## Evaluation Form – Technical Background Review

**Student Name:** Luis Pimentel

**Project Advisor:** Dr. Micheal West

**Team Name:** APPL River Robot Team 4

**Team Members:** Tan Tonge, Jin Bae, Alexander Chantaphaeng

_______ / 30 Technical Content

- Current state-of-the-art and commercial products
- Underlying technology
- Implementation of the technology
- Overall quality of the technical summary

_______ / 30 Use of Technical Reference Sources

- Appropriate number of sources (at least six)
- Sufficient number of source types (at least four)
- Quality of the sources
- Appropriate citations in body of text
- Reference list in proper format

_______ / 40 Effectiveness of Writing, Organization, and Development of Content

- Introductory paragraph
- Clear flow of information
- Organization
- Grammar, spelling, punctuation
- Style, readability, audience appropriateness, conformance to standards

**_______ / 100 Total - Technical Review Paper**

**Path Planning for Autonomous Surface Vehicles**

## Introduction

Autonomous Surface Vehicles (ASVs) provide a platform for deploying maritime-sea applications in river, lake, and sea environments. These can range from industrial applications in international commerce shipping, to applications in sea-life monitoring and pollution reduction. While humans have navigated water environments for centuries, the advent of robotics technologies has allowed autonomous operation of these water vessels with the goal of reducing personnel cost and improve safety by eliminating human error. Key to enabling these autonomous capabilities is the technology of path planning that allows an ASV to autonomously plan a route within its environment. This technical review offers an overview of the industrial and government applications enabled by path planning for ASVs, a problem formulation that is key to understanding path planning, and a brief discussion of state-of-the-art path planning algorithms currently being implemented on ASVs.

## The Autonomous Surface Vehicle Market

### *Industry*

Path planning has enabled the autonomous operation of maritime applications that previously required supervised and manned operation. This has led to an unprecedented growth in the ASV market, as reports find that its global market is expected to grow 13.2% from $522.6 Million USD in 2020 to $1.2 Billion USD by 2027 [1]. Commercial applications for ASVs are used in the shipping industry, which transports commercial goods through international waters, often navigating complex and challenging environments. A Norwegian company, Wilhelmsen and Kongsberg Maritime, is leading the effort by introducing the world's first autonomous shipping company [2]. Furthermore, investments to advance safety capabilities in ASV technologies has been made by companies such as Intel and Rolls Royce [3]. Similarly, human-interaction applications for ASVs are also prominent in industry, as shown by Rolls Royce and Finferries' Autonomous Ferry that aims to transport people autonomously through water [4].

### *Government*

The ASV market also includes the government, through the defense industry which has made large investments in advancing these technologies for military applications. A Congressional Research Service Report shows that the US Navy has requested $579.9 million in FY2021 research and development funding to develop and enable autonomous navigation technologies of ASVs and similar autonomous maritime vehicles [5]. Furthermore, government interest in ASV applications is also related to environmental issues and research. For example, the UK based National Oceanography Centre has deployed a fleet of ASVs to autonomously navigate the UK's seas in search for marine animals, sea pollution, and to collect scientific research data related to oceanography [6].

## The Path Planning Problem

### *Problem Formulation*

We begin by defining the path planning problem as a problem that aims to find a series of waypoints that allow an ASV to travel from its starting position to its goal position [7]. In order to begin solving this problem, the ASV must understand its environment through sensory information. Examples of these sensor can include stereo vision cameras, thermal imaging cameras, LIDAR, and marine radar [8]. The scope of this review does not cover how the ASV interfaces with these sensors, but we assume that they are used to build a *roadmap* that encapsulates physical obstacles and other environmental constraints under which the ASV must navigate. Given this *free configuration space* [9] – the state space that is achievable by the ASV given the obstacles and constraints of its environment – the *path planner* can search through this space to find a geometrically achievable and (optionally) optimal path. Given this, we must break up the path planning problem into two sub-problems: *global planning* and *local planning* [7]. The goal of global planning is stated as before: to find a route between a starting state and a goal state given the *entire* free configuration space. The local planning problem differs from this in that it is only concerned with the local configuration space of the robot, considering dynamic obstacles that may be present as an ASV is following a global plan. This allows the ASV to deviate from the original plan, in order to avoid the obstacle, and then for it to re-route back to the original global plan. While these subproblems are similar, the literature around path planning distinguishes heavily between them. This creates an interesting paradigm where very different algorithms and techniques can be used between two very similar problems. This makes path planning an exciting and active research field.

