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Efficient algorithms for navigation of underwater vehicles with communication constraints. An overview

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Because of the Autonomous Underwater Vehicles (AUVs) potential for use in marine and oceanographic research, as well as in sectors like environmental monitoring and oil and gas development, underwater exploration and offshore wind energy, research in the underwater environment has gained a lot of attention in recent years. AUV navigation in the complicated and unpredictable underwater environment is one of the biggest challenges. Research in underwater technology has advanced dramatically, and current AUVs with proper path planning can operate for prolonged periods of time at vast depths to complete the underwater operations. This study investigates several paths planning techniques, classifying them as local or global strategies, and incorporates classical, graph-based, and intelligent optimization algorithms to improve navigation and obstacle avoidance. The examination focuses on the history of these approaches, demonstrating their increased efficiency in dynamic and complicated situations. This overview addresses the challenges that AUVs encounter in the maritime environment, notably in terms of course navigation planning and communication constraints. When applying these algorithms to AUV path planning issues, researchers frequently include extra limitations and goals unique to underwater environments, such as currents, obstructions, energy consumption, and communication constraints. It places a strong emphasis on navigating an ideal path between the starting to the end point. The global and local components of the path planning method are used to address underwater navigation under communication constraint. The several path-planning techniques

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for AUVs using efficient navigation algorithms are briefly discussed in this review study based on their advantages and disadvantages. A suggestion for additional research on AUV path planning is made on effectiveness of the reported path planning the strategies will serve as a catalyst to inspire researchers within the field to concentrate on specific issues identified for the future advancement of AUVs. The global and local path planning methods are used to address navigation based on tradition, group intelligent optimization and graph search algorithms.

Key words: AUV, navigation strategies, path planning, optimization, communication constraints, underwater communication constraints

1. Introduction

Globally, ideas and initiatives in underwater environment are applied to societal concerns as technology advances. AUVs have an extensive list of uses in civilian as well as military uses, which includes underwater, the field of geoscience underwater pipeline assessment, cooperative investigation and research, visual assessment of hydroelectric dams, marine exploration, etc. in the midst of complicated and unreliable marine environments [1–4]. Control architectures for the AUVs and sensor data bus-based control architecture are the thrust research area in underwater exploration. The research method for navigating path uses high resolution camera/ sensors to elucidate the actual AUV position and velocity to enhance the vision-based localization accuracy in the underwater AUV environment [5]. The outcome of the camera position and improved navigation method was implemented based on the localization and mapping approach used in path planning. The sensors connected in AUV are used for application purposes, designated for task allocation, such as communication-constrained path planning. Underwater path planning control is complicated by communication constraints such as long propagation delays, Doppler dispersion, loss, route disruption, multi path fading, and high error probability, low bit rates, packet delays, and packet dropouts. A sensor data bus increases system design flexibility by allowing high-level control to respond quickly to low-level sensor input. Algorithms are reviewed based on the procedures carried out to confirm its effectiveness by discussing their advantages and disadvantages.

Underwater robotics has created a new area of technology, and there are several strategies for exploiting and developing this new technology to address economic and social concerns. It highlights how vital AUVs are to modern society since they provide maritime surveillance, which can lead to innovations and improved river/ocean safety. Current technologies Numerous techniques using remotely operated vehicle (ROV) or AUV have been explored by researchers to address the issue of aquatic lifeforms without contaminating the water. AUVs are a dependable instrument that are used for searching, identifying, and retrieving seabed material. For such applications, path planning and avoiding obstacles pay the critical role for AUVs to achieve the aforementioned requirements. It is impossible to anticipate an accurate mathematical model for a certain arrangement in engineering applications because natural systems contain a lot of unexpected and unexplained phenomena [6].

Path planning technology for AUVs primarily encompasses modelling techniques and search algorithms for trajectories. Over the last ten years, advancements in AUV path planning technology have progressed at an impressive rate. AUVs encounter greater challenges compared to land-based robots, as they navigate through intricate and unpredictable underwater settings while considering various factors such as water pressure, currents, and terrain. Notably, 3D path planning presents multiple challenges, particularly in ensuring the robustness of algorithms for real-time navigation adjustment. Although robust methods can function rapidly, they need support to adapt to the erratic underwater conditions. In barrier-free environments, such general path planning approaches can prioritize aspects like travel duration, energy efficiency, and current. Underwater ecosystems are intricate systems were obtaining precise information about potential dangers prior to course planning can be exceedingly difficult, if not unfeasible. Although global route planning may help in determining the ideal path, an AUV still needs local route scheduling to maneuver around invisible and constantly altering impediments, such as boats, waves, and underwater species. Latest advancements in intelligent algorithms have shown promise in addressing these challenges, yet further progress is essential to enhance their efficiency and adaptability [5]. Due to the numerous barriers present underwater, designing paths in these environments ranks among the most challenging tasks. AUVs are increasingly recognized as essential tools for the exploration of marine biodiversity. Core technologies like trajectory planning are essential for enabling autonomy in AUV operations. Numerous algorithms exist for trajectory planning, leveraging these models to determine optimal solutions and navigate efficiently through unpredictable environmental conditions. Figure 1 depicts the differentiation of path planning algorithms into local and global path planning. It divides global path planning into three categories: traditional, graph-based, and group intelligent optimization methods, with several techniques listed for each. These algorithms aid in efficiently discovering ideal paths for autonomous navigation. An AUV possesses numerous potential trajectories from its initial location to the target destination. Nevertheless, there are scenarios in which specific parameters, such as the minimal distance, the course of action. The most common criterion is selecting the minimum possible distance that can be travelled in the least time. For better clarity, this has been divided into two components. In the global path planning phase, the AUV establishes a predefined trajectory. The goal of global path planning is to minimize cost while choosing the shortest path during navigation. A trajectory consists of a series of segments passing through designated nodes or waypoints. In primary planar transit, the cost of a trajectory is directly influenced by its length, risk, and partitioning expenses.

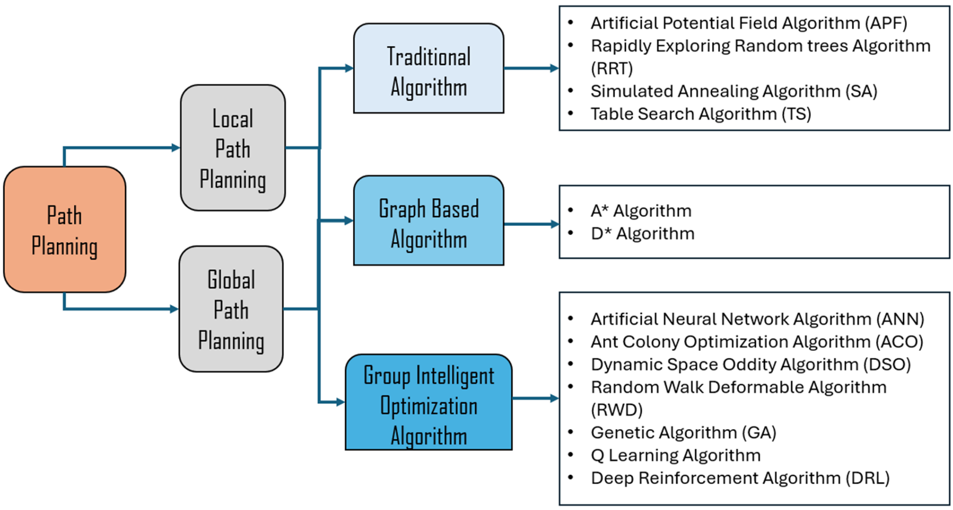


Figure 1: Types of AUV path planning methods

Several general approaches have been put forth by researchers to help AUVs plan their global paths around known obstructions. A* algorithms, GA, PSO, DE algorithms, ACO algorithm, ACBO algorithm, coverage path planning (CPP), and fast marching are some of these [7–18]. It is suggested that swiftly exploring random trees technique be used to accommodate dynamic restrictions. A method for quickly browsing random trees is suggested to handle dynamic limitations. The APF algorithm is used to reduce the chance of collision for AUVs in case of local path planning. By predicting possible challenges and the extent that caused the collapse this method introduces an APF to the task's objectives, assisting an AUV in avoiding impediments and minimizing the danger of hitting something. A model-predictive control technique is used for path planning, and consideration is also given to optimal vehicle dynamics management. The global plan unit determines the desired route and acceleration, whilst the impression module identifies impediments including traffic limits. These data are supplied into the motion planning system [19].

