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AUTONOMOUS ROBOT PATH PLANNING METHODS ANALYSIS

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Abstract. *Path planning algorithms for mobile robots are analyzed from the point of view of the possibility of their use for autonomous systems. Particular attention is paid to the analysis of the classical approaches possibility for the implementation of autonomous path replanning based on sensory data in the incompleteness and fuzziness of information conditions. Among the algorithms of the classical approach, the most adaptive ones turned out to be those that use artificial potential fields and the Monte Carlo method (sampling-based). It is shown that most algorithms, including those based on the approach of computational intelligence, provide replanning only on the basis of constant updating of global information about the environment. It was revealed that the hybrid approach to solving the path planning problem is the most adaptive, combining the techniques of global and local planning. The methods of this approach combine classical planning models with models based on computational intelligence. In addition, it is shown that the question of the homogeneity of the integration of solutions to various navigation tasks and the mutual influence of errors arising at each of the stages remains unexplored.*

INTRODUCTION

Robotics is an integral branch of knowledge encompassing mechanics, electrical and computer engineering, computer science, decision theory, artificial intelligence, etc. The listed areas serve as a theoretical basis for various stages of design and creation of robots. The first four areas provide the development and integration of hardware components of robotic systems. In turn, the theory of decision making, and artificial intelligence is the basis for the construction of high-level control algorithms, including intellectual and cognitive ones.

The classical goal of mobile robotics at the cognitive level is to solve the navigation problem, which is to provide the robot with the ability to navigate the terrain, accurately plan and pass paths, create a map of the environment and localize objects on it, patrol territories, etc.

The most important and researched task of the above is path planning. There are methods for solving it based on different approaches. Several reviews [1–3] are devoted to these methods, in which their advantages and limitations were investigated. The performed analyzes show the efficiency of path planning algorithms for robots in dynamic and partially unknown environments, with different kinematic schemes, etc. However, the questions posed by the requirements for the functioning of a mobile robot in autonomous mode remain unsolved [4, 5]. The incompleteness and fuzziness of information about the environment lead to the use of knowledge about the path in motion control and to replan the path based on the situation that is formed on data from the sensors. Therefore, for autonomous robots, it is important that the tasks of path planning, robot localization, and situational replanning are integrated into a single system with a single model for representing knowledge about the path, motion control commands, and the situation in the environment. The purpose of this review is to identify approaches and models for the path planning of robots that meet the integration requirements for the criterion of homogeneity of knowledge representation and data processing methods based on this knowledge.

THE PROBLEM OF AUTONOMOUS ROBOT NAVIGATION

An autonomous robot can navigate with different initial knowledge of the environment. The following situations can be distinguished: 1) the environment is known and does not change during the movement (known static environment); 2) the environment is known, but it can undergo changes – obstacles on the path of movement may accidentally arise (known dynamic environment); 3) the environment is unknown and invariable (unknown static environment); 4) the environment is unknown and can change (unknown dynamic environment).

In [6] the navigation process of a single mobile robot is presented and described in the form of a cycle consisting of a sequence of the following tasks: perception of information about the environment, localization, and mapping of the environment, path planning, and motion control.

Perception of information about the environment is a task that consists of reading, processing, generalizing, and interpreting data received from the robot's sensor systems.

Localization and mapping of the environment are two interrelated tasks that ensure the binding of objects to the map of the environment (known in advance or built independently). The most important case of localization is self-localization – the determination by the robot its own position in the environment. The role of localization and mapping in the navigation cycle can be different, depending on the amount of initial knowledge and the available sensory information.

Path planning is the task of constructing the optimal path of the robot from the starting to the goal point according to a certain criterion. Depending on the amount of initial knowledge, global and local path planning are distinguished. Global path planning is possible in situations with a known environment. The problem of local path planning is solved in cases of unknown environments, using sensor data (sensor-based approach).

