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Path Planning Technologies for Autonomous Underwater Vehicles-A Review

DAOLIANG LI, PENG WANG, AND LING DU
College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China
China-EU Centre for Information and Communication Technologies in Agriculture, China Agricultural University, Beijing 100083, China
Key Laboratory of Agricultural Information Acquisition Technology, Ministry of Agriculture, China Agricultural University, Beijing 100083, China
Beijing Engineering and Technology Research Centre for Internet of Things in Agriculture, China Agricultural University, Beijing 100083, China

Corresponding author: Daoliang Li (dliangl@cau.edu.cn)

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ABSTRACT An autonomous underwater vehicle (AUV) is an economical and safe tool that is well-suited for search, investigation, identification, and salvage operations on the sea floor. Path planning technology, which primarily includes modeling methods and path search algorithms, is an important technology for AUVs. In recent years, the AUV path planning technology has rapidly developed. Compared with land robots, AUVs must endure complex underwater environments and consider various factors, such as currents, water pressure, and topography. Challenges exist in terms of online obstacle avoidance, three-dimensional environment path planning, and the robustness of the algorithms. Adapting a complex environment and finding a suitable path planning method comprise the main problem that must be solved. In this paper, we summarize the principles, advantages, and disadvantages of modeling and path search technologies for AUVs. The most prominent feature of this paper is to summarize the improvement methods of various technical shortcomings and improve the original methods, such as dynamic obstacle avoidance, optimization path, coverage, and processing speed. In addition to summarizing the characteristics of each algorithm, this paper intuitively demonstrates the experimental environment, the real-time nature, the path planning range of the AUV, and so on. We also discuss the application scenarios of various modeling and path search technologies for AUVs. In addition, we discuss the challenges of AUVs and the direction of future research.

INDEX TERMS AUV, path planning, model building, path search.

I. INTRODUCTION

The 21st century is the century of oceans, which account for 71% of the world's total area of oceans. Oceans are rich in mineral resources, marine biological resources, and renewable energy sources, such as tidal energy and wave energy. Oceans are important assets for the sustainable development of human society [1]. Therefore, the development of oceans and the associated competition have become the strategic focus of many developed countries, and these goals have become pursued with increasing fierceness. Compared with other underwater vehicles that can be explored, such as manned ships, and float platforms, AUVs have numerous advantages such as underwater payload capacity, maneuverability, and depth of activity despite their high cost and short battery life. In a variety of marine technologies, autonomous underwater vehicles (AUVs) can be used for comprehensive surveys and studies in areas where the depth cannot be reached by general diving technology; their ability to accomplish various missions have brought marine development into a new era [2].

An AUV is an important part of a robot [3] because it possesses a variety of sensors, which are not limited by time and space, and autonomous navigation and obstacle avoidance capabilities; in addition, AUVs can autonomously perform specific underwater tasks [4]. AUV development involves high technologies, such as mechanics, fluid mechanics, hydroacoustics, optics, electronic communication, navigation, automatic control, computer science, sensor technology, bionics, artificial intelligence, and many other contemporary achievements. The important application value of AUVs has received an increasing amount of attention by scientists and technologists in the civil and military fields, and in-depth

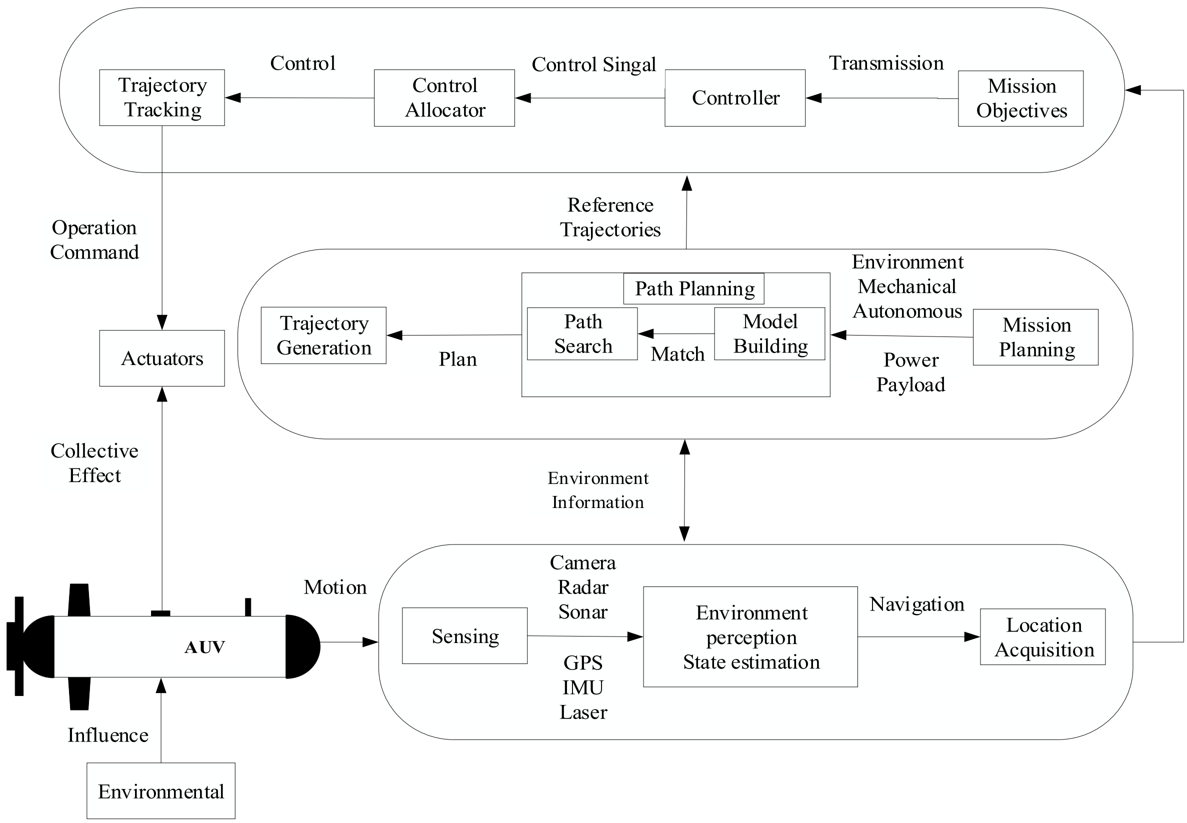

FIGURE 1. **The relationship of AUV autonomous navigation structure.**

research has been conducted [5], [6]. In the field of marine engineering, AUVs are employed for the structural inspection of dams, installation/disassembly of underwater bases, observation of underwater targets, and search and rescue; they also aid divers. In the field of marine scientific research, AUVs can be deployed to conduct data collection in a marine environment, investigate underwater shipwrecks, perform geological and geomorphological exploration of the seabed, and explore petroleum and other resources. In the military field, AUVs are used in mine countermeasures, target detection, intelligence gathering, surveillance and reconnaissance, environmental data collection and anti-submarine warfare. As human activity space gradually expands into the marine sector, AUVs will have an important role in ocean exploration [7], [8].

An AUV is an underwater development tool for human exploration of oceans with the greatest potential, especially for underwater observation and underwater operations [9]. In recent years, the attention given by various countries to marine resources has promoted the vigorous development of underwater vehicle technology. Scientific research support and funding for AUVs have increased, and considerable progress has been made in path planning techniques. The development of AUV path planning technology lags behind AGV (Automated Guided Vehicle), because AGV is in a two-dimensional static environment that is less affected by environmental factors, and AUV is more subject to the requirements of complex dynamic environments. Many modeling methods and path search algorithms are only available for 2D environments [23]. Even compared with the UAV (Unmanned Aerial Vehicle), which is also a three-dimensional path plan, AUV has the problems of high experimental cost, poor underwater visibility, ocean current interference, and difficulty in recovering after loss [65]. To achieve autonomous navigation of underwater robots, a variety of techniques is required to collaborate on an AUV. We describe the relationship of various technologies in Fig. 1. Path planning is an important link. Its task is to determine an initial state (position and attitude) to reach the target state (position and posture) without a collision path in an environment with obstacles according to a certain evaluation standard based on the establishment of an environmental model [10], [11]. First, to improve the performance of an AUV, we must improve the efficiency of the AUV, including mechanical improvements (reduce friction and improve material strength), automation (path planning and path tracking), and reduced loads. Second, we must improve the capability of AUV batteries [164]. This paper reviews the development of path planning technology with regard to automation technology. The steps of AUV and their path planning techniques are similar to those of AGV and UAV. The main parts of path planning include environmental modeling and path search. Before an AUV uses a search

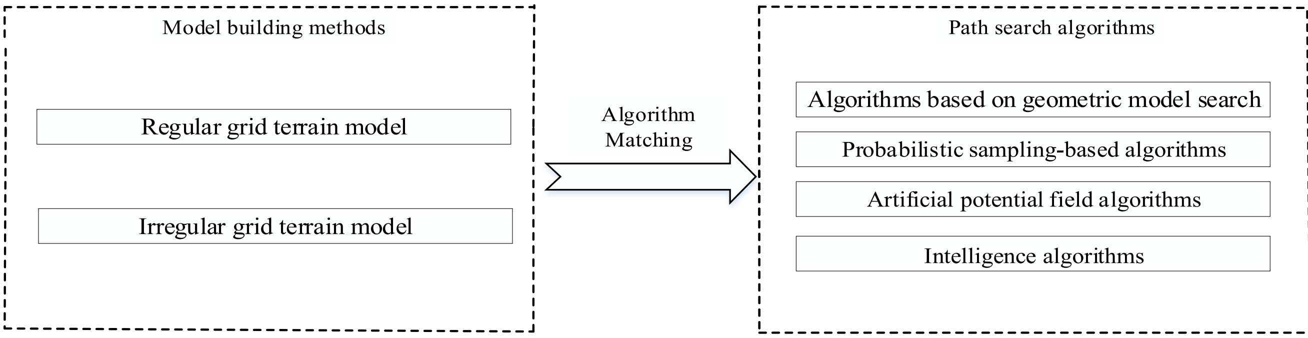

FIGURE 2. Path planning technologies for AUV.

algorithm for path planning, we must describe the physical environment of an AUV as a form of computer identification. This process is referred to as environmental modeling, and reasonable environment modeling is beneficial to reduce the number of searches. Different path search algorithms are based on different environmental models. Each search algorithm has unique characteristics. The search speed, robustness, search path length and smoothness are suitable for 2D/3D underwater environments, and differences in online searches may exist. We also discuss the improved algorithms in the text. A suitable 2D/3D model should be built according to the complexity of the underwater environment and the requirements of the path search algorithm [155], which is responsible for searching the feasible space of the path from the environment model and producing a feasible path. For the search path problem for path planning in a two-dimensional environment, researchers proposed numerous theories and methods, some of which can be easily extended to three-dimensional space. However, some methods are not easily achieved in three-dimensional space because robots are extended to 3D space after the campaign space, and its kinematics and dynamic constraints become very complex [13]. However, the existing two-dimensional path planning technology cannot satisfy the needs of the ocean exploration field. Many technologies for 3D path planning have also been proposed. Although the computation of 3D path search algorithms is complex, they are more suitable for modeling complex environments. The following factors must be considered in AUV path planning: the underwater environment has uncertainty and dynamic characteristics (especially the influence of the ocean), the real-time nature, effectiveness and optimality of the planning algorithm, and the ability to satisfy the constraints of AUV ontology motion [14].

