Dorigo [16-18], developed in works [19-21] and software implemented in study [22].

Currently, a combination of metaheuristics is actively used for search control [23-28].

1.3. Goals

Object of study. Finding the best route.

Subject of study. Meta-heuristics-based methods for finding the optimal route.

Purpose of study is to increase the efficiency of finding a quasi-optimal route using the metaheuristic method.

To achieve this goal, it is necessary to solve the following tasks:

1. Create a method based on the ant algorithm and simulated annealing for the traveling salesman problem.

2. Formulate the problem of the shortest path in the world of tiles.

3. Develop a method based on the ant algorithm and simulated annealing for the problem of the shortest path in the world of tiles.

4. Carry out a numerical study of the proposed optimization methods.

2. Formulation of the problem

The problem of improving the efficiency of solving the traveling salesman problem and the shortest path problem in the world of tiles based on the ant algorithm is presented as the problem of finding such an ordered set of operators $\{A^1, A^2\}$, the iterative application of which ensures finding such a solution x^* (vector of vertices), in which $F(x^*) \to \min$, moreover, the structure of the solution x, fitness function $F(\cdot)$ (route length) and the operator of forming the solution A^1 (forms a vector of vertices based on the probability of an ant transition between allowed vertices, which is calculated based on the previous pheromone level, edge weight and random pheromone level) depend on the problem being solved, and the structure of the operator for changing the pheromone level A^2 (the change in pheromone level is calculated based on the previous pheromone level and the pheromone increment) is independent.

3. Methods

3.1. Method based on the ant algorithm and simulated annealing for the traveling salesman problem

The cost function (target function) is defined as

$$F(x) = d_{x_M, x_1} + \sum_{i=1}^{M-1} d_{x_i, x_{i+1}} \to \min_x,$$

where $d_{x_i, x_{i+1}}$ – weight of an edge between a pair of vertices (x_i, x_{i+1}),

x – vertex vector, $x = (x_1, ..., x_M)$, moreover $\forall x_i, x_j \in V \ \ i \neq j \to x_i \neq x_j$,

V – set of vertices,

M – vertex vector length.

The method consists of the following steps:

1. Initialization.

1.1. Setting the maximum number of iterations N, ant population size K, vertex vector length M.

1.2. An ordered set of vertices $V = \{1, ..., M\}$ and the edges weights matrix $[d_{ij}]$, $i, j \in \overline{1, M}$, calculated based on Euclidean distance are given.

1.3. The value of the target function of the best vertex vector is set, i.e. $y^* = \infty$.

1.4. The initial pheromone level $\tau_{ij}(0)$ is randomly initialized on the edge (i, j) in the form

$$\tau_{ij}(0) = \begin{cases} U(0,1), & i \neq j \\ 0, & i = j \end{cases}, \ i, j \in \overline{1, M},$$

where $U(0,1)$ – a function that returns a uniformly distributed random number in a range $[0,1]$.

1.5. The initial annealing temperature T_0, $T_0 > 0$, cooling factor β, $0 < \beta < 1$ are set.

2. Iteration number $n = 1$.

3. The annealing temperature is calculated in the form

$$T(n) = \beta^n T_0.$$

4. Ant number $k = 1$.

5. The operator of forming the solution for the k-th ant.

5.1. The first vertex becomes the current vertex, i.e. $i = 1$, and the new vertex of the vertex vector, i.e. $x_{k1} = 1$.

5.2. Set of forbidden vertices is initialized $V^{tabu} = \{1\}$.

5.3. The set of allowed vertices is calculated as the difference between the set of vertices and the set of forbidden vertices in the form

$$V^{permit} = V \setminus V^{tabu}.$$

5.4. The probabilities of transition of the k-th ant from the current vertex i to other vertices are calculated based on the normalized product of the previous pheromone level, the inverse edge weight, and a random pheromone level in the form

$$p_{ij} = \begin{cases} \left(1 - \exp\left(-\dfrac{1}{T(n)}\right)\right)\dfrac{\tau_{ij}(n-1)(1/d_{ij})^2}{\sum_{l \in V^{permit}} \tau_{il}(n-1)(1/d_{il})^2} + \\ \quad + \exp\left(-\dfrac{1}{T(n)}\right)U(0,1), \qquad j \in V^{permit} \\ 0, \qquad\qquad\qquad\qquad\qquad j \notin V^{permit} \end{cases},$$

$j \in \overline{1,M}$.

