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Review on path planning for obstacle avoidance oriented to micro-/nanorobots

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Abstract: Path planning algorithms are indispensable for controlling micro-/nanorobots through complex and unknown environments in the biomedical and medical fields. With the tasks performed becoming more complex, higher-quality paths are required to avoid obstacles for ensuring the safe and efficient movement of micro-/nanorobots. A comparative analysis of path planning algorithms is conducted to elucidate the algorithm's application and optimization for different environments. According to the environment modeling approach, existing path planning algorithms are classified into searching, sampling, and dynamic aspects. Searching path planning algorithms directly retrieve the global path possessing minimum cost from the modeled static waypoints. Sampling path planning algorithms employ randomly sampled waypoints within the target space, which eliminates the necessity for environmental modeling. Dynamic path planning algorithms utilize local paths to regulate the motion of micro-/nanorobots in real time. Deep learning networks based on big data will become an important research direction for the control and navigation of micro-/nanorobots. The advantages and limitations of path planning algorithms in varied spatial contexts are elucidated through detailed examples and descriptions, providing a comprehensive understanding of performance and applicability. This review underscores recent advancements in this emerging domain and stands as a testament to the dynamic landscape of micro-/nanorobotics and the continual pursuit of superior motion control solutions.

Keywords: biomedicine; micro-/nanorobot; obstacle avoidance; path planning

1. Introduction

Micro-/nanorobots, a noteworthy sub-field of robotics, have shown great potential for applications in the biological and medical fields [1–7]. With micro-/nanorobots performing more delicate tasks, higher demands of path planning are required to generate a more efficient path by interacting with the real world [8–10]. Path planning algorithms for micro-/nanorobots have applications in nanomanipulation [11,12], drug delivery [13,14], and non-invasive diagnosis [15,16], which are essential for determining the motion direction and for controlling the posture of micro-/nanorobots [17,18].

The complexities of the microscopic and in-body world increase the demands on the automated control of micro/nanorobots [19]. Deploying an optimal path planning algorithm is a key step to achieve sophisticated tasks, such as obstacle avoidance [20] and multi-robot cooperation [21]. Using optimal paths as the reference for navigation can significantly reduce collision risks and control complexity without human intervention [22].

The accurate control and trajectory tracking of micro-/nanorobots via optimized algorithms has become a central focus of contemporary research [23,24]. Researchers continually develop advanced methods to ensure that micro-/nanorobots can adapt to dynamic conditions [25–27]. The continued advancements in path planning algorithms are pivotal in unlocking the full potential of micro-/nanorobots. The published number of articles on path planning algorithms for micro-/nanorobots are shown in Figure 1.

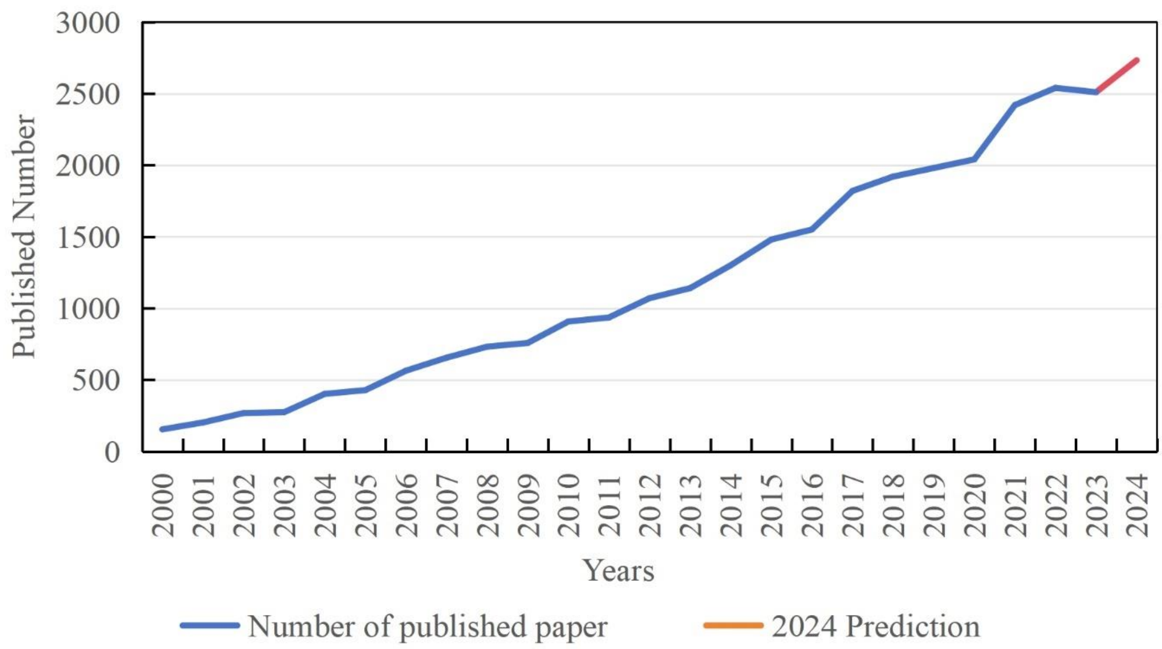

Figure 1. The number of papers related to path planning for micro-/nanorobotics. Data are collected from Google Scholar in August 2024 using search keywords: “path planning” and “micro-/nanorobotics”.

This study reviews the path planning algorithms for micro-/nanorobots, providing a theoretical basis for future research directions and technological breakthroughs. The general process of path planning for micro-/nanorobots includes modeling the environment, generating paths, and modifying paths [28,29]. According to the environment modeling approach, existing path planning algorithms can be classified into three categories including searching path planning [30], sampling path planning [31], and dynamic path planning [32]. The tree classification schemes for path planning in micro-/nanorobots are shown in Figure 2.