This article reviews the path planning techniques of AUVs and analyzes the pros and cons of various technologies. The structure of this paper is illustrated in Fig. 2. Researchers can refer to this document to understand the AUV path planning techniques, find inspiration and choose the correct methods for better scientific research. This article is divided into four sections. The significance of AUVs and the development of the technology are discussed in the first section. The establishment of the model, which primarily involves the rule model and the irregular model, is discussed in the second section. Path search techniques are presented in the third section, which primarily include the geometric model search method, probabilistic sampling-based algorithms, artificial potential field algorithms, and intelligence algorithms. Finally, our conclusions are presented in the fourth section.

II. MODEL-BUILDING METHODS FOR PATH PLANNING

The definition of an environment model is an abstract or formal description of the structure and function of the environmental system [11]. Prior to path planning, the AUV should change the original form of the external environment into a work form that is suitable for the internal environment of the planning. The reasonable modeling method is beneficial for reducing the amount of calculation in the path planning, which accelerates the speed of operation and reduction in storage. Different planning methods for AUVs should be modeled based on different environments [155]. The model is divided into two types according to the types of components. The first type is the regular grid representation model, which primarily represents the surface of the seafloor by a regular grid of squares, cubes, rectangles and cuboids. The second type is the irregular grid representation model, in which triangular, polygonal or irregular shapes serve as the basis of the model unit. We compare the two methods in Table 1. The environment in which we apply the methods of various environmental models is classified in Fig. 3.

A. REGULAR GRID TERRAIN MODEL

The regular grid terrain model employs a regular shape to express underwater environment information. For the regular grid model, each component is identical and its data structure is simple, easy to manage, store, and retrieve. Thus, the memory space is small, and the construction of complex models based on the seafloor environment is not needed. The choice of grid size will directly affect the performance of the search algorithm [13]. If the grid selection is small, and the environmental resolution is high, although the amount of environmental information is stored and the interference signal is relatively increased, the decision-making workload

TABLE 1. Underwater model establishment method.

Model building methods	Applied environments	Specific method	Advantages	Disadvantages	References
Regular grid terrain model	1) Low requirement for modeling accuracy 2) Simple undersea environment 3) Few obstacles	Grid model	1) Simple establishment process 2)Easy to implement and store	1) Low efficiency 2) Not suitable for large scale space search	[17] [18] [19] [20] [165] [22]
		Cell tree model	1) Simple establishment process 2) Easy to implement and store 3) The efficiency higher than Grid model	1) Difficult to match irregular ground patterns 2) The obstacles cannot be too small	[12] [29] [30] [31] [32] [33] [58] [84] [166]
Irregular grid terrain model	1) Low requirement for modeling accuracy 2) Complicated undersea environment	Voronoi diagram model	1) Completely describe the seabed terrain structural features 2) High storage efficiency.	1) Complex modeling 2) Taking up a lot of space	[40] [41] [42] [43] [44] [185]
		Delaunay triangulation model	1) Be used for large volume of terrain information 2) Easy to update 3) Variable resolution	1) Complex modeling 2) Taking up a lot of space	[36] [46] [47] [48] [49] [50]
		Visibility graph space model (c-space model)	1) Easy to find the shortest path 2) Using the predefined basic shape to describe the surrounding environment	1) Can't re-construct the view 2) Lack of flexibility	[4] [52] [53] [205] [86]

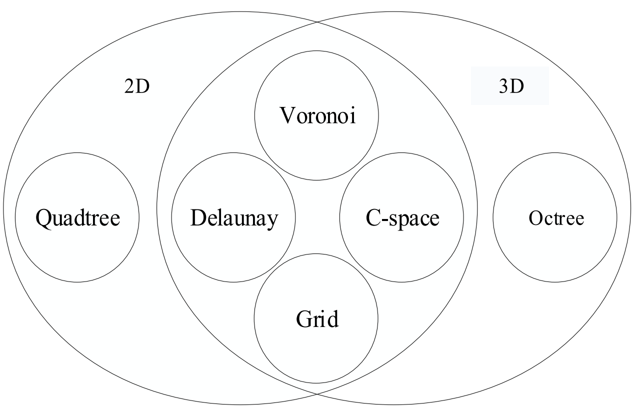

FIGURE 3. Environmental model applicable environment.

is increased, which eventually reduces the real-time performance of the system and causes slower planning [15]. Conversely, although the anti-jamming capability is strong, the amount of stored environmental information is small, and the speed of decision-making is accelerated. Due to the decrease in resolution, the model it is not conducive to planning an effective path in a dense obstacle environment. The selection of the grid size is also related to the performance of the sensor and the volume of the AUV. The size of the grid is based on the size of the AUV, and it should usually satisfy the requirement that the mobile AUV can safely move within a free grid. This model is very convenient for the analysis and calculation of terrain; thus, it is extensively employed [16].

1) GRID MODEL

The grid method divides an AUV workspace into a regular grid. Each grid can have two states: a free grid and an obstacle grid. In a two/three-dimensional grid, a black square/cube represents the obstacle in the raster array, and a white square/cube represents the free space. Because this method is simple and easily implemented, it is one of the most common modeling methods for AUVs [17]. It has the ability to represent irregular obstacles and applies to all types of traditional or intelligent algorithms; thus, it is employed in underwater 3D space path planning of AUVs in the environment modeling in [18]–[20]. However, this space partition contains a vast amount of data, which occupies most of the resources of a system. For an extensive range of underwater environments, Wang *et al.* [22] and Tanakitkorn *et al.* [165] disregard the water depth, which simplifies a three-dimensional space to a two-dimensional underwater environment model based on the grid method for an AUV. Although the environmental information is lost, it saves the system space and achieves satisfactory results.

2) CELL TREE MODEL

Due to the low efficiency of the grid method for an AUV, the octree model is proposed based on the grid method, and it overcomes the defects of the uniform grid method. An octree has a large advantage in its algorithmic structure: if a pointer is used for a link between a node and its children, the tree has to be fully instantiated [29]. An octree model is a recursion of free space into multiple subspaces, and the obtained subspace can have three states: free subspace, obstacle subspace and mixed subspace. For the mixed subspace, we must continue to divide the space until all subspaces are free subspaces or obstacle subspaces [24], [25]. Zhang [166] uses the octree model to reflect a real underwater environment. However, this model has three main drawbacks. First, since the initial space (or image) is transformed in the tree data structure, the spatial neighborhood of each block is not easily defined. Second, the paths of the AUV generated by the octree are suboptimal because they are limited to the parts between the block centers. Third, many smaller obstacles exist in the environment, for which its use can be less efficient; thus, it is primarily applied between the larger obstacles for AUV path planning [1284]. Hornung *et al.* [29] exploit a new open source framework for 3D environment models based on the octree model that has three main features. The first feature relates to the exploration of an unknown environment and represents the capabilities of an undeveloped area. The second feature represents the probability state. The third feature represents the next state, which is calculated according to the probability function to the initial position state, in such a manner that not only the protection is protected from noise but also the map can be modified when the environmental information changes. They use an octomap to zoom in or out as needed and refer to the octomap for an AUV in more detail in article [31]. If a nearby obstacle is perceived during the mission, Hernandez *et al.* [30], [32] use the open source framework to adjust and plan a collision-free path in an unknown environment for AUV. However, they conduct experiments in two-dimensional space and disregard the influence of depth. Their next experimental plan is to expand into three-dimensional space and consider the impact of sea currents on path planning. A quadtree model that does not consider depth is also applied to underwater model building. Compared with the octree model, which can be applied to three-dimensional space, the quadtree model for an AUV can only be applied to two-dimensional space due to its structural characteristics [33]. However, it can record information of all regions and effectively compress the information in the two-dimensional environment [34].

B. IRREGULAR GRID TERRAIN MODEL

An irregular grid terrain model expresses an underwater environment with irregular graphics for an AUV; this model chooses the shape of the graphics according to the submarine topography [35]. Compared with the regular grid terrain model, the modeling is more complex and consumes a large amount of space. However, it can completely describe the structural features of the seabed terrain and has high storage efficiency. This model can be used for a large volume of terrain information, is easily updated, and has variable resolution according to the shape of the seabed terrain, which enables the terrain to be simplified [47].

1) VORONOI DIAGRAM MODEL

The Voronoi diagram, which is also known as the Thiessen polygon or Dirichlet diagram, consists of a series of continuous polygons that are composed of vertical bisectors that connect the straight lines of two neighbors [37]. The vertices of a Voronoi graph simultaneously belong to three Voronoi polygons, and each Voronoi polygon has only one node. This method can contain a large amount of data for a complex terrain, is convenient when considering the topography of the seabed, and can facilitate simplification of the terrain. The greatest advantage of Voronoi diagram-based environment modeling is that the path in the road map is the Voronoi edge, which is the mid-perpendicular to the discrete center of an obstacle, which can ensure that the AUV is far from the obstacles during operations [38]. However, the storage is large, and the path length is not guaranteed to be optimal. Dong *et al.* [185] mark the position of an obstacle in a two-dimensional Voronoi diagram and generate an approximate path to connect the initial and the targets via the Voronoi processor. In the field of model building, compared with two-dimensional space, the Voronoi map is extensively employed in three-dimensional model building. They simplify the 3D underwater environment to generate a 3D Voronoi diagram that produces a global roadmap, which is a common modeling method that ensures a safe path for an AUV. Some examples of underwater modeling for AUV using Voronoi diagrams are provided in [40]–[43]. The advantage of the Voronoi diagram is that the generated path is relatively safe and located far from obstacles, and the path search is conducted on the curves or surfaces; however, the generated path is not very smooth. In response to this problem, Candeloro *et al.* [44] added a Fermat spiral segment that is based on the Voronoi diagram model and proposed a curvature continuous model-building algorithm for an AUV; the spiral of Fermat is used to smooth the path and provide curvature.

