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A new tow maneuver of a damaged boat through a swarm of autonomous sea drones

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Abstract: Given the huge rising interest in autonomous drone swarms to be employed in actual marine applications, the present paper explores the possibility to recover a distressed vessel by means of the other agents belonging to the swarm itself. Suitable approaches and control strategies are developed and tested to find the highest performance algorithms. Different rules are exploited to obtain a correct behaviour in terms of swarm interaction, namely collective and coordinated, and individual. An innovative feedback control strategy is adopted and demonstrated its effectiveness. Extensive simulation runs have been conducted, whose results validate the approach.

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1. INTRODUCTION

Sea drones have the potential to revolutionize maritime business, reducing time, cost and risk of several operations. The recent extraordinary evolution of the robotic technology, together with the increase of computational capabilities and the use of intelligent sensors, has driven the intense implementation of robot swarms, i.e. cooperative and coordinated sets of intelligent agents able to achieve common goals. One of the major challenges in this research field is related to the identification of intelligent control logics capable of managing a large number of robots working jointly for a common purpose. The control systems, acting on every single agent, are meant for a collaborative configuration. This duality is the key to achieve high flexibility and the power to face and manage unpredictable events.

This paper presents an innovative decentralized control system applied to autonomous driving boats whose task is the transport of a damaged or in distress boat by encircling it. The proposed algorithm, named Feedback Local Optimality Principle or FLOP Antonelli et al. (2018), Pepe et al. (2018), Nesi et al. (2019), coordinates the individual robots independently, allowing pushing and containment maneuvers only.

The concept of swarm Mohan and Ponnambalam (2019) arises from the social behavior of fishes, birds or insects that are used to cooperate in order to fulfill a global goal for their community as a whole. Different research aspects are studied and developed such as control approaches (of both the single agent and the entire swarm formation), communication among the robots, coordination strategies, learning methodologies, transportation problems. The employment of swarm based strategies has effectively proven the reliability and robustness towards failures and unpredicted events during operations; a resilience evaluation for swarm algorithms is reported in Varughese et al. (2017). This latter is of particular interest in the scope of autonomous goods and material handling, where in the near future the appearance of autonomous robotic couriers is likely to happen Arbanas et al. (2016).

Another potential remarkable application for cooperative robotic swarms deals with Search and Rescue activities. Particularly, if in other domains (ground, air) such frameworks are more advanced and robotics swarms result in more effective operations, the marine environment poses bigger challenges, in terms of both sensing capabilities and control performance. In general, many surveys and overviews conducted on existing rescue robotics systems underline how there is much further work to be carried on; in particular, work in Murphy (2012) highlights how robotics systems employed in real disasters are still too tied to human supervision, as well as they usually consists of single-robots working alone. Specifically dealing with search and rescue in marine environments, a focus on the potentiality of autonomous underwater vehicles is provided in Murphy et al. (2008), pointing out that there is much work still to be performed in order to become effective and timely in actual applications. A more recent experience described in Matos et al. (2016) confirms the need of further development and technology consolidation. Because of the benefits provided, a number of studies have been steered toward the development and employment of swarm-based approaches for the guidance and control of fleets of autonomous platforms in marine and maritime contexts. The work Bibuli et al. (2014) presented the

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integration of a swarm aggregation scheme with a path-following guidance module for USVs (Unmanned Surface Vehicles): the swarm algorithm allowed the vehicles to maintain a fixed-range formation, while the guidance system drove the entire team along a desired path. The work has been further extended including a path-planner module allowing the employment of the swarm formation within harbor contexts Bibuli et al. (2018). A number of researches have been oriented towards the problem of providing support to ships, e.g. tug operations for berthing aid. The work Esposito et al. (2008) presents a strategy that allows a swarm of autonomous tugboats to cooperatively move a large object on the water, keeping into account the actuator limitations and complex hydrodynamics; however it only examines some different tugboat configurations without considering the approach strategy. Furthermore, in the latter work, the vehicles are identical and also the distressed agent is part of the robotic swarm (making the towing operation more difficult); finally, in Esposito et al. (2008) a PID control is employed. A similar problem is faced in Braganza et al. (2007) where a team of autonomous vessels is commanded to perform a cooperative towing operation employing an adaptive position controller. A complementary result is provided by the work Bui et al. (2012), where a nonlinear observer is designed in order to estimate the state of a vessel towed by multiple autonomous boats; a sliding mode controller is further developed in order to guide the motion of the vessel by means of the autonomous towing platforms.