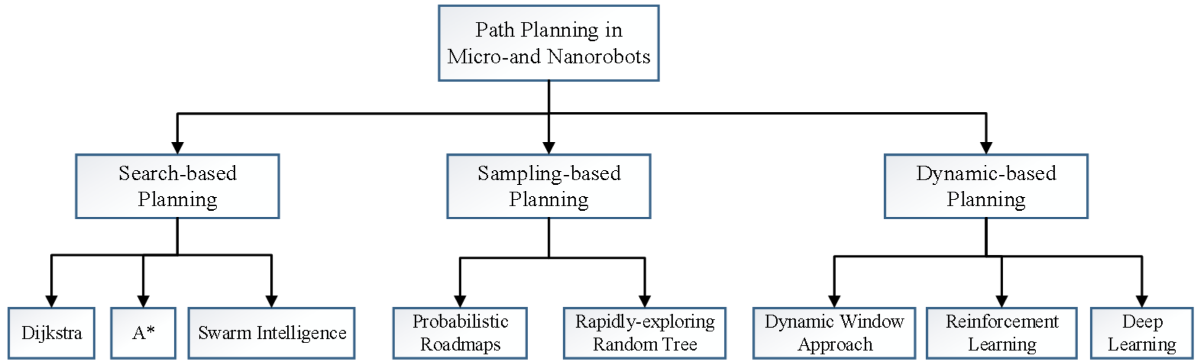

Figure 2. The classified path planning algorithms for micro-/nanorobots.

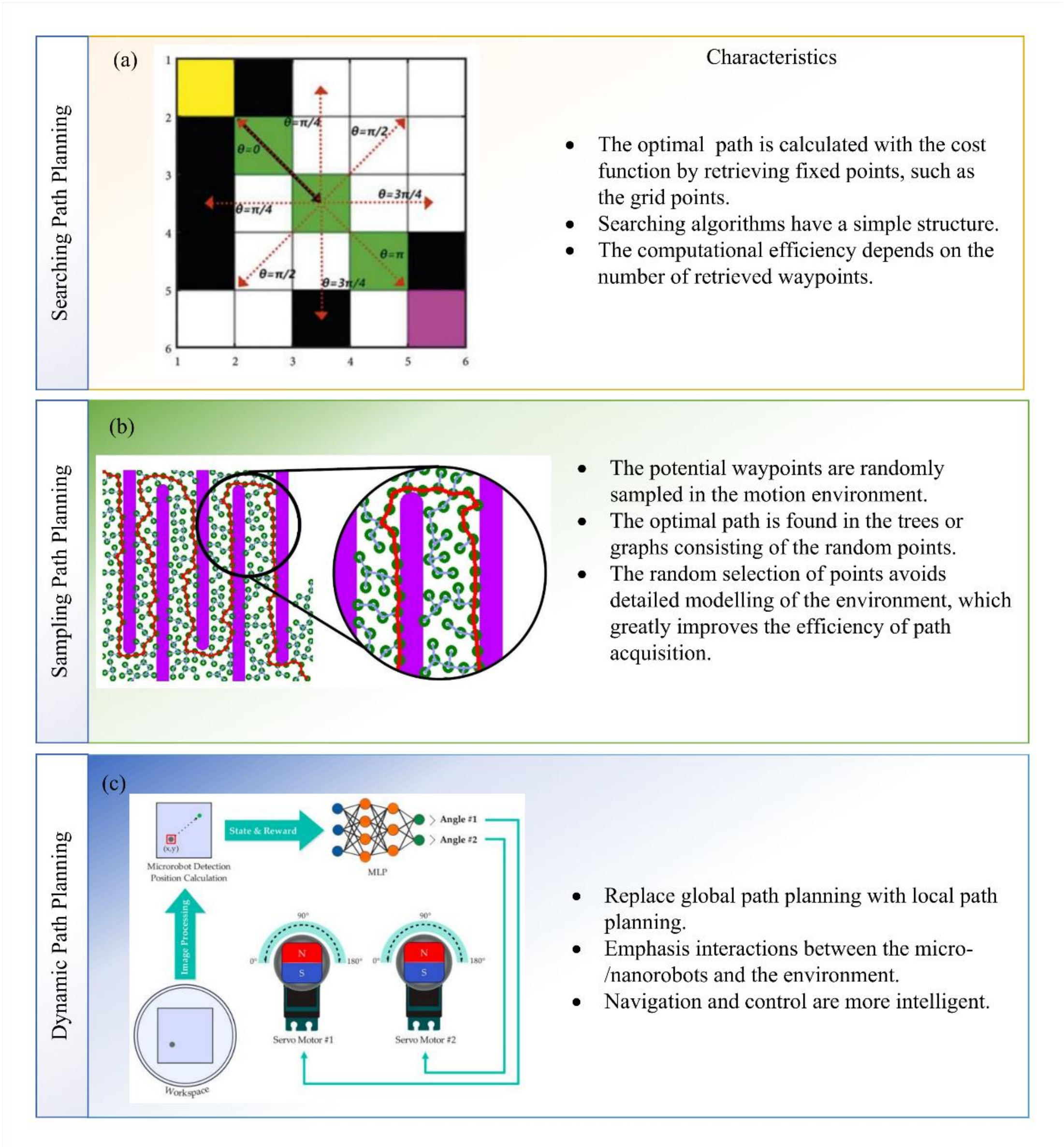

Figure 3. The characteristics of path planning algorithms for three different categories. (a) The retrieval grid with the ant colony algorithm for the searching path planning, reproduced from [33]. (b) The path tree of the Rapidly-exploring Random Tree for sampling path planning, reproduced from [34]. (c) The controlling workflow of reinforcement deep learning for dynamic path planning, reproduced from [35].

Searching path planning models the navigable space using static waypoints [36]. The optimal path is calculated according to the designed cost function by searching static waypoints. Searching path planning algorithms have a simple arithmetic logic structure. Computational efficiency depends on the number of retrieved waypoints.

Sampling path planning randomly places waypoints multiple times within the target area, which overcomes the limitations of static waypoints [37]. The optimal path is found according to trees or graphs connected by the sampled waypoints. The randomly sampled waypoints avoid modeling the environment, which greatly improves the efficiency of path planning.

Dynamic path planning involves interacting with the surrounding environment to control the movement direction of micro-/nanorobots in real time [38]. The motion path of a micro-/nanorobot consists of step-by-step local paths generated by the dynamic path planner. This allows real-time control in complex dynamic environments. The characteristics of path planning algorithms are concurrently listed under different classifications in Figure 3.