5.5. The next vertex is selected j_c in the form

$$j_c = \arg\max_j \{p_{ij}\}, \quad j \in \overline{1,M}.$$

5.6. The selected vertex is included in the set of forbidden vertices, i.e. $V^{tabu} = V^{tabu} \bigcup \{j_c\}$, and becomes the new vertex of the vertex vector, i.e. $x_{k,|V^{tabu}|} = j_c$.

5.7. If not all vertices are selected, i.e. $|V^{tabu}| < M$, then the selected vertex becomes the current one, i.e. $i = j_c$, go to 5.3.

6. The value of the target function is calculated $y_k = F(x_k)$.

7. If the value of the target function is less than the best value of the target function, i.e. $y_k < y^*$, then replace the best vector of vertices, i.e. $x^* = x_k$, and calculate the value of the target function for it, i.e. $y^* = F(x^*)$.

8. If the current ant is not the last, i.e. $k < K$, then increase the number of the ant, i.e. $k = k + 1$ go to 5.

9. Pheromone level change operator.

9.1. The increment of the pheromone is calculated on the edge (i, j) or edge (j, i)

$$\Delta\tau_{ij}(n) = \sum_{k=1}^{K} \frac{\chi_{Q_{ij}}(x_k)}{y_k}, \quad i \in \overline{1, M-1}, \quad j \in \overline{i+1, M},$$

$$\chi_{Q_{ij}}(x_k) = \begin{cases} 1, & x_k \in Q_{ij} \\ 0, & x_k \notin Q_{ij} \end{cases},$$

where Q_{ij} – set of vectors of vertices that contain edges (i, j) or (j, i).

9.2. The change in the pheromone level is calculated based on the previous pheromone level and the pheromone increment in the form

$$\tau_{ij}(n) = \tau_{ji}(n) = \left(1 - \exp\left(-\frac{1}{T(n)}\right)\right)\tau_{ij}(n-1) +$$

$$+ \exp\left(-\frac{1}{T(n)}\right)\Delta\tau_{ij}(n),$$

where $i \in \overline{1, M-1}$, $j \in \overline{i+1, M}$.

10. If the current iteration is not the last, i.e. $n < N$, then increase the iteration number, i.e. $n = n + 1$, go to 3, otherwise stop.

3.2. Method based on the ant algorithm and simulated annealing for the shortest path problem in the world of tiles

Formulating the shortest path problem in the world of tiles.

Assume there is a rectangular world of tiles (Tileworld). All cells in this world are squares of the same size and can be tiles or obstacles. Moving is possible only across tiles, and from the current tile you can only move to the tile in its neighborhood, which is the Moore neighborhood (Fig. 1). A tile can only be visited once. There is one initial tile and one target tile in the maze. Goal is to find the shortest path from the initial tile to the target one.
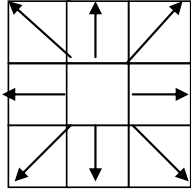
Fig. 1. An example of all allowed movements
on tiles in the Moore neighborhood

The world of tiles can be represented as a graph in which the vertices corresponding to the obstacles are always isolated. Such vertices can be excluded from consideration and the task will get reformulated from the graph theory point of view.

Let be $G = (V, E)$ – undirected weighted graph in which V – the set of vertices corresponding to the tiles, with the capacity M, E – the set of edges between all these vertices with the capacity M^2. The coordinates of each vertex are an element of an integer set of pairs $(1, ... Z_1) \times (1, ... Z_2)$, where Z_1 – number of cells horizontally, Z_2 – number of cells vertically. The weight of an edge is calculated as the Chebyshev distance between its vertices. Moving along the graph is possible only along the edges, the weight of which is 1 and on which the movement has not yet occurred. There is one initial vertex a and one target vertex b. Task is to find the shortest path from the initial vertex a to a target one b.

