A Two Layered Optimal Approach towards Cooperative Motion Planning of Unmanned Surface Vehicles in a Constrained Maritime Environment

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Abstract: Efficient motion planning of multiple unmanned surface vehicles (USVs) in a dynamic maritime environment is an important requirement for increasing mission efficiency and achieving motion goals. The current study integrates two approaches of intelligent path planning and virtual target path following guidance for multi-agent USV framework to perform a coordinated and cooperative navigation of USVs in a constrained maritime environment. In the current study, a safety distance constrained A* approach produces an optimal, computationally efficient and collision free path which is later smoothed using a spline to provide an optimal trajectory as input for virtual target based multi-agent guidance framework to navigate multiple USVs. The virtual target approach provides a robust methodology of global and local collision avoidance based on known positions of vehicles. The combined approach is evaluated with the different number of USVs and in different environmental scenarios to understand the effectiveness of approach from the perspective of practicality, safety and robustness.

Keywords: Path Planning, Multi-Vehicle Systems, Path Following, Unmanned Surface Vehicles

1. INTRODUCTION

Motivated by the increased presence of autonomous agents, research organizations and industrial firms are putting their effort in the development of unmanned vehicles, able to operate autonomously in the marine environment. Current state of high-performance marine vehicles operating in marine environment, which were once just a figment of our imagination as a prototype tool, are consolidated reality of today's maritime framework, employed in the most diverse array of applications ranging from reconnaissance in hostile areas to operations in dangerous weather conditions to name a few.

A substantial research has been conducted in the last two decade towards increasing autonomy of the USVs, being the basis of the near-future autonomous ships. Moreover, a step further in the development of autonomous systems is the capability of operating in a team, so as to improve the overall system performance in terms of cost and safety. With this final objective of allowing a multi-USV agent team to navigate autonomously within a commercial route such as coastal area or an harbour, a number of problems have to be solved in order to provide the essential capabilities to the system to operate in an autonomous and safe manner.

The first need is the realization of a path planning system, capable of computing an optimal route within a constrained maritime environment in a computationally effective manner. Towards optimal path planning of USVs, evolutionary approaches such as Ant Colony Algorithm (ACO) (Song, 2014) or Particle Swarm Optimisation (PSO) (Song et al., 2015) and grid-based heuristic approaches (Casalino et al., 2009; Singh et al., 2017) have been adopted in the literature. Traditionally, grid-based search techniques have been found most efficient in generating path in fastest computation time, which is an important on-board requirement for real time USV operations (Mohanty and Parhi, 2013). Many studies have been conducted on the subject of grid based path planning in the area of USVs from different perspectives of collision avoidance, heading constraint,environmental disturbances and energy consumption (Kim et al., 2012, 2014; Lee et al., 2015; Svec et al., 2011). In the present context of autonomy required in the marine environment, autonomous navigation of USVs in a practical marine environment needs to be cognizable of three important issues, namely, safety, reliability of the mission and likelihood of the success (Statheros et al., 2008).

The navigation within common commercial routes requires the compliance with the International Regulations for Preventing Collisions at Sea (COLREGs) suggested by In-

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ternational Maritime Organization (IMO) (IMO, 1988).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 et al. (2009). Lee et al. (2004) used a fuzzy logic approach for navigating a USV in a dynamic environment in compliance with COLREGs. A COLREGs based A* approach was proposed for way point navigation of an USV complying with rule 14 of COLREGs in an environment cluttered with static and moving obstacles (Naeem et al., 2012).Kuwata et al. (2014) used a velocity obstacle approach for navigating a USV in compliance with COLREGs.