In the following, the state-of-the-art and development trends of path planning algorithms for micro-/nanorobots are discussed in detail. Then, the final section presents conclusions and opportunities for future research in this field.

2. Searching path planning

Searching path planning algorithms identify an optimal path that minimizes the cost function by traversing static waypoints, which are modeled from environmental data by grids [39] or pixels [40]. Static waypoints efficiently retrieve the optimal path in frequently updated environment maps [41]. The searching path planning algorithms include the Dijkstra algorithm [42], the A* algorithm [43], and the swarm intelligence algorithm [44].

2.1. Dijkstra algorithm

The Dijkstra algorithm, a foundational method in searching path planning, was proposed by Dijkstra in [45], which can enable collision-free navigation for micro-/nanorobots in complex and dynamic environments [46]. After modeling static waypoints from the obtained environment data, an expanding circular search area is created with the starting point at the circle's center. The static waypoints are retrieved to generate a graph $G=(V,E)$ for calculating the edge weights by the path cost function [41], where V denotes a set of graph nodes as retrieved waypoints and E represents a set of potential local paths for calculating the path cost. The lowest-cost node is recorded as a new leaf node until arriving at the target point.

In [47], an autonomous navigation system based on the Dijkstra algorithm was proposed to control a microsphere vehicle through a nanoscale maze by a magnetic field generator. Real-time environmental images are acquired using a microscope charge-coupled device camera, and then the accessible space is extracted from the images via a coordinate system. The Dijkstra algorithm extends the leaf node with the lowest cost, thereby adjusting the traditional breadth-first search strategy [48]. By continuously comparing the costs of different paths, the algorithm ultimately searches for an optimal and collision-free route. Although real-time changes in the environment and multiple potential paths can impact navigation, the Dijkstra algorithm adapts the path planning based on real-time data, allowing the robot to respond flexibly to dynamic environmental changes.

To navigate the micro-/nanorobots to the goal point in the 2D space meanwhile to avoid obstacles in the moving path, Mobadersany *et al.* [49] applied the Dijkstra algorithm to navigate the micro-/nanorobots. To extend the navigation in 3D space, Vincent *et al.* [50] proposed a trajectory planning method for micro-manipulation based on a three-dimensional space matrix. This algorithm is mainly suitable for the presence of obstacles in the workspace. Obstacles along the path are marked by modifying the association matrix.

The Dijkstra algorithm traverses all existing points to find the shortest path with the lowest cost value, featuring a straightforward operational logic. The time complexity of the Dijkstra algorithm is $O(n^2)$ [51], as it examines all static waypoints. Consequently, the calculation time to determine the shortest path increases exponentially with the number of nodes, resulting in low efficiency in dynamic environments.

2.2. A star (A) algorithm*

The A* algorithm is proposed by narrowing the search area based on the end-point information [52]. The cost function of the A* algorithm combines the heuristic cost and goal cost to calculate the shortest path from the static waypoints [53]. The fitness cost function significantly influences the selection of the best path. Distinct from the Dijkstra algorithm that uses global search, the heuristic function in the A* algorithm makes the path retrieval process more purposeful [54]. The cost function $f(n)$ is expressed as:

$$f(n) = g(n) + h(n) \tag{1}$$

where n is the position information of current waypoints. $h(n)$ represents the heuristic function to calculate the distance from the nth node to the goal node. $g(n)$ represents the path function to calculate the goal cost from the start to the nth node.

To control the autonomous navigation of a peanut-like magnetic-drive swimming microrobot in a complex micro maze, Fan *et al.* [55] utilized the A* algorithm to generate the shortest and optimal path with defined start and endpoints. An extended algorithm and appropriate binarized environment maps were employed to deconstruct the loss function to ensure a safe distance between the microrobot and the wall.

Path modification methods are proposed to improve the motion efficiency of micro-/nanorobots. Since, the optimal path calculated by the A* algorithm may adhere to obstacles, which presents a challenge for controlling the microrobot [56]. To avoid the micro-/nanorobots close to the obstacles in operation, the wall-avoiding method is proposed in [17] by adding a distance function based on the cost function of the A* algorithm. The cost function of the wall-avoiding path planning is expressed as follows:

$$f(n) = g(n) + h(n) + d(n) \tag{2}$$

where $d(n)$ denotes a distance function that is inversely proportional to the distance between the current waypoint and the obstacle. Further, the distance function is defined by the radial lengths of internal and external circumferences of microrobots.

To manipulate microrobot movement in liquid 3D space for vivo medical applications, Dong *et al.* [57] proposed a path strategy that combines the A* algorithm and the minimum jerk method, enabling the generation of an obstacle-free and smooth path. After obtaining the 3D grid maps from both cameras, the optimal path is retrieved and recorded several times in a repetitive search loop using the A* algorithm. Both the heuristic function $h(n)$ and the path function $g(n)$ are defined as the Euclidean distance. The A* algorithm may retrieve local paths where the acceleration and velocity cannot be satisfied. The minimum jerk method is proposed to satisfy the path's derivative and continuity constraints by applying the squared jerk's integral as the path cost function. Further, waypoints away from the boundary of the obstacle are added to avoid collision with the obstacle.

The integration of control parameters and environmental data into a novel cost function enables the rectification of the original path. The optimized cost function enhances the obstacle avoidance efficiency of the A* algorithm and reduces the operational difficulty of the micro-/nanorobot.

2.3. Swarm intelligence algorithm

Swarm Intelligence (SI) algorithms simulate the genetic, predatory, and group behavior of organisms [58]. Since exiting the positive feedback mechanism, the SI algorithms are used to solve the path planning problem for micro-/nanorobots [59]. Common SI algorithms include Genetic Algorithm (GA) [60] and Particle Swarm Optimization (PSO) [61].

To control a snakelike magnetic microrobot swarm (SMS) under microscopic visual navigation, a path planner based on the GA was proposed in [62]. The SMS is constructed from peanut-shaped hematite colloidal particles, driven by rotating magnetic fields, which enable it to form a dynamic equilibrium chain. The GA optimizes the generation and motion control of the SMS for efficient and precise navigation. By integrating the GA into the path planning process, the SMS achieves high-precision trajectory tracking at desired velocities in both simple and complex environments. This approach ensures efficient swarm generation, enabling the SMS to navigate through curved and branched narrow channels with high mobility.