In the maritime environment, AUVs encounter severe course of communication issues, such as dynamic impediments and environmental uncertainty [20]. Communication restrictions are an important consideration for path planning since underwater acoustic channels have limited capacity, significant delay, and signal attenuation [21]. These restrictions impede real-time data interchange, making it difficult for AUVs to collaborate in multi-agent systems and react to unexpected challenges. As a result, decentralized decision-making and predictive planning are critical to ensure efficient and dependable navigation [15, 22, 23]. Table 1 compares the possibilities for global versus local path planning. An offline Method is a stationary path planning technique that use offsite computation

Table 1: A few studies focused on the elements that distinguish the two methodologies

No.	Author [ref no.]	Key aspect	Algorithm used	Global path planning	Local path planning
1	Li et al. [24]	Ensures complete coverage while minimizing local extremum issues	Hierarchy Coverage Path Planning (HCPP)	Generates an optimized traversal sequence of coverage tasks to maintain connectivity	Plans a path between coverage cells while avoiding local extremums and fragmentation
2	Feng et al. [25]	Ensures efficient and collision-free path planning for multi-AUV formations	Varied-width A* (VWA*) Algorithm	Plans an optimal navigation scheme considering both path feasibility and formation control	Adjusts formation shape dynamically and adapt to environmental changes and maintain navigation efficiency
3	Si et al. [26]	Ensures efficient and adaptive path planning with real-time correction	Improved A* + Dynamic Window Approach (DWA) + Fuzzy PID Controller	Improved A* algorithm generates an optimal global path while considering environmental changes	DWA enables real-time path adjustments, while Fuzzy PID refines control to maintain smooth and precise navigation
4	Cui et al. [27]	Ensures safe and energy-efficient dynamic path planning and tracking for deep-sea mining vehicles	Quatre-Artificial Potential Field (QuatAPF) + MPC	Utilizes four specialized artificial potential fields to compute an optimal navigation path while ensuring safety, efficiency, and energy conservation	Uses Model Predictive Control (MPC) to enable precise navigation and accurate tracking of the planned path while dynamically adapting to environmental changes

to create collision-free paths when complete environmental data is available. On the other hand, it is difficult to monitor all data about the environment in actual time/ physical surroundings, especially if communication constraint is present.

This paper consists of 5 sections. Path planning algorithms are discussed in Section 2. Section 3 provides a review of the global path planning and Section 4 is about the local path planning. Section 5 presents the conclusion of this paper.

2. Path planning algorithms for AUV

In this section, the different path planning algorithms which are used for AUV is discussed. The traditional algorithms, graph-based algorithms and group intelligent algorithms are discussed in detail.

2.1. Traditional path planning algorithms

Some of the first and most popular algorithms for determining a whole path from a start to a destination location in a known environment are referred to as traditional global path planning algorithms. Numerous fields have investigated and used these algorithms extensively, such as computer games, autonomous navigation, and robotics. Some of the traditional global paths planning algorithms are as follows.

2.1.1. Artificial potential field (APF) algorithm

In 1986, Khatib proposed APF as an immediate solution to path planning of robots. AUVs rely on path planning to navigate in unpredictable underwater environments, resulting in nearly ideal routes. However, the APF technique can easily achieve a local minimum.

Figure 2 is the representation of the working model using APF algorithm. The APF technique is extensively utilized for AUV path planning because of its straight forwardness and effectiveness in ensuring smooth navigation. Nonetheless, traditional APF encounters issues such as local minima, unreachable targets, and challenges in adapting to dynamic environments. Ma et al. executed and refined a quadrotor path planning algorithm, tackling local minimum problems by enhancing APF methods [28]. Zhu et al. observed that AUVs could become ensnared in closed loops when they fail to identify a viable path [29]. The technique of velocity synthesis combined with APF successfully navigates around dynamic ocean currents and moving entities [30, 31]. Ge et al. devised an improved potential field (IPF) method for multi-AUV target pursuit, integrating dispersion, homodromous, and district-difference metrics to boost coordination [32]. Zhuang et al. investigated collaborative local path planning for several AUVs, employing a two-stage re-planning approach to circumvent unforeseen dynamic

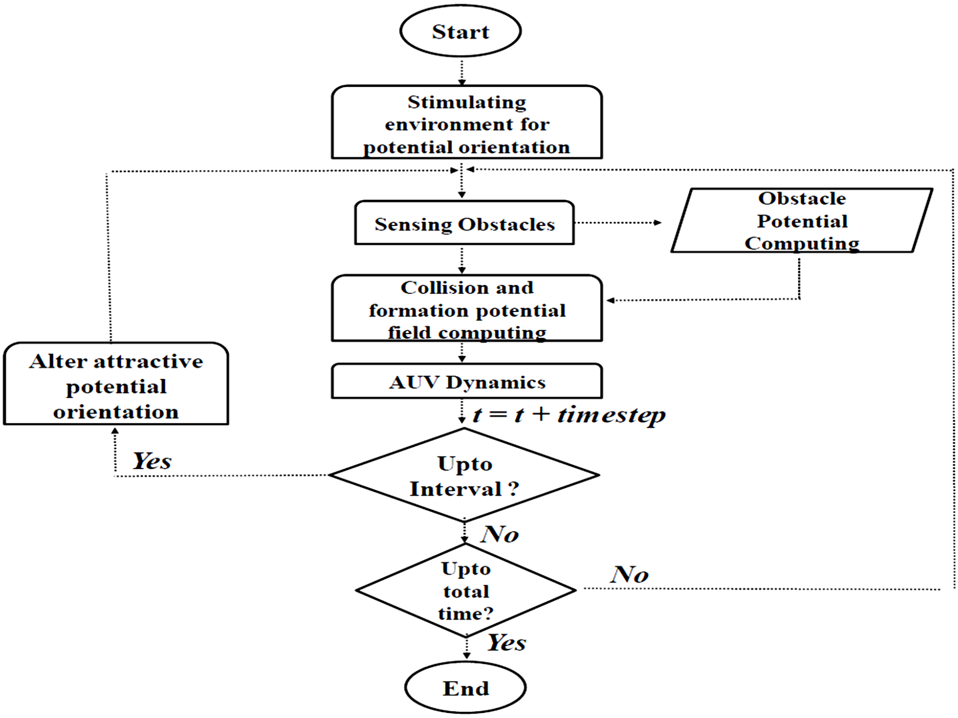
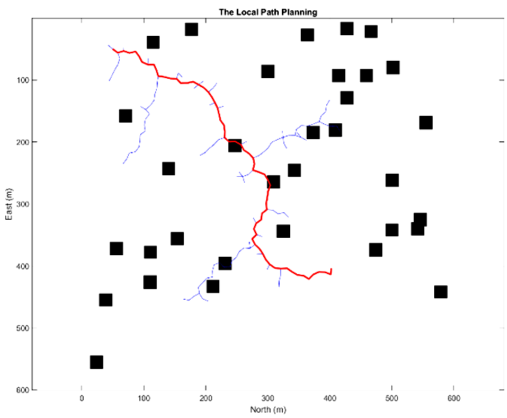


Figure 2: Flowchart of APF

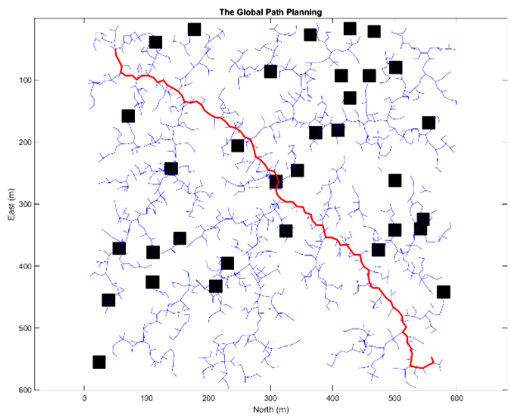
disturbances [33]. Wang et al. merged APF with velocity synthesis to enhance underwater navigation, building upon their previous research on APF-driven navigational control [34]. Fan et al. presented a revised APF method that integrates the Visibility Graph Technique to evade dynamic barriers, presuming that AUVs cannot communicate underwater due to time lags or data loss [35]. Xin et al. advanced APF by incorporating decision trees to mitigate local minima, variations in barriers, and concave environments, introducing a leader-follower strategy for multi-AUV collaboration [36]. Wang et al. utilized a rotation matrix and stringent attenuation factors to bolster attractive potential and collision prevention, launching AUV-Self Potential (SP) technology for seabed exploration [37]. C. Liu et al. modified APF for intricate marine settings by integrating environmental parameters like water depth and shifting ocean currents [38]. Fu et al. fused APF with ACO to enhance global path planning, showcasing that hybrid strategies increase both global and local path planning effectiveness [39]. These innovations collectively enhance AUV navigation, facilitating real-time course planning and dependable collision avoidance.

