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Optimal Path Planning of Unmanned Surface Vehicles

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Abstract

The ever increasing number of unmanned marine vehicles in the ocean environment has led to the need for efficient and optimal path planning of such vehicles. This paper summarises current methodologies adopted for optimal path planning of single unmanned surface vehicles and studies associated with swarm of unmanned surface vehicles. This review also discusses the challenges and scopes, which can act as objectives, for future research towards path planning of such marine craft.

Keywords: Optimisation, Path Planning, Swarm, Unmanned Surface Vehicles

Introduction

In the present economic world order, there is a greater need of exploring oceans for resources as well as for future needs. Historical ice coverage of Arctic in September 2007[1] and in situ data collected from surface vehicles directing improvements in weather forecasting[2] have shown the potential of marine vehicles towards outlining range of future missions. Marine vehicles of various classes are used for such missions based upon the requirement, environment and cost involved. Most unmanned surface vehicles (USVs) possess low payload and endurance capability. In order to overcome these short comings, it is important to move them cooperatively as a fleet to perform operations. The benefits include wide mission area, improved system robustness and increased fault-tolerant resilience[3].

Marine vehicles can be broadly classified as shown in Figure 1. This classification is based on the displaced volume of the vehicles. Each class of vehicles require different autonomy due to diverse nature of their missions and uncertainties involved in their operational environments. Trans-oceanic voyages of ships, as well as, mission-oriented small time voyages of USVs encounter various obstacles and uncertain environments. Research and development in areas of artificial intelligence, advanced smart sensors, wireless networks and optimisation techniques provide larger scope for contribution in areas of maritime technology[4-5]. The present paper summarizes the literature related towards optimal path planning of single USVs and studies related to swarm of USVs.

Fig.1 here

The paper has been organised in its four sections. The section after the introductory material comprises of the compilation of notable developments towards optimal path planning of USVs. Next consideration is given to the review of studies towards operation of multiple USVs in a marine environment. Within the third section, the challenges and scope towards future study in the area of path planning of USVs is considered. Conclusions of the review study are explained in the final section.

Materials and Methods

Classification and Architecture of USVs

Unmanned vehicles can be classified into four categories namely, unmanned aerial vehicles (UAVs), unmanned underwater vehicles (UUVs), unmanned ground vehicles (UGVs) and unmanned surface vehicles (USVs). USVs are watercraft of small (<1 tonnes) or medium (100 tonnes) size in terms of water displacement. The technology of USVs dates back to World War II but major efforts towards development and understanding the technology started in the 1990s after the successful implementation of USVs in the 1990-1991 Gulf war[6]. Basic purposes of USVs are military, surveillance, environmental monitoring, ocean and scientific research and exploration of hydrocarbons.

Classification and developments of USVs based on their application has been explained by Motwani[7] and shown in Figure 2. A few USV prototypes are shown in Figure 3.

The general architecture of USV operation in maritime environment has three basic systems namely, control and path planning, communication and monitoring and obstacle detection and avoidance (ODA), which are responsible for mission planning and execution as shown in Figure 4. The present policies and law do not allow operation of USVs in maritime environment with the risk of injury and property damage[8]. This leads to the requirement of development of path planning techniques in compliance with International regulations for Avoiding Collisions at Sea (COLREGs). Owing to technical similarities in UGVs and USVs i.e. similar degree of freedom, similar uncertain environment etc. compared to UAVs, path planning techniques can be extended from mobile robots to surface vehicles.

Fig.2 here

Fig.3 here

Fig.4 here

Environmental Mapping

In order to implement the path planning techniques, mapping the environment becomes the initial step. Environment mapping can be qualitative or quantitative and converts world space into configuration or Cspace [9]. The reduction of a physical space in Cspace helps in quick implementation of algorithms and manageable storage in computers. The Cspace for marine vehicles are dynamic in nature and are highly variable, spatially as well as temporally. Effect of current, winds, tides, etc. needs to be incorporated into mapping so that a robust virtual real-time environment in the simulation can be generated. Qualitative mapping comprises of nodes and arcs, with vertices representing features or landmarks while quantitative mapping comprises of data structures based on way -points or sub-goals [5]. Qualitative and quantitative form of spatial representation is shown in Figure 5. The abstraction of path planning is shown in Figure 6.

Fig.5 here

Qualitative representation expresses space in terms of connections between landmarks and dependent upon perspective of robot while quantitative representation express space in terms of physical distances of travel and present bird's eye view of the world. Quantitative representation can be used to generate qualitative representation and is independent of orientation and position of robot.

Fig.6 here

Popular mapping techniques are meadow maps, Voronoi diagrams, regular occupancy grid and quadtree mapping and are shown in Figure 7 which are grid-based or metric techniques on which heuristic and evolutionary optimisation methods can be applied effectively. These mapping techniques transform space into a physical space having co-existence of robot and obstacles. Meadows map transform the space into convex polygons, which represent safe regions for robot to traverse, and involves selection of best polygons to transit. The midpoints marked on convex polygons become graph nodes for the path planner. Voronoi diagrams are a popular mechanism for representing Cspace and are constructed through generation of Voronoi edges equidistant from all points and their meeting point is called vertex. The vehicle follows Voronoi edges to avoid collision. Regular occupancy grids are generated through superimposition of 2D Cartesian grid on Cspace. The centre of each element in the grid becomes a node leading to highly connected graph. Owing to high storage cost of regular occupancy grid, in quadtree mapping, Cspace is represented with a large 2D grid size with grids, in which the vehicle moves, is subdivided into smaller grids. A detailed explanation can be found in Mooney[10]. Higher computational requirement is a major drawback of such techniques against local path planning techniques. This requirement increases with the representation of the environment with finer grids. Incomplete representation of various real time maritime environments is a major deficiency with these algorithms. Most path planning studies in USVs are restricted with validation of path planning algorithms in such a self-generated environment than in real time environment[3]. A novel study Gadre et al.[11] proposed a method to generate topological maps of the natural environment for path planning algorithms to generate dynamically feasible trajectories in a short time. This method of generating environment is still not tested in motion planning of USVs and provides an exciting prospect towards more realistic simulations for path planning.