As feasible routes have been defined, an USV needs a robust algorithm to guide itself along the desired track, where trajectory tracking and path following are two well known approaches adopted in literature. Trajectory tracking is concerned with development of control approach to force USV reach and follow a time parameterised trajectory. Sliding mode control (SMC) (Fahimi and Van Kleeck, 2013), backstepping technique (Liao et al., 2014) and Lyapunov method (Liu et al., 2014) are few well known nonlinear control techniques applied in last decade for USV trajectory tracking. Considering low manoeuvring capability of USV, path following technique has been found more practical and effective approach for an USV control. Line-of-sight (LOS) guidance law (Breivik and Fossen, 2005) and its combination with several non linear control methods for stabilizing speed (Healey and Lienard, 1993), heading (Fossen and Pettersen, 2014) and disturbances (Borhaug et al., 2008) towards minimising cross-track and along-track error have been proposed in the literature.

As soon as the number of the employed autonomous vehicles increases, a methodology for formation maintenance and motion coordination is required to ensure the proper guidance of the overall team. Three main approaches namely, *Leader-Follower* (Liu and Bucknall, 2015), *Coordinated Path Following* (Ghabcheloo et al., 2006) and *Virtual Target* (Bibuli et al., 2009) have been adopted in the cooperative task handling of USVs. The *Virtual Target* approach has been able to guarantee a better global convergence and remove singularities by reducing amount of data exchange to overcome bandwidth limitations compared to other two approaches.

To the best of the authors knowledge, only splines of primitive shapes with no optimal characteristic has been chosen in literature towards cooperative motion planning of USVs. The current work is the integration of an optimal path planning approach (as described in Sec. 3) with a *Virtual Target* approach proposed in Bibuli et al. (2009).This extension of optimal path planning to multi-USV framework (following the idea developed in Bibuli et al. (2014)) leads to optimal convergence of motion goals leading to removal of theoretical singularities of path following. In addition to that, the current study considers shoreline effect of an real time marine environment into account towards multi-USV motion goals.

This work is organised as follows : section 2 describes the methodology adopted in this paper; a brief introduction to the constrained A* path planning algorithm has been described in the section 3; concept of basic path-following with multi vehicle coordination are described in section 4 while in section 5 results of coordinated vehicles motion are presented. Lastly, conclusions are reported in section 6.

2. METHODOLOGY

The current study adopts a two layered approach towards the multi-USV framework. In the higher level of the hierarchy, a robust path planner based on constrained A* approach is adopted to generate optimal waypoints, which are later smoothed using the polyfitting operation. This smoothed trajectory is given as an input to the lower level guidance system based on virtual target approach integrated with a swarm aggregation algorithm based on attraction- repulsion strategy. Fig.1 shows a schematic of the methodology adopted in the present paper.

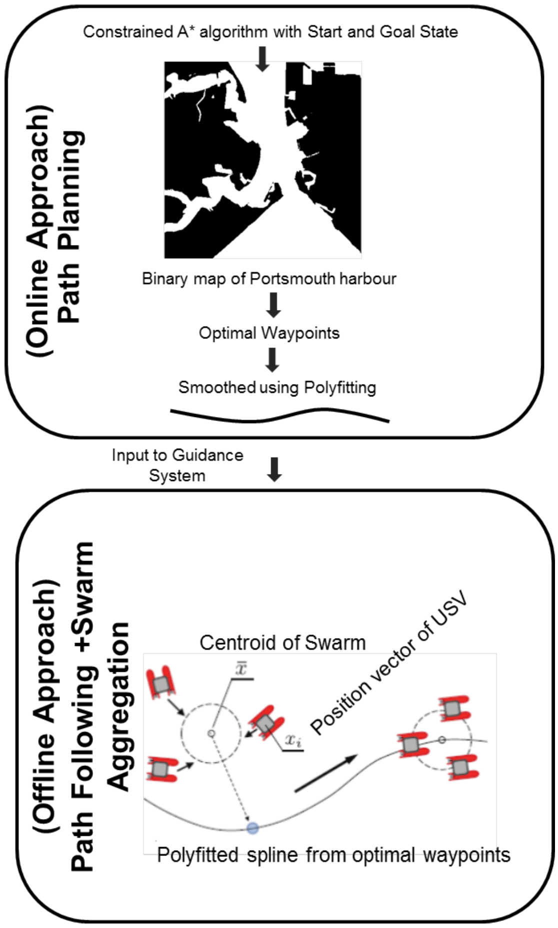

Fig. 1. Schematic of integrated path planning, path following and swarm aggregation approach