2.1.2. Rapidly exploring random trees (RRT) algorithm

The RRT technique generates a planning path without the need for an environment by randomly selecting points from a tree. This approach is highly efficient and easy to utilize in extended multidimensional situations. The RRT algorithm involves randomly distributing locations in a search space and linking them to form a robot's mobility path. Tan et al. illustrate the process of a fundamental RRT algorithm [41].



(a)



(b)

Figure 3: RRT algorithm based on local and global path planning [40]

The RRT algorithm is extensively utilized for AUV motion planning because of its capability to navigate intricate underwater settings. Figure 3a and 3b show RRT-based path planning: the first exhibits local path planning with a sparsely planted tree, while the second depicts global path planning with a more complete study of the surroundings. Tan et al. presented the Manucurve Automation (MA) model, which incorporates RRT to streamline motion planning while guaranteeing optimal trajectories [42]. Hernández et al. introduced the homotopic RRT, which leverages sonar-generated topological graphs to enhance path planning efficiency in two-dimensional environments [43]. Li et al. advanced Li-RRT, which improves the direction of tree growth for AUV navigation, while Lijun et al. [44]. Integrated path smoothing, convergence, and angle considerations to enhance AUV trajectory planning. An innovative method that merges RRT* with Bezier curve optimization was also proposed, boosting real-time applicability [45, 46]. Li et al. expanded RRT for target interception within dynamic three-dimensional environments by employing rolling planning and junction screening [47]. Zhang et al. optimized Bi-RRT for uncharted underwater regions, ensuring paths that are smooth and continuous [48]. Yuan et al. introduced an RRT cache technique to improve real-time navigation in dynamic conditions [49]. These innovations collectively enhance AUV path planning by increasing efficiency, adaptability, and immediate responsiveness.

2.1.3. Simulated annealing (SA) algorithm

SA is a probabilistic optimization technique inspired by the metallurgical annealing process, wherein controlled heating followed by gradual cooling aids in refining structures by minimizing imperfections. In the realm of global path planning, SA identifies optimal or near-optimal routes between a starting point and a destination by initializing with a temperature (T), an initial path (either random or heuristic-based), and a cooling schedule that governs the reduction of temperature over time [21]. The algorithm investigates all viable paths, probabilistically accepting or dismissing new paths depending on the current temperature. At the outset, with a high temperature, suboptimal paths are accepted to facilitate broader exploration. As the temperature lowers, the algorithm becomes increasingly discerning, refining the best paths identified while evading local minima. The process iterates until a defined stopping criterion is satisfied, continuously generating new paths, assessing costs through a specified function, and updating the existing path. Although it is computationally intensive and does not always guarantee an optimal solution, SA remains a well-established approach in global path planning due to its extensive research and application across multiple fields. Algorithm 1 offers a structured approach to AUV path planning that employs SA. The algorithm iteratively explores and probabilistically accepts new paths based on a cooling schedule to optimize the route while avoiding local minima.

Algorithm 1. SA algorithm for path planning

1. Initialize Parameters
   - Set initial temperature T, cooling rate \alpha, and stopping temperature T_min.
   - Define max iterations per temperature.
2. Generate Initial Path
   - Create an initial feasible path.
   - Compute its cost.
3. Iterate Until Convergence
   - WHILE T > T_min:
     FOR iteration = 1 to max_iterations:
     Modify the current path to create a new candidate.
     Compute cost \Delta E = cost_{new} – cost_{current}.
     IF \Delta E < 0, accept new path.
     ELSE accept with probability P = exp(–\Delta E / T).
     Reduce temperature: T = \alpha * T.
4. Return Optimized Path
   - Output the best path with the lowest cost.

2.1.4. Table search (TS) algorithm

TS methods are a classical class of methods for global path planning, especially in contexts that resemble graphs or grids. With each cell or node representing a place and the connections between nodes representing possible paths or transitions, these techniques make use of a discretized representation of the environment. These algorithms' main goal is to find the best or almost best route between a given starting node and a desired goal node, efficiently navigating across the empty space and avoiding impediments or limitations.

TS techniques are strong because they can efficiently lead the exploration process by using heuristics and data structures to direct the process in a systematic manner [20]. They function by keeping track of a priority queue or a group of nodes that need to be assessed and then ranking the investigation of those nodes according to predetermined standards, like the cost of the path already taken or an approximation of the remaining cost to reach the objective. The algorithm can then definitively identify whether or not a viable path exists. This iterative procedure continues until the goal node is reached or all feasible paths have been exhausted. These algorithms are still relevant and frequently used in many different sectors even though they are considered conventional because of their efficiency, simplicity, and capacity to produce deterministic answers in well-defined contexts.

2.2. Graph search (GS) algorithm

GS algorithms constitute a family of techniques employed to find paths or navigate through graphs, which consist of nodes (vertices) interconnected by edges. In path planning, these algorithms depict an environment as a graph, where nodes represent locations or states, and edges delineate transitions between them. The goal is to minimize a cost function, such as path length, energy usage, or travel time, while determining an optimal or near-optimal path from a starting node to a goal node [145]. Utilizing heuristics or specialized methods, these algorithms systematically explore nodes, traverse edges, and monitor explored and unexplored paths through data structures like queues or sets. The search proceeds iteratively until the goal node is reached, or all potential paths have been examined. Various strategies aid in eliminating redundant searches, prioritizing promising routes, and navigating graph structures efficiently [146].

2.2.1. A* algorithm

The A* algorithm is a key path-planning technique commonly utilized in autonomous robot navigation; however, it experiences reduced planning speeds when close to environmental and communication constraints. To tackle this issue, Wang et al. proposed the EBS-A* method, which integrates expansion distance, bidirectional search, and path smoothing to enhance navigation efficiency and ensure safe maneuvering through complex environments [50]. Chen et al. improved A* with a visibility checking technique and sparse point distribution, optimizing AUV path planning [51]. Yan et al. expanded A* sub nodes to accommodate anisotropic current flow, decreasing search space and enhancing efficiency [52]. Wang and Pang utilized A* for tracing chemical plumes in aquatic settings, combining it with a Markov decision process for identifying sources [34]. Li et al. created a multi-directional A* approach to decrease search nodes while ensuring optimality is preserved [53]. Min et al. proposed a dual-layer (global and local) method for AUV path planning, resulting in smoother trajectories [54]. Vadapalli and Mahapatra introduced a polytropic method grounded in hydrodynamics, enhancing planning precision by refining control algorithms [55]. Chunxi Cheng and colleagues pointed out the computational difficulties of assessing the f function on extensive maps, underlining the necessity for additional optimization [56]. Improvements to A* generally center on optimizing heuristic assessments and node development techniques to boost speed and effectiveness in intricate settings. Algorithm 2, describes a structured approach to AUV path planning in which the algorithm maintains an open list (nodes to be evaluated) and a closed list (evaluated nodes), iteratively selecting the node with the lowest f-score (f = g + h) until the goal is met or no path is found.

Algorithm 2. A* Algorithm for path planning

1. Initialize open_list (priority queue) and closed_list (empty set)
2. Create start_node with position (start_x, start_y) and set g = 0, h = heuristic (start, goal), f = g + h
3. Add start_node to open_list
4. While open_list is not empty:
   (a) Select node with the lowest f-score from open_list → current_node
   (b) If current_node is the goal:
       Reconstruct and return the path
   (c) Move current_node from open_list to closed_list
   (d) For each neighbor of current_node:
       i. If neighbor is in closed_list, skip it
       ii. Calculate tentative_g = current_node.g + cost(current_node, neighbor)
       iii. If neighbor is not in open_list OR tentative_g < neighbor.g:
          - Set neighbor.g = tentative_g
          - Set neighbor.h = heuristic (neighbor, goal)
          - Set neighbor.f = neighbor.g + neighbor.h
          - Set neighbor.parent = current_node
          - If neighbor is not in open_list, add it
5. If no path is found, return failure

2.2.2. D* algorithm

D* (D-star) is an incremental path planning algorithm designed for dynamic environments where edge or node traversal costs change. Unlike Dijkstra's algorithm, which finds the shortest path in a fixed environment, D* adapts in real-time by updating paths based on new environmental data. Initially, it performs a Dijkstra-like search using known information. As the agent navigates, it detects changes like new environmental or communication constraints or altered traversal costs, updates the graph, and efficiently re-plans the path from its current location to the goal. D* uses heuristics to focus re-planning efforts on affected graph segments, reducing computational overhead.