In order to generate a map of a real-time environment, simultaneous localisation and mapping (SLAM) is adopted which becomes the basis for path planning techniques. A sensor provides topographical data of the region where vehicle is operating and global path planning techniques are applied to find optimal routes. SLAM and path planning are co-requisites towards increasing autonomy and efficiency of USVs operation in the marine environment.

Fig.7 here

A detailed review of SLAM and its various modules for autonomous mobile robots is explained in Dhiman et al. [12].The feasibility of SLAM in the absence of GPS-based communication for a USV by building and incorporating parametrized map of a bridge pier structure within obstacle detection and avoidance algorithm was demonstrated by Han and Kim[13] and validated with outdoor experiments. In these operations, sensors are prone to noise and errors and there is a requirement of high storage space to collect the continuous data coming from sensors. Along with this, extensive computation is required to process and map the data. Some studies like Park et al.[14]and Zeng et al.[15] have adopted a hybrid approach of mixing quantitative and qualitative approaches to counter the extensive data and noise from sensors[5].

Global and Local Path Planning

The second stage after mapping the environment is the application of path planning techniques. Path planning techniques for USVs can be divided into local and global approaches. The classification is shown in Figure 8. Offline or global approach is used when complete information the marine environment is known while the online or local approach is used when marine environment keeps changing during navigation of marine vehicles. Global approaches comprise of evolutionary and grid based methods. Evolutionary methods are adopted and mimicked from nature while grid based methods search for optimality within a configuration space. Evolutionary approaches have the advantage of handling multi- objectives in path planning although convergence of such methods is not guaranteed in a finite time and one ends up in a sub-optimal solution. Grid based methods are effective in finding optimal solutions in a configured environment although extensive computation does not allow effective real-time implementation in a complex or larger environment. Local approaches are suitable for real-time implementation but solutions can get trapped in local minima.

All path planning techniques are subjected to finding obstacle free path in a Cspace with certain optimisation objectives. Such objectives vary for single and multiple USVs. Figure 9 shows path planning objectives for single and multiple vehicles.

Fig.8 here

COLREGs in Path Planning of USVs

Finding optimal and collision-free trajectories in a dynamic ocean environment with multiple USVs operating is a major technical challenge. Towards this, International Collision Regulations (COLREGs, 1972) was introduced by International Maritime Organisation (IMO) [16-18] to be followed by all maritime organisations around the world and explained in detail by Coldwell[19] and Cockroft and Lameijer[20]. Most path planning studies are concerned with a single USV and take into account time and external collision avoidance as optimisation objectives. Collision avoidance strategies need to adhere to COLREGs. A notable review comprising of research conducted in the past decades towards path planning algorithms of marine vehicles and their development in compliance with COLREGs can be found in the work of Tam and Bucknall[21].Optimal trajectories are generated by heuristic and grid-based method but in order to implement COLREGs, it becomes important to search for feasible trajectories than the optimal one. A detailed review towards motion planning and obstacle avoidance for a USV can be found in work of Statheros et al.[22]. Most studies have only considered four basic rules of COLREGs for incorporation in the path planner for USVs for increased autonomy. This is owing to the fact of the trade-off between full autonomy, computational time, complexity, real-time implementation and diverse range of missions. These four rules are listed below [5]:

1. **Rule 14 - Head-on Situation**: When two power-driven vessels are meeting on reciprocal or nearly reciprocal courses so as to involve risk of collision, each shall alter her course to starboard so that each shall pass on the port side of the other. See Figure 10(b).
2. **Rule 15 - Crossing Situation**: When two power-driven vessels are crossing so as to involve risk of collision, the vessel which has the other on her own starboard side shall keep out of the way and shall, if the circumstances of the case admit, avoid crossing ahead of the other vessel. See Figure 10(c).
3. **Rule 16 – Action by give-way vessel**: Every vessel which is directed to keep clear of another vessel shall, so far as possible, take early and substantial action to keep well clear.
4. **Rule 17 – Action by stand-on vessel**: Where one of two vessels is to keep out of the way, the other shall keep her course and speed. The latter vessel may, however, take action to avoid the collision by her manoeuvre alone, as soon as it becomes apparent to her that the vessel required to keep out of the way is not taking appropriate action in compliance with these rules.