The cost function (target function) is defined as

$$F(x) = \sum_{i=1}^{L-1} d_{x_i, x_{i+1}} \to \min_x ,$$

where $d_{x_i, x_{i+1}}$ – weight of an edge between a pair of vertices (x_i, x_{i+1}), $d_{x_i, x_{i+1}} = 1$,

x – a vector of vertices describing movement along the graph, $x = (x_1, ..., x_L)$, moreover $\forall x_i, x_j \in V$ $i \neq j \to x_i \neq x_j$,

L – vertex vector length, $L < M$,

x_1 – initial vertex, $x_1 = a$,

x_L – target vertex, $x_L = b$.

The method consists of the following steps:

1. Initialization.

1.1. Setting the maximum number of iterations N, ant population size K, vertex vector length M.

1.2. An ordered set of vertices $V = \{1, ..., M\}$ and the edges weights matrix $[d_{ij}]$, $i, j \in \overline{1, M}$, calculated based on the Chebyshev distance are given.

1.3. The number of the initial vertex a and target vertex number b are set.

1.3. The value of the target function of the best vertex vector is set, i.e. $y^* = \infty$.

1.4. The initial pheromone level $\tau_{ij}(0)$ is randomly initialized on the edge (i, j) in the form

$$\tau_{ij}(0) = \begin{cases} U(0,1), & i \neq j \\ 0, & i = j \end{cases}, \ i, j \in \overline{1, M},$$

where $U(0,1)$ – a function that returns a uniformly distributed random number in a range $[0,1]$.

1.5. The initial annealing temperature T_0, $T_0 > 0$, cooling factor β, $0 < \beta < 1$ are set.

2. Iteration number $n = 1$.

3. The annealing temperature is calculated in the form

$$T(n) = \beta^n T_0 .$$

4. Ant number $k = 1$.

5. The operator of forming the solution for the k-th ant.

5.1. The initial vertex becomes the current vertex, i.e. $i = a$, and the new vertex of the vertex vector, i.e. $x_{k1} = a$.

5.2. Set of forbidden vertices is initialized $V^{tabu} = \{a\}$.

5.3. The set of allowed vertices is calculated as the difference between the Moore neighborhood and the set of forbidden vertices in the form

$$V^{permit} = V^{neigh} \setminus V^{tabu},$$
$$V^{neigh} = \{j \mid d_{ij} = 1\}, \ j \in \overline{1, M}.$$

5.4. If there is a dead end (there are no allowed vertices), i.e. $\left| V^{permit} \right| = \varnothing$, then go to 5.1.

5.5. The probabilities of transition of the k-th ant from the current vertex i to other vertices are calculated based on the normalized product of the previous pheromone level and a random pheromone level in the form

$$p_{ij} = \begin{cases} \left(1 - \exp\left(-\dfrac{1}{T(n)}\right)\right) \dfrac{\tau_{ij}(n-1)}{\sum\limits_{l \in V^{permit}} \tau_{il}(n-1)} + \exp\left(-\dfrac{1}{T(n)}\right) U(0,1), & j \in V^{permit} \\ 0, & j \notin V^{permit} \end{cases}$$

where $j \in \overline{1, M}$.

5.6. The next vertex is selected j_c in the form

$$j_c = \arg \max_{j}\{p_{ij}\}, \ j \in \overline{1,M}.$$

5.7. The selected vertex is included in the set of forbidden vertices, i.e. $V^{tabu} = V^{tabu} \bigcup \{j_c\}$, and becomes the new vertex of the vertex vector, i.e. $x_{k,|V^{tabu}|} = j_c$.

5.8. If not all vertices are selected, i.e. $|V^{tabu}| < M$ and the target vertex is not reached, i.e. $j_c \neq b$, then the selected vertex becomes the current one, i.e. $i = j_c$, go to 5.3.

6. The value of the target function is calculated $y_k = F(x_k)$.

7. If the value of the target function is less than the best value of the target function, i.e. $y_k < y^*$, then replace the best vector of vertices, i.e. $x^* = x_k$, and calculate the value of the target function for it, i.e. $y^* = F(x^*)$.