3. PATH PLANNING

In the online planning, a constrained environment of Portsmouth harbour is chosen as the area of interest as shown in Fig.1. A safe distance A* approach as shown in Fig.2 is being applied to the harbour environment, leading to the generation of optimal waypoints. In this approach, fixed start and goal states are chosen with 8-connectivity resolution in configuration space i.e. a binary map of the harbour where obstacles (black region) are represented by 1 and open space (white region) is represented by 0. USVs are non-holonomic vehicles, which disable them to make sharp manoeuvres leading to the requirement of smoothed trajectory. A zigzag trajectory is produced from the waypoints generated from the proposed approach. The chosen waypoints for smoothed trajectory are tabulated in Table 1. The waypoints are chosen so that complexity of the navigation in a constrained harbour is accounted in the offline approach. The generated trajectory from the safety distance constrained A* approach and smoothed trajectory from chosen waypoints are shown in Fig.3.

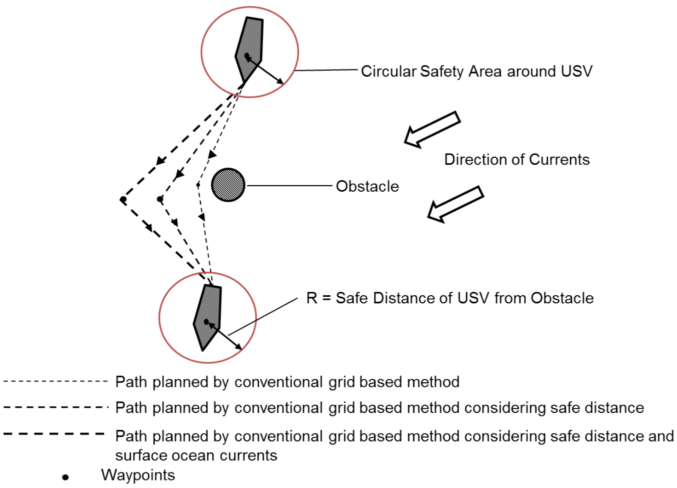

Fig. 2. A schematic showing the path generated by a convectional grid based path planner compared against the path generated by a grid based path planner by considering safety distance and sea surface currents

Table 1. Chosen optimal waypoints (WP) from path planner

	Start	WP 1	WP 2	WP 3	Goal
x (pixels)	238	261	272	285	299
y (pixels)	212	251	271	284	312

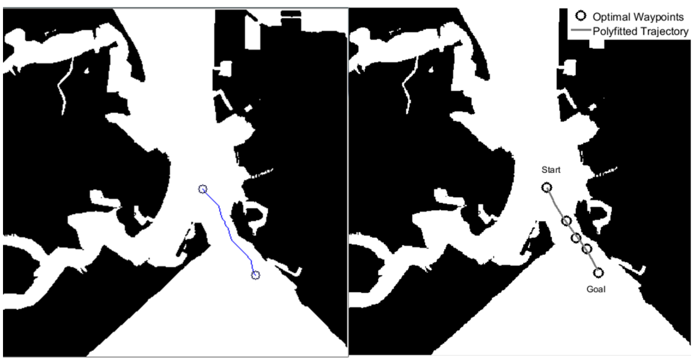

Fig. 3. Generated (left) and smoothed trajectory (right) from the optimal waypoints produced by the path planner. Binary map of 800 x 800 resolution is considered for the current study with one pixel representing 3.6 m on a real map

The chosen waypoints are fitted to an polynomial parameterised in terms of $\gamma \ \forall \ \gamma \in [0{,}61]$. Parametric equations, $P_d(\gamma)$ used as an input towards offline approach of path following and swarm aggregation are shown below:

$$P_d(\gamma) = \begin{cases} x(\gamma) = \gamma + 238, \\ y(\gamma) = -0.000325(\gamma+238)^3 + 0.2637(\gamma+238)^2 \\ .. - 72.5508(\gamma+238) + 6505 \end{cases}$$