Lee et al.[23] used a fuzzy logic approach for navigating a USV in a dynamic environment in compliance with COLREGs. Benjamin et al.[24] presented rules of navigation for USVs complying to COLREGs using a multi-objective optimization method, Interval Programming. Four basic rules of

COLREGs were incorporated through four objective functions and feasible trajectories were generated. The proposed method was validated with two kayaks in a real time operation. Zhuang et al.[8] used a velocity obstacle concept to develop an obstacle-free path planning algorithm for USV navigation, complying to rule 14 and rule 15 of COLREGs. Naeem et al.[25] proposed a direction priority sequential selection (DPSS) based path planner in compliance with Rule 14 of COLREGs for way point navigation of an USV. The proposed method was tested in various scenarios of static and dynamic obstacles in the simulation. Svec et al.[26] proposed a model predictive trajectory planning complying with reactive obstacle avoidance (ROA) and deliberative obstacle avoidance (DOA) and in compliance with COLREGs. Results obtained from simulations were verified with the experiment on a USV platform. Xie et al.[27] simulated an obstacle avoidance approach using a modified artificial potential field approach whereas Zhang et al.[28] also proposed a novel navigation algorithm for USVs based on Sarsa on-policy reinforcement learning algorithm in complicated marine environments.

Fig.9 here

Fig.10 here

DOA and ROA based Navigation of USVs

Most path planning techniques work in conjugation with the navigation sub system. Most path planning techniques follow way point navigation and are subjected to DOA and ROA approach to ensure a robust autonomous architecture for USV operation in real time. DOA refers to far field obstacle avoidance approach where the environment is determined using long range sensors while ROA refers to near field approach where the environment is determined using short range sensors. Most path planning techniques are simulated and tested offline with an assumption that sensors incorporated on USV for DOA and ROA will provide correct information of the environment during which motion and path planning algorithms will take corrective measures to avoid the collision. . For effective implementation, design of a robust control system is required to follow the generated path. First real-time implementation of obstacle avoidance using wireless communication in compliance with COLREGs on the SCOUT USV was discussed in Benjamin and Curcio[29]. Whilst Larson et al.[6] discussed the autonomous navigation and obstacle avoidance approaches and challenges of real time operation with ROA and DOA approaches. The real-time implementation of projected obstacle area method was conducted with SEADOO Challenger for safe manoeuvring in the presence of obstacles.

Control Approaches for USVs

With regards to control techniques for surge and yaw control under control and path planning in Figure 4, several methods such as proportional integral derivative (PID) [30], H∞ [31], linear quadratic Gaussian (LQG) [32], model predictive control (MPC) [33] have been proposed. Review towards control algorithms and a comparison of linear and non-linear control approaches for USVs can be found in Sharma et al. (2014)[34].Owing to the requirement of offshore industries for underwater inspection and monitoring of offshore establishments, much research towards path planning and control of autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) has been instigated, however, this area is out of the scope of this review. Whereas an extensive review of guidance laws for marine vehicles is discussed in Naeem et al.[35], a detailed review on developments in areas associated such as path planning guidance with the autonomy of USVs is explained in Campbell et al.[5].

Results and Discussions

Optimal Path Planning of USVs with Time as an Objective

To find a feasible path in shortest time is another objective of path planning. Ebken et al.[36] explained the hardware and software architecture of the SSC San Diego USV and briefly described the path planning approach based on the CMU Morphin algorithm[37] used for determining the minimal time path during real time testing of the vehicle. Casalino et al.[38] have proposed a three-layer path planning architecture comprising of DOA and ROA approaches based on a visibility graph technique and a A* algorithm to find a path having minimal time for an USV. Salrieh and Gorbani[39] used a Gauss spectral method to determine an optimal trajectory for a high-speed boat using a non-linear mathematical model. This novel approach takes into account the dynamics of the vessel and was found computationally less expensive in terms of storage and time. Svec et al.[40] developed a moving object following trajectory planning of an USV based on lattice-based trajectory planning to generate a dynamically feasible and optimal path and verified the simulation against experiment trails. Recently, evolutionary approaches have been brought in to the path planning of USVs. Song et al.[41]

proposed an improved ant colony algorithm (ACO) for a global path planning algorithm of a USV. The proposed approach needs less computational time and produces a smooth path. Song et al.[42] proposed a modified PSO algorithm based on a particle model for obstacle avoidance and compared results against path generated using a conventional PSO and smooth path planning algorithms. Proposed algorithm produced a shorter and smoother path against a conventional PSO and smooth path planning algorithms. In order to combine the advantages of the global and local path planning algorithms, a combinatorial approach has been proposed using an angle potential field and a modified ACO by Wu et al.[43]. This approach provides an optimal result in terms of path length.

Path planning of a swarm of USVs

Swarm is defined as multiple autonomous agents moving cooperatively to fulfil global objective of a scientific or technological mission. This term is often observed in nature. Each autonomous agent is modelled as a particle and characterised by its position and a function describing its dynamics. The cooperative behaviour of swarm of vehicles can be classified into two categories: (a) formation control and (b) path planning or trajectory generation. Extensive research has been conducted to understand the cooperative behaviour of swarm of UAVs and UGVs operating in static and dynamic environments.

Literature pertaining to swarm of UAVs and UGVs shows that cooperative control follows four approaches namely, leader-follower [44], behaviour based approach [45], virtual structure[46] and artificial potential function [47]. In the leader-follower approach, one vehicle acts as a leader and generates the reference trajectory for other vehicles. The behaviour of the leader decides the behaviour of the swarm. In the behaviour based approach, the behaviour is decided on weighted average of individual actions of each vehicle, where actions can be formation keeping, obstacle avoidance etc. In the virtual structure approach, the complete swarm formation is considered as a rigid body and dynamics of each agent is derived from the dynamics of a rigid body. This flexible approach can accommodate all forms of formation and is a decentralized behaviour. Finally, artificial potential function approach control the swarm geometry and inter-member spacing through vector fields created by repulsive and attractive potential fields. Path planning approaches have already been discussed in detail in the previous section which can be coupled with formation control approaches for motion planning of swarm of vehicles. A detailed review of literature towards cooperative path planning of aerial and mobile robots can be found in work of Wang and Phillips[48].

