Ocean Engineering 129 (2017) 301–317

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

A multi-layered fast marching method for unmanned surface vehicle path planning in a time-variant maritime environment

Rui Song, Yuanchang Liu*, Richard Bucknall

Department of Mechanical Engineering, University College London, Torrington Place, London WC1E 7JE, UK

ARTICLE INFO

Keywords:
Anisotropic fast marching
Marine environment
Path planning
Surface currents
Unmanned surface vehicle

ABSTRACT

Concerns regarding the influence of the marine environment, such as surface currents and winds, on autonomous marine vehicles have been raised in recent years. A number of researchers have been working on the development of intelligent path planning algorithms to minimise the negative effects of environmental influences, however most of this work focuses on the platform of autonomous underwater vehicles (AUVs) with very little work on unmanned surface vehicles (USVs). This paper presents a novel multi-layered fast marching (MFM) method developed to generate practical trajectories for USVs when operating in a dynamic environment. This method constructs a synthetic environment framework, which incorporates the information of planning space and surface currents. In terms of the planning space, there are repelling and attracting forces, which are evaluated using an *attractive/repulsive vector field construction process*. The influence of surface currents is weighted against the obstacles in the planning space using a *4-regime risk strategy*. A trajectory is then calculated using the anisotropic fast marching method. The complete algorithm has been tested and validated using simulated surface currents, and the performance of generated trajectories have been evaluated in terms of different optimisation criteria, such as the distance and energy consumption.

1. Introduction

Unmanned surface vehicles (USVs) can be used in various marine applications. When operating individually, USVs can be deployed in pollutant tracking missions (Xu et al., 2006) as well as environmental and hydrographic surveys (Caccia et al., 2005). In addition, when collaborating with autonomous underwater vehicles (AUVs), a USV can be used as the mother ship to monitor a mission (Alves et al., 2006) and as a platform for the launch and recovery of AUVs (Ferreira et al., 2006). To successfully complete such missions, it is necessary to improve reliability and autonomy of the USV.

Path planning is a critical part in the USV's development, with the aim of using the algorithm to determine the optimal trajectory to guide the USV's voyage. It not only determines the level of autonomy of the vehicle, but it is also the premise of the reliability of a mission and the likelihood of success (Statheros et al., 2008). When developing the algorithm, factors such as the total path distance as well as safety are main concerns (LaValle, 2006). In addition, the quality of the generated trajectory, such as smoothness and continuity, also needs to be taken into account (Smierzchalski, 1999). Path planning algorithms can be generally divided into two categories: the pre-generative approach (path generated prior to launching the USV), such as Chen et al. (1995), and the reactive approach (path generated while the vehicle is *en route*), such as Kamon and Rivlin (1995), which is regarded as the 'dynamic path planning approach'. To calculate the path, different computational methods can be applied such as genetic algorithms (GAs), graph search techniques and artificial potential field methods amongst others.

GAs generate a population of possible paths which are evolved iteratively, using genetic operators (such as the mutation and crossover) (Goldberg, 1989) to pursue optimal results. However, drawbacks to GAs include a lack of convergence, which means the generated path may be suboptimal, as well as a lack of consistency, which makes the vehicle's trajectories difficult to track.

Compared with GAs, graph search techniques such as A* and Dijkstra's methods have better consistency and convergence because they use a discretised representation of the environment, known as a grid map. However, as a result of the non-holonomic constraint of the vehicles, a further path smoothing procedure is needed (Petres et al., 2007). Moreover, the computational time can be potentially high. The computational time is proportional to the number of grid points on the map, which is in turn dependent on the resolution of the graph (finer or coarser). Rapidly exploring random tree (RRT) approaches introduced by LaValle (1998) do not need to explicitly set any resolution

* Corresponding author.
E-mail address: yuanchang.liu.10@ucl.ac.uk (Y. Liu).

http://dx.doi.org/10.1016/j.oceaneng.2016.11.009
Received 26 February 2016; Received in revised form 17 September 2016; Accepted 12 November 2016