To prevent nanorobots from getting lost during travel to the target region, the directed PSO algorithm was proposed in [63]. This algorithm can deliver the entire swarm of nanorobots to the target region after only a small number of iterations. When at least one nanorobot reaches the goal point, the goal information is broadcast to all robots, reducing the number of iterations required. Experiment results show that the directed PSO algorithm can deliver all nanorobots to the target area more efficiently than traditional algorithms.

To guide the multifunctional magnetic spore for drug delivery, a PSO-based path planer was designed in [30]. The PSO path planner evaluates the fitness of each particle using a cost function, typically taking into account factors such as path length and collision risk to ensure no collision with the obstacles. Simulation results of the PSO-based optimal path planner after modeling the environment data are shown in Figure 4.

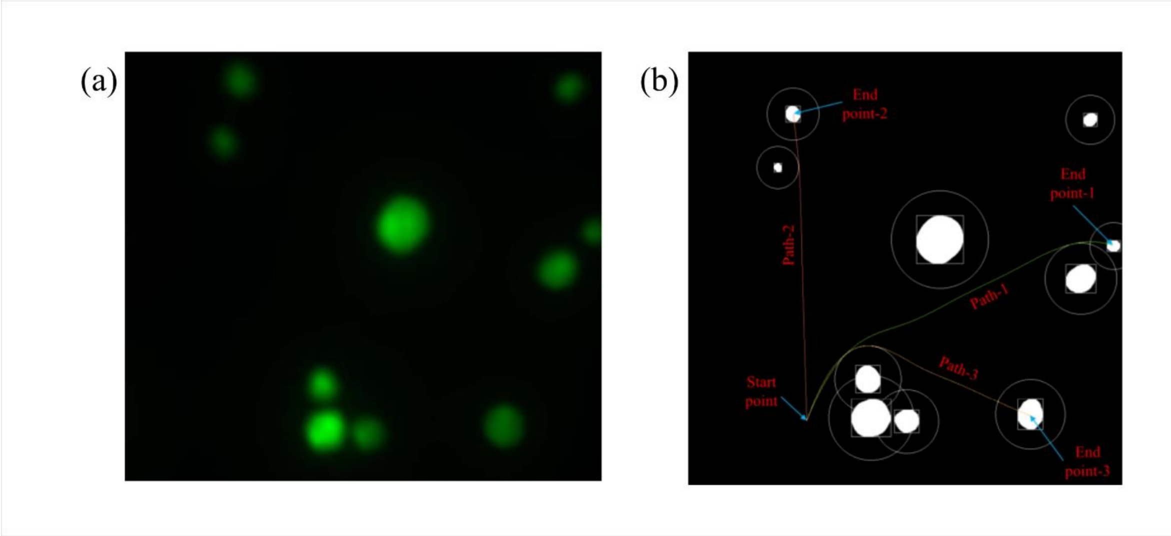

Figure 4. Simulation results of the PSO-based optimal trajectory planner after parameter tuning. (a) Captured experimental scenario. (b) Illustration of the three path-planning results with different targeted cells. Reproduced from [30] with permission. Copyright 2020 IEEE Transactions on Automation Science and Engineering.

Zheng *et al.* [64] introduced the idea of the artificial potential field to optimize the PSO algorithm. The main concept is to establish a virtual force field in the working environment of the mobile microrobot, where the target point generates an attractive potential field and the obstacles generate a repulsive potential field. The motion environment of the microrobots is modeled using the grid method, where obstacles are marked on the grid. The artificial potential field technique is then applied to assign potential field values to each grid point. Using the PSO algorithm, a path is planned that follows a trajectory of decreasing potential field values.

Overall, searching path planning algorithms can quickly calculate the optimal path in environments with a limited number of nodes, which is leveraged for the preliminary path planning of nanorobots [65].

3. Sampling path planning

Sampling path planning algorithms randomly sample waypoints from environmental data [66]. The sampled waypoints provide greater flexibility in the shapes of the micro-/nanorobot's path. Sampling path planning algorithms include probabilistic roadmaps [67] and rapidly exploring random trees [68].

3.1. Probabilistic roadmaps

Kavraki *et al.* [69] proposed a motion path planning algorithm for robots in static workspaces called the Probabilistic RoadMap (PRM) algorithm. The PRM has been successful in retrieving paths in high-dimensional spaces, which includes three main steps for avoiding obstacles. First, waypoints are randomly sampled within the specified target area, and waypoints proximate to obstacles are removed. Second, all selected waypoints are connected by straightedges to generate a graph, with edges not blocked by obstacles regarded as potential localized paths. Finally, the shortest path from start to end is determined from the potential localized paths.

A path planner utilizing the PRM algorithm was proposed by Dey *et al.* [70] for micromanipulators. Initially, the PRM algorithm is employed to address obstacles within the working environment, generating a roadmap through random sampling and collision checks. Subsequently, the start and goal positions are incorporated into this roadmap. Finally, the greedy algorithm is deployed to ascertain the optimal or shortest path between these positions.

The advantage of the PRM is randomly selecting waypoints from the movement space, which can quickly retrieve the optimal path through the selected waypoints. Therefore, the PRM algorithm can reduce the time of modeling the environment to improve the computational efficiency of paths. However, the random selection of waypoints produces the optimal path which cannot equal the shortest arrival path.

3.2. Rapidly-exploring random tree

Different from the sampled waypoints to generate a graph, the Rapidly-exploring Random Tree (RRT) is proposed to describe the optimal path by a random tree [71]. The algorithm quickly and efficiently searches the high-dimensional space to find the planned path from the starting point to the goal point. The randomly sampled waypoints guide the search through the restricted area [72]. Since environmental data modeling is avoided through collision detection of the sampled points, the RRT algorithm offers a viable solution for the path planning of micro-/nanorobots in high-dimensional spaces with complex constraints [73].

To achieve automatic obstacle avoidance in micro-robot vascular environments, Fan *et al.* [74] modified the artificial potential field combined with the RRT algorithm. Meanwhile, the RRT algorithm is used for path planning of multi-agent micro-/nanorobots. Salehizadeh and Diller [34] proposed the unidirectional-RRT motion planner to control the movement of two nanorobots through a narrow slit.

