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A comparison of optimization techniques for AUV path planning in environments with ocean currents

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HIGHLIGHTS

- A QPSO algorithm is introduced for AUV path planners.
- Important optimization techniques applied to AUV path planning are compared in several test scenarios.
- Monte Carlo trials were also run to analyse the performance of these optimization techniques.
- The weaknesses and strengths of each optimization technique have been stated.

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ABSTRACT

To date, a large number of optimization algorithms have been presented for Autonomous Underwater Vehicle (AUV) path planning. However, little effort has been devoted to compare these techniques. In this paper, an quantum-behaved particle swarm optimization (QPSO) algorithm is introduced for solving the optimal path planning problem of an AUV operating in environments with ocean currents. An extensive study of the most important optimization techniques applied to optimize the trajectory for an AUV in several test scenarios is presented. Extensive Monte Carlo trials were also run to analyse the performance of these optimization techniques based on solution quality and stability. The weaknesses and strengths of each technique have been stated and the most appropriate algorithm for AUV path planning has been determined.

1. Introduction

Path planning for AUVs in the ocean has become crucial for many applications, ranging from security and acoustic surveillance, to collection of ocean data at specific locations, for ocean prediction and monitoring. A path planner should be capable of rapidly reacting to fast changing environments and finding a trajectory that safely leads the AUV from its initial or current position to its destination using either a chosen minimal energy or time-related cost criterion [1].

In the past few decades, a variety of approaches have been developed and applied to the AUV path planning problem. These include Dijkstra's algorithm, A* algorithm, Field D* algorithm, Fast Marching (FM) algorithm, RRT and Artificial Potential Field. Details of these algorithms are presented in Section 2 of this paper. Although several path planning methods have been proposed for autonomous vehicles, several difficulties still remain for AUV-oriented applications. Path planning for AUVs that operate across a large geographical area is a large-scale optimization problem. The computational requirements grow exponentially for high dimensional search space. In order to speed up the planning process and reduce the memory requirement, most conventional path planning approaches project the 3D environment to 2D space. However, this 2D space cannot completely embody all the 3D information, including currents, bathymetry and obstacles of the ocean environment. Evolutionary algorithms have been proven to be an efficient and effective way of dealing with non-deterministic polynomial-time (NP) hard problems [2]. Also, evolutionary algorithms are population based optimization techniques and

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amenable to be implemented on a parallel machine to achieve super linear speed-up with the number of processors [3].

The genetic algorithm (GA) [4–6] and the particle swarm optimization (PSO) [7,8] are two well-known forms of evolutionary algorithms that are generally recognized to be effective optimization techniques for solving path planning problems. Quantum-behaved particle swarm optimization (QPSO) is a new evolutionary algorithm first proposed by Sun et al. [9]. The inspiration of QPSO came from quantum mechanics and the trajectory analysis of PSO [10]. In QPSO, the particle is assumed to have quantum behaviour and to be in a bound state, and is further assumed to be attracted by a quantum potential well centred on its local attractor, thus having a new stochastic update equation for its position [9]. Later, a global point known as the mean best position was introduced into the algorithm in order to enhance the global search ability of the QPSO algorithm [9]. Recently, the QPSO algorithm has been successfully utilized to solve optimization problems in many engineering applications such as electromagnetic design [11], composite structures design [12], engineering design [13], image processing [14], economic power dispatch [15], to name only a few.

In this study, an QPSO based path planner is developed and its performance is compared with other existing path planners based on classic A*, RRT and its improved version RRT*, as well as evolutionary algorithms such as GA, PSO in relation to the problem of finding the optimal trajectory for an AUV. Various scenarios are used to access the performance. Moreover, a thorough robustness assessment is presented for each algorithm to compare the effectiveness of these proposed path planners.

The rest of this paper is organized as follows. In Section 2, a literature review of the optimization techniques for path planning is given. Section 3 describes the path planning missions and formulates the optimization problem. Section 4 introduces path planners based on A*, RRT and improved version RRT*, GA, PSO and QPSO methods. The simulation tests and robustness assessment using Monte Carlo trials are presented in Section 5. Conclusions are then presented in Section 6.

