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SURVEY

An Overview of Machine Learning Techniques in Local Path Planning for Autonomous Underwater Vehicles

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ABSTRACT Autonomous underwater vehicles (AUVs) have become attractive and essential for underwater search and exploration because of the advantages they offer over manned underwater vehicles. Hence the need to improve AUV technologies. One crucial area of AUV technology involves efficiently solving the path planning problem. Several approaches have been identified from the literature for AUV global and local path planning. The use of machine learning (ML) techniques in overcoming some of the challenges associated with AUV path planning problems such as safety and obstacle avoidance, energy consumption, and optimal time and distance travelled remains an active research area. While there is literature on global and local path planning that explores different techniques, there is still a lack of paper that provides an overview of the application of ML for local path planning. Hence the main objective of this paper is to present an overview of the state-of-the-art application of ML techniques on local path planning for AUVs. The ML algorithms are discussed under supervised, unsupervised, and reinforcement learning. The challenges faced in real-life deployment, simulated scenarios, computational issues, and application of ML algorithms are discussed, with future research directions presented.

INDEX TERMS Machine learning, local path planning, autonomous underwater vehicle (AUV), real-time path planning, underwater.

I. INTRODUCTION

Autonomous underwater vehicles (AUVs) have become attractive for underwater search and exploration due to the many advantages they offer over manned underwater vehicles. The areas of application of AUV include mapping of the seafloor in oil and gas exploration, data collection and monitoring in oceanography and coastal management, tracking of pipeline and underwater cables, and security and acoustic surveillance. Due to the importance of AUV technologies, researchers constantly seek to improve their effectiveness [1]. One crucial area involves efficiently solving the path planning problem which is important for many applications including data collection, ocean predictions, and monitoring. The foundation of an AUV's navigation system and essential to its underwater operation is path planning. The importance of path planning for the safe and effective navigation of AUVs cannot be overstated [2].

According to [3], the path planning problem denotes calculating an optimal or near-optimal route for a single AUV or multiple AUVs to a targeted destination from a start point based on stated optimization objectives and ocean environment details and constraints. While solving the path planning problem, the characteristics of the robot(s) must be respected and collision with obstacles avoided [4]. Depending on the demands of the application, path planning optimization objectives may include path length, time consumption, energy consumption, or safety. Path design for

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AUVs has traditionally been linked to safety circumstances; nevertheless, other performance aspects are also significant. Global and local path planning are two general categories of path planning. Global path planning is the process of finding a solution to path planning issues in predetermined environments [5], [6], [7], [8]. Where the destination target is not fixed and the environment is dynamic or unpredictable, global path planning is unsuitable. Local path planning also known as real-time path planning or online path planning is hence suited for unknown environments. The local path planning algorithm as implied generates the desired path for AUV in real-time or near real-time.

Several approaches have been identified from the literature for AUV local path planning. They include rapidly-exploring random trees (RRT) [9], [10], fuzzy logic algorithms [11], [12], and machine learning (ML) techniques such as supervised and reinforcement learning [13]. Fig. 1 illustrates some of the local path planning approaches.

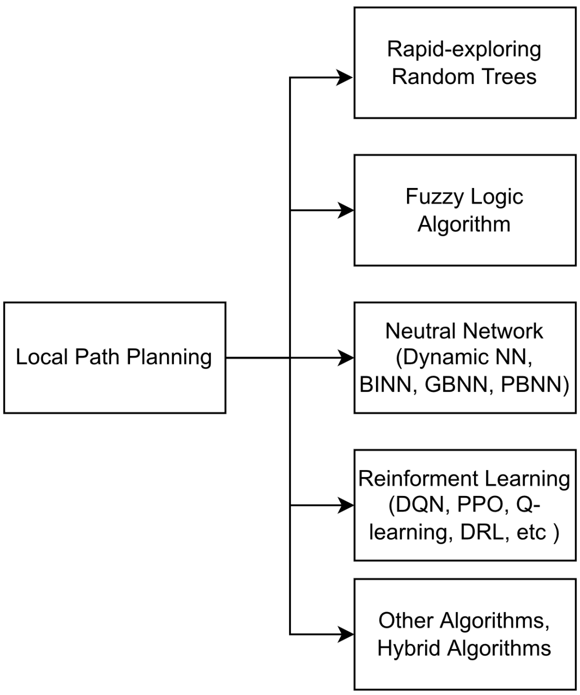

FIGURE 1. Local path planning approaches.

As a result of the success of ML techniques in the field of computer vision and image processing, the use of ML techniques is attracting research interest for AUV obstacle avoidance and path planning. Hence, the focus of this paper is to provide an overview of the applications of ML techniques for AUV path planning. In particular, we survey existing works on ML techniques for local path planning. The ML techniques are discussed under three main categories: supervised, unsupervised, and reinforcement learning.

Related works have provided a survey on the application of ML to path planning [3], [13], [14], [15]. In [3], an overview of the issues with path planning, re-planning, and optimization techniques for AUV missions was presented. The study did not cover ML techniques. Cheng et al. [13] provided an overview of different algorithms for global path planning and local path planning. A review of ML path planning methods for AUV was presented in [14]. However, the major focus was on the application of the underwater internet of things (UIOT). While some of these works have provided some level of discussion on the ML techniques such as the Neural network, and reinforcement learning [13], [14], there is still a lack of paper that provides an in-depth discussion of ML techniques for local path planning. To address this gap, this paper provides an overview of the ML techniques related to local path planning, a review of up-to-date literature on ML technique application to local path planning, explores some unresolved issues in this field and offers an analysis and comparison of various local path planning methods.

The remainder of this paper is arranged as follows: Section II describes the AUV modelling, ocean environment and performance metrics and Section III discusses the types of ML techniques. Section IV reviews the ML approach in the local path planning algorithm for AUVs. Section V discusses some of the challenges and findings and Section VI concludes the paper.