Motion control is the task of ensuring the passage of the path without deviations, providing speed control in the direction of the movement of the robot. To solve the problem, control systems with linear regulators (PID controller and its variants [7]), fuzzy controllers [8–10], neural network controllers [11], and model predictive control [12] are used. Motion control is of particular importance for nonholonomic systems [6].

CONFIGURATION SPACE

To solve the navigation problem, the concept of a workspace $\mathcal{W}$ is introduced, in which a robot and obstacles exist. Points $q \in \mathcal{W}$ occupied by obstacles form a set $\mathcal{O}$. Obviously, taking into account the shape, physical dimensions, and kinematic nature of the robot, the set of points at which the robot can be located less than $\mathcal{W} / \mathcal{O}$. In order to determine all points in space where the robot can be located without colliding with obstacles, the concept of configuration space $\mathcal{C}$ is introduced [17]. The set of all points $q \in \mathcal{C}$ at which the robot can be located without colliding obstacles is free space $\mathcal{C}_{free}$, the rest of the configuration space $\mathcal{C}_{obst} = \mathcal{C} / \mathcal{C}_{free}$ is the space occupied by obstacles.

If the purpose of navigation is to reach the goal point q_{goal} from the start point q_{init}, then mathematically, the task is to find a sequence of intermediate points $q \in \mathcal{C}_{free}$ connecting q_{init} with q_{goal} in such a way that for any pair of adjacent points from the sequence the condition $(q_i, q_{i+1}) \in \mathcal{C}_{free}$ is satisfied.

CLASSICAL PATH PLANNING METHODS

Methods of this class are divided into four groups [13]: 1) methods of construction of roadmaps (RM, skeletonization); 2) methods of cell decomposition; 3) methods of artificial potential fields (APF); 4) sampling-based methods.

Methods from the first two groups reduce the path planning problem to a graph search problem. [14]. To solve the graph search problem, Dijkstra's algorithm, and its heuristic improvements A *, D *, Focused D * D * Lite, etc. are used.

Roadmap methods are reduced to the formation of a RM graph $G = (V, E)$ based on the environment map and the solution of the search problem on the obtained graph [15]. This group of methods includes visibility graphs [16] and Voronoi diagrams [17].

Roadmaps based on visibility graphs. This method generates a RM G as follows: the vertices of the graph are the start point q_{init}, the goal point q_{goal}, and the vertices of obstacles q_{obst}. Vertices $q_i \in V$ and $q_j \in V$ are connected by an edge if $(q_i, q_j) \in \mathcal{C}_{free}$. The method provides the construction of an optimal in length path between the start point and the goal point, but it has significant drawbacks: firstly, the size of the graph grows too quickly with an increase in the number of obstacles, which causes low performance in complex environments; secondly, the resulting path passes too close to obstacles; thirdly, the method works with polygonal obstacles [6, 18].

Roadmaps based on Voronoi diagrams. Unlike visibility graphs, the method based on Voronoi diagrams forms the RM G in such a way as to maximize the distance to obstacles: each point q of the resulting RM is equidistant from the nearest obstacles. This method leads to an unjustified increase in the length of the route for open spaces and can be computationally difficult for environments with complex obstacles [14].

There are methods that combine visibility graphs and Voronoi diagrams, for example [19, 20].

Cell decomposition methods divide the map of the environment into a set of non-intersecting cells, for each of which a characteristic point is selected. Based on the characteristic points, a graph describing the environment is formed [15]. There are exact and approximate cell decomposition [21].

Exact cell decomposition includes the following methods: trapezoidal decomposition [22], boustrophedon decomposition [23], and Morse decomposition [24].

Trapezoidal decomposition. In this method, decomposition into cells is performed by drawing parallel lines through the vertices of obstacles. These lines are the lateral boundaries of the cells, the other boundaries are either the boundaries of the map or the sides of the obstacles. The resulting cells are trapezoids (or triangles).