Nomenclature

Roman symbols

A	a matrix that determines the strength of the simulated currents data
AR	anisotropic ratio
C	a constant equalling to ρ/c
c	the nominal speed of the USV
C_{free}	collision-free space
C_{obs}	obstacle space
C-$space$	configuration space
D_{att}, D_{rep}	attractive and repulsive potential fields
D_{cum}	the length of ith path segment
d_i	the length of ith path segment
d_{SA}	the minimum distance that the USV should keep away from the obstacle
$e_{\vec{p}}$	the unit vector of USV heading at $\vec{p}$
$\boldsymbol{F_{att}}$, $\boldsymbol{F_{rep}}$	attractive and repulsive vector fields
$\boldsymbol{F_{base}}$	base layer vector field
$\boldsymbol{F_{env}}$	environment layer vector field
$\boldsymbol{F_{syn}}$	synthetic vector field
h	step size
J	the integration of the relative velocity of USV to the surface currents
$\vec{M}$	intersection point of the optimal path and $\vec{p_i}\vec{p_j}$
min_Obs	the minimum distance to the obstacles
$\vec{n}$	local ellipse direction
$\vec{p}$	grid point position
$\vec{p}_i$, $\vec{p}_j$	neighbouring points of $\vec{p}$
$\vec{p}_{obs}$	obstacles' locations
$\vec{p}_{start}$, $\vec{p}_{goal}$	positions of start and goal points
r	wave propagation speed along θ
R_{β_1,β_2}	risk regime
r_a, r_b	major and minor radii along the X and Y axes of the local ellipse frame
$\vec{r}_a$, $\vec{r}_b$	the major and minor axes of the local ellipse frame
Δt	time step
$U(\vec{p})$	wave arrival time at $\vec{p}$
$u_{\vec{p_i}\vec{p_j}}(\vec{p})$	temporary cost at $\vec{p}$
$\boldsymbol{V_u}$, $\boldsymbol{V_v}$	two orthogonal components of currents vector field
W	the total energy cost
W_i	the power consumption at each position

Greek symbols

α	propagation scale limit
β_1, β_2	field weightings of $\boldsymbol{F_{env}}$ and $\boldsymbol{F_{base}}$ respectively
φ	angle between $\vec{n}$ and X axis
ρ	the water density
$\tau(\vec{p})$	wave propagation speed related to $\vec{p}$
$\tau(\vec{\theta}(t))$	wave propagation speed related to $\vec{p}$ and orientation
$\vec{\theta}(t)$	cost/speed vector

parameters so the RRT method has the ability to explore the environment space quickly and uniformly using a random sampling scheme. However, the RRT approach is not suitable in the scenario of dynamic path planning as they are incapable of providing a global optimal solution with the least distance cost (Lolla et al., 2014).

Potential field algorithms search the path by constructing an artificial potential field (APF) to weigh the influences of obstacles and goal points (Andrews, 1983; Khatib, 1986). These algorithms are computationally efficient, but are susceptible to the local minima problem (the vehicle can be trapped in a U-shaped obstacle) (Andrews, 1983). To address the defect of these algorithms, Wu et al. (2015) have proposed a modified APF method to improve the performance of path planning. The local minima problem has been addressed by integrating a wall-following method, which enables the vehicle to move away from the 'trapped' point by following the edge of the obstacle. In addition, a combinatorial strategy has been proposed by combining the APF with the ant colony optimisation (ACO). The ACO is utilised for global path planning with the generated path being used as the primary guidance route. When the vehicle encounters a moving obstacle, or experiences a change of the environment, the APF will be used as a local path planner to modify the path and avoid collisions. However, such an algorithm may increase the computational burden because additional algorithms are added. An alternative is to create the potential field which has no local minima. Garrido et al. (2008) therefore applies the fast marching (FM) method to construct such a field by simulating electromagnet wave propagation. The wave starts from the mission start point and continues to iterate until reaching the end point. The generated field will only have one global minima point which is located at the start point with the potential value being 0.

It should be noted that the majority of the aforementioned studies focus on generating a collision free path but ignore environmental impact on the vehicles. The marine environment is an uncertain, complex and volatile space which impacts path planning as evidenced from experiments carried out by Song (2014) when a discrepancy caused by surface currents was found to exist between a planned path and the actual trajectory track taken by a USV. Such discrepancy can jeopardise marine vehicles' missions, especially when vehicles have limited operating speed and relatively small dimensions and displacements. It is therefore very important to consider the influences of environmental factors when developing the path planning algorithms for marine vehicles.

Agarwal and Lermusiaux (2011) used the level set method to solve the environmental influence problem for AUV path planning. Petres et al. (2005) used the anisotropic fast marching (AFM) method to address similar problems but in an environment where relatively stronger currents exist. The AFM is an improved version of the FM method with higher computational efficiency than the level set method (Agarwal and Lermusiaux, 2011). Also, the optimal collision free path generated by the AFM is able to provide the guaranteed convergence, which has been intuitively explained in Konukoglu et al. (2007) and mathematically proven in Mirebeau (2014). However, these studies have only been applied on AUV platforms, where only the constraints of deep ocean currents and collision avoidance (limited distance to the obstacles) are considered. For surface vehicle navigation, additional constraints such as wind, tidal currents and traffic regulations such as COLREGs also need to be considered, for which the conventional AFM cannot implement.

To address the shortcomings, an improved AFM named as the multi layered fast marching (MFM) method has been proposed with initial work presented in Song et al. (2015). However, the improved AFM only considers a time-invariant environment with no surface currents changes. Additionally, an obstacle's impact on the USV is assumed to be uniform regardless of location changes. In this paper the framework has been improved by adding a geometrical analysis to assist with minimising the negative effects from both physical obstacles (coastal lines and islands) and environmental factors, such as currents and wind. An *attractive/repulsive vector field construction process*, a *4-regime risk strategy* and two *operation handlers* have been developed to process and evaluate the environmental conditions. These modifications make important improvements to the method with the main focus being on generating a feasible trajectory in the presence of dynamic