Algorithm 3, offers a structured method to AUV path planning in which the D algorithm* dynamically updates paths by keeping an open list of nodes to evaluate and iteratively improving cost estimates, altering routes as the environment changes until the goal is met or no path exists. The key advantage of D* lies in its incremental nature, enabling efficient path re-planning without restarting the entire process. If the heuristic is admissible (does not overestimate actual costs), D* finds the optimal path given updated cost information. Additionally, it requires less memory than some other dynamic path planning methods, utilizing a "state-value table" to store and update cost data efficiently. These features make D* a powerful choice for real-time navigation in uncertain or evolving environments.

Algorithm 3. D* Algorithm for path planning

1. Initialize open_list (priority queue) and insert goal_node with k = 0.
2. While open_list is not empty:
   (a) Select node with the lowest k-value $\longrightarrow$ current_node.
   (b) Remove current_node from open_list.
   (c) If current_node is the start_node, return the optimal path.
   (d) For each neighbor of current_node:
      i. Compute new cost g_new = g(current) + cost (current, neighbor).
      ii. If g_new < g(neighbor):
         - Update g(neighbor) and parent(neighbor).
         - Compute new k-value: k = min (g_new, old k-value).
         - Insert/update neighbor in open_list with new k-value.
3. If start_node is not reached, return failure.

2.3. Group intelligent optimization algorithms

Group intelligent optimization algorithms draw inspiration from the collective actions of decentralized, self-organizing systems like ant colonies, flocks of birds, and swarms of bees. These algorithms are extensively utilized in optimization issues, like AUV path planning, where they determine the best or nearly the best paths while taking into account limitations environmental barriers, ocean currents, and energy usage. They function via a population of potential solutions that are progressively enhanced through collaboration and interaction among individuals.

These algorithms effectively navigate search spaces by imitating natural behaviors such as pheromone trails, flocking, swarming, and foraging, successfully managing intricate and non-convex underwater settings. Their flexibility enables them to react to changing circumstances while preserving computational efficiency. Nonetheless, they do not always ensure convergence to the global optimum and necessitate precise parameter adjustment. Researchers frequently improve these algorithms by integrating constraints tailored to AUV navigation, including current influences, environmental and communication restrictions. Several popular swarm intelligence optimization algorithms used for AUV path planning consist of ACO, PSO, and ABC algorithms.

2.3.1. Artificial neural network (ANN) algorithm

ANN are commonly employed in AUV path planning by emulating brain functions to enhance navigation and adapt to environmental constraints. Post-training, an AUV employs ANN-driven control to analyze sensor information and execute autonomous choices. Schiller and Tench utilized neural networks for steering AUVs, improving their adaptability and reliability [57]. González et al. created a neural architecture for tracking trajectories, merging a biologically inspired network with an adaptive neurocontroller for autonomous navigation [58]. Figure 4 is the architectural framework of an ANN, typically encompasses the input layer, hidden layer and output layer.

Yana and Zhub introduced a genetically inspired neural network that prevents collisions without needing pre-trained data, utilizing a dynamic neural landscape enhanced with templates [59]. Li et al. presented a dynamic neural network that modifies neuron activity instantaneously in response to environmental input [60]. Zhu et al. developed a brain dynamics-inspired method to enhance autonomous navigation, incorporating a D-S inference rule for fusing sensor data to enhance mapping precision [61]. Ni et al. created a bio-inspired neural network (BINN) for real-time navigation, employing virtual targets to enhance path planning [62]. Ding et al. introduced a strategy for multi-AUV formation control, utilizing backstepping control and ANN for trajectory following [63].

Although ANN is effective in enhancing AUV navigation, the BINN method encounters challenges, such as reduced efficiency stemming from insufficient prior environmental knowledge. Additional studies are required to boost real-time flexibility and refine AUV route planning in shifting and unfamiliar underwater environments. Algorithm 4, offers a structured approach to ANNs in which the

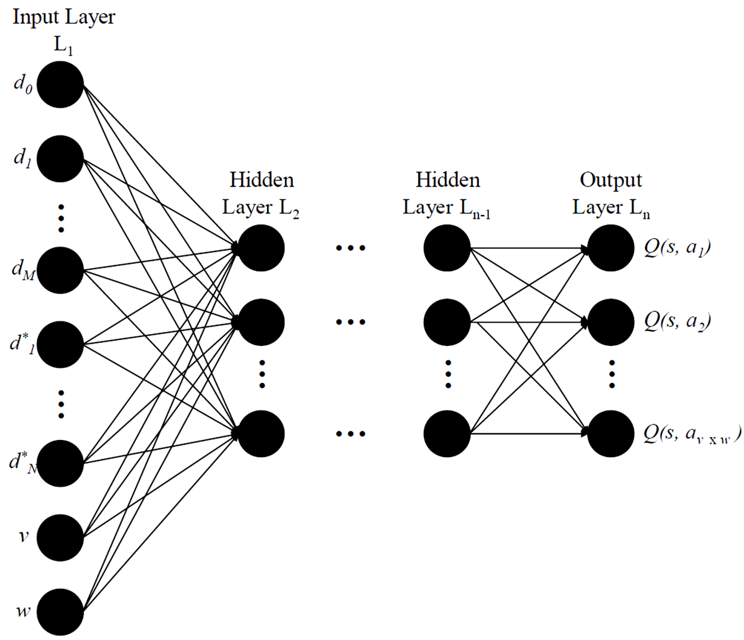


Figure 4: Layers of ANN algorithm [20]

model learns patterns by altering weights via forward propagation, computing errors, and iteratively optimizing via backpropagation and gradient descent until convergence or a stopping criterion is achieved.

Algorithm 4. ANN Algorithm for path planning

1. Initialize network with input, hidden, and output layers.
2. Randomly initialize weights and biases.
3. For each training epoch:
   (a) For each training sample (input, target):
      i. Forward Propagation:
         - Compute activations for each layer using:
           output = activation_function(W * input + b).
      ii. Compute loss using the chosen loss function.
      iii. Backpropagation:
         - Compute gradients of loss w.r.t weights and biases.
         - Update weights using gradient descent:
           W = W – learning_rate * gradient.
4. Repeat until convergence or max epochs reached. Use trained ANN for predictions on new data.

2.3.2. Dynamic space oddity (DSO) algorithm

The DSO method is a navigation strategy designed for rapid adaptation in changing surroundings. It creates a velocity space that encompasses all potential

AUV speeds at any moment and chooses the best speed according to a cost function, taking into account elements like path length, energy use, and mission-related goals. The DSO algorithm works exceptionally well in unpredictable underwater settings featuring moving hindrances such as rocks, shipwrecks, and marine constructions.

Maurya et al. presented the Modified DSO (MDSO) approach, combining DSO with a potential field method for dynamic environmental changes [72]. Petres et al. utilized DSO for navigating AUVs in harbor settings, effectively steering clear of both fixed and dynamic environmental constraints [73]. Hernández et al. introduced a path-planning technique for 3D AUV navigation based on omnidirectional DSO, utilizing a virtual force field strategy while factoring in energy usage and communication limitations [74]. Pereira et al. integrated DSO with a potential field approach for enhanced AUV path planning, showcasing its efficacy in simulations as well as in practical experiments [75].

Even with its achievements, researchers are still investigating hybrid methods and adjustments to enhance DSO for particular underwater environments. Integration with AUV control systems, various path-planning algorithms, and environmental factors such as bathymetry and currents further improve its versatility and effectiveness.