4. MULTI-VEHICLE PATH-FOLLOWING

The aim of allowing a team of USVs to execute a cooperative path-following along a desired track, generated through the above-mentioned methodology, is realized by means of the coordinated path-following framework initially developed in Bibuli et al. (2014). The proposed method is based on the integration of a *virtual-target* based path-following algorithm with a swarm aggregation technique. A brief description of the two sub-modules and their functional integration is reported in the following of this section.

4.1 Basic Path-Following

By referring to Fig. 4 and assuming the vehicle's motion restricted to the horizontal plane, the task consists in the zeroing of both the position error vector $\underline{d}$, i.e. the distance between the vehicle and the virtual target attached to the *Serret-Frenet* frame $< f >$, and the orientation error $\beta = \psi - \psi_f$, where ψ and ψ_f are the vehicle's direction of motion and local path tangent respectively, expressed with respect to the earth-fixed reference frame $< w >$. Following the geometrical and kinematical analysis carried

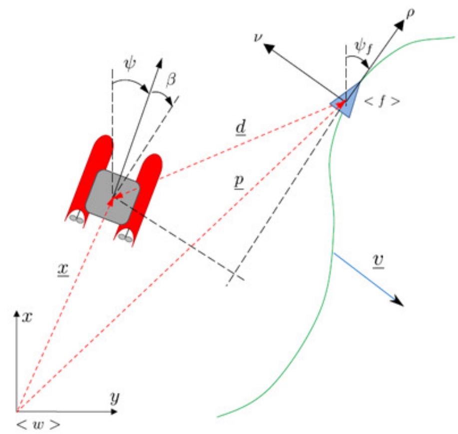

Fig. 4. Path-Following modeling framework

out in Bibuli et al. (2009), the distance error model, expressed with respect to the frame $< f >$, has the following form:

$$\begin{cases} \dot{\rho} = (c_c\,\nu - 1)\,\dot{s} + U\cos\beta \\ \dot{\nu} = -c_c\,\dot{s}\,\rho + U\sin\beta \end{cases} \tag{1}$$

In order to solve the path-following problem for a single-vehicle system, the aim is to develop a proper approach angle function ψ^*, designed to reduce the linear error components (ρ and ν) to zero. The desired angle ψ^* is a function of the cross-track error ν summed with the local path tangent, thus $\psi^* = \psi_f + \varphi(\nu)$, where the function $\varphi(\nu)$ is required to satisfy the following constraints:

$$|\varphi(\nu)| < \frac{\pi}{2} \quad ; \quad \nu\varphi(\nu) \leq 0 \quad ; \quad \varphi(0) = 0$$

Relying on a low level controller, providing an auto-heading regulator capable of tracking desired orientation profiles, it can be stated that considering the candidate Lyapunov function $V_\psi = \frac{1}{2}(\psi - \psi^*)^2$, the low level controller provides a behavior such that $\dot{V}_\psi \leq 0$, i.e. the vehicle orientation converges to the desired angle $\psi \to \psi^*$ and it can be rewritten as $\beta \to \varphi(\nu)$. Moreover it's worth noticing that when $\dot{V}_\psi = 0$, an invariant set is defined, in which the condition $\beta = \varphi(\nu)$ holds. The task of the path-following controller design is achieved by the definition of the Lyapunov function $V = \frac{1}{2}(\rho^2 + \nu^2)$; computing the time derivative of the function V, the following expression is obtained:

$$\dot{V} = \rho\dot{\rho} + \nu\dot{\nu} = -\rho\dot{s} + \rho U \cos\beta + -\nu U \sin\beta = \dot{V}_\rho + \dot{V}_\nu$$