8. If the current ant is not the last, i.e. $k < K$, then increase the number of the ant, i.e. $k = k+1$ go to 4.

9. Pheromone level change operator.

9.1. The increment of the pheromone is calculated on the edge (i,j) or edge (j,i)

$$\Delta\tau_{ij}(n) = \sum_{k=1}^{K} \frac{\chi_{Q_{ij}}(x_k)}{y_k},$$

$$\chi_{Q_{ij}}(x_k) = \begin{cases} 1, & x_k \in Q_{ij} \\ 0, & x_k \notin Q_{ij} \end{cases},$$

$$i \in \overline{1,M-1}, j \in \overline{i+1,M},$$

where Q_{ij} – set of vectors of vertices that contain edges (i,j) or (j,i).

9.2. The change in the pheromone level is calculated based on the previous pheromone level and the pheromone increment in the form

$$\tau_{ij}(n) = \tau_{ji}(n) = \left(1 - \exp\left(-\frac{1}{T(n)}\right)\right)\tau_{ij}(n-1) +$$
$$+ \exp\left(-\frac{1}{T(n)}\right)\Delta\tau_{ij}(n),$$
$$i \in \overline{1,M-1}, j \in \overline{i+1,M}.$$

10. If the current iteration is not the last, i.e. $n < N$, then increase the iteration number, i.e. $n = n+1$, go to 3, otherwise stop.

4. Experiments

A numerical study of the proposed optimization methods was carried out using the MATLAB package.

Ant population size is set as $K = 100$, maximum number of iterations $N = 100$, initial temperature $T_0 = 106$, cooling factor $\beta_0 = 0,94$.

For the task:

- "traveling salesman" the search for a solution was performed on the standard database berlin52 (traditionally used to test methods for solving the "traveling salesman" problem);

- "about the shortest path in the world of tiles" the search for a solution was performed on the standard database https://digitalcommons.du.edu/gridmaps2D, which is described in the work [25] (traditionally used to test methods for solving route finding problems in the world of tiles).

The function of decreasing the annealing temperature is determined by the formula $T(n) = \beta^n T_0$ and is shown on Fig. 2.
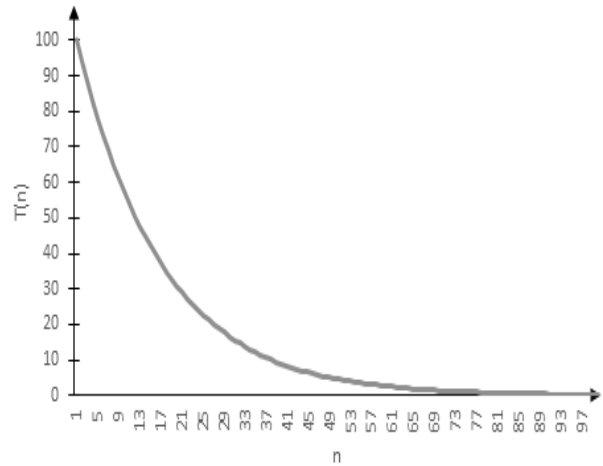

Fig. 2. Annealing temperature decreasing function

The dependence (Fig. 2) of the annealing temperature on the iteration number shows that the annealing temperature decreases with an increase in the iteration number.

In this case, the fraction of a random level of pheromone is determined in the form $p(x) = \exp(-1/T(n))$ and is shown on Fig. 3.

The dependence (Fig. 3) of the fraction of the random pheromone level on the annealing temperature shows that the fraction of the random pheromone level decreases with decreasing temperature.