2) DELAUNAY TRIANGULATION MODEL

Delaunay triangulation is a one-to-one correspondence with the Voronoi diagram and the three node Voronoi polygon that connects three concurrent nodes form a Delaunay triangle [45]. For this reason, this model has the same advantages and disadvantages as the Voronoi diagram model. However, the modeling method based on the Delaunay triangle model only needs to change the vertex coordinates of the storage edge when the obstacle moves, and reconstruction of the triangulation network is not needed. As a reciprocal Voronoi graph, Delaunay triangulation empty circle characteristics and minimum angle maximization properties ensures that no Delaunay triangulation exists in too slender and narrow a triangle, which renders the triangulation construction more reasonable and accurate, because it maximizes the minimum inner angle of all triangulations [46]. Thus, this model is extensively applied numerous times in the path planning of AUVs in map building [46]–[50]. An improved growth algorithm of the triangulation was designed for an AUV that fuses the idea in the divide-and-conquer algorithm by Wang *et al.* [36]; it expands the baseline based on the regional discrimination principle of the linear equations and searches for the third point using the minimum cosine criterion, which accomplishes realistic 3D seabed terrain vector modeling based on measurement of the data of a sea trial.

3) VISIBILITY GRAPH SPACE MODEL (C-SPACE MODEL)

The visibility graph space method is also referred to as the c-space model. According to the size and shape of moving objects, the c-space model expands obstacles according to the proportion and narrows the robot to be small. The free space is constructed using the predefined basic shape to describe the robot and the surrounding environment, and the free space is represented as a connected figure [51]. For obstacles with different regular geometric entities in sparse and dense areas of the sea floor, Li *et al.* [4] and Wang and Xiong [52] proposed a path planning algorithm that is based on visibility graph geometry theory for an AUV, which models a 3D ocean model with conventional geometric entities for planning and simulating a path in the 3D environment. Englot *et al.* [205] and Petres *et al.* [86] modeled using the c-space method and applied to real AUV path planning experiments. Gal [53] proposed an improved visibility graph space model for an AUV, which primarily reduces the number of building nodes to achieve a fast calculation time. Based on this information, the spiral algorithm is added to better achieve obstacle avoidance. The advantage of the visibility graph model are intuitive: the shortest path can be easily identified. The disadvantage is that once the starting point and the target point change, the view has to be reconstructed; thus, a lack of flexibility exists. This method has poor local path planning capability and is suitable for global path planning and path planning within the continuous domain [54].

In the analysis of the aspects of modeling, different environmental models are created as required for AUVs. Conventional grid terrain models use rule shapes to express underwater environmental information. The model is simple and requires a small amount of computation but it does not accurately reflect the seabed environment. This model is suitable for an environment with a low requirement for modeling accuracy—a simple undersea environment with few obstacles. Compared with regular grid terrain models, irregular mesh modeling is computationally more complex and can realistically reflect the environment of the seabed. The irregular mesh model is suitable for modeling with high accuracy and a complex undersea environment. Due to the influence of underwater environmental clarity, and because it is a dynamic environment, establishing an accurate underwater model for an AUV is challenging. Unlike two-dimensional modeling of the ground, the computational complexity of three-dimensional modeling increases as the dimension increases. Therefore, many studies disregard the height information in complex 3D modeling and create a 2D model on a cross-section of the underwater surface. Although the computational complexity will be reduced, a two-dimensional model cannot fully reflect the three-dimensional underwater environment. With an increase in the computing speed and the need for a complete environment, underwater 3D modeling will replace 2D modeling and become mainstream.

III. PATH SEARCH ALGORITHM FOR PATH PLANNING

The path search algorithm is a method that is based on an established environment model and searches for the path between the starting point and the end point of the plan [55]. The primary problem that these AUVS must solve when they are free to operate in space is a path acquisition problem. This problem usually depends on the position information of the robot and the target point. A reliable and effective algorithm is needed to obtain an optimal trajectory to connect two points while satisfying various types of constraints, such as avoiding obstacles and objects, a minimum turning radius, maximum acceleration, maximum energy consumption and low time consumption [56]. The AUV path search algorithm has achieved fruitful results and has been extensively applied, and the factors that must be considered in an AUV path search algorithm include environmental uncertainty and dynamic characteristics, real-time, validity and optimality of the planning algorithm, and satisfy the constraints of the robot body's ability to move [57]. For the problem of path searching in a two-dimensional environment, the researchers proposed numerous theories and methods, some of which can be easily extended to three-dimensional space; but some methods are difficult to implement in 3D space. The main reason is that the kinematics and dynamics constraints become very complex when the robot's active space is extended to 3D [58]. This section summarizes the existing literature in four parts: methods based on a geometric model search, probabilistic sampling-based algorithms, an artificial potential field algorithm, and an intelligence algorithm. The two-dimensional and three-dimensional path search methods applied to AUVs are analyzed and compared regarding their advantages and disadvantages, and then improved algorithms are derived. The real-time performance, optimization performance, and dependence on the environment model of the algorithm are also considered, with a comparison, and references are provided for future in-depth research. In Tables 2 to 5, we summarize and comment on the application of various path search methods for AUVs. In Tables 3 and 4, a special column is not listed in the table since the path search scope is point to point. The premise of all the algorithms in Table 3 is that the environment information of the plan needs to be known, all of which are global search, and the algorithm of Table 4 is unknown to the environment, all of which are local search, so Tables 3 and 4 do not list the global/local column. Table 2 is a single AUV, so we did not list the number in Table 2. At the same time, we compare the performance of four different search algorithms in Table 6.

A. ALGORITHMS BASED ON THE GEOMETRIC MODEL SEARCH

Geometric model search algorithms are classical path search algorithms, which belong to the category of discrete optimal programming [59]. This part of the algorithm is more traditional; the implementation process is relatively simple, the technology is relatively mature, and the establishment of the model is very strict, which is closely related to the results of the implementation of the final planning path. We summarize the relationship among several algorithms for the AUV in Fig. 4 and note that the current two algorithms—Boustrophedon decomposition and Internal Spiral Algorithm (ISA)—remain the main coverage class path search algorithms of current robots.

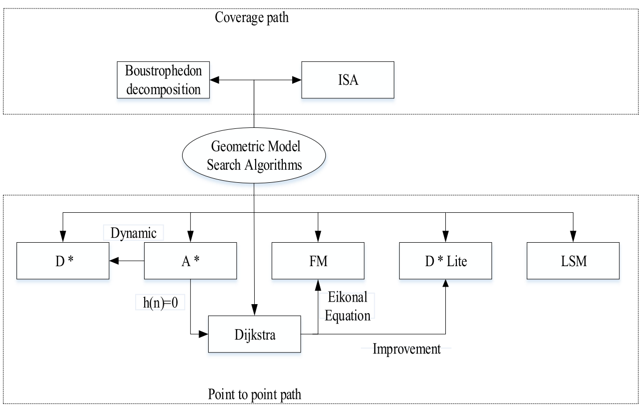

FIGURE 4. **The relationship of geometric model search algorithms.**

1) DIJKSTRA'S ALGORITHM

Dijkstra's algorithm applies a greedy strategy that employs a breadth-first search to settle the single-source shortest path issue with weighted digraphs or undirected graphs; it declares an array to hold the shortest distance from the source point to each vertex and saves while finding the set of vertices for the shortest path, the algorithm eventually obtains a shortest path tree [60]. Arinaga *et al.* [61] applied Dijkstra's algorithm to a global path search for AUVs in an underwater environment; the algorithm can avoid a set of obstacles and reach the end. However, the experiment remained only in the simulation stage and did not consider the environmental impact on the path search; their next step is to conduct experimental verification in the tank. Eichhorn [62] solved the AUV single-source shortest path problem using weighted directed graphs that are based on the classical Dijkstra algorithm, and the addition of time information as an additional dimension in the graph has the advantage of using the Dijkstra algorithm to generate exact solutions in a time-varying environment. Soulignac *et al.* [199], [200] proposed a method for AUV path planning, it similar to the Dijkstra's algorithm called sliding wavefront expansion method, which combines the effective cost function and the continuous motion model, the simulation results show good global optimality. Kirsanov *et al.* [63] improved the Dijkstra algorithm to improve the AUV dynamic obstacle avoidance problem; only two-dimensional paths were used in the experimental simulation. Although the modified path length increased by 0.18 percent, the proposed algorithm takes into account the current elements and corrects the path appropriately. Because Dijkstra's algorithm traverses all nodes and obtains the shortest path, the shortest path is obtained with a high success rate and satisfactory robustness [64]. However, traversing nodes and low efficiency are fatal shortcomings when they are applied to large-scale complex path topological networks [60].

2) A* ALGORITHM

The A* algorithm adds the estimated cost of the target point to the current node based on Dijkstra's algorithm [66]. Dijkstra's algorithm is equivalent to the case in which the valuation section of the A* algorithm is zero. The A* algorithm is the most efficient direct search solution for the shortest paths in a static road network and is a common heuristic for many other problems. The algorithm can be further understood by the formula $f(n) = g(n)+h(n)$, where the left side of equation $f(n)$ represents the cost estimate of the object from the initial state through state n to the target state, the right side of equation $g(n)$ is the actual cost from the initial state to state n in the state space, and $h(n)$ is the estimated cost of the best path from state n to the target state [72]. Choosing the evaluation function $f(n)$ in the A* algorithm is extremely important, and the choice of the evaluation function is related to the planning of the shortest and best path of the AUV [68]. An advantage of using the A* algorithm to obtain a heuristic path with a low cost and optimal solution is that it can be interrupted and recovered in time during the planning process. In [69], the role and advantages of the A* algorithm in the path search task of the AUV underwater complex environment are proved. During modeling and simulation, Garau *et al.* [71] and Li *et al.* [67] considered the influence of marine environmental factors, such as ocean currents, and implemented a path search with the A* algorithm. Lefebvre *et al.* [70] added a hierarchical technique to the A* algorithm to increase the processing speed. The simulation proved that the path length was increased by 2%, but the processing speed was increased by 10%. Yan *et al.* [194] proposed an improved

TABLE 2. Geometric model search algorithms.