A swarm of USVs in an oceanic environment is another major challenge for better temporal and spatial coverage of the oceanic environment. A swarm of USVs is a multi-objective problem where the vehicles have to find an obstacle-free path while maintaining the shape of the fleet of USVs to the maximum extent. Objectives associated with multiple USVs path planning can be found in Figure 8. There are basically three control structures to maintain the shape of USV fleets, namely, leader-follower, virtual structure and behaviour based approach[3]. A detailed review towards multi-robot coordination can be found in Yan et al.[49]. Heuristic approaches have been found better in dealing with such multi-objective problems. The next important consideration is the selection of formation shape for the fleet. Line, column, diamond and wedge shapes are the most popular geometric patterns[5]. Maintaining and switching a USV formation shape in compliance with COLREGs during collision situations has been shown in Figure 11. Very few studies have been commenced towards the development of a robust path planning algorithm for a swarm of USVs. Bishop[50] demonstrated real-time planning and control architecture for a platoon of USVs. Schneider et al.[51] proposed a Kalman filter based navigation for three unmanned marine vehicles with narrow bandwidth communication moving in a wedge-shaped formation whereas Frey et al.[52] explained navigation of swarm of USVs based on the basic law of physics. This decentralised approach demonstrated a reduction in energy consumption by use of a short range self-contained processing unit than a leader one. Abidin et al.[53] proposed a fly optimisation algorithm (FAO) for a swarm of mini USVs in the range of 8 to 24 vehicles. Recent work of Liu and Bucknall[3] successfully demonstrated implementation of a path planning method based on the fast marching (FM) approach for USVs as a fleet of vehicles in a dynamic environment for various scenarios.

Fig.11 here

Challenges and Scope for the Future

A review of path planning of USVs shows that other than the work of Wu et al.[43], no attempt has been made towards the development of hybrid algorithms to obtain global optimality without getting trapped in local minima. Most studies have taken only one or two rules of COLREGs for simulation and experimental validation. USV operation in the maritime environment still does not possess any particular set of laws and guidelines. It is, therefore, important to develop future path planners in adherence to COLREGs. Although total implementation of COLREGs is not a requirement considering the diverse range of missions for USVs, however, there is a requirement for incorporating four basic rules of COLREGs in path planning approaches in order to maintain semi-autonomy. Most of the studies have been simulated in the self-generated environment and there is a need to simulate path planning algorithms in maps generated from the real-time environment. Other than work of Gadre et al[11] and Liu and Bucknall[3], no other work has made an attempt towards this. In order to implement algorithms in real time, there is a need to develop algorithms which are computationally less demanding. Only the work of Larson et al.[6], Benjamin et al.[24] and Svec et al.[40] have made attempts towards real-time implementation of such algorithms. Swarm operations of USVs is still an open area where not many developments have occurred and understanding the dynamics of the fleet of USV in compliance with the COLREGs needs to be investigated. Most studies with USV path planning assume dynamic obstacles and USV at a constant speed. There is a requirement to develop mathematical models which can incorporate kinematics of dynamic obstacles and USV in path planners with least computational effort.

Conclusions

This review paper systematically surveyed the optimal path planning approaches adopted for single and swarm of USVs and their respective advantages and drawbacks. Initially, optimal path planning approaches currently adopted in literature for single USVs is analysed with ROA, DOA and SLAM techniques in two respects, static and dynamic environment. This is followed by path planning approaches adopted for swarm of USVs. Finally, on basis of the investigation of the related literature, challenges and prospects for future research avenues with single and multiple USVs has been presented.

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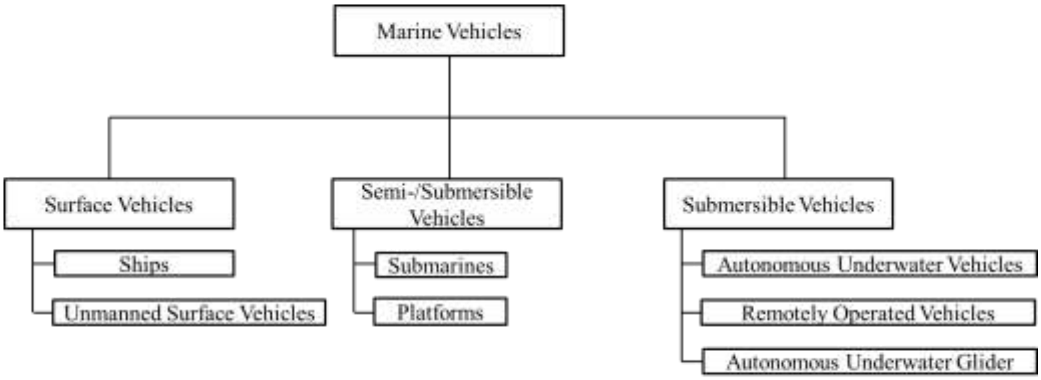

Fig.1-Classification of marine vehicles[54]