substituting $\dot{\rho}$ and $\dot{\nu}$ with the equation system (1) and defining $\dot{V}_\rho = -\rho\dot{s} + \rho U \cos\varphi(\nu)$ and $\dot{V}_\nu = -\nu U \sin\varphi(\nu)$. The speed of the reference frame $\dot{s}$, i.e. the velocity of the virtual target moving along the path, can be used as an additional control variable. Imposing

$$\dot{s}^* = K_\rho \rho + U \cos\beta \tag{2}$$

as the desired virtual target speed, where K_ρ is a tunable controller parameter, the function $\dot{V}_\rho$ assumes the negative form $\dot{V}_\rho = -K_\rho \nu^2 \leq 0$. About $\dot{V}_\nu$, recalling the above-mentioned assumption on the attraction to the invariant set defined by $\dot{V}_\psi = 0$, β can be substituted by $\varphi(\nu)$, obtaining $\dot{V}_\nu = \nu U \sin\varphi(\nu)$. Selecting the function $\varphi(\nu)$ as

$$\varphi(\nu) = -\psi_a \tanh(K_\nu \nu) \tag{3}$$

with K_ν as a tunable controller parameter and ψ_a the maximum approach angle with respect to the local tangent ψ_f, the term $\nu U \sin\varphi(\nu)$ is ≤ 0 because of the assumption made on the function $\varphi(\nu)$.

Being the terms $\dot{V}_\rho$ and $\dot{V}_\nu \leq 0$, thus entailing $\dot{V} \leq 0$, the global asymptotic stability for the path-following guidance system is proven.

4.2 Vehicle Coordination

The goal of coordinating an USV team to converge to and maintain a motion configuration, while at the same time moving along a desired reference path is realized through the definition of the following control input:

$$\dot{x}_i = u_i^s + u^g \tag{4}$$

where the term u_i^s, different for each USV, is the control effort required to reach a collective behavior while the term u^g, common to all the USV, refers to the expected trajectory of the fleet centroid, computed with reference to section 4.1 as:

$$u^g = \begin{bmatrix} u^* \cos\psi^* \\ u^* \sin\psi^* \end{bmatrix} \tag{5}$$

where u^* is the desired speed for the formation along the path and ψ^* is the reference guidance angle computed by the path-following module.

Considering a swarm composed of n robots, the following aggregation dynamics for each robot i is given:

$$u_i^s = \sum_{j \neq i} g(x_i - x_j) \tag{6}$$

where $g(\cdot)$ is the interaction function representing the function of attraction and repulsion between neighboring robots. In particular, $g(\cdot)$ is defined as:

$$g(y) = -y \left[g_a(\|y\|) - g_r(\|y\|)\right], \quad \forall\, y \in \mathbb{R}^m. \tag{7}$$

where $g_a(\cdot)$ is the attractive function and $g_r(\cdot)$ is the repulsive contribution, constrained by the following assumptions:

$$\begin{aligned} g_a(\|x_i - x_j\|) &\geq \alpha \\ g_r(\|x_i - x_j\|) &\leq \frac{\beta}{\|x_i - x_j\|^2} \end{aligned} \tag{8}$$

In order to maintain a practical equilibrium between the swarm formation term u_i^s and the path-following guidance term u_g, the u_i^s component is modified as follows:

$$\dot{x}_i = k_{sat} \frac{\sum_{j \in \mathcal{N}_i(t)} g(x_i - x_j)}{1 + \left\|\sum_{j \in \mathcal{N}_i(t)} g(x_i - x_j)\right\|}, \tag{9}$$

where $k_{sat} > 0$ is the saturation gain.

The stability of the overall system, originated by the interconnection between the path-following and swarm aggregation modules, is formally proven in Bibuli et al. (2014).