II. MODELING OF AUV

In this section, the data capture for environmental modelling and mathematical equations that describes the motion constraints of the AUVs and the performance metrics is described. The mathematical model for the ocean current is discussed and the performance metrics for local path planning are presented.

A. ENVIRONMENTAL MODELING

Path planning is generally categorized into global path planning and local path planning. Global path planning refers to the solution to path planning problems in known environments while local path planning involves path planning in an unknown underwater environment. Fig. 2 depicts the AUV underwater environment which includes the global grid map, goal or destination, local grid map, and obstacles in the environment. The O represents the current location of the AUV and the radius denotes the scanning radius of the sonar. The radius of the scanner of a typical AUV varies depending on the type (long range, medium, small). For instance, Autosub Long Range AUV by National Oceanography Centre has a range of 6000 km [16], [17].

The global grid map is usually known or unknown before a mission while the local grid map is obtained using pictures collected from the AUV's sonar, as illustrated in Fig. 2. The images from the sonar are collected as raw data and used to build the map of the local environment. The path planning algorithm determines the AUV's next navigation location based on local environment information. For example, image processing is applied to the sonar image in the local path to detect an obstacle and a bio-inspired neurodynamic model is applied to generate a collision-free path [18].

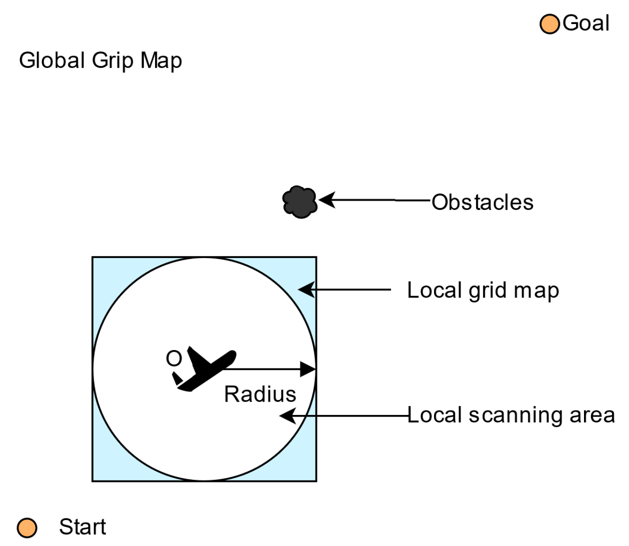

FIGURE 2. Illustration of the AUV environment.

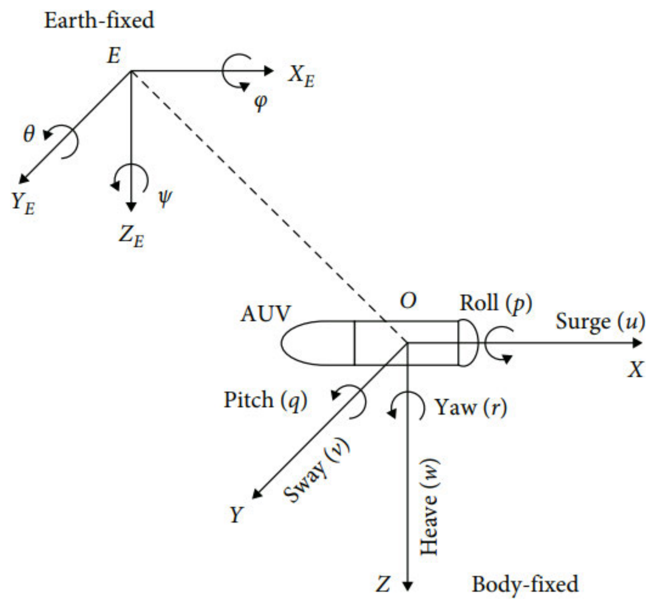

FIGURE 3. EFF and BFF coordinate system [2].

TABLE 1. The AUV 6DOF parameters [2].

DOF	Description	Position and Euler Angles	Forces and moments	Linear and Angular Velocities
1	Surge	x	X	u
2	Sway	y	Y	v
3	Heave	z	Z	w
4	Roll	ϕ	K	p
5	Pitch	θ	M	q
6	Yaw	ψ	N	r

Generally, the navigation of the AUV is done using sensors such as the digital compass, depth sensors, and wireless communication devices among others.

B. AUV MOTION CONSTRAINTS MODELING

AUV modelling takes into consideration the AUV's motion as well as the forces acting on the AUV. Path planning algorithms are meant to take into consideration the AUV's mobility restrictions to produce a viable path. The kinematic and dynamic models may be used to model these motion limitations quantitatively. The mathematical model of the motion of the AUV also is described using two coordinate systems: earth-fixed frame (EFF) and body-fixed frame (BFF) as shown in Fig. 3 [19].

Six degrees of freedom are used to move an AUV in 3D space: surge, roll, sway, pitch, heave, and yaw. Each dimension of the AUV has a velocity component for rotation and translation. The parameters of an AUV have six degrees of freedom (6DOF), as shown in Table 1 (6DOF). Both the EFF coordinate system and the BFF coordinate system are used to explain the AUV's mobility in the underwater environment.

The kinematic model is used to model the geometric aspects of the AUV motion and can be expressed as:

$$\dot{\eta} = J(\eta)v \tag{1}$$

where $\eta = (x, y, z, \phi, \theta, \psi)^T$ are the AUV's location and vector of direction regarding the earth's coordinate system; In the BFF coordinate system, $v = (u, v, w, p, q, r)^T$ represents the linear and angular velocities, while $J(\eta)$ signifies the Jacobian transformation matrix.