Approach	Comment	Reference	Global /Local	Improvement	On/off line	2D/3D Environment	Simulation / Experiment	Point to point/ Coverage
Dijkstra	1) High success rate 2) Good robustness 3) Low efficiency	[61]	Global	/	off	2D	Simulation	Point to point
		[62]	Global	/	on	2D	Simulation	Point to point
		[63]	local	Dynamic obstacle avoidance	off	2D	Simulation	Point to point
		[199] [200]	Global	Dynamic ocean current	off	2D	Simulation	Point to point
A *	1) Low cost 2) Be interrupted and resumed lately 3) handle different difficulty terrain	[69]	Global	/	on	2D	Simulation	Point to point
		[71]	Global	/	off	2D	Simulation	Point to point
		[67]	local	/	on	2D	Simulation	Point to point
		[70]	Global	Processing speed	off	2D	Simulation	Point to point
		[194]	Global	Processing speed	off	3D	Simulation	Point to point
		[55]	Global	Optimizing path	off	2D	Simulation	Point to point
D*	1) Stability 2) Effective obstacle avoidance	[75] [76]	local	/	off	2D	Simulation	Point to point
D* Lite	1) Quicker planning speed 2) Suitable dynamic path planning	[78]	local	/	on	3D	Experiment	Point to point
		[79]	local	Environmental adaptability	on	3D	Experiment	Point to point
FM	1) Good performance in convergency 2) Fulfill demand of real-time for AUV control system	[82]	Global	/	on	2D	Simulation	Point to point
		[84]	Global	/	on	2D	Experiment	Point to point
		[83]	Global	/	off	3D	Simulation	Point to point
		[85]	Global	Dynamic obstacle avoidance	on	2D	Simulation	Point to point
		[86]	Global	Dynamic ocean current	on	2D	Simulation	Point to point
LSM	1) Effectively simulate the dynamic process 2) Slow processing speed	[88] [89] [90]	Global	/	off	2D	Simulation	Point to point
		[91] [92]	Global	Dynamic ocean current	off	2D	Simulation	Point to point
		[196]	Global	Processing speed	on	2D	Simulation	Point to point
Boustrophedon	1) Simple realization process 2) Low efficiency	[95]	Global	/	on	3D	Experiment	Coverage
		[96] [97]	Global	Improve coverage	off	2D	Simulation	Coverage
ISA	1) Simple realization process 2) Low efficiency	[100]	Global	/	off	2D	Simulation	Coverage
		[101]	Global	Processing speed	on	3D	Simulation	Coverage
Others		[102]	Global	Reliability of the planning	on	2D	Experiment	Point to point
		[103]	Global	Processing speed	on	3D	Experiment	Point to point
		[104]	Global	Dynamic obstacle avoidance	on	2D	Simulation	Point to point
		[105]	local	Local obstacle avoidance	on	2D	Simulation	Point to point
		[69] [106]	Global	Dynamic obstacle avoidance	on	2D	Simulation	Point to point
		[107]	local	Dynamic obstacle avoidance	on	3D	Experiment	Point to point
		[108]	Global	Environmental adaptability	on	3D	Simulation	Coverage
		[145]	Global	Environmental adaptability	off	2D	Simulation	Coverage
		[203]	Global	Dynamic ocean current	off	2D	Simulation	Point to point

A* algorithm; the main difference is that a circular search is added, and the main role of the circular search is reflected in the extended node, which solves the discretization and discontinuity of the traditional extended node for an AUV with improved efficiency and traversability. In addition, the virtual terrain is constructed to convert the underwater 3D path planning into 2D path planning. The search space dimension is reduced by one level, and the search speed is also accelerated.

TABLE 3. Probabilistic sampling-based algorithms.

Approach	Comment	Extension algorithm	Improvement	Reference	On/off line	2D/3D environment	Simulation / Experiment	Single/Multi AUV
PRM	1) Accurate modeling 2) Simple operation 3) Solve high dimension space 4) Search path is not the optimal solution	/	/	[114]	on	2D	Simulation	Single
				[62]	on	3D	Experiment	Single
RRT	1) Perfect probability 2) Fast search speed 3) Solve high dimension space 4) Poor real time application 5) Search path is not the optimal solution 6) Easy to fall into the problem of local minimum	/	/	[118] [120]	on	2D	Simulation	Single
		/	/	[119]	off	2D	Simulation	Single
		RRT*	Local minimum	[121] [122]	on	2D	Experiment	Single
		RRT*	Local minimum	[31] [32]	on	3D	Experiment	Single
		RRT*	Local minimum	[123]	on	3D	Experiment	Multi
		Bi-RRT	Processing speed	[124] [206]	on	2D	Simulation	Single
		Li-RRT	Processing speed	[125]	off	2D	Simulation	Single
		DD-RRT	Optimization path	[126]	off	2D	Simulation	Single
		H-RRT	Processing speed	[127]	on	2D	Experiment	Single
		Smooth-RRT	Optimization path	[128]	on	2D	Simulation	Single

TABLE 4. Artificial potential field type algorithm.

Approach	Comment	Improvement	Reference	On/off line	2D/3D environment	Simulation / Experiment	Single/Multi AUV
APF	1) simplicity 2) Easy implementation 3) Easy to fall into local minima 4) Suitable for dynamic local obstacle avoidance	/	[133] [134]	on	2D	Simulation	Single
		Dynamic obstacle avoidance	[135] [138]	off	2D	Simulation	Single
		Dynamic obstacle avoidance	[136]	on	2D	Simulation	Multi
		Optimization path	[137]	on	2D	Simulation	Single
		Local minima	[139]	on	2D	Simulation	Single
		Local minima	[140]	on	3D	Simulation	Single
		Stability	[141]	off	2D	Simulation	Single
		Optimization path	[201]	on	3D	Experiment	Multi
BUG	1) Small calculation 2) Fast speed 3) Not the optimal path	/	[120]	on	2D	Simulation	Single
		/	[142]	on	3D	Simulation	Single

The experimental simulation proves that this algorithm is more suitable for motion limitation; the processing speed increased by 25.3% and search path length is reduced by 5.3%. However, the A * algorithm gradually determines the next path grid by comparing the heuristic function values of the current path's neighbor grids. When multiple minimums exist, the A * algorithm cannot guarantee the optimal path of the search. The improved A* algorithm designed by Zhang *et al.* [55] is applied to the global path search of complex ocean current disturbances in coastal environments. First, a stable ocean current model is constructed according to the characteristics of ocean currents. Second, by analyzing the speed and force of an AUV in ocean current navigation, the conditions of the A* algorithm for the outward extension

TABLE 5. Intelligence algorithms.

Approach	Comment	Reference	Global/ Local	Improvement	2D/3D Environment	On/off line	Simulation / Experiment	Single /Multi AUV	Point to point/ Coverage
PSO	1) Good robustness 2) Fast convergence speed in the initial stage of search 3) Slow convergence speed in the late stage of search	[146]	Local	/	2D	off	Simulation	Single	Point to point
		[163]	Global	/	2D	on	Simulation	Single	Point to point
		[20]	Global	/	3D	off	Simulation	Multi	Point to point
		[147]	Local	Convergence speed	2D	off	Simulation	Multi	Point to point
		[148]	Global	Dynamic obstacle avoidance	3D	on	Simulation	Single	Point to point
		[149] [150]	Global	Optimizing path	2D	on	Simulation	Single	Point to point
		[168]	Local	Optimizing path	2D	off	Simulation	Single	Point to point
ACO	1) Good robustness 2) Low convergence speed in the initial stage of search 3) Fast convergence speed in the late stage of search	[154]	Global	/	2D	off	Simulation	Single	TSP
		[155]	Global	/	3D	off	Simulation	Single	Point to point
		[94]	Global/ Local	Dynamic obstacle avoidance	2D	off	Simulation	Single	TSP
		[34]	Global	Local optimum	2D	off	Simulation	Single	Point to point
		[153]	Global	Local optimum	2D	on	Simulation	Single	TSP
		[156]	Global	Local optimum	2D	off	Simulation	Single	TSP
		[12]	Global	Local optimum	3D	off	Simulation	Single	Point to point
WPA	1) Good convergence and robustness 2) Good global optimization	[158]	Global	/	2D	on	Simulation	Single	Point to point
		[159]	Global	Convergence speed	3D	off	Simulation	Single	Point to point
SA	1) Slow convergence, randomness 2) Easy to fall into local minimum	[161]	Global	/	2D	on	Experiment	Single	Point to point
		[202]	Global	Local minimum	2D	on	Experiment	Single	Point to point
GA	1) Extensive adaptability 2) Local optimal solution 3) Poor stability 4) Slow processing speed	[166]	Global	/	2D	on	Simulation	Single	Point to point
		[27]	Global	/	2D	on	Simulation	Single	Coverage
		[167]	Local	/	2D	on	Simulation	Single	Point to point
		[168] [169]	Local	/	2D	off	Simulation	Single	Point to point
		[26]	Global	Convergence speed	3D	off	Simulation	Single	Point to point
		[197]	Global	Convergence speed	3D	on	Simulation	Single	Point to point
		[94]	Global/ Local	Dynamic obstacle avoidance	2D	on	Simulation	Single	TSP
		[57]	Global	Optimizing path	3D	off	Simulation	Single	TSP
		[170]	Global	Local optimal solution	2D	on	Simulation	Single	Point to point
		[165]	Global	Energy consumption	2D	off	Simulation	Single	Point to point
DE	1) Similar to the GA 2) The robustness of DE is better than GA	[172]	Global	/	3D	on	Simulation	Single	Point to point
		[175]	Global	/	2D	off	Simulation	Single	Point to point
		[176]	Global	Convergence speed	3D	on	Simulation	Multi	Point to point
		[185]	Global	/	2D	on	Simulation	Single	Point to point