However, the randomly sampled waypoints usually result in the calculated path that is neither the shortest nor the most direct, which increases the overall tortuosity [75]. In the course of practice, the path composed of randomly selected path points was not smooth enough, which caused the micro-/nanorobot to be unable to respond quickly to changes in direction. Consequently, to facilitate the navigation of micro-/nanorobots, it is essential to optimize the initial paths calculated by the RRT algorithm.

To navigate magnetic microrobots in complex and large-workspace human body environments, Liu *et al.* [37] proposed an improved RRT algorithm based on the evolutionary strategy. Especially, three limitation requirements of evolutionary strategy are designed to achieve a shorter, smoother, and safer path: (1) Paths are calculated by the RRT algorithm; (2) The journey length, path smoothness, and distance from obstacles are taken into account; (3) The path is not blocked by obstacles. To fulfill the requirement (2), three cost functions have been devised as follows:

$$f_l = \sum_{k=1} \text{Distance}(r_k, r_{k+1}) \tag{3}$$

$$f_a = \sum_{k=2}^{n-1} \text{Angle}(r_{k-1}, r_k, r_{k+1}) - \pi \tag{4}$$

$$f_d = \min\left(\left\{\text{Distance}(r, o) : r \in R, o \in O\right\}\right) \tag{5}$$

where f_l represents the Euclidean distance between the waypoints. f_a represents the angle change of the path. f_d denotes the minimum distance between the path point and the surface of an obstacle.

A Rapidly-exploring Random Tree Star (RRT*) algorithm is proposed to ensure that the generated optimal tree is the shortest path [76]. Furthermore, an enhanced bidirectional RRT* algorithm was proposed to realize path planning and motion control of microrobots [77]. Using an image-guided motion controller, the generation process of the optimal path consists of three steps: (1) obtaining the initial path based on RRT*; (2) establishing collision Buffer Layers to avoid all obstacles; (3) Smoothing the path. The proposed path planning algorithm enables clusters of microrobots to accurately approach moving targets with greater efficiency.

4. Dynamic path planning

As the operating environment becomes more complex, dynamic path planning algorithms remain significant challenges for micro-/nanorobots to avoid unknown and moving obstacles [78]. Unlike searching and sampling path planning, dynamic path planning algorithms simplify global paths into local steps for micro-/nanorobots [79]. The algorithm for real-time motion direction calculation in micro-/nanorobots is classified as dynamic path planning.

Consequently, contemporary research in robotics focuses on developing dynamic path planning algorithms to ensure the safe operation of micro-/nanorobots [80,81]. Current dynamic path planning algorithms include the dynamic window approach, reinforcement learning, and deep learning. These algorithms combine the dynamic environment and the micro-/nanorobot's motion state to predict the direction of travel in real time [82].

4.1. Dynamic Window Approach

The Dynamic Window Approach (DWA) is an obstacle avoidance algorithm for local path planning, which is widely applied in the path planning of micro-/nanorobots. The objective cost function $G(v, \omega)$ of the DWA algorithm scores the trajectory based on the feasible and angular velocities to obtain the best combination to drive the robot's motion along the local paths [83]. The cost function is illustrated as follows:

$$G(v, w) = \delta\left[\alpha \cdot heading(v, w) + \beta \cdot dist(v, w) + \gamma \cdot V(v, w)\right] \tag{6}$$

where α, β, and γ are the weighted parameters. $heading(v, w)$ represents the heading angle function. $dist(v, w)$ denotes the safety evaluation function. $V(v, w)$ is the speed magnitude evaluation function.

In unknown and complex environments, the DWA algorithm entails the step-by-step exploration of dynamic paths from a starting point to a target area, considering the vital dynamics of nanorobots [84].

An optimal path is determined with the DWA integrated linear quadratic regulator to deliver the target drug via nanorobots [85]. The cost function J_{LQR} of the linear quadratic regulator is designed to minimize the sum of all state errors and the control input. The total cost function J is expressed as follows:

$$J = \omega G(v,w) + (1-\omega) J_{LQR} \tag{7}$$

To address the low success rate of microrobots traversing obstacle-dense environments by employing the DWA algorithm, Zeng *et al.* [86] proposed the obstacle avoidance planning algorithm based on the multi-module enhanced dynamic window approach. The suggested path planner optimizes the heading angle function and obstacle function. The heading angle function is optimized below:

$$heading'(v,w) = Round(d_m / v) \tag{8}$$

where $heading'(v,w)$ is the optimized heading function. $Round(\cdot)$ is the rounding function. d_m represents the predicted time step and vice versa.

The optimized obstacle function $dist'(v,w)$ records the distance between the trajectory and the nearest obstacle. Further, the target point function $\mathrm{target}(v,w)$ is added after the microrobots have passed through the dense obstacles, improving the navigation capability of the robot. The evaluation function $G'(v,w)$ of the multi-module enhanced dynamic window approach is shown as follows:

$$G'(v,w) = \delta\left[\alpha \cdot heading'(v,w) + \beta \cdot dist'(v,w) + \gamma \cdot V(v,w) + \phi \mathrm{target}(v,w)\right] \tag{9}$$

The speed and angle of the micro-/nanorobot are dynamically calculated by minimizing the cost function of the DWA. Optimizing the loss function and modeling the operating environment can markedly enhance the efficiency of nanorobots in complex environments.

4.2. Reinforcement Learning

Reinforcement Learning (RL) enables nanobots to follow the shortest path to reach their target by making decisions at each point along the way [87,88]. The framework of the reinforcement learning algorithm is shown in Figure 5.

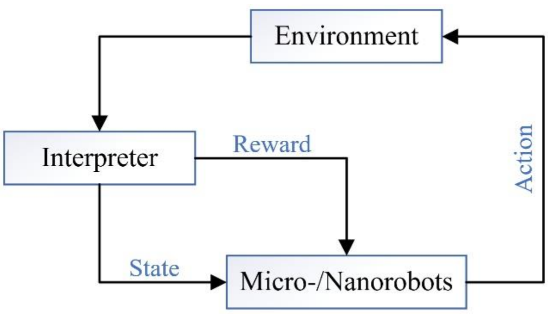

Figure 5. The framework of the reinforcement learning algorithm.