A Jacobian transformation matrix expressed in terms of the Euler angles maps the velocity expressed in the body-fixed frame to the earth-fixed frame where the number of degrees of freedom is equal to the number of rows and the number of generalized coordinates to the number of columns respectively [20], [21], [22].

$$J(\eta) = \begin{bmatrix} J_1(\eta) & 0_{3\times 3} \\ 0_{3\times 3} & J_2(\eta) \end{bmatrix} \tag{2}$$

$$J_1(\eta) = \begin{bmatrix} c\psi c\theta & s\psi c\theta & -s\theta \\ c\psi s\theta s\phi - s\psi c\phi & s\psi s\theta s\phi + c\psi c\phi & c\theta s\phi \\ c\psi s\theta c\phi + s\psi s\phi & s\psi s\theta c\phi - c\psi s\phi & c\theta c\phi \end{bmatrix} \tag{3}$$

$$J_2(\eta) = \begin{bmatrix} 1 & s\phi t\theta & c\phi t\theta \\ 0 & c\phi & -s\phi \\ 0 & s\phi / c\theta & c\phi / c\theta \end{bmatrix} \tag{4}$$

The dynamic model explains how the force on the AUV and its motion are related. Furthermore, it links the force and moment to the object's location and speed. The 6DOF dynamic model for AUVs takes the following general form:

$$M\dot{\boldsymbol{v}} + \boldsymbol{C}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{D}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{g}(\boldsymbol{\eta}) + \boldsymbol{A} = \tau \tag{5}$$

where $g(\eta)$ indicates the gravitational forces and moments (hydrostatic), M represents the inertia matrix, $C(\boldsymbol{v})$ represents the Coriolis-centripetal matrix, $D(\boldsymbol{v})$ represents the hydrodynamic damping and lift matrix, $A = [a_1, a_2, a_3]^T$ represents uncertainty and disturbance parameter matrix and

$\tau = (X, Y, Z, K, M, N)^T$ represents the vector of external forces and moments [23].

Additionally, the AUV's body structure will have an impact on dynamics because as it moves, the AUV will exert drag and lift forces on the water it is moving through [24].

C. OCEAN CURRENTS

The model of ocean currents also is important to simulate a realistic experience. There have been several approaches to modelling ocean currents. In most literature [21], [25], [26], [27], [28], [29], ocean current is assumed to be constant, irrational and bounded The body-fixed relative velocity of the AUV is therefore given as

$$V_a = V - V_c = [u_r, v_r, r, 0, 0, 0]^T \tag{6}$$

where V_a is the resultant ground velocity of the AUV resolved in a 2D horizon, V is the speed of the AUV unhindered and V_c is the velocity of the ocean current as illustrated in Fig. 4.

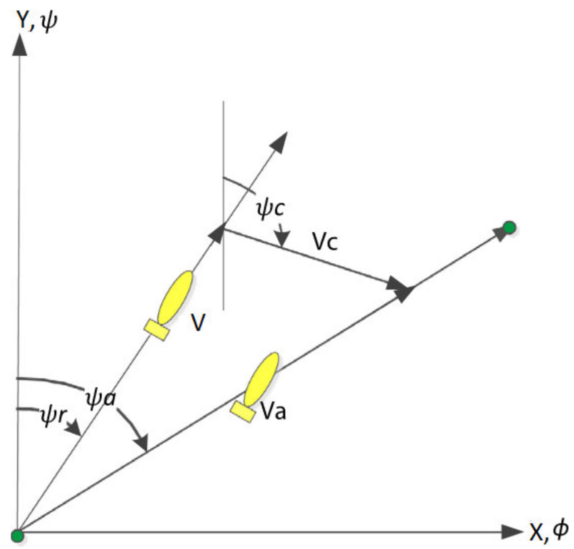

FIGURE 4. **The resultant velocity of AUV under the influence of the ocean current in 2D space.**

Expanding (6) in terms of northeast velocity V_a is written as:

$$V_{ay} = |V| \sin \psi_r + |V_c| \sin \psi_c \tag{7}$$

$$V_{ax} = |V| \cos \psi_r + |V_c| \cos \psi_c \tag{8}$$

where V_{ay} and V_{ax} are the north and east velocity components of the AUV, respectively. The desired direction of the vehicle is therefore as follows:

$$\frac{V_{ay}}{V_{ax}} = \tan \psi_a = \frac{|y_i - y_{i-1}|}{|x_i - x_{i-1}|} \tag{9}$$

V_a and ψ_a are obtained by solving equations (7)-(9) as simultaneous equations.

In [30], a different approach is used to simulate ocean currents. Ocean currents are added into the simulation as random velocities by a first-order Gauss-Markov process with Gaussian white noise based on [31] and [32].

Hence, the AUV kinematic equations for horizontal plane motion (3DOF) with the effect of ocean current can be expressed in terms of the relative surge and sway velocities as follows:

$$\dot{x} = u_r \cos \psi - v_r \sin \psi + V_{cx} \tag{10}$$

$$\dot{y} = u_r \sin \psi - v_r \cos \psi + V_{cy} \tag{11}$$

$$\dot{\psi} = r \tag{12}$$

where ψ, r are the yaw angle, and yaw rate respectively, u_r and v_r, surge and sway speed components respectively of the velocity of the AUV, and $V_{cx} V_{cy}$ are the east and north components of the ocean current velocity [25], [31].

D. PERFORMANCE METRICS

The path planning problem is solved based on at least one objective i.e. it may be time, distance, energy, or safety depending on the application requirements. Fig. 5 shows a typical path planning path for an AUV from source to destination while avoiding obstacles and following waypoints.