2. Literature overview

This section presents a detailed literature review of the state-of-the-art AUV path planning techniques with discussion of their assumptions and drawbacks. A brief comparison of path planning techniques for AUV is available in Table 1. Two important properties of path planning algorithms are the completeness and the optimality of the algorithm. Two forms of completeness are probabilistic completeness and resolution completeness. An algorithm is called Resolution completeness if it is guaranteed to find an existing solution in finite time as long as the resolution of an underlying grid is fine enough. Most resolution complete planners are graph search methods such as Dijkstra, A* and Field D*. In contrast, an algorithm is considered probabilistically complete if the probability of finding a path approaches 100%. Several sample-based methods, such as RRT and evolutionary algorithms are probabilistically complete. The performance of a probabilistically complete planner is shown by the rate of convergence. Optimality is the property that the planner computes the optimal path with respect to some criterion, e.g., minimal time, energy consumption or distance. Probabilistic optimality and resolution optimality are similarly to the definition of probabilistic completeness and resolution completeness.

- **Graph search schemes**

Graph-based methods are a classical path planning approach that lies in the category of Discrete Optimal Planning [27]. A grid-shape graph represents the search space with the edges labelled indicating the cost of travelling from a vertex to one of its neighbours. Dijkstra's algorithm is probably the first graph method adapted to search for a minimum cost paths, it computes every possible path from a starting point to a specified destination point [16]. With its heuristic searching ability, the A* algorithm [28] has proven to be more efficient. The heuristic function provides an estimate of the cost of the best route that passes through a particular node. The algorithm keeps track of the cost of the route leading up to a particular node along with the heuristic cost function to determine which node it must visit next. Carroll et al. [17] applied A* on a quad-tree search space, which was adapted to the ocean currents field, i.e. it has higher resolution where the ocean currents vary more spatially; or more formally, where the gradient of the ocean currents is greater. Overall, these grid-based graph search method are commonly criticized for their discrete state transitions which unnaturally constrain the motion of a vehicle to limited directions. There exists a number of variants of A* that are worth mention. Any-angle methods, like Theta* [29,30], try to obtain shorter paths alleviating the angle discretization problem caused by the search grid. The Field D* algorithm uses a linear interpolation-based method to allow continuous heading directions, but these variants of A* still not fix the problem of computationally expensive to employ in high-dimensional problems [18].

- **Fast Marching and Level Set Methods (FM & LSM)**

The FM algorithm can be regarded as a continuous version of Dijkstra's algorithm. It uses a first order numerical approximation of the nonlinear Eikonal equation. FM algorithm have been recently applied for AUV path planning by [31]. A heuristically guided version of FM, known as FM*, maintains the accuracy of the FM algorithm along with the efficiency of the A* algorithm; however it is limited in that it uses a linear anisotropic cost function to improve the algorithm computational efficiency. The FM* scheme is improved in [32] by using wavefront expansion to calculate shortest time paths and also determines the departure time of the vehicle from the starting point. The LSM is a more general technique than the Fast Marching algorithm for wavefront expansion [33]. This method had been applied for path planning in flow fields. The time-optimal path is generated by solving a particle tracking equation backward in time after it evolves a front from the vehicle's start location until it reaches the goal [20]. The level set method provides the ability to solve more complex problems, but it takes longer computation time than Fast Marching.

- **Artificial Potential Field (APF)**

An artificial potential field for global path planning based on a linear energy cost-function was originally proposed by Warren [21]. Since then, it has been widely used by the robotics community and many problem specific developments have been made to this algorithm [34]. The key idea of this approach is to introduce an artificial potential field on the obstacles that prevents vehicles from getting very close to them, thus, generating safe paths. Kruger [22] then replaced the single term cost-function with one that incorporates a mixture of various linear terms, including energy, obstacle regions, distance, time and excess speed. Potential fields have also been used for underwater path planning in [8] with a cost function measuring the total drag experienced by the vehicle, total travel time and any obstacles in the field. After generating a feasible set of tracks, an optimization is performed on these tracks. This algorithm has the advantage of being inexpensive, thus allowing for easy real-time computations to adapt the vehicle path. However, it has the drawback of producing locally optimal solutions. Another problem with potential field methods is their adaptation to dynamic ocean currents. It is very inefficient to re-compute the potential field for the whole map for each time instant.

- **Rapidly-exploring Random Trees (RRT)**

Rapidly-exploring Random Trees (RRT) have also been used to solve the path planning problem. RRT incrementally grow a