TABLE 5. ***(Continued.)*** **Intelligence algorithms.**

ANN	1) Poor generalization performance 2) Slow processing speed 3) Powerful learning 4) Good robustness	[180] [181] [184]	Global	/	3D	on	Simulation	Single	Point to point
		[178]	Global	/	3D	off	Simulation	Multi	Point to point
		[183]	Global	/	3D	off	Simulation	Single	Coverage
		[182]	Global	/	3D	off	Simulation	Multi	Point to point
		[179]	Global	/	3D	on	Simulation	Single	Coverage
		[39]	Global	Convergence speed	3D	on	Simulation	Single	Point to point
		[186] [187]	Global	Ocean current	3D	off	Simulation	Multi	Point to point
		[9]	Global	Dynamic obstacle avoidance	2D	off	Simulation	Single	Point to point
		[28]	Global	Dynamic obstacle avoidance	3D	on	Simulation	Multi	Point to point
Others		[191]	Global	Convergence speed	3D	on	Simulation	Single	Point to point
		[192]	Global	Ocean current	2D	on	Simulation	Single	Point to point
		[193]	Global	Dynamic obstacle avoidance	3D	off	Simulation	Single	Point to point
		[188]	Global	Processing speed	3D	off	Simulation	Single	TSP
		[190]	Global	Convergence speed	2D	off	Simulation	Single	TSP
		[161]	Global	Optimizing path	2D	on	Experiment	Single	TSP
		[151]	Global	Ocean current	2D	on	Experiment	Single	Point to point
		[198]	Global	Dynamic obstacle avoidance	3D	on	Simulation	Multi	Point to point

TABLE 6. **Performance comparison of four path search algorithms.**

Method	Real-time degree	Experimental	Global/Local	speed	Algorithm maturity	Environmental dependence	Development heat
Geometric Model Search	High	High	Medium/ Medium	Medium	High	Low	Medium
Probabilistic Sampling	High	Medium	High/Low	Medium	High	Low	Medium
Artificial Potential Field Type	High	High	Low/High	High	High	Low	Medium
Intelligence Algorithms	Medium	Low	High/ Low	Low	Low	High	High

of the adjacent two nodes are determined. In addition, Bezier curve theory is applied to optimize the path.

3) D* ALGORITHM

The routing algorithm of the Mars rover core in the United States employs the D* algorithm [73]. The D* algorithm is very effective in searching a route in a dynamic environment. The D* algorithm is a dynamic A * algorithm and an incomplete replanning algorithm that use original planning information. With a combination of optimality and real time, the D* algorithm completes a combination of global planning and local information, with a combination of offline planning and online planning [74]. In [75] and [76], D* algorithm employed to ensure an AUV's path implementation. Miotto *et al.* [75] integrated the D* algorithm, B-spline curve generator and model predictive control algorithm to form a guidance and control path planning system. Experimental simulations show that this method can achieve dynamic obstacle avoidance.

4) D* LITE ALGORITHM

The D* Lite algorithm is based on the Dijkstra algorithm and is oriented to the algorithm of the optimal path search problem, with the starting point changing with time and a fixed target point [72]. This algorithm is simpler than the Dijkstra algorithm, and its planning; therefore, its suitability for an underwater dynamic path search is proven in [76] and [77]. The high efficiency of the D* Lite algorithm for an AUV in an underwater environment is proven in [78] by simulation in 2D and 3D environments. DAO* can quickly replan the framework according to changes in the environment at any time during the exercise while accounting for the uncertainty of motion. Chung and Huang [79] combine the DAO* algorithm with the D* Lite algorithm and propose a new planning system. Experiments have shown that the algorithm successfully navigates in an unknown environment that involves large motion uncertainties and increased speed by 2% while reducing the length of the search path by 5%. However, the D* Lite algorithm cannot adaptively address the complex path search of an environment. When the local environment is carefully planned, it will cause a substantial loss of time and efficiency [80].

5) FAST MARCHING ALGORITHM (FM)

The fast marching (FM) algorithm is similar to Dijkstra's algorithm, with the exception that the Dijkstra algorithm updates with the Euclidean distance between two nodes, whereas the FM method updates with an approximate partial differential equation reduced by the nonlinear Eikonal equation [81]. The FM method is an interface evolution tracking algorithm that is based on level set theory. The simulation results in [82]–[84] show that the method has satisfactory reliability and convergence and can satisfy the real-time requirements of an AUV control system. Yu and Wang [83] considered the maneuvering constraints of an AUV, such as the turning radius, safety depth and risk of avoiding collisions with obstacles. The FM algorithm was applied to a large 3D environment of the AUV and solved the search after the AUV became lost by navigating security and energy consumption issues. Yu *et al.* [85] proposed a hybrid search fast travel method (HSFM) that is based on the FM algorithm. This new algorithm renders an AUV more competitive in underwater dynamic obstacle avoidance, while reducing the path and time and introducing multiple constraints and decision criteria, such as currents, shoals, coral reefs, dynamic obstacles and navigation rules, and the underwater current is processed according to the relationship between the gradient line and the characteristic line in the speed curve. The simulation shows that the 3D continuous smooth path can be effectively generated in an underwater discrete representation, and the time of the HSFM algorithm replanning satisfies the requirements of online planning time. Compared with the MSA* and A* algorithms, HSFM has significant advantages in terms of the time and cost. Petres *et al.* [86] proposed a new FM algorithm combined with the A* algorithm, which improved the accuracy of the path search and enabled limited curvature. This finding is convenient for AUVs of various sizes, and a resolution scheme is designed to improve the speed of travel.

6) LEVEL SET METHOD (LSM)

The level set method (LSM) employs a backtrack isometric contour to obtain the optimal path. When applied to the path search, the greatest advantage of the LSM is that it can effectively simulate the dynamic process. Therefore, this method can be used to solve the problems caused by underwater dynamic factors [87]. Subramani *et al.* [88] and Lolla *et al.* [89], [90] used the LSM to coordinate the problem of ocean current processing with the planning time. In [89], an optimization scheme is designed to integrate 3D ocean modeling and a time-optimized LSM. This scheme can predict ocean currents and facilitate the rapid coordination of AUV development of dynamic control schemes. The level set method was also developed in [91] and [92] to predict the time-optimal path of an AUV in a powerful, continuous and dynamic ocean current. Unlike the article in [89], an accurate partial differential equation is added to the article in [91] and [92] that govern the stochastic time optimal reachability fronts and time-optimal path. A disadvantage of the LSM is that some obstacles fail to capture all of their interests when they are embedded in other obstacles, and the risk of lacking data exists due to a gap in the obstacle causes a slow processing speed. Xu *et al.* [196] proposed a highly efficient and improved method of level set calculation. When an AUV detects a new obstacle, it rebuilds only part of the level set, which substantially improves the efficiency of the LSM and renders it suitable for moving the AUV's navigation path planning. Using the level set method for global path planning on a raster map, the results are smoother than the traditional search method path. With an increase in the map size, the amount of calculation rapidly increases with the scale of the map using the LSM for global path planning. The idea of a narrowband level set is to limit the task of constructing the level set to a specific area. Outside the given area, the algorithm is not processed, and the amount of computation is reduced, whereas the improved narrowband level set algorithm can be applied to AUV underwater path planning [93].

7) BOUSTROPHEDON DECOMPOSITION ALGORITHM

The boustrophedon decomposition algorithm is commonly employed; it is a simple coverage path search method. The algorithm needs to divide the total environment into subareas and then cover them by a simple ''comb'' reciprocation [57]. Paull *et al.* [95] applied the cattle cultivation method to realize the coverage path search of AUVs. Although the realization process is simple, the uncovered area will also increase with an increase in the obstacles. The improvement is to perform a second reciprocal advance that is perpendicular to the first direction of travel. Although the efficiency is reduced, the coverage is effectively improved. Garcia and de Santos [96] achieved online coverage of AUVs by detecting all critical points and providing online generation of adjacency graphs. This algorithm can be applied to underwater environments while performing an online path search for automatic underwater robots. Galceran and Carreras [97] proposed a new algorithm for an AUV that is based on a decomposition algorithm to improve the coverage and add surface gradients to the underlying algorithm. The algorithm scans each cell and determines the best direction; it is used to cover each cell on a turn-by-turn basis to maximize the lap spacing in the search path, simulation results show that path search length is reduced by 34%.

8) INTERNAL SPIRAL ALGORITHM (ISA)

Similar to the principle of the boustrophedon decomposition algorithm, the internal spiral algorithm (ISA) enables an automatic underwater robot that moves along the boundary of the covering area. The robot moves the obstacle along the edge or adopts an obstacle avoidance strategy, and it moves ''spiral'' and arrives at the center of the environment [98]. Compared with the ''comb'' font path, the ''spiral'' path has a difficult problem due to the lack of a distinct turning point. The robot needs a sign that indicates when to enter the next inner circle [99]. Due to its simple implementation process, the ISA has applications in covering path searches of AUVs [100]. Based on the internal spiral path search algorithm, Lee and Lee [101] combined the internal plane terrain coverage algorithm and the mixed decision module and proposed a hybrid terrain covering framework that includes technology for an AUV that accounts for the three-dimensional environment of various surface conditions and enables the efficient exploration of all environments. We identified and selected the most appropriate technology according to the changes in the inclined surfaces. Simulation results show that although the coverage rate has decreased by 0.3%, the processing speed has increased by 15.5%, the search path length has decreased by 32.1%, and the energy utilization rate has increased by 55%.