2.3.3. Ant colony optimization (ACO) algorithm

The ACO method, proposed by Dorigo et al., is a swarm intelligence approach aimed at addressing NP-hard optimization challenges [64]. Motivated by the way ants communicate and find the best routes using pheromones, ACO allows artificial agents to work together in exploring and enhancing pathways according to the intensity of pheromones, which grows over time on the most effective paths [12, 65]. In their research on AUV path planning, Wang and Xiong created an ACO-based method that employs a workspace grid model to improve visibility-driven navigation [66]. Ma et al. introduced an enhanced firework ACO that dynamically boosts pheromone deposition, maintaining the integrity of solution quality [67]. Furthermore, He et al. combined ACO with PSO to improve AUV motion control in difficult underwater settings, adjusting the pheromone matrix each time the algorithm attains a stationary state [69, 70]. This refined ACO-PSO hybrid approach was enhanced for changing environments, boosting real-time path optimization [71].

Figure 5 shows the principles of ant travel. Ants travel along various paths to their food source, releasing pheromones along the way. Other ants, including the same ant, then follow the pheromone trail. Pheromone decay is a time-dependent function; therefore, the concentration of pheromones is highest along the shortest path. Most of the ants follow the most frequently traveled path. Although ACO

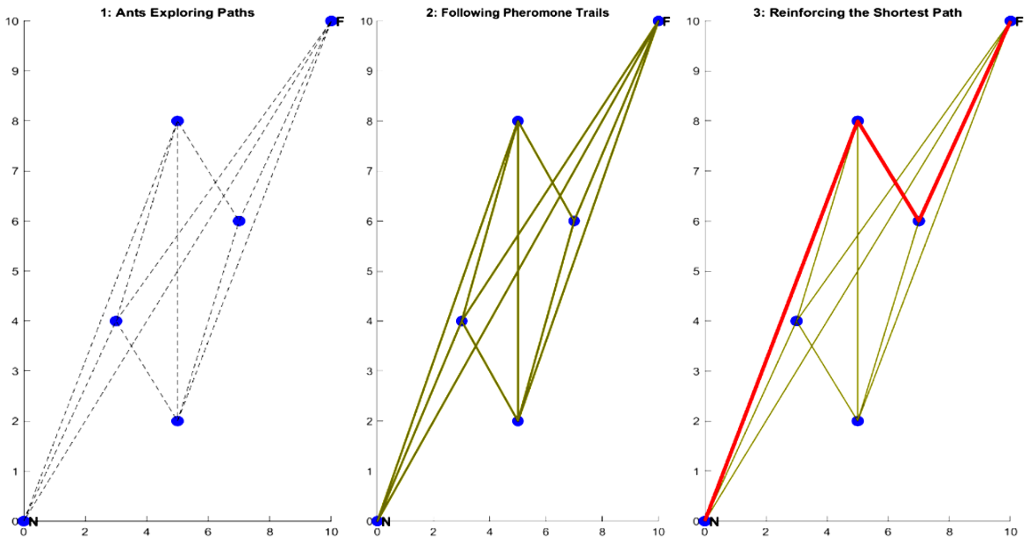


Figure 5: Mechanics of ACO

has benefits in effectively finding paths without constraints, it experiences slow convergence. Nonetheless, utilizing distributed computing and feedback loops can improve search efficiency. Additional studies are required to enhance ACO for intricate AUV navigation, providing quicker and more dependable route planning. Algorithm 5, offers a structured approach to ACO.

Algorithm 5. ACO Algorithm for path planning

1. Initialize parameters (number of ants, pheromone levels, evaporation rate, etc.)
2. Initialize pheromone trails on all paths
3. Repeat until the stopping condition is met:
   (a) For each ant:
      i. Construct a solution by probabilistically choosing paths based on pheromone levels and heuristic values
      ii. Evaluate the solution
   (b) Update pheromones:
      i. Evaporate pheromones on all paths
      ii. Reinforce pheromones on paths used by the best solutions
4. Return the best solution found

2.3.4. Random walk deformable (RWD) algorithm

The RWD algorithm serves as a path-planning method intended for robots that possess intricate shapes or flexible structures, rendering it especially effective for maneuvering through tight or crowded spaces. In AUV path planning, the RWD algorithm assists vehicles in navigating through shipwrecks, underwater ravines, or caves by representing the AUV as a flexible entity able to change its form within set boundaries. The algorithm navigates the configuration space, encompassing all potential shapes and locations, through random walks, dynamically modifying the AUV's shape to discover viable paths.

A major benefit of RWD is its capacity to traverse complex environments that traditional rigid-body path-planning algorithms find difficult to manage. By adding deformability, it allows AUVs to navigate narrow areas that rigid objects cannot reach. While the RWD algorithm has not been thoroughly examined for AUV use, associated studies have investigated concepts in deformable path planning. Petillot et al. suggested a technique based on deformable targets, whereas Ögren and Leonard presented a dynamic window approach that accounts for vehicle shape [76, 77]. Moving constraints, first presented by Fiorini and Shiller, may improve deformable path planning [78]. Additional relevant methods involve elastic bands, stochastic roadmaps for flexible objects, motion planning for jointed robots, RRTs for flexible forms, serpentine robot motion planning, and path distortion techniques [79–83].

Although RWD has not been extensively studied regarding AUV navigation, adding deformability to path-planning techniques might greatly enhance AUV agility in tightly restricted and dynamic underwater settings. Figure 6, de-

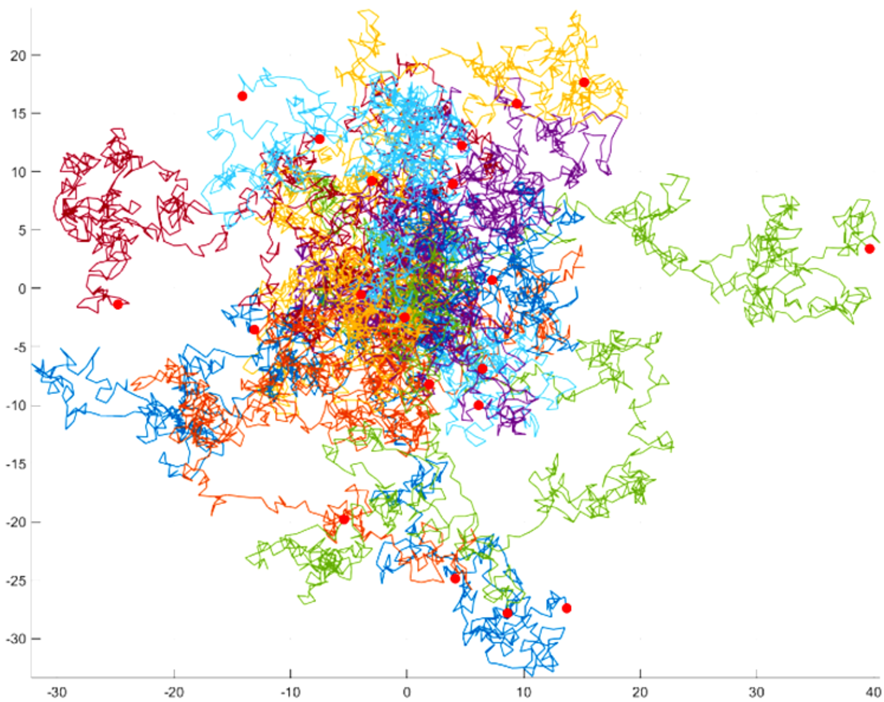


Figure 6: RWD algorithm

picts a RWD method, in which numerous particles begin at an initial point and move in random directions at each step. These routes deform dynamically over time, giving rise to diffusion or stochastic movement patterns. Future studies may improve these methods to boost real-time flexibility and effectiveness for deformable AUVs.

2.3.5. Genetic algorithm (GA)

GA are optimization methods based on natural selection, repeatedly advancing solutions via selection, crossover, and mutation. In AUV path planning, GA begins with a varied collection of possible paths and improves them to determine the best route while taking into account vehicle limitations and the aquatic environment. By imitating natural evolution, GA effectively investigates search spaces to identify high-quality solutions. Scientists have improved GA by altering genetic operators, fitness assessment standards, and population selection methods to boost stability and speed of convergence.