1) SAFETY

Safe conditions involve taking a path devoid of obstacles or dangerous areas i.e., obstacle avoidance. In general, path planning for AUVs has been associated with obstacle avoidance or safety of the path. A typical vehicle may not have information about the locations of an obstacle. However, as the AUV transverses, through the area, the AUV must have the ability to sense or change its location with time. Other AUVs can also be seen as obstacles in the case of multiple AUVs. The AUV is required to be able to calculate and change its route in real-time. How this is done fulfils the safety objective function [3]. The issues of obstacle avoidance have been well-researched using non-ML methods. For instance, [33] tackles path planning using artificial potential field (APF) algorithms. Others include Dijkstra's algorithm [34], [35], A* algorithm [36], and the D* algorithm [37] have also been employed for the path planning algorithm. Common challenges of these methods include susceptibility to local minima and a lack of compatibility with high-dimensional applications.

2) ENERGY CONSUMPTION

Since AUVs have relatively small battery life, the objective is to keep energy consumption minimal while travelling in the ocean environment with ocean currents [38], [39]. The amount of energy an AUV uses is determined by its hydrodynamic design, speed, onboard cargo, and trajectory. The energy consumption is not limited to the movement of the AUV but also the energy consumed by communication units to aid the movement of the AUV. Several approaches have been reported in the literature to optimize energy consumption. This includes simplifying computational complexities, avoiding obstacles and hazardous areas that can cause unwanted errors, finding a shorter path to destinations, adapting to the speed of the current field [40] or taking advantage

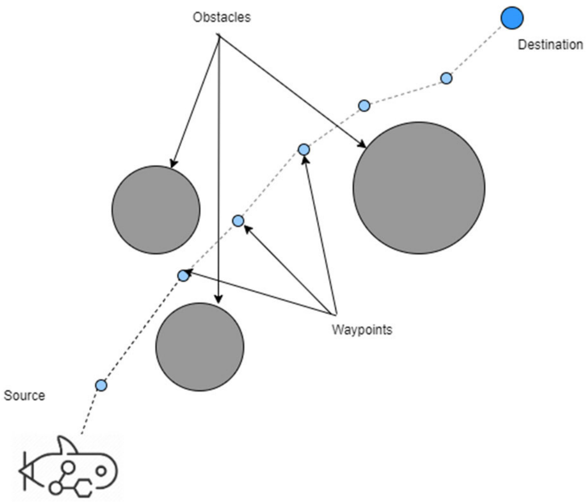

FIGURE 5. A typical path planning a path for AUV.

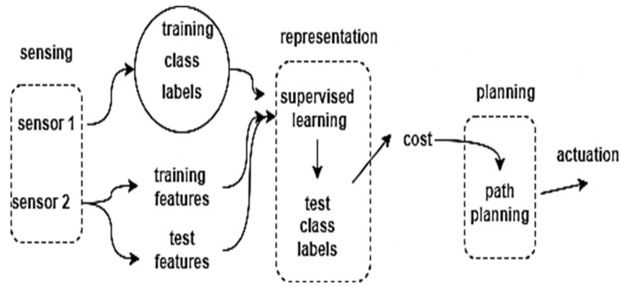

FIGURE 6. A typical path planning for AUV using supervised learning.

of the ocean current [41]. To optimize energy consumption, trajectory optimization algorithms have been explored in [42], [43], and [44].

3) TIME TRAVELLED AND PLANNING DISTANCE

The path planning problem is also usually optimized to reduce the time travelled, planning time, or distance to the destination. Increasing the speed of AUV at the expense of energy consumption, avoiding obstacles, and finding short paths of travel are some ideas for minimizing time travelled. In the current fields, level set methods [45] are developed for path planning, where the time-optimal path of the AUV is obtained by resolving a particle tracking equation. In low-dimensional areas, these deterministic techniques have shown to be extremely effective, but in high-dimensional environments, they have shown to be much less effective [3].

4) AGE OF INFORMATION

Contrary to the independent AUV, cooperative AUV systems are considered more efficient and accurate in some underwater exploring tasks [46]. To efficiently manage the path-planning in cooperative AUVs system and also overcome the limitations of acoustic waves used in underwater communication the internet-of-underwater-things (IoUT) have been explored in [46] and [47]. In AUV-assisted IoUT, the age of information (AoI) plays a critical role [48], [49], [50]. The AoI is the amount of time elapsed between the last received data and newly updated data. To achieve optimal trajectory planning the minimum AoI [46], average AoI [49] and peak AoI [48] are considered useful metrics for path planning.

III. MACHINE LEARNING TECHNIQUES

While there has been a lot of study on handling the path planning problem, in both single and multiple AUV applications, very few of the solutions incorporate ML approaches hence the focus of this paper. The study of computer algorithms that can automatically learn from experience and get better over time without being explicitly programmed is known as ML [51]. ML algorithms are most useful in an extensive variety of applications where developing conventional algorithms for task performance is difficult to achieve. They have aided and continued to assist in several paradigms in almost all fields of human endeavours. The three major kinds of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning are discussed as follows.

A. SUPERVISED LEARNING

Supervised learning involves creating a function that learns to correctly connect an input to a particular output based on a well-labelled set of input-output data pairs [4]. There are two types of supervised learning issues: regression problems and classification challenges. Fig. 6 depicts a typical application of supervised learning to path planning algorithms.

Training examples and labels can be provided from onboard sensors (self-supervised learning). The robot can be trained to evaluate the cost of deciding on a path. Based on its evaluation and learning a decision is made about its path planning. The algorithm in the regression attempts to offer a continuous-valued output, whereas the classification method intends to provide a label or discrete-valued output.

Supervised learning techniques provide several advantages such as less computational complexity compared to unsupervised and reinforcement learning. However, it requires human intervention for labelling data and training data. Some examples of supervised learning are linear regression, random forest, support vector machines, logistic regression, artificial neural network, convolutional neural network, recurrent neural network, K-nearest neighbour, and Naïve Bayes.

