A Review of Machine Learning Path Planning Algorithms for Autonomous Underwater Vehicles (AUV) in Internet of Underwater Things (IoUT)

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Abstract

The introduction of the Underwater Internet of Things (UIoT), an extension of the Internet of Things (IoT) underwater has become powerful technology necessary to develop the Smart Oceans. Autonomous Underwater Vehicles (AUVs) play a crucial role in Internet of IoUT technology largely because of their mobility and longer energy storage. However, AUV technologies face major challenges such as path planning problems due to the hostile and dynamic nature of the underwater environment. The path planning problem is about finding an optimal path from the start to the endpoint of the AUV. Machine learning is an approach to tackling this problem. While there are numerous ways to address this challenge, machine learning algorithms are few. This paper provides an overview of the path planning problem and review machine learning path planning algorithms for both single and multiple AUVs and gives directions for future research.

***Keywords*:** Autonomous underwater vehicle, machine learning, path planning, reinforcement learning, neural networks, internet of underwater things, internet of things.

1. Introduction

Internet of Underwater Things (IoUT) is a novel class of the Internet of Things (IoT) that enables Smart interconnected underwater objects. This IoUT allows monitoring and tracking on vast unexplored water areas. Location or object tracking and monitoring in IoT areas such as [1] cannot be applied in underwater things on IoUT. As for that, different methods, approaches need to be explored in IoUT to guarantee fully internet system cover underwater. As about 71% of this earth is covered by the ocean, it is very important to have system support cover in IoUT.

Several technologies developed to fulfill the needs in IoUT such as Autonomous Underwater Vehicle (AUV). AUV plays an increasingly important role in ocean exploration specifically like monitoring, tracking and routing. System applied by the internet specifically in Routing Optimization is also an important role model like in [2] but to handle it underwater it is also such a big challenge. Others like AUV Unmanned Underwater Vehicles (UUV) that are self-propelled and independently operating in six degrees of freedom and can conduct planned missions independently also can be considered great technology applied in IoUT. The other class of UUVs is remotely operated vehicles (ROV)

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which are powered and operated from a station with a cord or remotely [3].

While AUVs have different designs and types such as gliders, hovering and intervention AUVs, the conventional AUV design is usually in torpedo-like shapes because of its advantages such as flexibility, better acceleration abilities, ease of launch and recovery [4]. AUVs are used in ocean exploration as well as mine counter-measures, deep-sea inspections, marine science, security patrols, pipe maintenance, search and rescue in hazardous environments [5].

Due to the importance of AUV technologies, researchers have sought to improve its effectiveness, part of which involves efficiently solving the path planning control problem which is crucial for many applications including data collection, ocean predictions, and monitoring.

According to [6], the path planning problem is defined as calculating a route to a targeted destination which optimizes stated objective functions with the current state of a single AUV or multiple AUVs and ocean environment details. While solving the path planning problem, the characteristics of the vehicle(s) must be maintained.

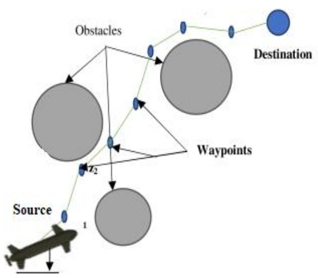

Fig. 1. A typical path planning path for AUV

The objective function to be optimized may be time, energy, or safety depending on the application requirements. Path planning for AUVs has generally been tied to safety conditions. **Fig. 1** shows a typical path planning path for AUV.

1.1 Safety

Safe conditions involve taking a path devoid of obstacles or dangerous areas. 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 their 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 fulfills the safety objective function [7].

1.2 Energy Consumption

Since AUVs have relatively small battery life, the objective is to keep energy consumption minimal. This can be done by simplifying computational complexities, avoiding obstacles and hazardous areas that can cause unwanted errors, finding the shorter path to destinations, or in some cases reduces the speed of AUV.

1.3 Time Travelled

Time is another objective to be optimized. Increasing the speed of AUV at the expense of energy consumption, avoiding obstacles that cause unnecessary details, and finding short paths of travel are some notable ways of minimizing time spent. It is noted that achieving path objective optimization can be interdependent on one another in more cases.

The prediction of paths along with these specified criteria (e.g., time, energy, data collected, and/or safety) optimized as a whole is therefore labeled path planning [8].

Over the last decade, there has been a lot of research and improvement on path planning in both single and multiple AUV applications. However, most of the development path planning algorithms incorporate little machine learning approaches.

This paper reviews the path planning algorithms with machine learning and seeking to establish the trend and find gaps and areas of possible improvements.

2. Machine Learning

Machine Learning algorithms are generally regarded as computer algorithms that can automatically learn and improve from experience without being explicitly programmed. The three main classes of machine learning algorithms are supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning algorithms train a system, based on examples of each category, to differentiate between different categories or classes of input. Common examples of supervised learning include neural networks, supervised regression support vector machines, adaptive boosting among others. In unsupervised learning, a model is developed by grouping similar unlabelled data. A common type is clustering.

In the case of reinforcement learning, data classification is not needed, rather, the agent learns through trial and error and with the concept of reward and punishment in an environment described by the Markov Decision Process. The most common type of reinforcement learning is Q-learning. The process of reinforcement learning was shown in **Fig. 2**.

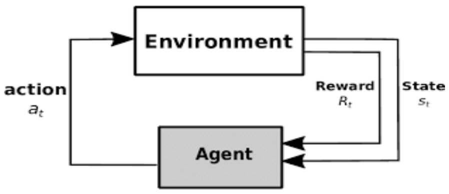

Fig. 2. Reinforcement learning process

2.1 Machine Learning in Path Planning Algorithm

Even though machine learning can assist path planning in other non- planning components of the system like the use of convolutional neural networks (CNN) to automatically segment side-scan sonar (SSS) images in [9] and k-clustering of images for easier computation as shown in [10], the focus this paper is to review the recent path planning algorithms made up of machine learning. The two broad categories of machine learning algorithms used in path planning are neural networks and reinforcement learning.