To deliver targeted drugs for treating cancer [89], nanorobots must reach the designated location safely and stably. In [90], the Q-learning, *i.e.*, reinforcement learning, was applied to obtain the optimal solution of the Markov Decision Process (MDP) [91] to predict the direction of operation of the micro-/nanorobot. The formation of a dynamic decision algorithm known as the MDP has been employed to address issues related to motion planning and execution by providing a mathematical framework. A policy for decision-making is required for the MDP. This policy should provide the probability of taking action when in the state S, as illustrated in Figure 6.

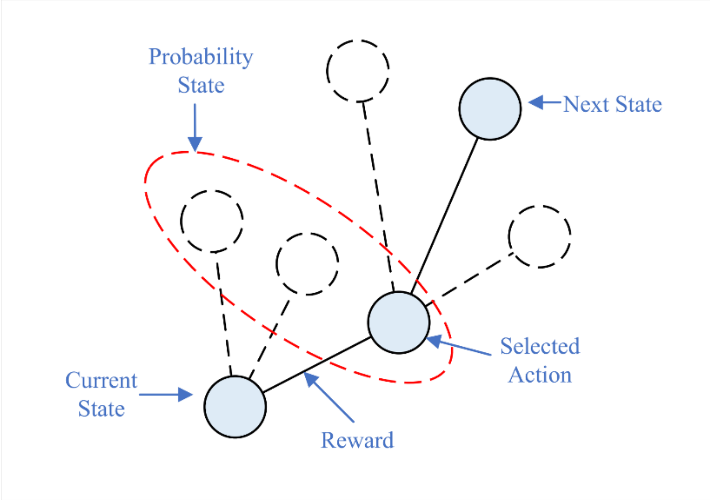

Figure 6. The framework of the Markov Decision Process.

The optimal strategy based on the Q-learning and the MDP is designed to generate the optimized local path. which is expressed as follows:

$$Q_{i+1}(s,a) = Q_i(s,a) + \alpha\left(r + \gamma \max_{a'}(Q_i(s',a')) - Q_i(s,a)\right) \tag{10}$$

where r represents the immediate reward. γ is the relative parameter of delayed rewards. s' denotes the new state. a and a' are the actions of states.

To improve the efficiency of microrobots navigating through blood vessels, Tabrizi *et al.* [92] proposed a path planner combining ant colony optimization with the RL. The suggested combination algorithm includes the linear learning step and the auxiliary learning step. In the linear learning step, the ant agents interact with the environment to obtain the real environment information. Then, the real statements are used to update the primary function. The optimization method improves the efficiency of path retrieval under a large motion. However, the ant colony optimization relies on repeated events that have occurred.

Controlling magnetic nanorobots to deliver cancer drugs in the complex and dynamic 3D vivo space requires path planning algorithms including a sense of generality and adaptability. Abbasi *et al.* [15] suggested the model-free path planner based on the RL algorithm to control the magnetic nanorobots, which reduces the average path length to reach the target, resulting in more accurate motion control of the nanorobots. To combine path planning and control, the suggested RL agents with a neural network are trained gradually from simulation, 2D navigation, and 3D navigation. The experiments show that the trained RL model has a huge improvement in control accuracy compared to the traditional control model.

In summary, the advantage of the RL algorithm is the real-time interaction between the micro-/nanorobots and the dynamic environment. By directly modeling the environment and motion state, the RL algorithm iteratively refines the control strategy, enabling precise positioning and navigation in dynamic environments. However, manual intervention is still necessary during the initial stages of training for different individual environments.

4.3. Deep learning

To perform more complex tasks and adapt to dynamic environments, establishing real-time interaction between micro-/nanorobots and surroundings is crucial [93]. Consequently, deep learning-based path planning algorithms, as efficient means of intelligent interaction, have become a current research focus [94]. This increases the flexibility and adaptability of micro-/nanorobots. Moreover, deep learning aids in processing complex imaging data, enhancing localization accuracy [95]. The descriptions and schematics for the five autonomy levels are illustrated in Figure 7.