In solving the path planning problem, artificial neural networks (ANN) and spiked neural networks (SNN) are the most common supervised learning techniques. They are discussed as follows:

1) ARTIFICIAL NEURAL NETWORK

An artificial neural network is a computational network model inspired by the structure of an animal brain of biological neurons. It is possible to view the network as a graph of nodes linked by edges. The edges relay activation information from one node to another, just like how electrical signals are

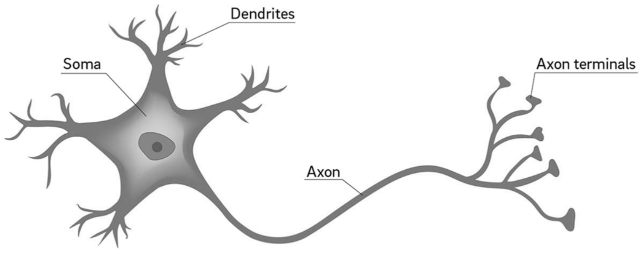

FIGURE 7. (a) Biological neuron.

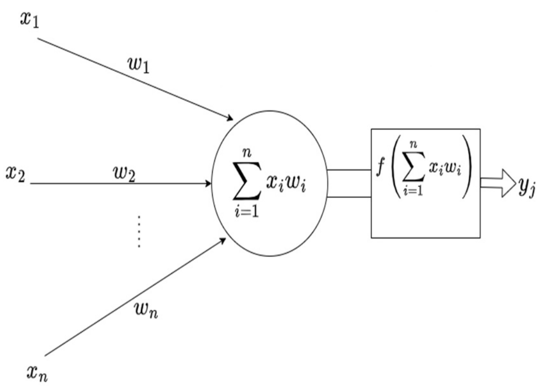

FIGURE 8. (b) Artificial neuron [53].

passed through biological neurons [52]. Fig. 7 and Fig 8. show illustrations of a biological neuron and an artificial neuron respectively.

Due to its great intelligence, the artificial neural network algorithm receives increasing attention. However, the majority of artificial neural network path planning algorithms have drawbacks, including extended learning times, weak generalisation abilities, sluggish processing speeds, and learning delays, making it challenging to ensure real-time path planning performance [54]. Despite their flaws, artificial neural network methods are nevertheless often utilised in AUV path planning because of their strong learning and adaptive capabilities, robustness, and parallelism [2] Spiked Neural Network (SNN).

In recent years, interest in the SNN has started to grow to get beyond the limits of conventional artificial neural network techniques [55]. The SNN is a model inspired by the biological neural network developed by using electric circuit elements to solve the differential equations of a uniform patch of a membrane in a biological neuron. A regular ANN and SNN vary in that an SNN makes an effort to more accurately resemble a biological neural network utilising a series of spikes.

A sequence of spikes is inputted into the SNN, and a series of spikes are produced as the output [56]. The differential equation that describes the neuron's membrane potential predicts when a spike will occur [57]. In principle, when a neuron reaches a specific potential, it spikes, resetting the neuron's potential.

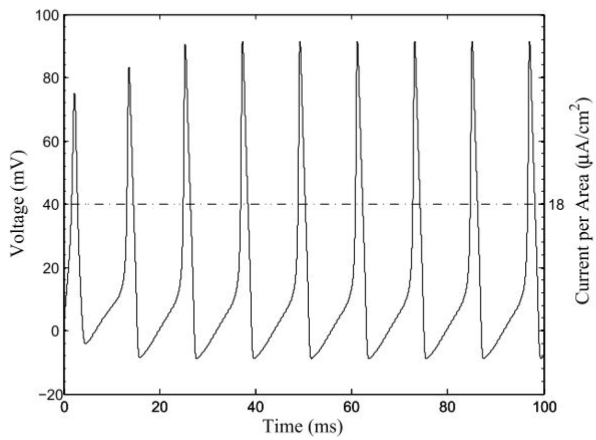

FIGURE 9. A Membrane potential (solid line) of a Hodgkin–Huxley neuron under a sustained current per area (dashed line) of 18 μA/cm^2 [58].

The Hodgkin-Huxley model, Izhikevich model, and leaky integrate-and-fire (LIF) model are some of the extensively used SNN-based neuron models [58]. For example, the Hodgkin–Huxley model of the neuron shown in Fig. 9 is described by a nonlinear ordinary differential equation below:

$$\mathrm{C_m}\frac{\mathrm{du}}{\mathrm{dt}} = -\mathrm{g_{Na}}\left(\mathrm{u}-\mathrm{V_{Na}}\right)\mathrm{m^3h} - \mathrm{g_k}\left(\mathrm{u}-\mathrm{V_k}\right)\mathrm{n^4} - \mathrm{g_L}\left(\mathrm{u}-\mathrm{V_L}\right) + \mathrm{I} \tag{13}$$

where u is the potential of the membrane; C_m is the membrane's effective capacitance; time is t, and the conductance of the sodium, potassium, and leak channels, are g_{Na}, g_k, and g_L, respectively. The reversal potentials of the sodium, potassium, and leak channels, respectively, are V_{Na}, V_k, and V_L; I denote the stimulation current; while m, n, and h are the coefficients in equation (13).

The Hodgkin-Huxley models are the most widely employed for local path planning even though LIF models are thought to be less computationally intensive than the Hodgkin-Huxley models [58]. Fig. 10 depicts a 2D architecture of the Hodgkin-Huxley-based bio-inspired neurodynamic model for local path planning. The 2D model represents the local environment around the AUV i. r_0 is the sensing radius of the AUV, while w_{ij} is the connection weight between i and one of the neighbouring neurons j.

B. UNSUPERVISED LEARNING

In unsupervised learning, the machine agent is trained without supervision i.e. training involves the use of the information without classification or labels and no form of external assistance. Hence, in unsupervised learning, the agent carries out the task of grouping the uncategorized data based on similar features, patterns, and differences [59]. Unsupervised learning is appropriate for user grouping and may be used for dimension reduction, pattern search, and clustering. K-means clustering, principal component analysis, and hierarchical clustering are examples of unsupervised learning techniques.