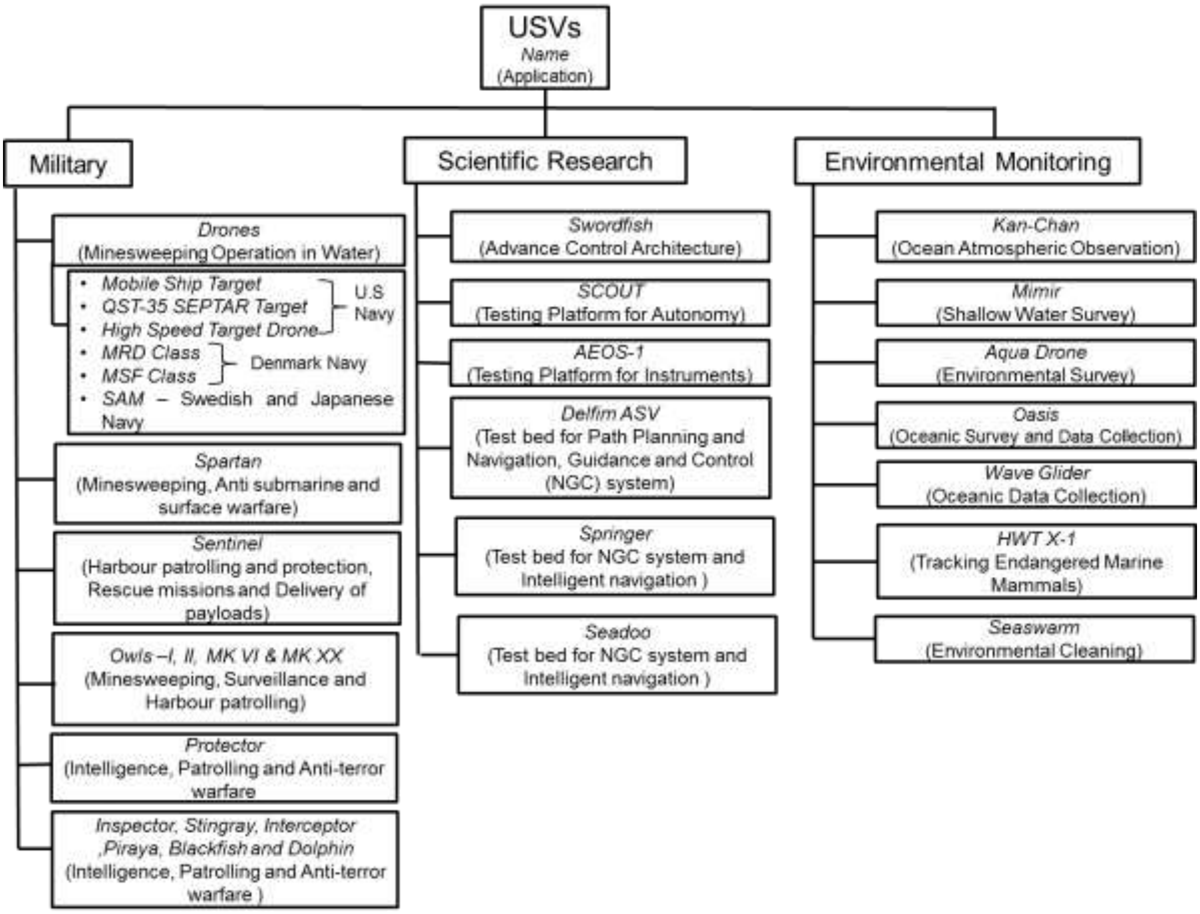

Fig.2-Classification of USVs based on application; Name (Application) [7]

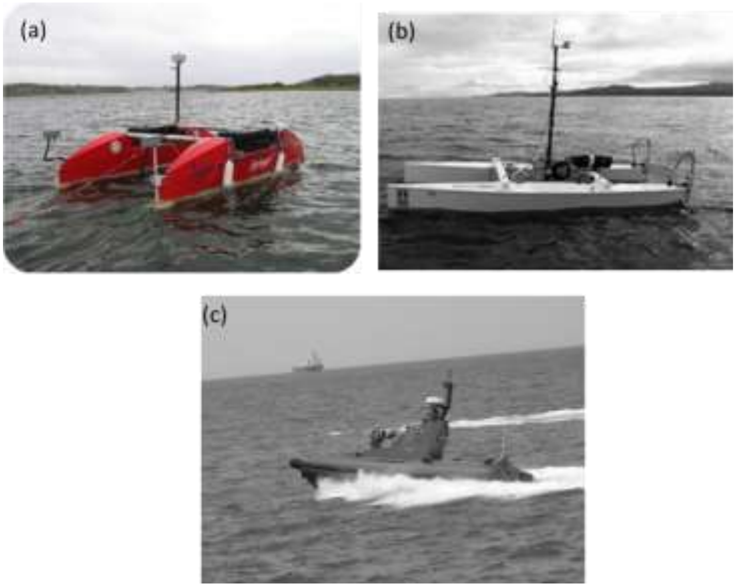

Fig.3-A few USV prototypes: (a) *Springer*[55]; (b) *Delfim*[56]; (c) *Protector*[57]