The results of the search for the shortest path in the world of tiles, which does not contain obstacles are presented on Fig. 4.
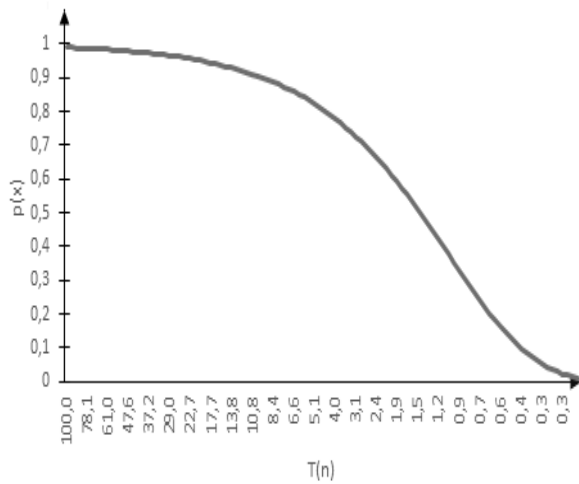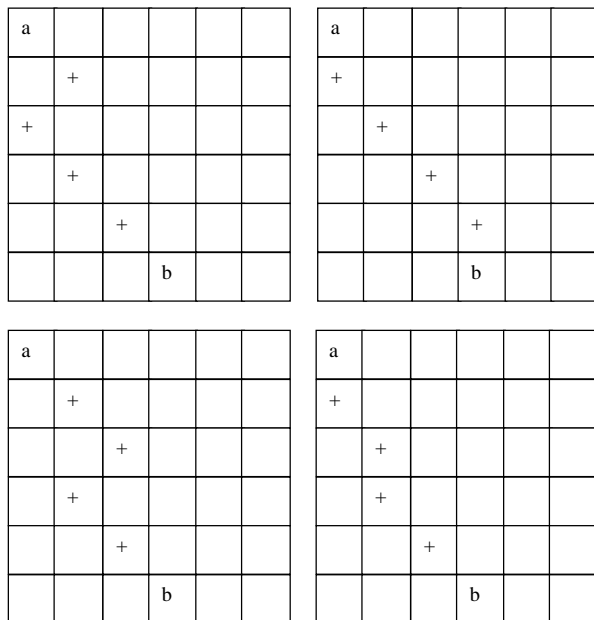
Fig. 3. Percentage of random pheromone level

Fig. 4. Search results for the shortest path in the world
of tiles, which does not contain obstacles.
The optimal path length is 5

distance, placing all the ants in the initial vertex, checking the occurrence of a deadlock, checking if the target vertex is reached, using the Moore neighborhood allows solving the tasks of the shortest path in the world of tiles.
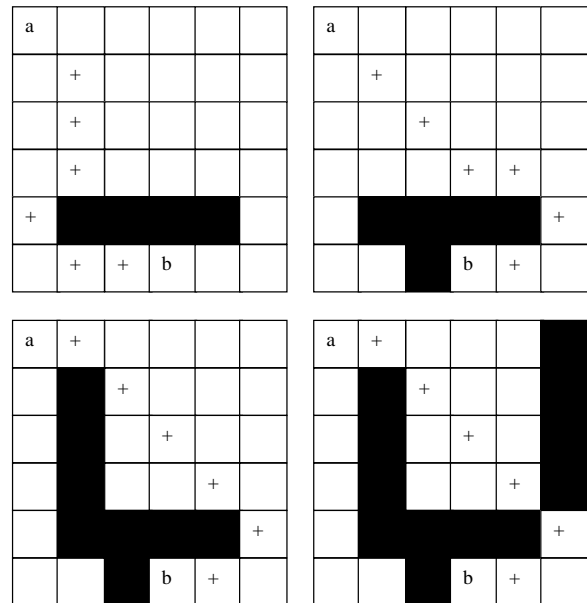

Fig. 5. Search results for the shortest path in the world
of tiles, which contains tiles and obstacles.
The optimal path length is 7

Table 1

Comparison of the proposed optimization methods
with existing methods based on the root-mean-square
error criterion for solving optimization problems

№ p/p	Task	Root-mean-square error of method	
		proposed	ant colony algorithm without simulated annealing
1	"traveling salesman"	0,04	0,08
2	"the shortest path in the world of tiles"	0,03	0,1

The search results for the shortest path in the world of tiles, which contains tiles and obstacles are presented on Fig. 5.

The results of the comparison of the proposed methods with the methods based on the ant algorithm without imitation of annealing and a random level of pheromone and described in [16–22] are presented in Table 1.