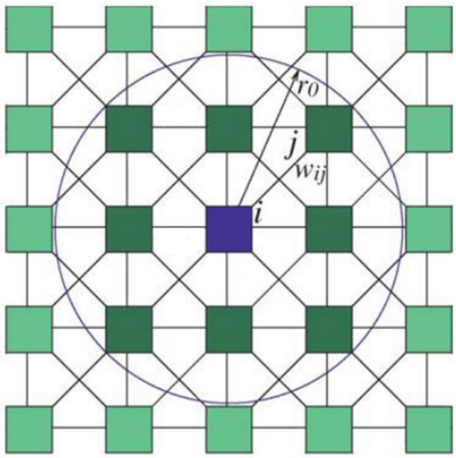

FIGURE 10. 2D Architecture of bio-inspired neurodynamic model for local path planning.

While unsupervised learning offers many advantages such as the ability to determine the inherent structure of unlabeled data, it is computationally harder than other machine learning methods since it lacks supervision and requires large data set to obtain meaningful results. It is also comparatively less reliable and accurate as it is difficult to get precise information to make dependable decisions. It is usually combined with other methods including human intervention for more meaningful output. Hence, it has not been used for local path planning for a single AUV. Nevertheless, unsupervised learning techniques such as self-organizing maps are deployed to handle task assignment allocation in Multi-AUV path planning scenarios [60], [61], [62].

C. REINFORCEMENT LEARNING

Reinforcement learning is an ML paradigm where the machine learns through trial and error and as such data classification is not needed [26]. In reinforcement learning, the computer is unaware of the actions to perform and must instead learn which acts are most rewarding via trial and error. The reward or lack of reward (punishment) gotten from its actions are indicative of how close the agent is to fulfil its objective [63]. The concept of reinforcement learning is a Markov Decision Process as shown in Fig. 11.

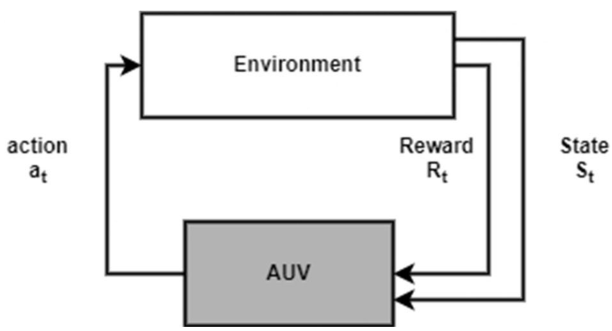

FIGURE 11. Reinforcement learning process.

There are different approaches to reinforcement learning techniques, the more common approaches used in path planning are Monte Carlos [64], Q-learning [65], Deep Q Network [66], Twin Delayed Deep Deterministic policy gradient algorithm [67], [68], Deep Deterministic Policy Gradient [69], [70], Soft Actor-Critic [71], Asynchronous Advantage Actor-Critic algorithm [72], [73], Trust Region Policy Optimization [74] and Proximal Policy Optimization (PPO) [72]. Each RL technique offers a performance improvement to the path planning methods.

The path planning strategies perform better due to each RL methodology. Particularly in unknown and unstable marine environments, RL algorithms work effectively in the motion planning process of the AUVs due to their adaptation to complex systems and the model-free characteristic [75].

IV. MACHINE LEARNING AIDED LOCAL PATH PLANNING

In this section, a review of the ML techniques in local path planning algorithms for AUVs is presented under two categories: supervised learning and reinforcement learning.

A. SUPERVISED LEARNING

Reference [76] proposes the use of a dynamic neural network for AUV path planning. Some advantages of their approach are 3D application and its optimization for time and safety. Additionally, it takes into account dynamic changing currents, However, the approach includes several assumptions of the AUV in simulation and has high computational complexity. Reference [77] uses Bio-Inspired Neural Networks for AUV path planning. The authors implement the method using real-life scenarios is implemented in real-life and consider both underwater and surface vehicles. However, real-life implementation is expensive and their approach lacks emphasis on path length, time and energy optimization as well as not being compared to other algorithms. Reference [18] uses BINN and sonar for image processing to plan paths for AUVs. It does not require proper knowledge and learning procedures, which is useful in situations where the environment is not well-known. However, this method is also computationally expensive and the need for image processing techniques since there is always an incomplete description of the local environment. Also, there is no comparison with other algorithms. Reference [78] uses potential field BINN for AUV path planning. It focuses on the optimization of energy and path length, which is crucial for long-duration missions. It has better performance when compared to the particle swarm optimization (PSO) algorithm. However, the authors do not consider ocean currents and are limited to 2D simulation. Reference [79] uses BINN and velocity synthesis for AUV path planning. One of the advantages of this method is its multi-AUV ocean current integration, which is useful in situations where multiple AUVs need to navigate together. Additionally, it achieves path time and length optimization and an improved BINN technique. However, the authors limit the focus to 2D simulation with many factors being simplified and do not consider dynamic targets in ocean currents. [80] uses dynamic BINN for AUV path planning. It is an

TABLE 2. Summary of supervised learning approaches in local path planning for AUVs.