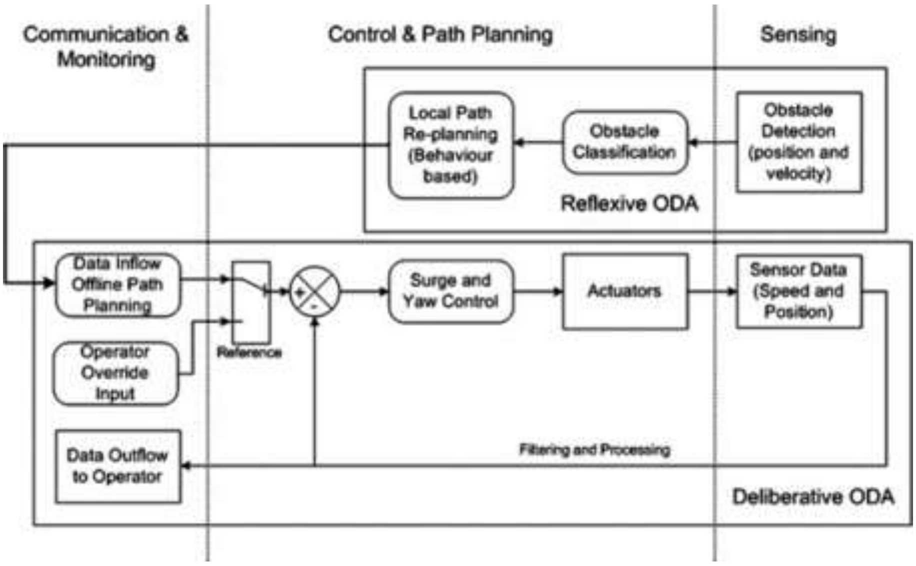

Fig.4-General architecture of USV operation in a maritime environment[5]

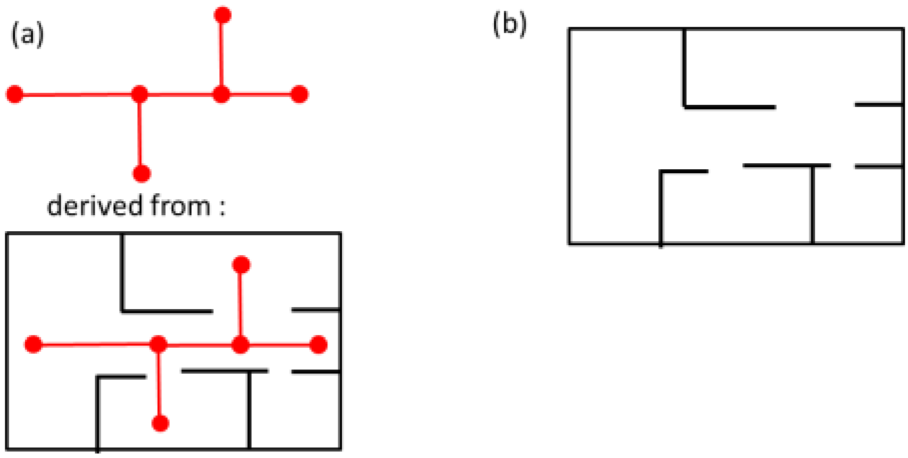

Fig.5-(a) Qualitative spatial representation[58]; (b) Quantitative spatial representation[58]