Zhang et al. proposed an adaptive genetic algorithm for path planning, utilizing five types of genetic operators to improve efficiency and stability [84]. Zhang additionally created a hierarchical GA-based global path-planning approach that minimizes memory needs while enhancing path viability [84]. Tao et al. enhanced GA by implementing adaptive crossover and mutation strategies to hasten convergence while maintaining collision-free navigation [85]. Hongli et al. incorporated immune system concepts into GA, enhancing population diversity and refining local search efficiency for AUV navigation in dynamic environments [86]. Tran et al. utilized GA to enhance B-spline trajectories, guaranteeing smooth paths while adhering to turning radius limitations [87]. Bresciani et al. introduced a Genetic Path Planner (GPP) that integrates informed planning of path with GA to enhance data collection and inspection coverage efficiency [88]. Cao et al. enhanced GA with multilayer coding and a tangent angle operator to boost the efficiency of path optimization [89].

As illustrated in Fig. 7, by starting with many options, GA can assist AUVs in route planning and navigating complex environments. The primary benefit of GA is its capability to identify optimal solutions without any prior understanding of the best method. It is especially useful for AUV path planning in unchanging environments, but incorrect parameter adjustments may result in slow convergence and less than optimal outcomes. Future enhancements might center on hybrid GA methods to significantly boost efficiency in changing underwater environments. Algorithm 6, outlines a Genetic Algorithm for path planning in which a developing population of potential solutions is selected, cross overed, and mutated to iteratively enhance path quality based on fitness evaluation until an optimal or near-optimal solution is discovered.

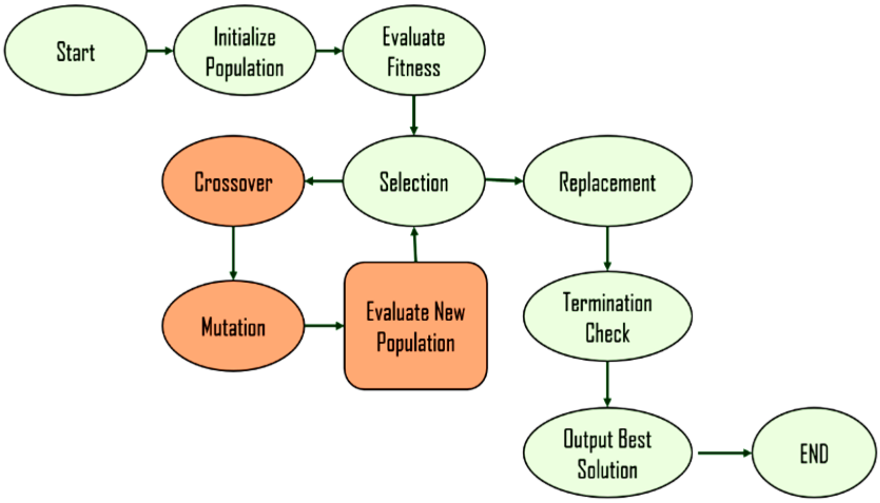


Figure 7: Flowchart of genetic algorithm

Algorithm 6. Genetic Algorithm

1. Initialize Population: Generate an initial population of candidate solutions.
2. Evaluate Fitness: Compute the fitness of each individual in the population.
3. Repeat Until Termination Condition is Met:
   (a) Selection: Select parent individuals based on fitness (e.g., roulette wheel, tournament selection).
   (b) Crossover: Apply crossover (recombination) to produce offspring.
   (c) Mutation: Introduce random mutations to offspring.
   (d) Evaluate Fitness: Compute the fitness of new offspring.
   (e) Survivor Selection: Replace individuals in the population with offspring (based on fitness).
4. Return Best Solution Found.

2.3.6. Q-learning algorithm

Q-learning, as described by Sutton and Barto, is a reinforcement learning (RL) method that utilizes trial-and-error learning to enhance long-term rewards [90, 97]. Figure 8 shows the state, reward and action employed in a Q-learning algorithm. In AUV route planning, Q-learning facilitates independent navigation by assessing the present state, choosing actions, and modifying behavior in response to obtained reward signals. Figure 8 depicts this process, where AUVs continuously enhance their strategies to improve path selection and maneuverability in complex environments.

Chen et al. developed an improved Q-learning approach, NCQL, that incorporates neural networks to enhance convergence rate and motion planning effec-

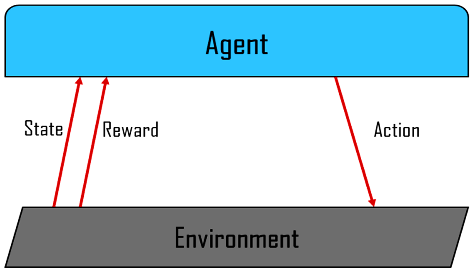


Figure 8: Q-learning algorithm

tiveness [91]. Shen et al. introduced a risk-averse RL method, showing decreased idle time in AUV activities [92]. Wang et al. utilized online RL for optimizing multi-AUV trajectory planning in icy conditions, attaining performance like benchmark techniques [93]. Cui et al. created a controller for adaptive trajectory tracking utilizing neural network-based reinforcement learning to manage external disturbances and nonlinear behaviors in AUV movement [94]. Zhang et al. used DDPG with adjustable constraints to improve path tracking [95]. Yan et al. employed RL-based localization to forecast the positions of AUV and sensor nodes, utilizing online value iteration for optimal positioning [96]. Ahmadzadeh et al. investigated policy learning driven by RL for recovering from thruster failures, utilizing multi-objective RL to reconcile competing objectives [98]. Yan et al. suggested RL-based simultaneous localization that doesn't rely on time synchronization problems in AUVs [99].

Although it has great potential, RL encounters difficulties in practical AUV applications because of extensive state spaces and restricted real-time testing. The intricacy of ocean ecosystems and unforeseen challenges necessitate comprehensive training for effective policy development. Future developments in RL-based AUV navigation ought to emphasize enhancing training efficiency and real-time adaptability for resilient autonomous underwater activities.

2.3.7. Deep reinforcement learning (DRL) algorithm

DRL combines deep learning with reinforcement learning, enabling autonomous systems to operate in intricate, nonlinear, and multidimensional settings. DRL has been extensively utilized for obstacle evasion in unmanned surface vehicles and is currently under investigation for AUV route planning [45, 100–103].

Cao et al. applied DRL for controlling AUV posture, employing Deep Deterministic Policy Gradient (DDPG) to train an AUV agent for managing movement in three degrees of freedom [101]. Wu et al. created a DRL framework for sensor-motor management, allowing AUVs to navigate visually without exact localization [104]. Xu et al. introduced a Soft Actor-Critic (SAC) method triggered by events for avoiding collisions, utilizing sonar information to create secure pathways [105]. Havenstrøm et al. utilized DRL to achieve autonomous path following and collision avoidance by managing AUV fins through a reinforcement learning-based agent [107].

Xu et al. tackled the issue of multi-AUV cooperative decision-making by employing an actor-critic framework alongside a Coding-Convolutional Network to analyze raw sensor data in conditions of low visibility [108]. The AUTORL framework boosts AUV path planning by automating the search for neural network architectures, leading to better convergence speeds and navigation effectiveness [109]. Chu et al. suggested a path planning strategy to underactuated AUVs that utilized a Double Deep Q Network (DDQN), employing a hybrid reward function to improve real-time navigation in ocean currents [31].

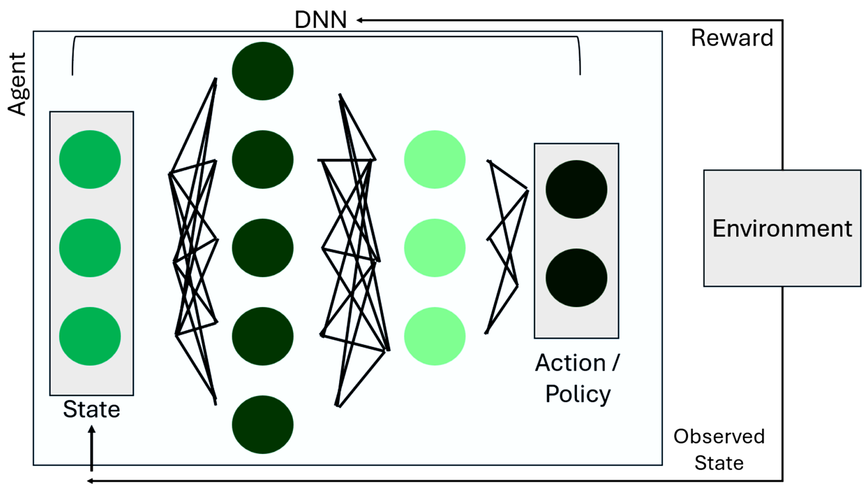


Figure 9: DRL Algorithm

Although it has great potential, DRL is infrequently utilized for AUV path planning because of its sample inefficiency and the challenges in fine-tuning neural network parameters. Figure 9, illustrates the layout of a DRL system. The Agent is made up of a Deep NN (DNN) that accepts the State as input, processes it through various layers, and returns an Action/Policy [110]. The agent interacts with the environment, gets observable states, and is rewarded for its activities, which aids in learning and optimizing future judgments. Subsequent studies ought to concentrate on enhancing data efficiency and refining learning frameworks for real-time AUV navigation.