Ref.	Method	Optimization Objectives	Remarks (Merits/Demerits)
[76]	Dynamic Neural Network	Path length, time, obstacle avoidance and safety	**Merits** • 3D application, improve time optimality and safety • Dynamic changing currents considered • Lower computational complexity **Demerits** • Several assumptions of AUV in simulation • Computational complexity can be improved
[77]	BINN	Safety and obstacle avoidance	**Remarks** • Real-life implementation • Considers underwater and surface vehicles **Demerits** • Not compared to other algorithms • Expensive implementation • Path length, time and energy optimization are not emphasized
[18]	BINN with sonar for image processing	Time, and obstacle avoidance	**Merits** • For the model, proper knowledge and learning procedures are not required. • AUV can make its way to its destination without knowing the entire environment. **Demerits:** • Computationally expensive • Not compared to other algorithms • Image processing techniques needed for information about the environment through sonar • Incomplete description of the local environment
[78]	Potential Field BINN	Path length, energy, safety and obstacle avoidance	**Remarks** • Energy, path length optimized • Improvement on BINN with Potential field • Better performance than particle swarm optimizations algorithm **Demerits** • No ocean current considered • Simulation limited to 2D
[79]	BINN +Velocit y Synthesis	Path length, obstacle avoidance, and safety	**Merits:** • Multi AUVs Ocean current integration • Energy efficiency, improved path time and length • Improved BINN technique • No prior training needed **Demerits:** • Limited to 2D simulation and no real 3D application. • Does not consider dynamic targets in an ocean current. • Many factors are simplified in 2D simulation.
[80]	Dynamic BINN (DBINN)	Safety, time, energy, and path distance	**Merits** • Improved BINN through a virtual target. Deals with a larger environment and changing targets • Improved energy consumption • 3D application **Demerits** • Low efficiency • The performance of the algorithm not evaluated with other methods • No consideration for ocean current • Limited to simulation
[54]	Glasius BINN	Energy consumption, time, and safety	**Merits** • Focuses on coverage path planning. • 2D underwater environment • Far Improved BINN • Lower computational complexity • Shorter planning time and distance • No prior learning procedure required **Demerits** • Does not consider ocean current • Limited to 2D environments.

TABLE 3. Summary of reinforcement learning approaches in local path planning for AUVs.

Authors	Method	Optimization Objectives	Remarks
[81]	Q-Learning +Path Smoothing Algorithm	Time and Distance	**Merits:** • Considers dynamic and kinematic models characteristics of AUV, disturbance effect of the ocean environment • Performs better than A*, RRT* and Dynamic programming based on Zermelo's problem • The smoothing algorithm is added to the RL algorithm **Demerits** • -Does not consider obstacle avoidance, only path distance and time. Limited to simulation
[82]	Q-learning + Neural Network	Safety	**Merits** • Achieves Obstacles avoidance in unknown and hostile environments • Considers Kinematic of AUV • Destination reached with real-time learning, • Achieves optimal path **Demerits** • Does not consider ocean current • does not focus on planning time and distance. Only obstacle avoidance • no performance comparisons
[83]	Actor Multi-Critic Reinforcement Learning	Safety, Energy Consumption	**Merits** • Obstacle avoidance was achieved, and energy optimization and security, • Improved reinforcement learning method and learning efficiency • Suitable for complex tasks and diverse applications **Demerits** • A lot of training is needed to map state to action and achieve obstacle avoidance • Ocean currents are not considered • Long training time and high computational complexity • No emphasis on path time and path distance only on obstacle avoidance • Excessive speed is not suitable for avoiding obstacles
[84]	Deep Deterministic Policy Gradient + Sumtree	Safety Optimal	**Merits** • overcomes the problem of under-driven AUVs travelling safely in underwater canyons, • Improves reinforcement learning method (DDPG) • combined the artificial potential field for improved reward design • Considers kinematics and dynamics of the AUV **Demerits** • The method only applies to specific applications, not general cases. • Ocean current is not considered • Path time and length are out of the scope of this method. • The method is computationally expensive
[85]	Deep Reinforcement Learning	Safety	**Merits** • Obstacle avoidance achieved • Considers Kinematic dynamics of AUV • Improved RL techniques (Deep reinforcement) **Demerits** • Emphasis on only obstacle avoidance, • Path distance or training time of path was not considered
[86]	Adaptative Dynamic Programming	Safety	**Merits** • Models the AUV system with wind, waves and ocean current environment • Considers kinetics and kinematics of the AUV

TABLE 3. ***(Continued.)*** **Summary of reinforcement learning approaches in local path planning for AUVs.**

			• Uses least square policy method to appropriate value function **Demerits** • no comparison with other methods • Obstacles are static • No mention of path time and path length
[75]	Asynchronous Multithreading Reinforcement Learning	Safety, Path Distance, Time	**Merits** • For Single and Multi AUVs • Focuses on global and local path planning processes • In some cases (a single AUV) outperforms other methods (RRT, Artificial Potential field) and reduces the computational load by conducting both global and local path planning • considers ocean current disturbance, moving obstacles and multi AUVs

improvement of BINN through virtual targets, which allows it to handle larger environments and changing targets, It achieves energy optimization but it still suffers low efficiency and does not consider ocean currents. It is also not evaluated against other methods. [54] uses Glasius BINN for AUV path planning. Their focus is on coverage path planning, its 2D underwater environment, it achieves improved BINN, lower computational complexity, shorter planning time and distance and no prior learning procedure required. However, it also does not consider ocean currents and is limited to 2D environments.

The summary of the various methods for path planning for AUVs with the set of optimization objectives and advantages and disadvantages are presented in Table 2.