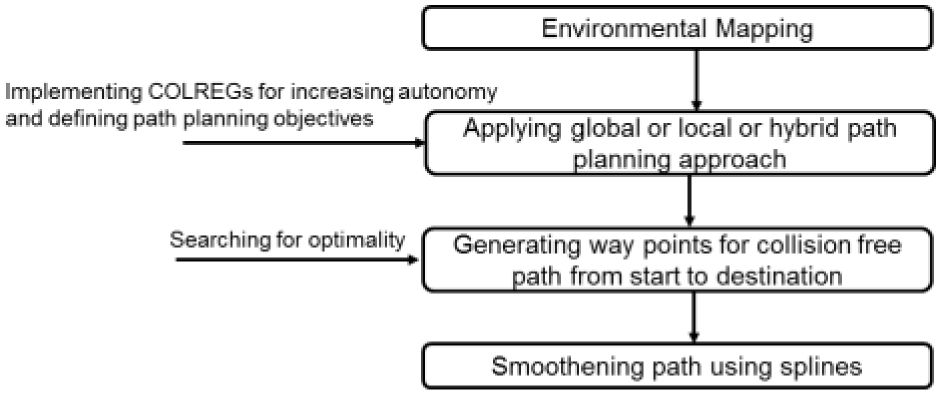

Fig.6-Path planning abstraction for USVs

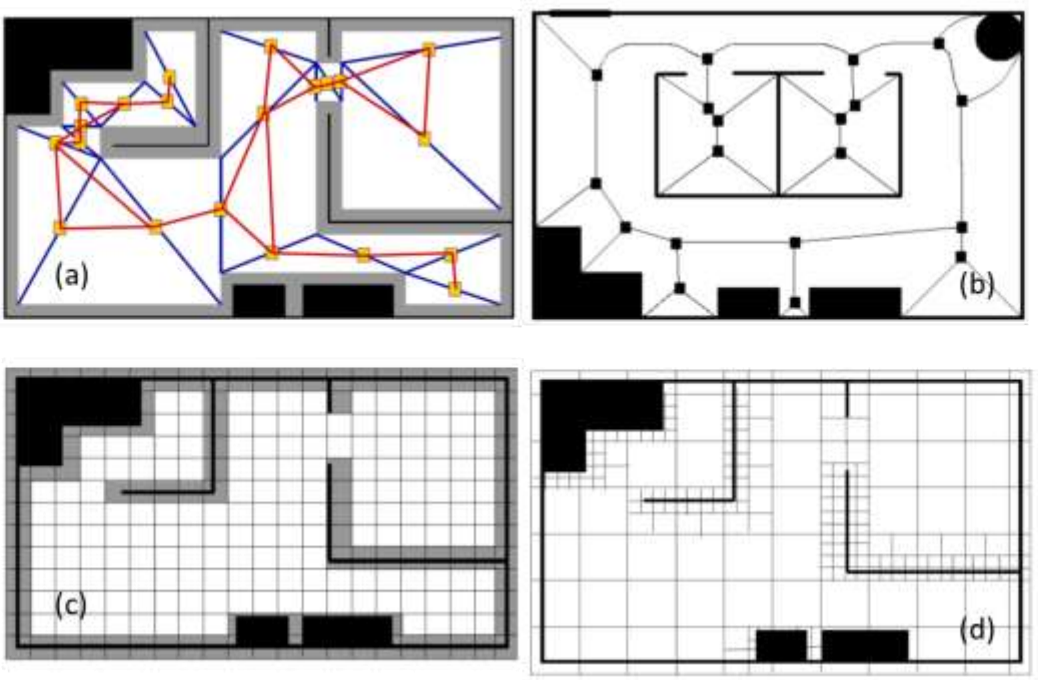

Fig.7-Grid-based environment mapping: (a) Meadows Map[10]; (b) Voronoi Diagram[10]; (c) Regular Occupancy Grid[10]; (d) Quadtree Mapping[10]

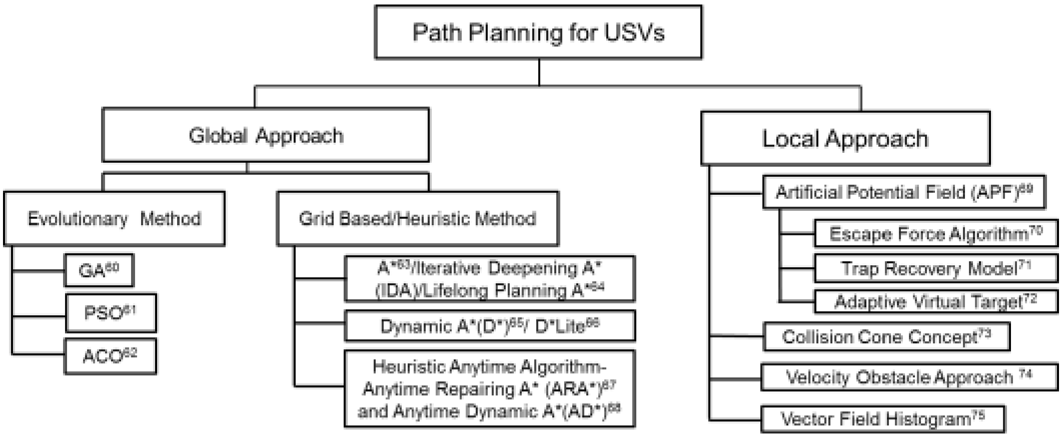

Fig.8-Path planning techniques for USV[5, 59]

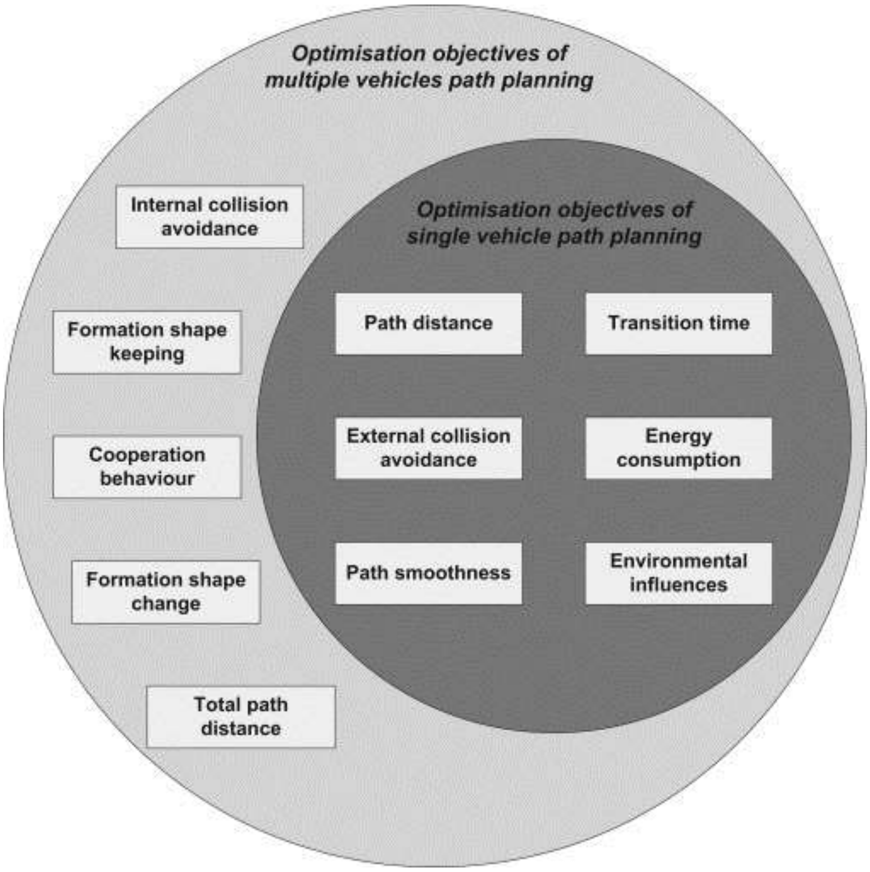

Fig.9-Path planning objectives for single and multiple USVs[3]