3. Local path planning algorithms for AUV

Local path planning algorithms for AUVs are essential in enabling safe and efficient navigation for complex underwater environments. These algorithms continuously analyze real-time sensor data to generate collision-free paths within the immediate vicinity of the vehicle. The main approaches encompass potential field algorithms, sampling-based techniques, and optimization-based strategies. Potential field algorithms depict the environment as a virtual force field, with environmental constraints creating repulsive forces and goals producing attractive forces to direct the AUV along the resulting vector. Sampling-based algorithms, like RRT and its variations (e.g., RRT*, Informed RRT*), effectively map out the configuration space to establish viable routes. Optimization-focused methodologies, such as Model Predictive Control (MPC) and trajectory optimization techniques, that aims at generating smooth and dynamically feasible paths by minimizing a cost function that takes into account factors like energy consumption, safety margins, and mission goals. These algorithms face specific challenges in the underwater realm, such as restricted sensor range, acoustic interference, and dynamic water currents [128, 133]. Recent advancements have been concentrated on the amalgamation of uncertainty quantification, multi-objective optimization, and techniques based on machine learning to improve resilience and adaptability. Researchers are also investigating the fusion of global path planning strategies with local algorithms to achieve more cohesive and forward-thinking navigation behaviors. The continuous advancement of these algorithms aims to enhance AUV autonomy, enabling the execution of more intricate missions in increasingly demanding underwater conditions.

3.1. Analysis of local path planning algorithms

Table 2: AUV local path planning algorithms in underwater environment

Algorithm	Year / References	Proposed method	Remarks
APF	2024 / [111]	Improved APF-AC algorithm	Reduces path length and iteration time, validated on AUV platform
	2022 / [112]	APF algorithm	Aims to enhance safety, avoid environmental constraints, and reduce traffic congestion
	2022 / [27]	Predictive APF algorithm	Reduces energy consumption and path length

Table 2 [cont.]

Algorithm	Year / References	Proposed method	Remarks
APF	2021 / [113]	APF algorithm	Novel APF algorithm with augmented reality for local minimum avoidance
	2021 / [114]	APF integrated into bidirectional RRT	Combines global and local planning for dynamic underwater environments effectively
	2020 / [115]	APF algorithm	Proposed waypoint tracking with collision avoidance
RRT	2023 / [118]	Cylinder-based heuristic RRT	improves AUV path efficiency and mobility significantly
	2022 / [116]	Improved RRT* algorithm	Focus on kinematics, steering, environmental and communication constraints, and articulated vehicle structures
	2022 / [117]	Improved RRT algorithm	AUV target search in 3D environment
	2022 / [2]	Improved AAF-RRT algorithm	Improved search ability and narrow passage traversal
	2022 / [119]	Improved heuristic Bi-RRT algorithm	Seamless and adaptive navigation with efficient maneuvering in dynamic environments
	2020 / [47]	Improved RRT	Improved algorithm enhances search speed, smoothness, and feasibility in simulations
ANN	2017 / [120]	Glasius Bio-inspired Neural Network (GBNN)	Proposed method ensures efficient coverage without overlaps or collisions
	2019 / [62]	GBNN	AUV covers workspace, escapes deadlocks, and has low overlapping rate
	2017 / [121]	Dynamic BINN	Paper introduces target attractor concept for neural network information transfer efficiency
	2014 / [122]	ANN	Path planning in a 3D environment
	2020 / [123]	ANN	Paper presents neural collision avoidance system for AUV
	2020 / [61]	BINN	Effective in distributing AUVs and reducing sailing distance
	2014 / [124]	BINN	Ensures efficient navigation in unknown dynamic environments through advanced optimization

Table 2 [cont.]

Algorithm	Year / References	Proposed method	Remarks
ANN	2020 / [126]	Improved ACO algorithm	Overcomes local extremum, poor quality, and low accuracy in traditional ACO
	2023 / [127]	Improved ACO	Algorithm ensures safe navigation, shortest path, and fewest turning times
	2019 / [125]	Voronoi-based ACO	Facilitate searching solutions
	2018 / [68]	ACO	Efficient AUV path planning
GA	2022 / [129]	GA	Proposed method finds smoother, faster routes
	2021 / [130]	Improved GA	Proving faster convergence rate
	2020 / [2]	GA	Overcomes local optimal solutions, saves time and costs effectively
	2017 / [132]	Hybrid-GA	Optimal path balances cruising distance and upstream-current avoidance for gliders
	2005 / [131]	Improved adaptive GA	Enhances stability, convergence, and real-time capability for AUV path planning
RL	2023 / [135]	HER-DDPG algorithm	End-to-end AUV local motion planning
	2023 / [105]	DQN-QPSO algorithm	Enhances navigation efficiency while reducing energy consumption
	2022 / [96]	Hybrid DDPG	AUV adaptive path planning and control
	2020 / [134]	Q-learning based tuna swarm optimization algorithm (QLTSO)	Outperforms other optimization algorithms with 100% planning success rate
	2018 / [93]	RL algorithm	Optimal AUV trajectories in constrained space
DRL	2022 / [136]	DRL	Implements event-triggered mechanisms to assess environmental conditions and ensure safe navigation
	2022 / [96]	DRL	Demonstrates robustness under ocean currents, delays, and sensing errors
	2020 / [137]	DRL	Enhances AUV path following efficiency

4. Global path planning methods for AUV

The environment provides a clear pathway, devoid of obstructions and external interference, for the AUV to navigate. Moreover, global path planning serves as an optimization technique that allows the AUV to determine the most efficient path from its starting point to its intended destination, disregarding any potential hindrances along the way. The fundamental goal of global path planning is to determine the best route from the starting point to the target area within the given environment, taking into account any constraint, constraints, and overall spatial layout. This approach has proven effective in enabling the AUV to consistently locate the shortest viable path. In their 2004 study, Hong-jian and colleagues introduced two methods for global path planning: GA and A* algorithms. They investigated several issues related to the GA method, including the system of coding, which uses digit grid controls and different chromosomes length, the technique for generating the initial sample, the fitness evaluation function, the evolution strategy, and the use of advanced genetic operators. Unlike ground or airborne robotic systems, AUVs have limited life of their batteries, making it difficult to recharge them quickly for subsequent operations. Consequently, it is crucial that AUV path planning prioritizes energy efficiency to maximize the vehicle's operational duration. Recognizing this constraint, [138] investigated grid-based path planning strategies for AUVs operating in environments with minimal current fields to minimize power consumption. This study introduced an edge-search technique to address a fundamental limitation of grid-based path planners, which typically only consider paths connecting adjacent grid nodes, overlooking potentially more efficient paths. Simulations demonstrated that the edge-search algorithm could identify comparable paths to the conventional eight-direction approach but with significantly reduced cost. Their approach employed quadtrees to model the two-dimensional horizontal plane, enabling efficient storage and compression of environmental data. This model then informed the implementation of an adaptive ant colony algorithm capable of Identifying routes that ensure a safe margin from environmental and communication constraints, thereby improving path utility. Sun and Zhang introduced a global path planning system built specifically for AUV path planning in varied marine situations [139]. Their algorithm evaluated potential solutions based on energy consumption and travel distance criteria. Simulations demonstrated the effectiveness of the method in identifying efficient two-dimensional horizontal plane paths that struck a balance between computational efficiency and path quality. This section focuses on global path planning strategies for AUVs navigating within predefined areas while avoiding stationary barriers. In the absence of known barriers, the method aims to prioritize clear and unobstructed pathways, while reducing route length and consumption of energy at its present pace.