5. Discussion

The advantages of the proposed methods:

1. Modification of the ant algorithm by calculating the length of the edges based on the Chebyshev

2. For calculation the probability of an ant going from the current vertex to other vertices at the initial iterations, the main role is played by the random pheromone level, which makes it possible to implement a random search, and at the final iterations, the main role is played by the normalized previous pheromone level, which makes it possible to implement directed

search. This is ensured by the use of simulated annealing and increases the accuracy of the search for a quasi-optimal route (Table 1).

3. To calculate the change in the pheromone level at the initial iterations, the pheromone increment plays the main role, which ensures the breadth of the search, and at the final iterations, the previous pheromone level plays the main role, which ensures the convergence of the method. This is ensured by the use of simulated annealing and increases the accuracy of the search for a quasi-optimal route (Table 1).

6. Practical value

The proposed methods make it possible to expand the area of application of metaheuristics based on the ant algorithm, which is confirmed by its adaptation for the specified optimization problems, and contributes to an increase in the efficiency of intelligent computer systems for general and special purposes. For the "traveling salesman" problem, the search for a solution was based on the standard berlin52 database, and for the problem "about the shortest path in the world of tiles", the search for a solution was based on the standard database https://digitalcommons.du.edu/gridmaps2D.

7. Summary

1. Was formulated the problem of the shortest path in the world of tiles on the basis of graph theory.

2. Modification of the ant algorithm by calculating the length of the edges based on the Chebyshev distance, placing all the ants in the initial vertex, checking the occurrence of a dead end, checking if the target vertex has been reached, using the Moore neighborhood allows us to solve the problem of the shortest path in the world of tiles.

3. Were proposed optimization methods due to the study of the entire search space at the initial iterations and the direction of the search at the final iterations, make it possible to increase the accuracy of the search for the quasi-optimal route.

Prospects for further research are the study of the proposed methods for a wide class of artificial intelligence tasks.

Contributions of authors: a method based on the ant colony algorithm and simulated annealing for the traveling salesman problem – **M. Chychuzhko**; formalization of the shortest path problem in the world of tiles – **T. Neskorodieva**; method based on the ant colony algorithm and simulated annealing for the problem of the shortest path in the world of tiles – **E. Fedorov**; numerical study of the proposed optimization methods – **V. Chychuzhko**. All authors have read and agreed to the published version of the manuscript.

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МЕТАЭВРИСТИЧЕСКИЙ МЕТОД ПОИСКА КВАЗИОПТИМАЛЬНОГО МАРШРУТА НА ОСНОВЕ МУРАВЬИНОГО АЛГОРИТМА И ИМИТАЦИИ ОТЖИГА

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На сегодняшний день для интеллектуальных компьютерных систем общего и специального назначения актуальной является задача поиска оптимального маршрута. В настоящее время существует проблема недостаточной эффективности методов поиска оптимального маршрута. Объектом исследования является процесс решения оптимизационных задач поиска маршрута. Предметом исследования являются методы поиска квазиоптимального маршрута на основе метаэвристик. Целью работы является повышение эффективности поиска квазиоптимального маршрута за счет метаэвристического метода на основе

муравьиного алгоритма. Для достижения поставленной цели в работе был создан метод на основе муравьиного алгоритма и имитации отжига для задачи коммивояжера, была сформулирована задача о кратчайшем пути в мире плиток, был разработан метод на основе муравьиного алгоритма и имитации отжига для задачи о кратчайшем пути в мире плиток. К преимуществам предложенных методов относится следующее. Во-первых, для вычисления вероятности перехода муравья из текущей вершины в другие вершины на начальных итерациях главную роль играет случайный уровень феромона, что позволяет реализовать случайный поиск, а на заключительных итерациях главную роль играет нормированный предыдущий уровень феромона, что позволяет реализовать направленный поиск. Это обеспечивается использованием имитации отжига и повышает точность поиска квазиоптимального маршрута. Во-вторых, для вычисления изменения уровня феромона на начальных итерациях главную роль играет приращение феромона, что обеспечивает широту поиска, а на заключительных итерациях главную роль играет предыдущий уровень феромона, что обеспечивает сходимость метода. Это обеспечивается использованием имитации отжига и повышает точность поиска квазиоптимального маршрута. В-третьих, модификация муравьиного алгоритма за счет вычисления длины ребер на основе расстояния Чебышева, размещения всех муравьев в исходную вершину, проверки возникновения тупика, проверки достижения целевой вершины, использования окрестности Мура позволяет решить задачи о кратчайшем пути в мире плиток. Проведенное численное исследование позволило оценить оба метода (для первого метода среднеквадратичная ошибка составила 0.04, а для второго метода составила 0.03). Предложенные методы позволяет расширить область применения метаэвристик на основе муравьиного алгоритма, что подтверждается его адаптацией для указанных задач оптимизации, и способствует повышению эффективности интеллектуальных компьютерных систем общего и специального назначения. Перспективами дальнейших исследований является исследование предложенных методов для широкого класса задач искусственного интеллекта.