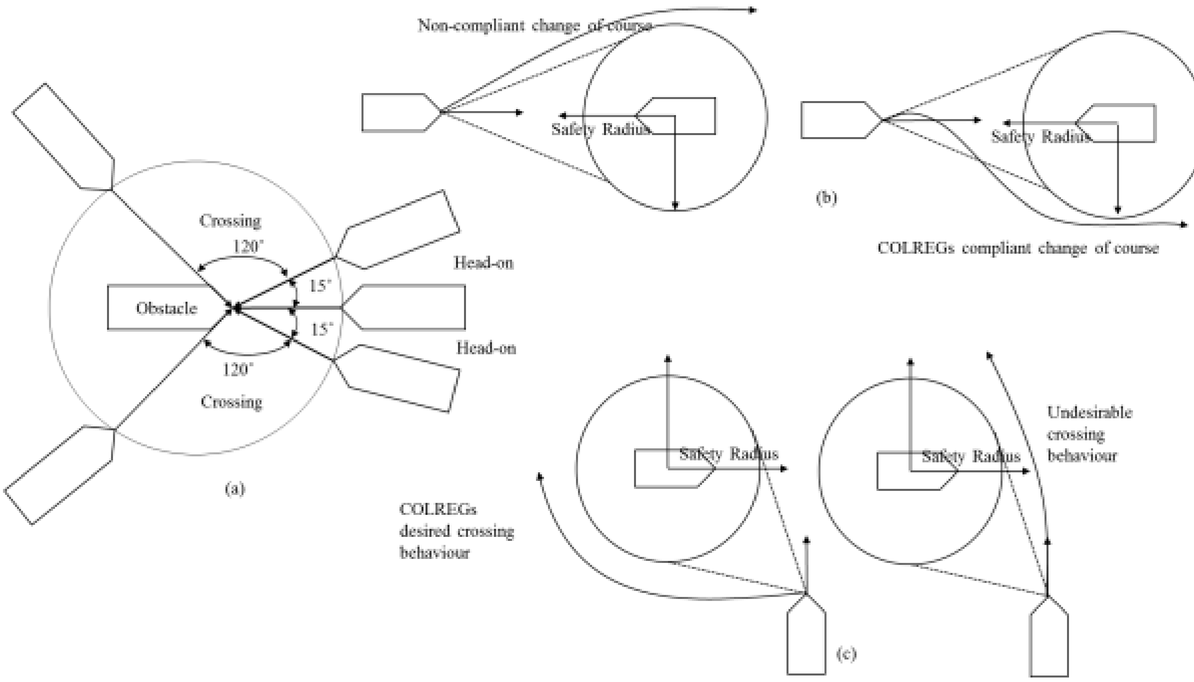

Fig.10-(a) Collision definition; (b) Head on collision; and (c) Crossing collision[8]

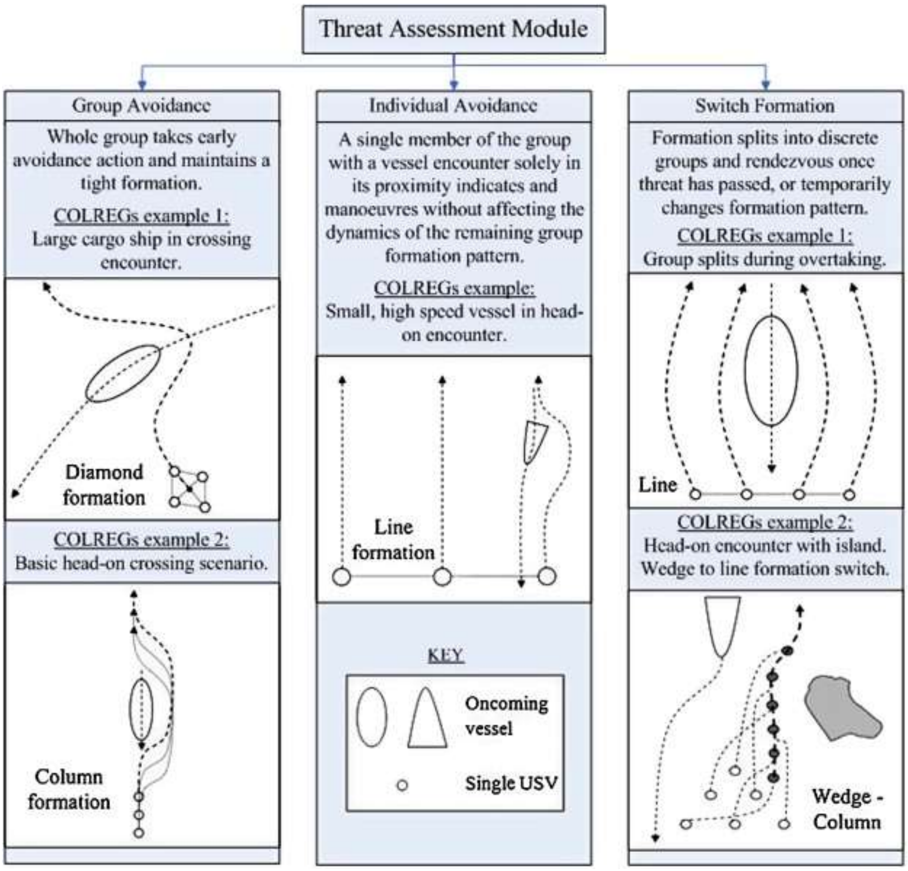

Fig. 11-Shape keeping and switching of a fleet of USVs in compliance with COLREGs[5]

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