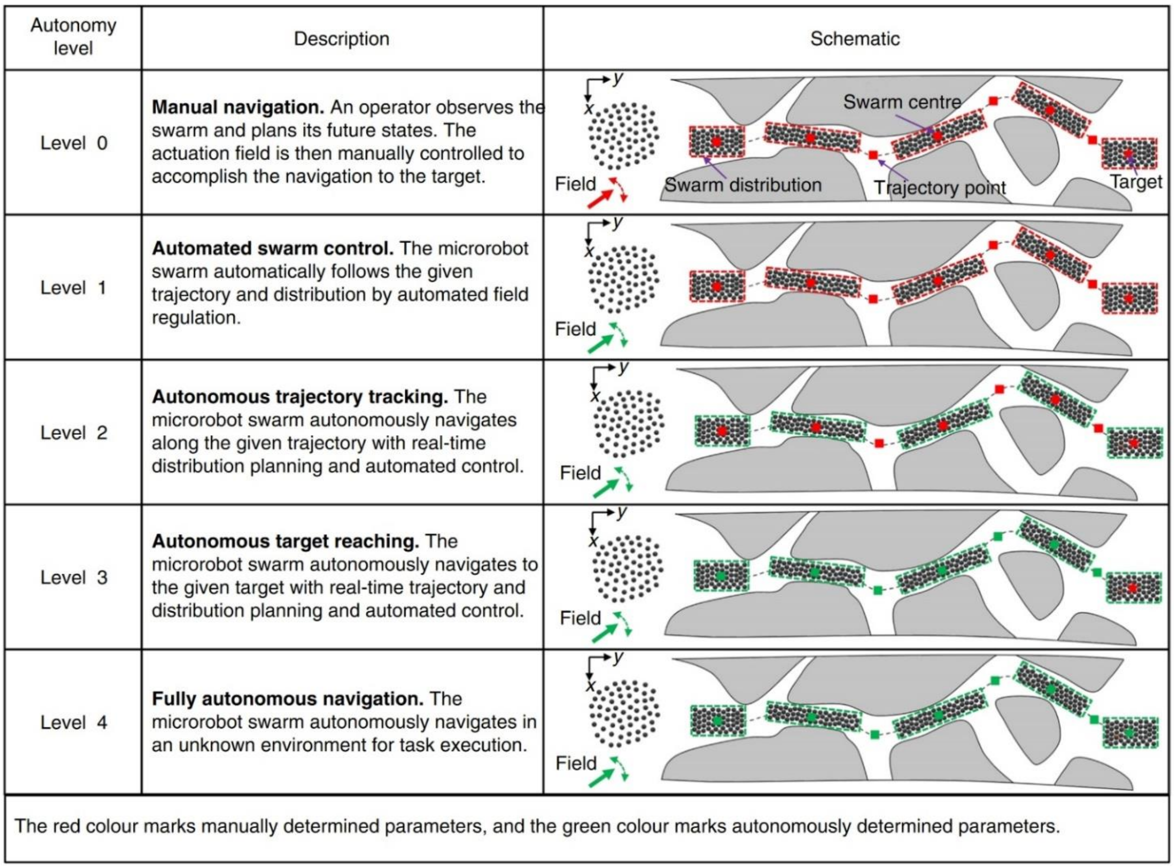

Figure 7. Descriptions and schematics for the five autonomy levels. Reproduced from [13] with permission. Copyright 2022 Nature Machine Intelligence.

Amar *et al.* [38] presented model-free deep reinforcement learning to intelligently and autonomously navigate magnetic microrobots in the real-world fluid surface. Based on reinforcement learning, deep neural networks are added to the process of the state and reward, which means the suggested navigation system does not need to model the motion state. The direction of the microrobot is directly predicted by the trained end-to-end model. The added deep neural networks can learn more space features than the complex math models in traditional reinforcement learning. Yang *et al.* [96] created a path planning framework using convolutional neural networks to analyze the environmental information, and then utilizing bioinspired reinforcement deep learning to generate the local paths. Further, neural networks are trained with varying obstacle shapes to obtain the optimal navigation strategies. The optimal state-action value function Q* (v, w) of reinforcement deep learning is shown below:

$$Q^{*}(v,w)=E\sum_{n=1}^{\infty}\gamma^{n}[R(s_{n})]+\phi(s_{n}) \tag{11}$$

where $E\sum_{n=1}^{\infty}\gamma^{n}[R(s_{n})]$ denotes the particle state at the time step n. $\phi(s_{n})$ represents the environmental parameters after convolution. The trained results allowed the nanorobots to autonomously determine the current direction of travel in unknown and complex paths.

Deep Neural Networks (DNNs) were also proposed for autonomous swarm orientation and distribution planning in [13]. The next optimal trajectory $[R_S, \alpha_S]$ is formulated as follows:

$$[R_S,\alpha_S]=\operatorname{argmin}\left\{-\frac{1}{N}\left(\|b_i-O\|\right)+w_1(R_s-R_c)+w_2\left\|\alpha_s-\alpha_{fwd}\right\|\right\} \tag{12}$$

where b_i is a boundary point of distributed swarms. O denotes the obstacle regions. R_s represents the shape ratio of swarm distribution. α_s and α_{fwd} is the forward direction.

The DNNs-based swarm orientation planning includes two sequence models: swarm shape planning and swarm orientation planning. The structures of the DNNs for swarm shape planning and swarm orientation planning are illustrated in Figure 8.

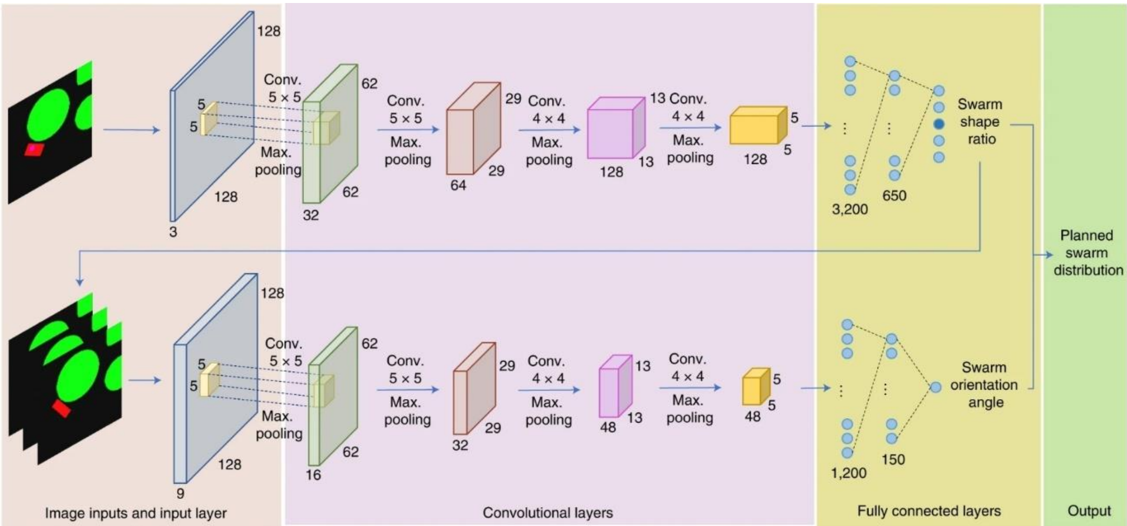

Figure 8. The structures of the DNNs for swarm shape planning and swarm orientation planning. Reproduced from [13] with permission. Copyright 2022 Nature Machine Intelligence.

The spatial features around the robot are extracted through convolutional and pooling layers. Further, the shape features of the swarm nanorobots are computed through full connection layers. The relationship between environmental obstacles and the shape of the swarm nanorobots is established. Lastly, according to the space features and shape features, the stance of the swarm nanorobots is predicted by the swarm orientation planning. Therefore, the DNN models enable autonomous changes in the shape of swarm nanorobots when facing different obstacles, improving the robots' possibility [97].

Consequently, deep neural networks can create connection relationships between dynamic environments and micro-/nanorobot's motion state. The operation parameters are directly given by the end-to-end model trained by the datasets of motion control, which allows the micro-/nanorobots to autonomously move in unknown surroundings. Deep learning will revolutionize the future of autonomous path planning for micro-/nanorobots.