5. RESULTS

In order to ensure that complexity of the multi-USV operation in a constrained maritime environment is captured, this section reports results of three and four vehicles performing swarm aggregation and path-following from a randomly generated initial formation towards a reference path generated from proposed path planner. Fig.5 and Fig.8 shows the aggregation behaviour combined with motion against the reference path for three and four USVs respectively. Initial, intermediate and final positions of the formation are shown in Fig.5 and Fig.8. The reported results account for external collision with the shoreline into swarm evolution through attractive and repulsive functions introduced in Bibuli et al. (2014). The collision avoidance with the shoreline is simply implemented by considering the shore profile as a set of repulsive fixed points which, within a certain distance, concur in the vehicle motion evolution. The motion of the vehicles with respect to mutual agent interactions and to distance from the shoreline can be varied acting on the parameters of the attractive and repulsive functions. Fig.6 and Fig.9 shows the reference velocity profile for three and four USVs respectively, where velocity of the i-th robot is $\|\dot{x}_i\|$. It should be noted that formation is function of initial position and evolution along a desired reference. In Fig.7 and Fig.10, actual surge speed and heading angle is compared with reference speed and orientation for three and four USVs framework respectively. In order to highlight the effectiveness of the combined approach, physical limits of an USV i.e. *Springer* is accounted in the guidance system by bounding the maximum and minimum manoeuvring speed between 0.2 m/s and 1.4 m/s as shown in Fig.6.

6. CONCLUSIONS

In this article, the integration of constrained A* path planner with virtual target path following guidance for multi-agent USV is reported. The easiness of integration, given by the modular composition of path-planner, vehicle formation aggregation and formation guidance procedures makes it applicable for real time marine environment. A set of results on three and four USVs demonstrates the validity of the combined approach with respect to robustness

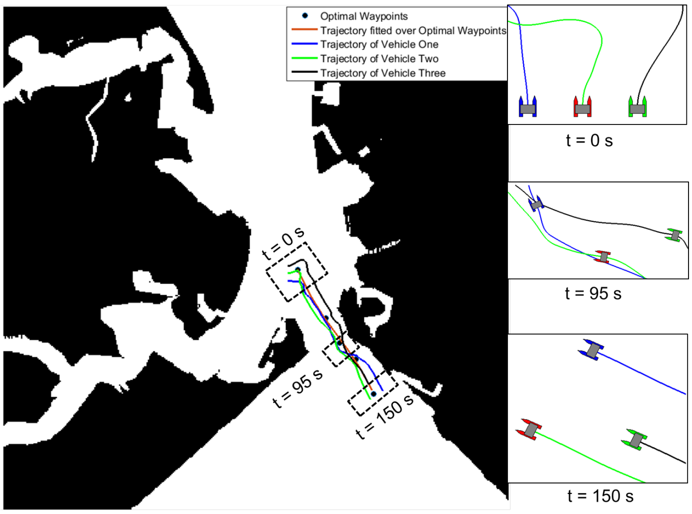

Fig. 5. USV motions during swarm aggregation combined with path-following guidance for three USVs

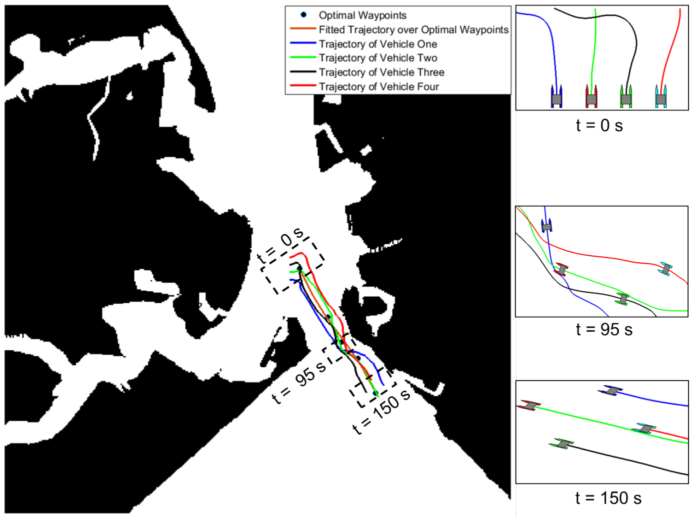

Fig. 8. USV motions during swarm aggregation combined with path-following guidance for four USVs