9) OTHER METHODS BASED ON A GEOMETRIC MODEL SEARCH

Yin *et al.* [102] proposed an AUV path planning algorithm that is based on sector scanning to reduce the frequency of a path search and they solved the problem of poor flexibility due to the nonresponse of the AUV operation and frequent control instruction problems in a path search. This approach improves the operability of the response path planning results. In the underwater environment with sparsely distributed obstacles, Cao and Sun [103] designed a planning algorithm for the shortest tangent path of an AUV. The algorithm effectively reduces the space complexity of the calculation; the implementation process is simple the amount of calculation is small, and the operation efficiency is effectively improved. In [104] and [105], the path search problem of AUVs in online obstacle avoidance in an underwater unknown environment with random shaped obstacles is investigated, and a real-time rolling path search method based on fuzzy control is proposed. Although this type of rolling optimization cannot obtain the ideal global optimal solution, it can repeatedly perform the optimization calculation for the deviation of each sampling time and can perform fast local obstacle avoidance in real time. A fuzzy BK-product method is proposed in [106] and [107] to address the dynamic obstacle avoidance problem of AUVs. The experimental results demonstrate that the proposed methodology enables AUVs to safely navigate through obstacles. The performance of dynamic obstacle avoidance of the fuzzy BK-product method and the A* algorithm under water were compared in [69]. The simulation results show that the fuzzy BK-product method algorithm for the path search of an AUV is substantially faster than the A* algorithm. Galceran *et al.* [108] did not overoptimize the AUV underwater navigation environment. By considering the vehicle's position uncertainty and the complex environment in an ocean, a replanning algorithm was proposed based on random trajectory optimization. The experiments show that the algorithm replans a path to handle the actual target structure perceived in situ. Morin *et al.* [145] proposed an offline hybrid algorithm based on traveling salesman problem and dynamic programming to solve the problem of coverage path planning with imperfect extended detection (CPPIED). It does not need to be customized for each environment, so it can adapt to the general complex seabed environment. Eichhorn *et al.* [203] used the TVE (time-varying environment) algorithm to solve the AUV ocean current interference problem. The simulation shows that this method has good robustness.

B. PROBABILISTIC SAMPLING-BASED ALGORITHMS

Probability sampling-based algorithms, such as the probabilistic roadmap method (PRM) [109] and the rapidly exploring random tree (RRT) [110], show superiority in their theoretical properties (in terms of probability integrity or asymptotic optimality), which renders them among successful methods for AUV path search. Note that the premise of completing the sampling algorithm is to have the corresponding environmental information of the operating area. This approach usually samples the environment as a set of nodes or other forms and then maps the environment or randomly searches to find a path. Although the search speed is fast, the search path is usually suboptimal, and finding the path in a narrow channel is difficult [111].

1) PROBABILISTIC ROADMAP METHOD (PRM)

The probabilistic roadmap method (PRM) establishes a roadmap by sampling in the position attitude space and using the A* algorithm or similar A* algorithm to query the path on the roadmap. The core of this approach is sampling and building the roadmap [112]. The PRM method can effectively avoid obstacles while accurately modeling in the posture space. The path planning problem for an AUV in underwater three-dimensional space and complex constraints is effectively solved in [113], and the underwater test is verified by this study. Huang *et al.* [114] employed the probabilistic roadmap method for automatic path search and designed the shortest path distance between two islands, which has been applied to the planning of submarine cables. When constructing the roadmap, the sampling of roadmap nodes is based on the random sampling technique, which incorporates randomness into the route search and prevents the final search route from being the optimal route [115].

2) RAPIDLY EXPLORING RANDOM TREE (RRT)

The rapidly exploring random tree (RRT) algorithm has a powerful spatial search ability: it uses a special incremental method to construct its search; this method can quickly shorten the expected distance between a random state point and the tree [116]. During the learning phase, the RRT does not need to sample the configuration space and build a roadmap, and it proves to be complete in probability. For single query problems, RRT is faster compared to PRM [117]. Tan *et al.* [118] and Heo and Chung [119] employ RRT algorithms to quickly and efficiently search an underwater space. Using the random sample points of the state space, the search for an AUV is guided to a blank area to complete the route setting for the initial route. However, the path searched by the RRT algorithm is not the optimal path, and no target exists in the search process; the resource consumption of the algorithm is relatively large, and is the algorithm is likely to suffer the problem of finding a local minimum [120]. Many variant algorithms of the RRT algorithm are extensively applied in path searches for AUVs. The RRT* algorithm can converge to the optimal solution, can implement a path search in a two-dimensional environment and can address multidimensional environments while using RRT* algorithms; since the algorithm is uniformly sampled, no local minimum conditions will exist [32]. Carreras *et al.* [121], [122] employed the RRT* algorithm to perform two-dimensional AUV path searches online. The 3D simulation results show that the adaptability of this method in real complex underwater environments is excellent. In [31] and [32], the RRT* algorithm was utilized to perform experiments on three-dimensional path planning for an AUV in real sea areas and achieved satisfactory results. However, the processing speed of the RRT* algorithm is substantially slower than that of the RRT, especially for large areas [21]. This method was also applied in the indoor water tank in [123], and the number of underwater vehicles was increased to four. Bi-RRT is a double-tree expansion algorithm that is more efficient than the RRT single-tree algorithm. This algorithm extends the random tree from both ends of the set path, and the initial point and the target point extend in opposite directions. After the random node is selected, the first tree is selected, and then the second tree is selected. The tree expands with the newly generated node as a random target and changes the expansion order of the two trees in the next iteration. Kim *et al.* [124], [206] applied the Bi-RRT algorithm to the autonomous navigation of an underwater hovering autonomous underwater vehicle (HAUV), and the autonomous hovering has considerable advantages in the inspection of the underwater environment. Simulation experiments show that this algorithm generates a stable and reliable path for the H-AUV. However, both Bi-RRT and RRT encounter the problem of being easily trapped in local minimums. Li *et al.* [125] proposed an improved algorithm for an AUV path search—Li-RRT. In contrast to the typical RRT, it utilizes the liveness of each node to guide the expanding process of the random search tree, and more efficient or useful nodes will pop out to enhance the property of exploration. Using the tools' attraction sequence, the theoretical analysis has indicated that liveliness-based RRT enhances the expanding speed. Simulations are also provided to show the effectiveness of Li-RRT. Yan *et al.* [126] proposed the DD-RRT algorithm, which differs from the traditional RRT algorithm; with this tool, the circular arc of the Dubin curve was increased. The simulation results show that the algorithm optimizes the path while the AUV practices autonomous obstacle avoidance, which is the most prominent point of this algorithm. Hernandez *et al.* [127] proposed the homotopy RRT (HRRT) algorithm, which uses topology information to guide the path search; this data improves the speed and practicability of the algorithm, and the results of the AUV simulation show that the new method improves the running speed compared with RRT. Yu *et al.* [128] proposed a routing optimization algorithm for the smooth-RRT algorithm, which increases the convergence factor, angle factor and greedy algorithm to improve the growth point, exploration point and optimization path of the extended tree; moreover, it satisfies the special requirements of the shortest distance and maneuverability of the AUV. The simulation results show that the method can quickly complete the path search, improve the search efficiency and shorten the planning distance.

C. ARTIFICIAL POTENTIAL FIELD TYPE ALGORITHM

The artificial potential algorithm [129] and BUG algorithm [130] are extensively employed in the field of online obstacle avoidance. They have low requirements for the complexity of the dynamic environment; the calculation is small whereas the speed of path search is very fast but it often does not obtain the optimal path. For large obstacles in a complex environment, failure may occur during the path search of AUVs.

1) ARTIFICIAL POTENTIAL FIELD (APF)

The APF algorithm was proposed by Khatib [129]. This algorithm was originally applied to the path search problem of the robotic arm in operational space and has been extensively utilized by robotic path planning [131]. The basic premise of this algorithm is to construct a potential function, in which obstructions generate repulsive forces, target points produce attractive forces, and the size and direction of the resultant force guides the speed and direction of the robot motion [132]. The path search based on the artificial potential field in the static environment is mature, and the global optimal path search algorithm in the dynamic environment is not mature due to its simplicity, security, speed, and ease of implementation. Solari *et al.* [133] and Subramanian *et al.* [134] applied this algorithm to an underwater dynamic path search. Their results indicate that accurate dynamic obstacle avoidance does not occur, the body of the AUV was swinging when walking in a narrow channel, and the "self-locking" phenomenon was caused by local minima. Because the underwater environment continually changes; this approach requires the path search algorithm to satisfy the real-time requirement and achieve certain accuracy. Thus, the traditional artificial potential field method cannot satisfy the requirements and must be improved. Regarding dynamic obstacle avoidance, Cheng *et al.* [135] added a velocity synthesis algorithm for AUVs to artificially avoid obstacles in the artificial potential field algorithm, simulation results show that the speed is increased by 15.1% while avoiding obstacles accurately. In [136], a dynamic formation model for Multi- AUV with a complex underwater environment was developed. This model combines the APF algorithm and particle swarm optimization (PSO) algorithm, and the role of the variable-size PSO is to find a path that is optimized by dynamically adjusting the number and distribution of path nodes. Saravanakumar and Asokan [137] combine the line-of-sight (LOS) method and APF algorithm for an AUV to develop autonomous path tracking and an obstacle avoidance algorithm. In addition to reducing the amount of computation during the heading correction, the LOS algorithm can optimize the trajectory of the AUV turning when the waypoint is changed. Das *et al.* [138] employed a clonal selection optimization algorithm to study the path search algorithm of AUV formation and added the APF algorithm for dynamic obstacle avoidance. Some improved algorithms have appeared to address the problem that this algorithm can easily fall into a local minimum. In [139], the APF algorithm is combined with the virtual force concept and is simulated in an unknown two-dimensional unstructured environment. The results show that this algorithm can overcome the local minimum problem that is associated with potential field methods. The directional search method is combined to complete the sampling of the potential field, and an algorithm for AUV named MPPF is developed based on the potential field method. Simulation experiments show that the local minimum in 2D space can be easily overcome by the multiple potential field method (MPPF) in [140]. The premise that the MPPF method is extended to a three-dimensional underwater environment to avoid local minima is to reduce the burden of the positive proportional factor of fine-tuning the potential function. In [141], in addition to automatic obstacle avoidance with the application of the APF algorithm, for problems with the AUV's body swinging while walking in a narrow passage, the state-dependent Riccati equation method is introduced to optimize the optimal high-order sliding mode control, which enhances the robustness of the AUV motion control and mitigates the chattering effect of the decoupling system. Fiorelli *et al.* [201] used the APF algorithm and virtual bodies method to control the Multi-AUV formation. The results of the marine experiments show that there is good control potential in gradient climbing and feature tracking cooperation.