B. REINFORCEMENT LEARNING

Reference [81] uses Q-Learning and path-smoothing algorithms for path planning. It considers the dynamic and kinematic model characteristics of the AUV and the disturbance effect of the ocean environment in its approach and has better performance when compared to *, RRT* and Dynamic programming based on Zermelo's problem. However, the method only focuses on path distance and time and not obstacle avoidance and it is limited to 2D simulation. Reference [82] uses Q-learning and neural networks for path planning. It achieves obstacle avoidance in unknown and hostile environments, while also considering the kinematics of the AUV. Additionally, it reaches the destination with real-time learning and path optimization. It, however, does not consider the effects of ocean currents, the planning time and distance, there is no comparison with other methods. The Actor Multi Critic Reinforcement Learning method is used in [83] for path planning. This method achieves obstacle avoidance and energy optimization. It improves the learning efficiency of the traditional reinforcement learning method and is suitable for complex tasks and diverse applications. Its drawbacks are long training time, high computational complexity and inability to avoid obstacles at excessive speed. The authors also do not consider ocean currents and do not emphasize path time and path distance. Reference [84] uses a combination of reinforcement learning and artificial potential field for path planning. It overcomes the problem of under-driven AUVs travelling safely in underwater canyons. Additionally, it improves the reinforcement learning method (DDPG) and considers the kinematics and dynamics of the AUV. However, the method only applies to the specific case of underwater canyons, does not consider ocean current, path time and length of AUV, and is computationally expensive. Reference [85] uses deep reinforcement learning for path planning. It achieves obstacle avoidance while considering the kinematic dynamics of the AUV. Additionally, it improves RL techniques (Deep reinforcement) but does not consider the path distance of AUV or the training time of the path. Reference [86] uses dynamic programming for path planning. It models the AUV system with wind, waves, and ocean current environment while considering the kinetics and kinematics of the AUV. It also uses the least square policy method to appropriate the value function. However, obstacles are static, and the path time and path length of AUV is not optimized. There is also no comparison with other methods. Reference [75] The Asynchronous Multithreading Reinforcement Learning method is used for path planning for both single and multi AUVs. The focus of the approach is on global and local path-planning processes, which improves the overall path-planning. It is shown to outperform RRT and Artificial Potential field methods in some cases as it reduces the computational load. Table 3 summarizes the various methods for path planning for AUVs using different reinforcement learning techniques. Each method has its own set of optimization objectives, advantages, and disadvantages.

V. DISCUSSION (CHALLENGES AND FUTURE WORKS)

In this section, challenges of the application of ML techniques in local path planning from the literature review are presented with recommendations and suggestions. The discussions are categorized as real-life deployment, simulated scenarios, computational issues, multi-AUVs, and ML algorithms.

A. REAL-LIFE DEPLOYMENT

A general observation from the review of the literature shows that most of the local path planning systems have only been tested through simulations. A study by [18] demonstrated the implementation of using local path planning to avoid obstacles in a lake. Although the results look promising several challenges need to be addressed in the real-life deployment of AUV local path planning. They include 1). hardware optimization for real applications is also a research issue from image processing to image and sensor technology, to energy consumption, management, and efficiency. Hence, further research and studies are needed for real-life deployment using ML techniques.

B. SIMULATED SCENARIOS

To simulate more realistic underwater scenarios, AUV path planning research must take into account ocean conditions. The conditions of the ocean are made up of strong currents, rugged terrain with uneven shapes, and barriers whose positions can be dynamic and unpredictable. With many papers published on [87]. Many publications on AUV path planning have been published, but very few have provided compelling field trial findings of AUVs operating in dynamic, crowded, and unpredictable ocean settings in AUV route planning [5]. From the current research, it is difficult to say whether the technologies produced thus far are dependable enough to tackle complicated maritime settings or are merely capable of performing specific objectives. The issue here is to create computationally efficient and rigorous frameworks that incorporate both environmental limits and vehicle control while also providing the vehicle with an optimal path [88]. Also, such developed frameworks should incorporate the testing and comparisons of multiple algorithms including ML-based algorithms. With the frameworks developed, there is the need to introduce ML techniques in ways that are optimal based on the objectives of the application. More effort has to be done to develop benchmarks for comparing algorithms and providing design specifications for path planning systems.

C. COMPUTATIONAL ISSUES

AUV path planning across a vast geographical area is an optimization challenge. The computing needs for tackling such high-dimensional problems rise sharply is the change in dimension and increase in the solution space. The initial learning phase of machine learning naturally adds to the computation complexities. Some applications find innovative ways to skip or reduce the learning phase in both reinforcement learning and bioinspired neural networks [6], [54], [75], [89]. Another idea to speed up the planning process and reduce memory requirements is to project the 3D world to 2D in the path planning algorithm [39], [90]. Unfortunately, this 2D area cannot include all of the 3D information about the ocean environment.

D. MULTI-AUVs

While there has been more study in recent years on multi-AUV route planning using non-ML methods, additional ML approaches in multi-AUVs need to be studied. More efforts should be made to establish a rigorous path planning guidance system for multiple marine vehicle synchronisation in ocean conditions [91], [88]. This system should be able to build paths for many vehicles while consuming the least amount of time across all participating vehicles and guaranteeing that the vehicles arrive at their meeting spot at the same. This system must also be light in terms of operating time and able to integrate many aspects impacting a specific mission, such as vehicle dynamics and environmental conditions. The particular properties of ocean current conditions, along with the varying capabilities of different vehicles, make cooperative path planning of several AUVs more difficult.

1) ML ALGORITHMS

The lack of initial training in the agent is an issue in ML path planning algorithms. While other algorithms follow a particular sequence. Real-time ML methods must learn almost always in real-time, this leads to initial poor performance or delays in path planning. There have been attempts to seek to speed the learning process by combining learning methods and using improved ML algorithms methods [55], [89], [92]. This area can also be improved with the advancement of ML in other areas on application like unmanned Aerial Vehicles (UAVs) [93]. Also, combined ML algorithms with non-ML algorithm for improved performance in terms of time of travel, safety, and energy efficiency is also an area of open research.

VI. CONCLUSION

This paper presents an overview of the state-of-the-art application of ML techniques on local path planning for AUVs. The ML algorithms are discussed, and the challenges are identified with future research directions presented. Overall, the main ML algorithms used in path planning include neural networks and reinforcement learning. While there has been a good amount of research into ML approaches in path planning, there are still several milestones to be achieved including energy efficiency, simulation scenarios, and effective ML approaches in cooperative path planning.

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