### *Control, Navigation and Guidance*

It is important to understand that path planning itself is a subproblem of the entire architecture that enables autonomous navigation for ASVs. To fully appreciate path planning, it must be placed in the context of the *Control, Guidance, and Navigation* modules of this architecture [7]. The *control module* in this architecture deals with generating time-based trajectories between waypoints found by the path planner, and considers the dynamics and control allocation of the ASV. The *guidance module* is where path planning resides, with the ability to detect targets, detect obstacles, and generate waypoints through global and local path planning. Finally, the *navigation module* consists of processing sensor data to perform state estimation, environment perception and situational awareness for the ASV. This architecture is a top-down approach as the navigation module informs the guidance module, which then informs the control module.

## Path Planning Algorithms

In this section we briefly describe how various path planning algorithms work. As in Vagale [10], we classify these algorithms under two approaches: *classical* and *advanced*. In classical algorithms, the free configuration space is represented as a graph of connected nodes that the planning algorithm must search through in order to find a path. Meanwhile, advanced algorithms are more novel and incorporate advanced techniques from fields such as control theory and machine learning.

### *Classical Approach*

One classical algorithm that has been implemented on ASVs is the Dijkstra Algorithm [11]. In this algorithm a map of the environment is received and turned into a grid-space representation. The cells of this grid are then turned into nodes of a graph where connectivity between nodes represents feasible transitions from one free-configuration state to the next. The Dijkstra Algorithm computes the shortest path from the start node (the initial state of the ASV in the grid-map) to every other node in the graph. With this we can return an optimal path any goal node (the goal state in the grid-map). This kind of algorithm is suitable for global path planning in a *static* environment. To deal with more complex and dynamic environments, sampling-based planning algorithms such as Rapidly Random Exploring Trees (RRT) have been implemented on ASVs to rapidly generate kino-dynamically feasible paths [12]. This algorithm also works by representing the free configuration space as nodes in a tree-based graph. First, given a starting node (the ASV's initial state), a node in the free configuration space is *randomly sampled*. Then, the vehicle is *steered* from the nearest node in the tree towards this new node given the kino-dynamics of the ASV. The resulting node is added to the overall tree, thus creating a possible path. This process is repeated until the ASV reaches the goal state through one of these possible paths.

### *Advanced Approach*

There are new advanced algorithms that utilize advanced techniques from the field of control theory to do local planning. One such algorithm implements *model predictive control* for local planning on an ASV [13]. This algorithm uses an advanced model for the dynamics of the ship's steering and propulsion system, the dynamics of forces due to wind and ocean current, and the dynamics of obstacles in the environment to do local planning. This algorithm is very robust to complex environments, dynamic obstacles, and uncertainty associated with sensors and predictions. However, these methods require an extensively known model of the entire system under consideration. To circumvent this problem, techniques from machine learning theory such as *deep reinforcement learning* have been used to implement algorithms for local planning on ASVs [14]. These algorithms use deep neural-networks to learn a model that can do local planning with no knowledge of the internal dynamics of the ASV, or the environment. This approach has high adaptability and robustness to previously unknown and complex environments and does not require extensive modeling.