5. Conclusion

This paper reviews path planning algorithms for obstacle avoidance in micro-/nanorobots. Considering the specific characteristics of the obstacle environment and the task requirements, calculation optimization, and path correction are conducted based on traditional path planning algorithms. Therefore, it is particularly important to analyze and summarize the optimization process for different algorithms. The continuous optimization of path planning algorithms saves time and reduces the investment in human and medical resources. The advantages and limitations of different algorithms are concluded in Table 1.

Table 1. The advantages and limitations of different algorithms.

Classifications	Algorithms	Advantages	Limitations
Searching	Dijkstra	Simple operation logic.	High time complexity.
	A*	Low time complexity compared with Dijkstra.	The path depends on the loss function.
	SI	Few parameters. High efficiency in global search.	Slow search speed. Low ability in local search.
Sampling	PRM	No modeling environment.	Obtaining the best path requires traversing all waypoints.
	RRT	Fast convergence. Fast obtaining optimal path.	The optimal path may not equal the shortest path. The obtained path is not smooth.
Dynamic	DWA	Good adaptability to dynamic scenarios.	Dependent environment and kinetic modeling.
	Reinforcement Learning	Fast response according to environments.	Requires separate modeling for different scenarios.
	Deep Learning	Autonomous adjustment of the operating direction according to the surrounding environment.	Requires environmental and operational datasets.

Searching path planning algorithms systematically retrieve and evaluate static waypoints to calculate global paths, ensuring accurate navigation. The Dijkstra algorithm is simple in operational logic but suffers from high time complexity. In contrast, the A* algorithm offers lower time complexity than Dijkstra. However, the effectiveness of the path heavily depends on the design of the cost function. The SI algorithm is distinguished by the minimal parameter requirements and high efficiency in global searches.

Sampling path planning algorithms overcome the limitations of fixed grids, which significantly enhances the flexibility and efficiency of path planning. The PRM algorithm does not necessitate environmental modeling. However, obtaining the optimal path still requires traversing all sampled waypoints. The RRT algorithm quickly converges and efficiently discovers paths, though these paths may not be the shortest and often lack smoothness.

Dynamic path planning algorithms interact with the environment in real time, allowing automatic adjustments for unexpected changes and obstacles. The DWA algorithm shows strong adaptability but depends on accurate environmental and kinematic modeling. Reinforcement learning algorithms can quickly respond to environmental changes but need distinct training for different scenarios. Deep learning algorithms can autonomously adjust their paths based on environmental inputs but demand extensive datasets for training and operation.

6. Opportunities

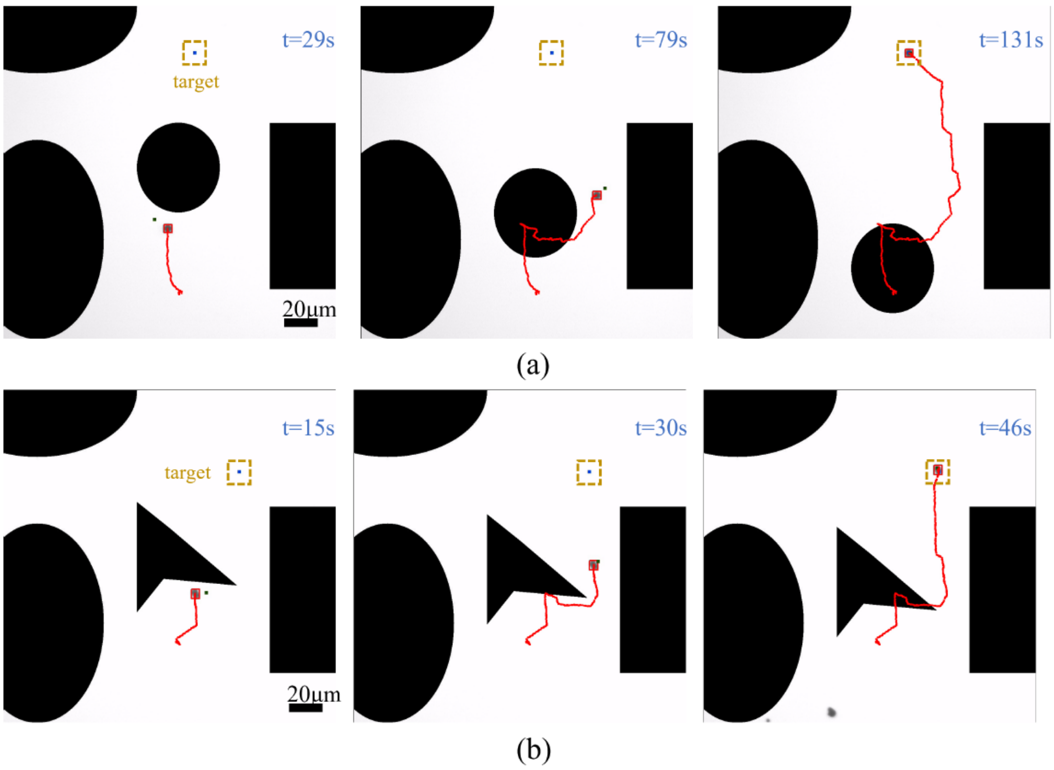

Figure 9. Path planning for dynamic environments based on deep learning. (a) Dynamic path planning with convex obstacles. (b) Dynamic path planning for non-convex obstacles. Reproduced from [98] with permission. Copyright 2023 IEEE International Conference on Robotics and Automation (ICRA 2023).

The integration of artificial intelligence with path planning will become one of the most promising areas. Particularly, deep learning algorithms can enable micro-/nanorobots to navigate complex and dynamic environments more efficiently and autonomously [98]. Figure 9 illustrates the motion planning results based on deep learning.

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Conflicts of interests

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication.

Authors' contribution

Conceptualization, L.Y.; formal analysis, T.Y.; investigation, T.Y.; resources, L.Y. and T.Y.; data curation, T.Y.; writing—original draft preparation, T.Y.; writing—review and editing, L.Y., T.P., and T.Y.; visualization, L.Y. and T.Y.; supervision, L.Y.; funding acquisition, L.Y. All authors have read and agreed to the published version of the manuscript.

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