2) BUG ALGORITHM

The bug algorithm is a fully stressed algorithm. In this type of algorithm, a mobile robot advances along the shortest straight line that connects the target point and the starting point; it uses an edge tracking method to bypass the obstacle when an obstacle is encountered and then proceeds along a straight line [130]. The AUV path is proved by simulation in underwater two-dimensional space; the BUG algorithm minimizes the computation of the robot while ensuring the convergence of the path [120]. However, the shortest path that is generated is not optimal. Putra *et al.* [142] utilized the bug algorithm to perform emergency obstacle avoidance in the local area of the AUV and proved the capability of a powerful emergency obstacle avoidance function by the simulation result.

D. INTELLIGENCE ALGORITHMS

Intelligence algorithms have an important and effective role in addressing the path search problem with the information in a complex dynamic environment; thus, this algorithm is suitable for the path search of AUVs. However, the intelligence algorithm is emergent and has widespread problems, such as slow processing speed, poor stability and real-time capability, and it can easily fall into a local optimum [143]. We classify them according to their characteristics in Fig. 5. With the development of technology, we believe that these algorithms will become mainstream.

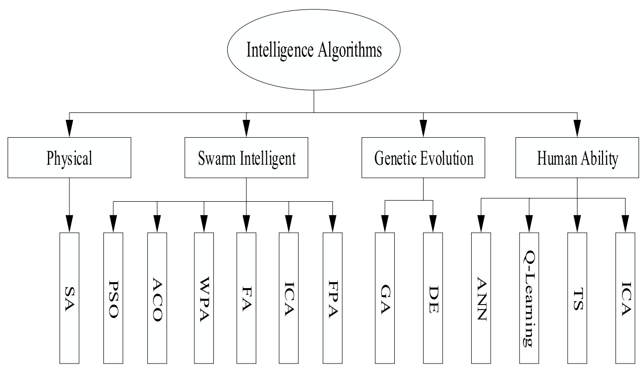

FIGURE 5. Classification of intelligent algorithms.

1) PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a heuristic algorithm that is based on the predation and return of bird populations [144]. The basic idea of finding the optimal path involves iterative methods in the process of bird movement via the individual cooperation mechanism in the group. Cao *et al.* [20] and Sun and Liu [146] have adopted the PSO algorithm for obstacle avoidance and trajectory optimization of AUV path searching functions, and simulation experiments show that this algorithm is simple, easily implemented and is not very sensitive to the population size and has excellent robustness and a fast convergence speed. However, the particle swarm optimization algorithm also finds that the optimal solution is the local optimal solution. The convergence speed of the algorithm in the initial stage of the search is fast, and the convergence speed in the late stage of the search is slow; thus, many improvements to this method have emerged. In [147], a cubic spline optimization algorithm based on the improved PSO algorithm is proposed to address Multi-AUV path search problems. Since the central path is described by a cubic spline, the path search is equivalent to the parameter optimization of a particular cubic spline. In this manner, the convergence of the path can be significantly improved. Zhuang *et al.* [148] proposed a hybrid PSO-LPM algorithm that combines the Legendre pseudospectral method (LPM) with the PSO algorithm. Compared with the standard PSO algorithm, the new hybrid PSO-LPM algorithm for an AUV can find better trajectories and successfully implement real-time obstacle avoidance in static obstacles and moving obstacles with different levels of positional uncertainty via replanning schemes. The stability of the proposed programming algorithm is verified by the Monte Carlo simulation method. Quantum Behavior Particle Swarm Optimization (QPSO) is an improved algorithm for the original PSO. The advantage of QPSO is the ability to assume that each particle in the population has quantum behavior rather than applying the updated standard of the speed and position used in PSO, simulation results show that the search path length is reduced by 2.3% in the absence of obstacles and by 2.8% in the presence of obstacles [149]. The particles of the quantum system appear at any position with a certain probability distribution, which enables the global search to be completed. Zeng *et al.* [150] employed the QPSO algorithm for the path search of AUVs. Simulations also showed that the path has a reasonable global search. It is worth mentioning that the control parameters of the PSO algorithm are relatively few and easy to control GA compared the QPSO algorithm, but the QPSO algorithm has fewer control parameters than the PSO algorithm [168].

2) ANT COLONY OPTIMIZATION (ACO)

The ant colony optimization algorithm (ACO) is a probabilistic algorithm that is inspired by ants to obtain the optimal path when searching for a path while searching for food. This algorithm has the characteristics of distributed computing, positive information feedback and a heuristic search. ACO is a heuristic global optimization algorithm in evolutionary algorithms [152]. Compared with other algorithms, the ACO algorithm has low requirements for the selection of initial lines and is highly robust. Advantages of the ACO algorithm is that it can be applied to the underwater 3D path search problem and its parameters are relatively small and do not require manual adjustment [204]. The ant colony algorithm can be used to solve some AUV problems that have not obtained a valid algorithm, such as the TSP problem [153]–[155]. However, the ant colony algorithm has a slow convergence rate and is easily trapped in a local optimum. In contrast to the genetic algorithm, the ant colony algorithm lacks early information and slow convergence in the later period. Therefore, many improved ant colony algorithms are proposed for underwater path searching [195]. Zhang and Jia [34] introduced a penalty factor in the ant colony algorithm to maintain a safe distance between the AUV and the barrier and combined the quadtree algorithm for a two-dimensional underwater path search simulation. The results show that dynamic obstacle avoidance is achieved, and falling into the local optimum is not easy. Based on the previous research, they replaced the quadtree algorithm with an octree tree algorithm. The same result also extends from the previous two-dimensional space to three-dimensional space; however, the simulation speed of AUV is slower than that in two-dimensional space. but the algorithm completed the search requirements for underwater three-dimensional space [12]. Wang *et al.* [156] proposed a hybrid adaptive ACO algorithm for AUV path planning. The simulation results show that the algorithm can effectively overcome the problem of slow convergence and can easily fall into a locally optimal solution, but the optimal path length is reduced by 14%. The ACO algorithm is characterized by slow convergence in the early stage and fast convergence in the later stage. Although the ant colony algorithm has reasonable feedback characteristics, the solution speed is slow due to the lack of an initial pheromone.

3) WOLF PACK ALGORITHM (WPA)

The wolf pack algorithm (WPA) simulates the predatory behavior of a wolf group and its prey distribution mode and abstracts three types of intelligent behavior—walking, calling and besieging—as well as and the "winner is king" wolf generation rule and the "strong person survival" of the wolf group renewal mechanism to realize the optimization in the complex search space. Shen *et al.* [158] use the algorithm to study the navigation and path planning of AUVs. The algorithm has satisfactory convergence and global optimization and strong robustness. However, the algorithm has more parameters to set than other methods and is relatively complex. Zhang *et al.* [159] added the Dubin curve by establish an underwater environmental threat model with AUV constraints. They proposed that the Dubin curve can be employed to satisfy the angle control constraints and adjust the turning radius to satisfy the control constraints. The simulation results show that the improved WPA does not prematurely converge has high convergence speed, excellent local search ability, high dimensionality, high precision and multipeak functions, and the search time is reduced by 6.3% while the search path is reduced by 57.3%.

4) SIMULATED ANNEALING ALGORITHM (SA)

The simulated annealing algorithm (SA) is an annealing process that mimics solid matter. By setting the initial temperature, the initial state, and the cooling rate to ensure that the temperature continually decreases, the probabilistic jump feature is used to perform a random search using the neighborhood structure of the solution space [160]. With the advantages of simple description, flexible use, and fewer restrictions on the initial conditions, Couillard *et al.* [161] applied the simulated annealing algorithm to the underwater path search and completed practical experiments. The results show that this algorithm for an AUV has a reasonable effect on a large turning radius. However, defects of the algorithm include slow convergence and poor randomness. At the same time, it is easy to fall into local minimum. In order to avoid local minima, Witt and Dunbabin [202] use simulated annealing or local random search with dynamic node allocation for refinement and use group search methods to increase search space. Experiments have shown that the proposed optimal path provides 32% energy savings compared to the straight-line task of equivalent total length and average velocity (estimated at 7.1 ampere hours) in still water.

5) GENETIC ALGORITHM (GA)

The genetic algorithm (GA) is a computational model that simulates Darwin's genetic selection and natural elimination in the process of biological evolution. The ideology of the GA originates from the natural laws of biogenetics and the survival of the fittest and is an iterative process search algorithm that is implemented according to the principles of genetics [162]. Similar to the PSO algorithm, the GA iteratively finds the optimal solution by a random solution and evaluates the quality of the solution via adaptability. Although the PSO has ''cross'' and ''change'' and the algorithm rules are simple, the GA has a memory function. Compared with the PSO, the advantage of the GA is that it can find the global optimal value according to the optimal value of the current search during the search process [163]. In [94] and [57], the GA algorithm is applied to AUV path planning to solve the traveling salesman problem (TSP). Ataei and Yousefi-Koma [57] use the GA algorithm to implement a global search in the 3D environment of the TSP problem. Zadeh *et al.* [94] designed a path planner to use GA algorithm for global search path and PSO algorithm for local search path. The simulation results show that the generated collision-free path solves the TSP very well. Since the GA only needs to know information about the objective function, it must be continuously differentiable and has a wide range of adaptability [188]. In [165]–[169], the genetic algorithm is used for path searching for AUVs and the findings prove that it can be applied to online path search and dynamics avoidance. However, its drawbacks are that it will fall into a local optimal solution, has poor stability and the calculation time is excess. The long computation time is a common weakness of all biointelligence algorithms. Note that the genetic algorithm has a rapid global search capability in the early stages of the population evolution, whereas the search speed is slow in the later period. However, the genetic algorithm can be easily combined with other algorithms and can fully exploit its advantages in an iterative approach. Cheng *et al.* [26] proposed a dynamic programming (DP) path planner for an AUV based on a GA algorithm. The DP-based deterministic crossover operator replaces the random-based crossover operator in the GA algorithm. The simulation results show that the speed of the proposed path planner is faster than the speed of the path planner based on the genetic algorithm. Wang *et al.* [170] employed an adaptive genetic algorithm to simulate the motion of an AUV. The results show that the stability of this method has been significantly improved, and the occurrence frequency of the locally optimal solutions has been reduced. At the same time, the speed has increased by 39.8%. Tanakitkorn *et al.* [165] presented a GA pathfinder with an improved fitness function for overactuated AUVs, which differs from previous research. Considering the energy consumed by the smooth path of the path search and the energy consumed by the AUV body to control the turn, the two factors are considered and then compromised to obtain the best solution. Yao and Zhao [197] proposed an improved GA algorithm that combines the Greywolf optimization (GWO). The GWO can make the GA algorithm behave like an ideal direction in the mutation process. The simulation shows that the convergence speed is faster, and the path search length is reduced by 0.73%.