2.2 Neutral Networks Algorithms

A neural network is a model of a computational network 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, analogous to how electrical signals are passed through biological neurons [11].

Table 1 shows the reviewed neural network algorithms in terms of their deployed environment, method, path cost, objective function, availability of obstacle avoidance, and the number of AUVs present

Table 1. Comparison of Supervised learning path planning algorithms

Authors	Type Of Environment	Method	Type Of Path Generated	Obstacle Avoidance	Path Cost	Single/ Multi
[12]	Unpredictable	BINM Neural Network	Optimal	Achieved	Moderate	Single
[13]	Unpredictable	BINN +Velocity Synthesis	Time &Energy Optimal	Achieved	Low	Multi
[14]	Unpredictable	Dynamic BINN (DBINN)	Energy And Time-Optimal	Achieved	Low	Single
[16]	Predictable	Extreme Learning Machine	Time & Energy Optimal	Achieved	Low	Single
[15]	Unpredictable	Glasius BINN	Time And Energy	Achieved	Low	Single
[17]	Unpredictable And Predictable	ANN +Evolutionary Algorithm	Time And Energy Optimal	Achieved	Low	Single

In [12] a topologically organized bio-inspired neurodynamic model based on a sonar map is constructed to represent the dynamic environment and inspire a collision-free path without any prior knowledge of the environment. [13] used an algorithm that combines the Biological Inspired Neurodynamic Model (BINM) and Velocity Synthesis (VS) to produce shorter search paths and thus reduce energy consumption for multiple AUVs compared to the traditional BINM. [14] deals with the shortcomings of BINN such as high computational complexity and long paths for larger environments and bigger obstacles, using a dynamic BINM.

[15] solves the BINN challenges using a Glasius BINN. In [16] an Extreme learning machine (ELM)s is used to generate an obstacle-free path at a fast speed. [17] combines evolutionary algorithm and artificial neural network to solve multi-objective and multi-stage path planning search operations.

2.3 Reinforcement Learning Algorithms

Reinforcement learning algorithms assume the world is a Markov decision process. An algorithm may try to infer some or all of the MDP by observing the effects of the actions it executes. The resulting estimation of the MDP can then be used to create a policy for future decisions. These types of algorithms are known as model-based methods. In contrast, model-free methods create policies that attempt to maximize reward without modeling the underlying dynamics of the MDP.

2.4 Analysis of Reinforcement Algorithms

Table 2 shows the reviewed reinforcement algorithms in terms of their deployed environment, method, path cost, objective function, availability of obstacle avoidance, and the number of AUVs present.

Han et al [18] use reinforcement learning for the path planning of multiple AUVs alongside an underwater acoustic sensor network for effective monitoring.

In [19], [20], a reinforcement learning algorithm is compared to evolutionary algorithms for path planning. The researchers show that reinforcement learning performs better than the biologically inspired algorithms in higher computational complexity.

Table 2. Comparison of reinforcement learning path planning algorithms

Authors	Type Of Environment	Method	Type Of Path Generated	Obstacle Avoidance	Path Cost	Single/ Multi
[18]	Predictable	Reinforcement Learning	Time And Energy Optimal	Achieved	Moderate	Multi
[21]	Predictable	Reinforcement Learning +Artificial Potential Field	Time-Optimal	Achieved	High	Single
[23]	Unpredictable	Adaptative Dynamic Programming	Optimal	Achieved	High	Single
[22]	Unpredictable	Q-Learning +Path Smoothing Algorithm	Time-Optimal	Achieved	Moderate	Single
[19] [20]	Predictable	Q-Learning And Evolutionary Algorithm)	Optimal	Achieved	Moderate	Single

In [21], reinforcement learning is used for the path planning of intervention AUVs for catching sea urchins in the deep seabed while in [22] reinforcement learning is used in path optimization for a marine vehicle in ocean currents. In [23], the researcher uses a more advanced form of reinforcement learning called adaptive dynamic programming to solve the complex calculations achieving optimal motion control coupled with the least square method.

3. Results Analysis and Recommendations

Based on the reviewed literature from **Table 1**, it is seen there has been more focus on the application of neural networks in single AUVs (83%) than in multiple AUV systems (17%) and the type of environment for the application of neural networks are mainly unpredictable (83%). While all reviewed literature achieved obstacle avoidance, most of them were also both time and energy optimal (83%) in the path generated with every low path cost. Also

For **Table 2**, it is seen also that more focus has been given to single AUV applications (80%) than multiple AUV applications (20%). Just like other machine learning algorithms, obstacle avoidance is achieved, however, few reinforcement learning algorithms (20%) achieve target energy optimization and the path cost of the reinforcement algorithms ranges from moderate to high. It is also noted that the type of environment that applies reinforcement algorithms are 60 %predictable and 40% unpredictable based on the reviewed literature. With this analysis, the following recommendation is given for future study:

There is a need for more research into the use of machine learning in the path planning of multiple autonomous underwater vehicles (cooperative path planning).

Also, from the reviewed literature it shows that reinforcement learning is more energy-intensive than neural network and other machine learning approaches in path planning. There is therefore needed to research more energy-efficient methods of path planning with reinforcement learning.

4. Conclusions

This paper reviews machine learning approaches to path planning. The main machine learning algorithms used in path planning include neural networks and reinforcement learning. While there has been a good amount of research into machine learning approaches in path planning, there are still several milestones to be achieved like energy efficiency with reinforcement learning and effective machine learning approaches in cooperative path planning.

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