4.1. Analysis of global path planning algorithms

Table 3 outlines advantages and disadvantages of path planning strategies for AUV navigation, which includes safe navigation by avoiding collisions. Compared to various path planning techniques of AUV, A* algorithm stands out as the simplest heuristic search method. technique as it functions without the need for pre-processing. Nevertheless, when executed in a massively parallel setup, a considerable number of nodes need to be evaluated, leading to inefficient searching. The genetic algorithm employs the principle of survival of the fittest to carry out multiple evolutionary processes. Since it requires adjusting more parameters and processing larger datasets, the convergence rate tends to be slower. The evolutionary algorithm surpasses the A* algorithm due to its enhanced global

Table 3: AUV global path planning algorithms in underwater environment

Algorithm	Year / References	Proposed method	Remarks
APF	2022 / [48]	Combine APF	Enhances the ability to adjust
	2022 / [27]	Combination of APF and Virtual Method	Finite time technique
	2022 / [42]	Improved A* Algorithm	Less time used for path searching and planning
	2021 / [115]	Neglecting effect of currents based APF	Current to get shortest path
	2015 / [31]	Modified APF	Preventing collisions with surrounding environmental constraints
	2015 / [31]	Improved APF	Succeed in determining a minimum point at the local level
	2013 / [30]	Multipoint Potential Field	Simple, direct, and relevant in real time
	2012 / [52]	Used polytropic approach	Better effectiveness
RRT	2022 / [47]	Improved RRT	–
	2020 / [35]	–	Obtain a feasible path
	2020 / [141]	Used cost function	Improve search efficiency by avoiding zigzag routes and refining existing ones
	2017 / [44]	Liveness-RRT	Increases the rate of growth
	2017 / [40]	Smooth RRT	Improve the search ability
	2015 / [116]	RRT*	Typically, the path is less than optimal
	2005 / [140]	Incorporate the formation of child nodes	Resolve high-dimensional space resolution

Table 3 [cont.]

Algorithm	Year / References	Proposed method	Remarks
ANN	2020 / [101]	Include improve recurrent	
	2020 / [134]	Combine Dynamic Neural	Network extensive neuronal activity spread
	2019 / [60]	GBINN	Point to point path approach neural Network
	2019 / [143]	ANN	Less calculation
	2017 / [62]	Lateral inhibitory effects being added	No training process is necessary
	2012 / [142]	Used dynamic Neural Network	Computation complexity
	2011/ [59]	BINN	Capability of nonlinear mapping
	2011 / [58]	BINN	Basic Learning Method
	1989 / [57]	Combine potential field NN	Enhancing the awareness and safety
ACO	2020 / [67]	Enhanced firework-ant colony hybrid algorithm	Provides helpful direction and boost optimization performance
	2020 / [68]	Used updated phero-mones	Improved search quality
	2009 / [66]	Used workspace grid model	Generate smooth path
GA	2020 / [91]	Improved GA	Fast convergence and high stability for improved efficiency and performance
	2020 / [2]	Improved Adaptive genetic technique	Enhanced clarity, stability, and quick global convergence
RL	2022 / [37]	Combine with the control-led content	Change the state, improve the perfor-mance
	2022 / [37]	Combine with the control-led content	Change the state, improve the perfor-mance
	2014 / [92]	Reoriented the object	Strong capacity for learning
	2019 / [34]	Using adaptive trajectory	Maximize long term reward
	2009 / [144]	Included self-learning agent	Navigating safely without prior knowl-edge of constraints

Table 3 [cont.]

Algorithm	Year / References	Proposed method	Remarks
DRL	2022 / [105]	Composed CCN	Strong robustness, high stability
	2021 / [107]	Used DRL controller	Manually design reward
	2020 / [106]	Deterministic Policy Gradient	Large sense range
	2019 / [60]	Asynchronous advantage actor critic (A3C)	Superior ability to generalize minimize size
	2017 / [40]	Deterministic Policy	Gradient mathematical model used

search capability and efficiency in identifying near-optimal solutions. DE algorithms share similarities with GA, incorporating genetic operators and selective crossover mutation. Research suggests that the DE algorithm is more reliable than the genetic algorithm for path planning. ACO and PSO are bio-inspired algorithms that mimic collective behaviors observed in nature, enabling faster adaptation to dynamic environments. The ACO and PSO algorithms represent bionic strategies that imitate the collective behavior found in biological systems. Collaboration among organisms facilitates quicker adaptation to their surroundings. The ACO algorithm relies on a positive feedback mechanism that motivates ants to navigate towards regions with high pheromone concentrations. The initially established pheromone distribution ought to be more substantial, which prolongs the search and decelerates convergence. Elevated pheromone concentrations result in quicker convergence rates during the later phases. In contrast to ACO algorithms, PSO algorithms leverage knowledge exchanged within groups, enabling faster early convergence. Conversely, PSO can significantly reduce search time because it involves fewer variables and memory operations. However, it is susceptible to stagnation at local optimum positions due to insufficient dynamic control over particle velocity.

AUVs employ CCPP algorithms to devise and implement a trajectory that comprehensively encompasses the entire area of interest, ensuring the absence of any gaps or overlaps. The intricacy of the environment and the specifications of the task dictate the selection between grid-based or graph-based CCPP algorithms. Grid-based methodologies are straightforward; however, they are computationally demanding when applied to extensive workspaces characterized by high-resolution grids. Conversely, graph-based algorithms exhibit greater adaptability to complex environments and irregular geometries. Optimization methodologies, including GA, PSO, ACO, and WWO, have the capacity to ascertain the most efficient path. Nonetheless, in contrast to FMM, these methodologies necessitate a fitness function specifically tailored to the path planning challenge. This requirement may render certain algorithms that are more difficult to implement and fine-tune effectively. CPP is an algorithm that designs routes linking all specified points within a given area. CPP is distinguished from FMM in that it does not engage in point-to-point path planning, thereby requiring a unique methodological approach. AUVs that utilize RL demonstrate enhanced decision-making capabilities and are capable of planning optimal routes without the necessity of prior knowledge. RL illustrates exceptional adaptability and flexibility within challenging and unpredictable environmental conditions. The representation of states in real-world scenarios necessitates specialized features. The suboptimal performance of AUV path planning in high-dimensional contexts can be attributed to the phenomenon known as “dimensionality disaster.”

This research utilized a systematic methodology to scrutinize the existing body of literature on AUVs, with the objective of comprehending the research methodologies employed by scholars and identifying the most used techniques for deriving conclusions.

5. Conclusions and future scope

This paper reviews recent research on planning pathways for autonomous vehicles (AUVs) locally and internationally, considering static and moving impediments. This paper discusses prominent techniques for determining optimal solutions, including path planning for 2-D and 3-D environments. The algorithm information is presented in a tabular format. The effective planning of paths is of paramount importance for underwater vehicles. This review delineates path planning into two categories in terms of traditional, graph based and group intelligent approach: global and local approaches. The article outlines the benefits and drawbacks of each algorithm, as well as potential upgrades for better performance. The A* algorithm is widely used for discovering paths in graphs and grids. GA and PSO are optimization techniques that can provide optimal solutions to unexpected problems. Differential evolution, a stochastic optimization technique, can be used to find a function’s global minimum. The “ant colony optimization” algorithm, modeled after ant foraging strategies, aims to find the shortest path to a food source. Nature-inspired algorithms, such as flower pollination and water wave optimization, can help solve global optimization problems. Coverage route design includes creating a path that covers a certain area. Choosing the appropriate algorithm depends on the application’s needs and the environment. The A* method may be suitable for grid-based climates. For increasingly difficult problems, a genetic algorithm or particle swarm optimization may be better options.

RL algorithms allow for experience-based learning and adaptation to diverse settings. This technique has applications in engineering design, financial modeling, and image processing. The success of an optimization algorithm depends on the problem and parameters employed. More study is needed to better understand the algorithm's strengths and shortcomings and improve its performance for various optimization tasks. There is no "one size fits all" solution to the route planning challenge. Algorithm selection depends on environmental conditions, environmental and communication constraints, and accuracy requirements. To choose the best algorithm for a specific application, researchers and practitioners must weigh the benefits and drawbacks of each option. Finally, the review paper provides a detailed overview of local path planning algorithms for autonomous vehicles. Additional research is needed to create algorithms capable of efficiently managing complex and dynamic aquatic environments. This review paper provides a valuable reference for researchers and professionals specializing in autonomous vehicle path planning.

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