6) DIFFERENTIAL EVOLUTION (DE)

The principle of the differential evolution algorithm is very similar to the genetic algorithm; however, in the mutation operation, individuals are perturbed using the difference vectors between individuals in the population to achieve individual variation [172], [173]. The robustness of the differential evolution algorithm is better than that of a genetic algorithm [174]. These algorithms have achieved satisfactory results on the AUV path search problem. Li *et al.* [175] employed the differential evolution (DE) algorithm to solve the obstacle avoidance problem in AUV three-dimensional path search and achieved excellent results in the simulation. At the same time, he proposed an improved differential evolution quantum artificial bee colony (DEQABC) optimization algorithm to solve the multi-AUV optimal task allocation method. The simulation results show that the DEQABC algorithm converges faster than the artificial bee colony (ABC) algorithm in terms of the running time and number of iterations and effectively improves the AUV distributed multi-tasking performance [176]. Mahmoud Zadeh *et al.* [27] used the four evolutionary path planning methods of PSO, BBO (Biogeography-Based Optimization), DE and FA to solve the underwater rendezvous problem. Simulation shows the FA planner shows better performance in making use of favorable current flow for AUV maneuverability and collision. In terms of minmum difference between the path time and rendezvous time (time optimality condition), the Performance of the PSO and DE path planner is better.

7) ARTIFICIAL NEURAL NETWORK (ANN)

The artificial neural network (ANN) is a type of network that simulates the thinking ability of the human brain and realizes the function of nonlinear algorithms using a large number of simulated neurons. The generalization performance of this algorithm is poor, and the processing speed is slow. Due to other powerful learning, adaptive capabilities and strong robustness, many applications exist in the AUV path search for collision avoidance [177]–[185]. In [28], the biologically inspired neural network (BINN) embedded in a self-organizing map (SOM) neural network. In this approach, the SOM neural network was developed to assign the Multi- AUV team to multiple target locations in an underwater environment. Then, in order to avoid obstacles and speed jumps for each AUV accessing the corresponding target location, BINN is used to update the weight of the winner of the SOM and implement Multi-AUV path planning and effective navigation. In addition, an ANN can be easily combined with other algorithms, and therefore, its improved algorithm and its combination with other algorithms have become a hot topic in the field of path search. Ni *et al.* [39] introduced the target attractor concept for an AUV to improve the computational efficiency of neural activity. Cao and Zhu [186] proposed an algorithm for Multi-AUV that combines ANNs and velocity synthesis (VS) to eliminate the effects of currents in a multirobot collaborative path search. Later, they mixed the bioinspired self-organizing map (BISOM) algorithm to ensure the stability of environmental modeling in [187]. Combined with the ant colony algorithm design synthesis algorithm in [9], the simulation completed the requirements of dynamic obstacle avoidance and a path search of an AUV and considerably improved the speed of the path search. The method was tested in [16] but the experimental object was limited to indoor mobile robots.

8) OTHER INTELLIGENCE ALGORITHMS

When addressing path search problems in the context of complex dynamic environmental information, inspiration from the natural world can have a very important role. In addition to the above, there are many other intelligent algorithms. The Q learning algorithm, which is similar to a dynamic programming algorithm, provides an agent in a Markov environment. Gautam and Ramanathan [188] uses the Q learning algorithm for a path search and compare it with a genetic algorithm, ant colony algorithm and particle swarm algorithm. The simulation results show that modeling this algorithm is simple and does not require extensive training data. The algorithm has been tested for the SLOCUM glider and can be extended for use in any standard AUV. However, the disadvantage of falling into a local minimum must not be disregarded. Bozejko *et al.* [190] employed a tabu search (TS) algorithm for an AUV to avoid the problem of falling into a locally optimal solution by introducing a flexible storage structure and corresponding promotion rules and avoided some satisfactory conditions by contempt criteria and then implemented global optimization. However, TS has a strong dependence on the initial solution. A better initial solution can increase the convergence speed of the TS, which renders the TS algorithm a better solution in the solution space. Barua *et al.* [151] used the method of ''chase the rabbit'' to plan the path of lemniscate shape, and the real underwater experiment by AUV showed that the algorithm has faster calculation speed. Even in the face of a powerful current, it can perform tasks steadily. Liu *et al.* [191] present a 3D path search method for an AUV based on a modified firefly algorithm (FA). The simulation results show that this method has a fast convergence speed and can find an effective path in the 3D environment. However, the FA-based method is a new swarm intelligence (SI) algorithm, which is not perfect in terms of theoretical research that has not been proven in terms of mathematical theory. In addition, this method does not temporarily support a dynamic underwater environment. The experimental scheme is based on the fact that the operating environment is static and has known obstacle information. Yordanova *et al.* [198] used the Markov model to predict the path state of Multi-AUV. It can be used for dynamic obstacle avoidance of Multi-AUV, but it is not suitable for long-term prediction in path planning system. In [192], it applied the imperialist competition algorithm (ICA) to solve the optimal path search problem of AUVs that run in clutter, turbulence and complex underwater environments. The ICA was employed to optimize the coordinates of a set of control points to generate a curved spline path. They tested the ICA-based path planner to find the best trajectory for AUV navigation in a variable ocean environment. Compared with PSO and GA, ICA has a high convergence precision, fast convergence and strong global convergence. In [193], the proposed improved IFPA is used to solve the AUV path search problem in both 2D space and 3D space and can find a path with a shorter sailing distance and effectively avoid threats.

Various methods of path searching of AUVs in 2D/3D underwater space are analyzed. We explain and analyze their basic working principles and application scope for these methods and compare their real-time abilities, the complexity of the algorithms, their environmental adaptability, and the smoothness of the planning paths. Many methods can be combined and applied; however, they will not change the limitations of various algorithms.

- Algorithms Based on the Geometric Model Search, they have the advantages of simplicity and convenience in constructing environmental obstacle information. The method can use various mature graph search algorithms to obtain optimal solutions, is suitable for static environments and offline planning, and is also most stable and mature. The algorithm is the best verification platform for new search algorithms.
- Probabilistic Sampling-based Algorithms are mature, and the search speed is fast. However, the search path is often not the optimal path; it is resource-consuming and largely dependent on the environment. The search path is suitable for a global offline path search.
- Artificial Potential Field Type Algorithms, they have low requirements for the complexity of the dynamic environment and low computational complexity, utilizes a fast path search and is extensively used in a local path search for rapid obstacle avoidance.
- Intelligent algorithms have an effective role in path searching with complex dynamic environment information; thus, this type of algorithm is very suitable for path searches for AUVs. However, problems exist, such as slow processing speed, poor stability, and easily falling into local optima, as listed in Table 5. Although this type of technology is not mature, research on this method has increased in recent years. This algorithm will become the mainstream of future research.

Due to the limitations of experimental conditions, the majority of the research remains in the experimental simulation stage, and most studies involve offline simulations. Although some studies have also been conducted in real underwater environments, they have not reached the level of robustness and reliability that can be applied in practice. Many mature algorithms are not sufficiently effective to adapt to a complex underwater environment, and some intelligent algorithms have problems such as immature algorithms, poor robustness and slow running speed. When performing complex tasks, they often require multiple AUV collaborations to complete the tasks. According to our observations, research in recent years has rapidly developed in the fusion of multiple algorithms, which combines the advantages of various algorithms that are fused into an improved algorithm or a new algorithm. For example, the genetic algorithm has a strong global search ability and robustness. Although it rapidly converges in the early stage, it cannot use the feedback of the system and easily generates a large number of unnecessary redundant iterations in a later stage, which causes a decrease in the convergence speed. To address the problem of slow convergence, many studies can combine a genetic algorithm and an ant colony algorithm to improve the parameters of the ant colony algorithm by the selection, crossover and mutation of genetic algorithm operators [157]. We believe that this hybrid algorithm will be observed in the path search of AUVs. In the future, a developer must address a strong flow field, irregular terrain and obstacles in an AUV underwater path search. This approach requires us to develop an efficient algorithm for a complex underwater environment.

IV. CONCLUSION

This paper summarizes the path planning technology of AUVs, including the modeling method and path search algorithm. Modeling methods are divided into two main categories: the regular grid terrain model and the irregular grid terrain model. The advantages and disadvantages of various modeling methods and the modeling methods for different environments are analyzed. Path search algorithms include four major categories: methods based on geometric model searches, probabilistic sampling-based algorithms, artificial potential field algorithms, and intelligence algorithms. We introduce the advantages and disadvantages, the basic principle and complexity, the robustness and the environment for all types of algorithms. The most important objective of this paper is to determine which algorithms are improved algorithms and the corresponding shortcomings of the algorithms. An AUV must function in a complex underwater environment and consider various factors, such as the water flow, water pressure and topography. In online obstacle avoidance, many challenges exist in 3D path planning and algorithm robustness. The robust method is fast but has difficulty adapting to the complex underwater environment. While the fast-developing intelligence algorithm has shown a strong adaptability to the environment in recent years, the development is not mature, and the speed of calculation is slow. In future research, we must increase the speed of 3D model calculations. Each path search algorithm has its own advantages and disadvantages. We need to combine the advantages of the algorithm for algorithm fusion. Although the research on intelligent path-based search technology has not yet matured, it still needs to be improved in terms of robustness. However, because it can adapt well to the seabed environment, related research has grown exponentially, which will become the focus of future development. Multiple AUV cooperation can be employed for complex underwater tasks. At the same time, there is a complex environment in the ocean, so how to overcome the current problem and avoid the local minimum problem is also an important research direction. Finally, we hope that the simulation results can be applied to underwater experiments with visible results.

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Authors' photographs and biographies not available at the time of publication.