Ключевые слова: метаэвристика; поиск оптимального маршрута; муравьиный алгоритм; имитация отжига; задача коммивояжера; задача о кратчайшем пути в мире плиток; уровень феромона; окрестность Мура.

МЕТАЕВРИСТИЧНИЙ МЕТОД ПОШУКУ КВАЗІОПТИМАЛЬНОГО МАРШРУТУ НА ОСНОВІ МУРАШИНОГО АЛГОРИТМУ ТА ІМІТАЦІЇ ВІДПАЛУ

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На сьогоднішній день для інтелектуальних комп'ютерних систем загального і спеціального призначення актуальним є завдання пошуку оптимального маршруту. В даний час існує проблема недостатньої ефективності методів пошуку оптимального маршруту. Об'єктом дослідження є процес вирішення оптимізаційних завдань пошуку маршруту. Предметом дослідження є методи пошуку квазіоптимального маршруту на основі метаевристик. Метою роботи є підвищення ефективності пошуку квазіоптимального маршруту за рахунок метаевристичного методу на основі мурашиного алгоритму. Для досягнення поставленої мети в роботі було створено метод на основі мурашиного алгоритму і імітації відпалу для завдання комівояжера, була сформульована задача про найкоротший шлях в світі плиток, був розроблений метод на основі мурашиного алгоритму та імітації відпалу для задачі про найкоротший шлях у світі плиток. До переваг запропонованих методів відноситься наступне. По-перше, для обчислення ймовірності переходу мурахи з поточної вершини в інші вершини на початкових ітераціях головну роль грає випадковий рівень феромону, що дозволяє реалізувати випадковий пошук, а на заключних ітераціях головну роль грає нормований попередній рівень феромону, що дозволяє реалізувати спрямований пошук. Це забезпечується використанням імітації відпалу і підвищує точність пошуку квазіоптимального маршруту. По-друге, для обчислення зміни рівня феромону на початкових ітераціях головну роль грає збільшення феромону, що забезпечує широту пошуку, а на заключних ітераціях головну роль грає попередній рівень феромону, що забезпечує збіжність методу. Це забезпечується використанням імітації відпалу і підвищує точність пошуку квазіоптимального маршруту. По-третє, модифікація мурашиного алгоритму за рахунок обчислення довжини ребер на основі відстані Чебишева, розміщення всіх мурах в вихідну вершину, перевірки виникнення тупика, перевірки досягнення цільової вершини, використання околиці Мура дозволяє вирішити завдання про найкоротший шлях у світі плиток. Проведене чисельне дослідження дозволило оцінити обидва методи (для першого методу середньоквадратична помилка склала 0.04, а для другого методу - 0.03). Запропоновані методи дозволяють розширити сферу застосування метаевристик на основі мурашиного алгоритму, що підтверджується його адаптацією для зазначених завдань оптимізації, і

сприяє підвищенню ефективності інтелектуальних комп'ютерних систем загального і спеціального призначення. Перспективами подальших досліджень є дослідження запропонованих методів для широкого класу задач штучного інтелекту.

Ключові слова: метаевристика; пошук оптимального маршруту; мурашиний алгоритм; імітація відпалу; задача комівояжера; задача про найкоротший шлях в світі плиток; рівень феромону; околиця Мура.

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