Boustrophedon decomposition. The method is a further development of trapezoidal decomposition. In this method, only those vertical lines are selected as cell boundaries, which can be extended on both sides of the vertex of the obstacle through which it is conducted, thus reducing the total number of cells obtained.

Morse decomposition is a generalization of decomposition by boustrophedon in case of non-polygonal obstacles. The boundaries of cells are formed based on critical points obtained using the Morse function.

Approximate cell decomposition includes grid-based decomposition [25, 26], quadtree based decomposition [27] and probabilistic decomposition [28].

Grid-based decomposition. This method involves the imposition on the map of the environment of a uniform square (triangular, hexagonal) grid. Each grid cell is assigned a value that indicates the presence or absence of interference in the cell. The accuracy of grid-based decomposition depends on the discreteness of the mesh. The disadvantage of this method is the rapid growth of memory required to store grids with a high level of map detail.

Quadtree based decomposition is an iterative method, which is the development of a grid-based decomposition: the map of the environment is divided into four equal rectangular segments, then each segment containing the obstacle (or part of it) is again divided into four equal subsegments and so on until all segments reach the minimum (predefined) size or will not contain obstacles. This method can be used only in a known static environment.

Methods of artificial potential fields build based on the map of the environment a function that describes the space with the help of a force field: the goal point has a low potential, and obstacles have a high potential. The robot is modeled as a particle moves from a point with high to a point with low potential [15]. The original method [29] has a significant disadvantage, which is the presence in the artificial potential field of zones of local optimums that prevent the robot from reaching the goal point. There are further developments in the method of artificial potential fields that eliminate this shortcoming, for example, based on the Laplace equation [30]. More modern variants of the method provide the movement of the robot in the conditions of moving obstacles: based on evolutionary algorithms [31], based on fuzzy artificial potential fields [32].

Sampling-based methods are the most modern of the classical algorithms. They use the Monte-Carlo method to solve the problem of path planning. This group of methods includes probabilistic road maps (PRM) [33], rapidly exploring random tree (RRT) [34].

Probabilistic road maps. This method builds a RM $G=(V,E)$ by randomly generating the coordinates of n points $q_{rand} \in \mathcal{C}$. Each point belonging to the free space $q_{rand} \in \mathcal{C}_{free}$ is added to the graph G. Points $q \in V$ are connected by edges with their neighbors q_{near} within a given radius r (if such a combination does not cross obstacles $(q, q_{near}) \notin \mathcal{C}_{obst}$). The disadvantage of this method is that to ensure sufficient accuracy of the road map, the number of points q_{rand} will be large [28].

Rapidly exploring random tree. The method iteratively builds a RM $G=(V,E)$. At zero iteration, the tree contains one vertex (a random free space point $q_{rand} \in \mathcal{C}_{free}$ or a start point $q_{init} \in \mathcal{C}_{free}$). In the following iterations, random points $q_{rand} \in \mathcal{C}_{free}$ are selected from the free space. On a straight line that connects a point q_{rand} with the nearest vertex of a tree $q_{near} \in V$, a new point is set aside at a given distance q_{new}. If $(q_{near}, q_{new}) \in \mathcal{C}_{free}$, then the vertex q_{new} and edge (q_{near}, q_{new}) are added to the tree G [13]. There are many improvements to RRT: RRG – provides the optimal route [35], RRT* – a tree-like version of the algorithm RRG [35], RT-RRT* – RRT variant, adapted to a dynamic environment by rearranging the tree from the point where there is a robot in real time [36].

The listed classical methods use artificial abstract points of the environment. The models assume that they are pairwise distinguishable; the localization problem is deterministic. Such models of knowledge representation about points of the path cannot be used by the situational movement control system in conditions of incomplete and fuzzy information. The integration of these models into the system of situational planning and control of a mobile robot is possible only at the conceptual level. This possibility is reflected in the table. 1, where it is represented by supporting local replanning.