[1] Global Industry Analysts, Inc, “Unmanned Surface Vehicle (USV) - Global Market Trajectory & Analytics,” Tech. Report. 4806204, July 2020

[2] Kongsberg Group, “Wilhelmsen and KONGSBERG establish world's first autonomous shipping company,” *kongsberg.com*, Apr. 3, 2018 [Online]. Available: https://www.kongsberg.com/newsandmedia/news-archive/2018/wilhelmsen-and-kongsberg-establish-worlds-first-autonomous-shipping-company/. [Accessed Mar. 7, 2021].

[3] Roll-Royce, “Rolls-Royce and Intel announce autonomous ship collaboration,” *www.rolls-royce.com*, Oct. 15, 2018. [Online]. Available: https://www.rolls-royce.com/media/press-releases/2018/15-10-2018-rr-and-intel-announce-autonomous-ship-collaboration.aspx. [Accessed Mar. 7, 2021].

[4] Roll-Royce, “Rolls-Royce and Finferries demonstrate world’s first Fully Autonomous Ferry,” *www.rolls-royce.com*, Dec. 3, 2018. [Online]. Available: https://www.rolls-royce.com/media/press-releases/2018/03-12-2018-rr-and-finferries-demonstrate-worlds-first-fully-autonomous-ferry.aspx

[5] R. O'Rourke, “Navy Large Unmanned Surface and Undersea Vehicles: Background and Issues for Congress” Tech. Report. R45757, Feb. 25, 2021

[6] The National Oceanography Centre (NOC), “Welcome to Marine Autonomous Systems in Support of Marine Observations (MASSMO), ” *projects.noc.ac.uk*, [Online]. Available: https://projects.noc.ac.uk/massmo/. [Accessed Mar. 7, 2021].

[7] A. Vagale, R. Oucheikh, R. T. Bye, et al., “Path planning and collision avoidance for autonomous surface vehicles I: a review” in *Journal of Marine Science and Technology,* vol 26, no. 1, Mar. 2021 doi: 10.1007/s00773-020-00787-6

[8] P. Robinette, M. Sacarny, M. DeFilippo, M. Novitzky and M. R. Benjamin, "Sensor Evaluation for Autonomous Surface Vehicles in Inland Waterways," in *OCEANS*, 2019, pp. 1-8, doi: 10.1109/OCEANSE.2019.8867468.

[9] S. M. Lavelle, *Planning Algorithms*, *1st ed.*, Cambridge*:* Cambridge University Press, 2006, pp. 79

[10] A. Vagale, R. Oucheikh, R. T. Bye, et al., “Path planning and collision avoidance for autonomous surface vehicles II: a comparative study of algorithms,” in *Journal of Marine Science and Technology*, vol 26, no. 1, Mar. 2021, doi: 10.1007/s00773-020-00790-x

[11] Y. Singh, S. Sharma, R. Sutton & D. Hatton, “Towards use of Dijkstra Algorithm for Optimal Navigation of an Unmanned Surface Vehicle in a Real-Time Marine Environment with results from Artificial Potential Field,” in *The International Journal on Marine Navigation and Safety of Sea Transportation*, vol 12, no. 1, Mar. 2018, doi: 10.12716/1001.12.01.14

[12] H. L. Chiang and L. Tapia, "COLREG-RRT: An RRT-Based COLREGS-Compliant Motion Planner for Surface Vehicle Navigation," in *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 2024-2031, July 2018, doi: 10.1109/LRA.2018.2801881.

[13] T. A. Johansen, T. Perez and A. Cristofaro, "Ship Collision Avoidance and COLREGS Compliance Using Simulation-Based Control Behavior Selection With Predictive Hazard Assessment," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 12, pp. 3407-3422, Dec. 2016, doi: 10.1109/TITS.2016.2551780.

[14] E. Meyer, A. Heiberg, A. Rasheed and O. San, "COLREG-Compliant Collision Avoidance for Unmanned Surface Vehicle Using Deep Reinforcement Learning," in *IEEE Access*, vol. 8, pp. 165344-165364, 2020, doi: 10.1109/ACCESS.2020.3022600.