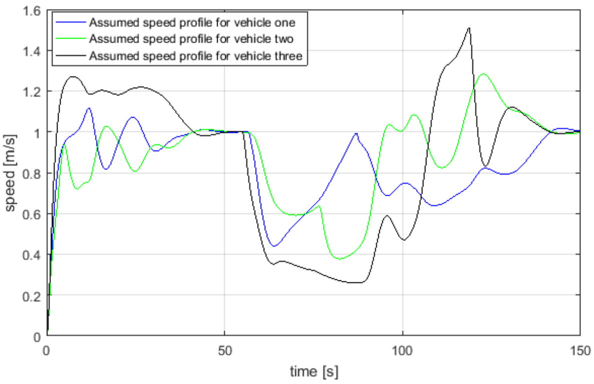

Fig. 6. USV speed profiles assumed during swarm aggregation evolution for three USVs

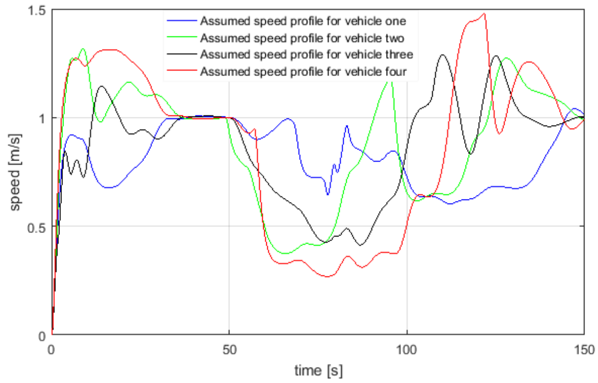

Fig. 9. USV speed profiles assumed during swarm aggregation evolution for four USVs

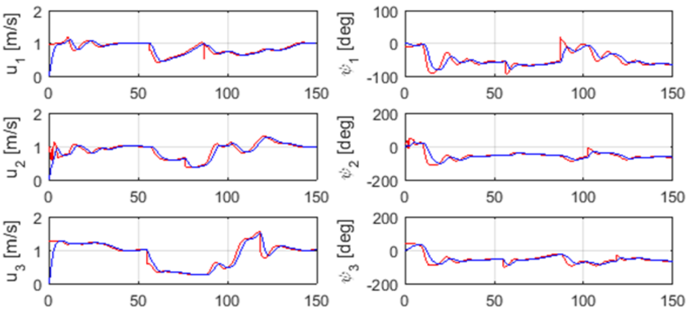

Fig. 7. USV speed and heading profiles during swarm aggregation combined with path-following guidance for three USVs

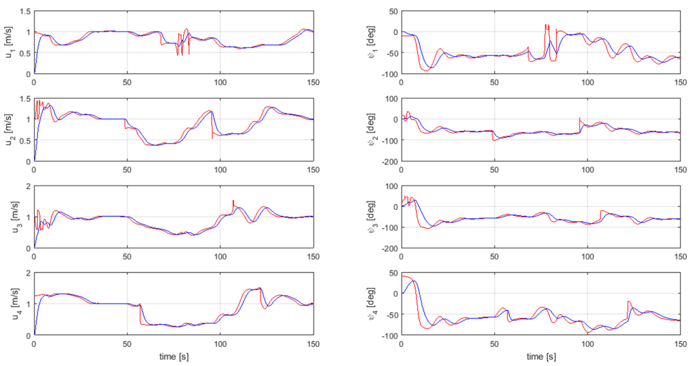

Fig. 10. USV speed and heading profiles during swarm aggregation combined with path-following guidance for four USVs

and collision avoidance. Future studies are focused on optimising the multi-agent USV framework by testing the combined approach with different reference path generated from varying safety distances and adaptive formation maintenance. In addition to that, effect of environmental disturbances such as sea currents will be incorporated in the offline and online level of the combined framework to evaluate the reliability of the overall system with respect to uncertain sea environment conditions.

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