Table 1. Comparison of the classical approach methods.

Method	Global replanning	Local replanning
RM based on visibility graphs	–	–
RM based on Voronoi diagrams	–	–
Trapezoidal decomposition	–	–
Boustrophedon decomposition	–	–
Morse decomposition	+	–
Grid-based decomposition	+	–
Quadtree decomposition	–	–
Probability decomposition	–	+
Classic APF	+	–
Laplace APF	+	–
Evolutionary APF	+	–
Fuzzy APF	+	–
PRM	+	–
RRT	–	–
RRG	–	–
RRT*	–	–
RT-RRT*	+	+

COMPUTATIONAL INTELLIGENCE BASED PATH PLANNING METHODS

Recently, algorithms that solve the problem of path planning based on computational intelligence models have begun to appear. Within this approach, there are methods based on fuzzy logic, neural networks, swarm algorithms [1, 3].

These methods fully include the remarks made above in relation to the classical methods of path planning. An additional limitation in using them in real-time in autonomous mobile systems is the need for large computing resources.

HYBRID METHODS OF PATH PLANNING

Hybrid methods combine global and local planning. This approach gives good results for the conditions of a known but dynamic environment. Examples of systems that implement hybrid algorithms are: global planning is carried out on a graph formed based on predefined characteristic points of the environment, local – based on a fuzzy controller [37]; sampling methods are combined with artificial potential fields using a fuzzy controller [38]; a simulated annealing algorithm and a fuzzy Takagi-Sugeno controller are combined [39]. Hybrid approaches best meet the above requirements of autonomous systems.

CONCLUSION

Currently, methods based on computational intelligence are being further developed. Methods using a hybrid approach are also being developed, combining classical global planning approaches with local planning approaches using sensory data.

A significant number of existing algorithms support the possibility of replanning, but this requires updating global information about the environment at any time. A more adequate situation for real tasks is when the robot has access to global information about the environment at the beginning of the task, and in the course of execution, this information is supplemented only locally, due to sensory data.

In research, not enough attention is paid to the development of approaches that provide a homogeneous integration of solutions to various navigation problems. The exception is the tasks of localization and mapping, which are solved simultaneously. Localization problems, path planning, and motion control in the works are considered separately, without considering the mutual influence of errors arising at each stage.

Existing studies pay little attention to solving the problem of incompleteness and fuzziness of information about the environment. Decisions arising based on incorrectly perceived information about the environment have certain consequences, the fight against which must be based on dynamic situational replanning.

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АНАЛИЗ НА МЕТОДИ ЗА АВТОНОМНО ОПРЕДЕЛЯНЕ НА РОБОТНИ ТРАЕКТОРИИ

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Ключови думи: *автономен мобилен робот, навигация, определяне на траектории*

Резюме: *Алгоритмите за определяне на траекторията на мобилни роботи се анализират от гледна точка на възможността за тяхното използване за автономни системи. Особено внимание се отделя на анализа на възможностите на класическите подходи за осъществяване на автономно препланиране на траектории на базата на сензорни данни при неопределеност и размитост на информационните условия. Сред алгоритмите на класическия подход най-адаптивни се оказват тези, които използват изкуствени потенциални полета и метода на Монте Карло.*

В представената работа се доказва, че повечето алгоритми, включително тези, базирани на подхода на изчислителната интелигентност, осигуряват препланиране на траекторията само на базата на постоянно актуализиране на глобалната информация за околната среда. Показано е, че хибридният подход за решаване на проблема с планирането на трасето е най-адаптивният, съчетаващ техниките на глобалното и местното планиране. Методите на този подход съчетават класически модели за планиране с модели, базирани на изчислителна интелигентност. В допълнение към изложеното е показано, че въпросът за хомогенността на интегрирането на решения за различни навигационни задачи и взаимното влияние на грешките, възникващи на всеки от етапите, е все още недостатъчно изследван.