In the present work, the problem of removing or re-positioning of a vessel in distress through a swarm of marine drones is considered. It is not unusual that a vessel needs to be assisted during marine operations. One of the major reasons of the assistance is failure, still it is not the only one. One of the possible examples is related to sail boats that have to enter the port. Their actuation is generally not able to perform a suitable maneuver within the port restricted space, and hence they are usually supported by one or more rubber boats. Indeed, particularly within very restricted spaces, a vessel may need to be turned or moved from a point to another one, due to lack in its maneuvering capabilities, e.g. because its actuation system is not suitable for that kind of motion. For these reasons, given the interest in the application, the paper presents an approach for the rescue maneuvering of a distressed vessel, exploiting a swarm of marine drones. The distressed vessel is assumed in a total breakdown, as the worst case is here addressed.

The proposed paper improves the exploitation of the swarm, with respect to the previously cited works, by introducing both individual approach strategies, i.e. internal avoidance and target reaching, and a smart aggregation scheme for the collective transportation of the distressed vessel. The final goal for the swarm is to transfer the distressed vessel from the breakdown location to an assigned target area. The rescuing swarm is built in new generation smart and soft materials, thus making the "pushing actions" possible without causing damages to the robotic structure itself.

Given the novelty of the proposed approach, only the methodological and theoretical aspects are dealt with at this stage, neglecting technological issues such as sensor modeling, communication infrastructures and non-destructive bumping. These issues will be faced as soon as a real-case framework will be set up for practical testing of the approach. The paper is organized as follows: a brief resume of the Feedback Local Optimality Principle is given in Section 2. In section 3 the dynamical system of each agent of the swarm is described, while in Section 4 different towing strategies are discussed. In section 5 some preliminary results are shown and the final conclusion is drawn in Section 6.

2. RESUME OF FLOP METHOD

The Feedback Local Optimality Principle, or FLOP, is based on classical variational approach, and it is part of a class of Variational Feedback Control (VFC) algorithmsAntonelli et al. (2018), Pepe et al. (2018), Nesi et al. (2019) Paifelman et al. (2019). The method succeeds in providing a feedback control law for a class of affine systems in the form $\dot{\boldsymbol{x}} = \boldsymbol{\phi}(\boldsymbol{x}) + \boldsymbol{B}\boldsymbol{u}$ by using a local optimality criterion. The classical theory is based on the maximization/minimization along the time interval $[0, T]$ of a performance index $\hat{J}$ which represents the integral of the cost unction $E(\mathbf{x},\mathbf{u})$ subjected to the dynamic expressed by the affine system so that:

$$min\hat{J} = \int_0^T E(\boldsymbol{x}, \boldsymbol{u}) + \lambda^T(\dot{\boldsymbol{x}} - \boldsymbol{\phi}(\boldsymbol{x}) - \boldsymbol{B}\boldsymbol{u})\,\mathrm{d}x. \quad (1)$$

where $\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda}$ are the state, control and Lagrangian multiplier vectors. The solution of (1) provides both the optimal control $\mathbf{u}^*(t)$ and the corresponding optimal trajectory $\mathbf{x}^*(t)$. The FLOP approach introduces a local optimality principle through the split of the original integral (1) into $N = T/\Delta t$ integrals, with Δt to be the time horizon of each new integral. The FLOP method introduces a weaker minimization concept, based on the minimization of each new integral, as it follows:

$$\min J = \sum_{i=1}^{N} \min J_i = \sum_{i=1}^{N} \min \int_{LB_i}^{UB_i} L(\dot{\boldsymbol{x}}, \boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda})\mathrm{d}t \quad (2)$$

where $L(\dot{\boldsymbol{x}}, \boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda}) = E(\boldsymbol{x}, \boldsymbol{u}) + \boldsymbol{\lambda}^T(\dot{\boldsymbol{x}} - \boldsymbol{\phi}(\boldsymbol{x}) - \boldsymbol{B}\boldsymbol{u})$, UB_i and LB_i indicates the upper and the lower boundary of the i -th integral. Classical theory starts with two boundary conditions, $\boldsymbol{x(0)} = \boldsymbol{x_0}$ and $\boldsymbol{\lambda}(T) = \boldsymbol{0}$. In analogy, FLOP method uses two boundary conditions for each integral to be minimized: $\boldsymbol{x}(LB_i) = \boldsymbol{x}(UB_{i-1})$ and $\boldsymbol{\lambda}(UB_i) = \boldsymbol{0}$. This approach, for the class of affine systems $\dot{\boldsymbol{x}} = \boldsymbol{\phi}(\boldsymbol{x}) + \boldsymbol{B}\boldsymbol{u}$, provides a feedback control law that permits to overcome one of the main drawbacks of the classical theories. As a drawback, the FLOP method is not able to produce the global optimum provided by classical theories, but only a local optimum, i.e.:

$$min\hat{J} \leq minJ \quad (3)$$

Equation (2), using the variational Euler-Lagrange approach and by discretizing it using $\Delta\tau$ as discretization step, leads to:

$$\begin{cases} \nabla_{\boldsymbol{x}} E|_{LB_i} - (\nabla_{\boldsymbol{x}} \boldsymbol{f}^T \boldsymbol{\lambda})|_{LB_i} + \frac{\boldsymbol{\lambda}|_{LB_i}}{\Delta\tau} = \boldsymbol{0} \\ \nabla_{\boldsymbol{u}} E|_{LB_i} - (\nabla_{\boldsymbol{u}} \boldsymbol{f}^T \boldsymbol{\lambda})|_{LB_i} = \boldsymbol{0} \qquad \forall i \in [1, N] \\ \frac{\boldsymbol{x_{UB_i}} - \boldsymbol{x_{LB_i}}}{\Delta\tau} = \boldsymbol{f}(\boldsymbol{x_{LB_i}}, \boldsymbol{u_{LB_i}}, t) \end{cases} \quad (4)$$

The continuous counterpart of (4) leads to an augmented form of the Pontryagin formulation:

$$\begin{cases} \nabla_{\boldsymbol{x}} E - \nabla_{\boldsymbol{x}} \boldsymbol{f}^T \boldsymbol{\lambda} - \dot{\boldsymbol{\lambda}} = \boldsymbol{0} \\ \nabla_{\boldsymbol{u}} E - \nabla_{\boldsymbol{u}} \boldsymbol{f}^T \boldsymbol{\lambda} = \boldsymbol{0} \\ \dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, t) \\ \dot{\boldsymbol{\lambda}} = \mathbf{G}\boldsymbol{\lambda} \end{cases} \tag{5}$$

where $\mathbf{G} = -(N/T)\boldsymbol{I}$ represents the chosen time horizon interval Δt . To be solved, the FLOP approach requires the penalty function $E(\mathbf{x{,}u})$ to be quadratic in the control variable u and can be nonlinear in the state variable x , so it is usually chosen as $E(\mathbf{x{,}u}) = \mathbf{u}^T\mathbf{R}\ \mathbf{u} + g(\mathbf{x})$. The FLOP control law can be written, after some math, as:

$$\begin{aligned} J &= \int_0^T \mathbf{u}^T\mathbf{R}\ \mathbf{u} + g(\mathbf{x}) + \lambda^T(\dot{\boldsymbol{x}} - \boldsymbol{\phi}\,(\boldsymbol{x}) - \boldsymbol{B}\boldsymbol{u})\,\mathrm{d}x \\ \boldsymbol{u_{FLOP}} &= \boldsymbol{R}^{-T}\boldsymbol{B}^T[\nabla_{\boldsymbol{x}}\boldsymbol{\phi}(\boldsymbol{x})^T - \boldsymbol{G}]^{-1}\nabla_{\boldsymbol{x}}\boldsymbol{g}(\boldsymbol{x})^T \end{aligned} \tag{6}$$

The usage of the FLOP method can provide some interesting advantages:

- since its intrinsic nature of being a feedback control, FLOP can account noises from sensors and errors from the mathematical modeling.
- the FLOP control has low computational cost and it can be used in online and real-time application.
- The FLOP control can take into account nonlinearities both in the dynamical system and in the cost function for the state variable. This leads to the possibility to have nonlinear agents (e.g. as unicycles, bike models) and high, localized cost functions (e.g. obstacles or internal avoidance).

3. SINGLE AGENT DYNAMICS

Here, the dynamical system used for the single agent of the swarm is described as a planar three DoF's model Naveh et al. (1999). Ignoring heave (vertical), pitch and roll motion, the dynamics is expressed as:

$$\begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{\psi} \\ \dot{u} \\ \dot{v} \\ \dot{r} \end{bmatrix} = \boldsymbol{M}^{-1} \begin{bmatrix} u\cos\psi - v\sin\psi \\ v\cos\psi + u\sin\psi \\ r \\ rv + F_{drag_u} \\ -ru + F_{drag_v} \\ F_{drag_r} \end{bmatrix} + \boldsymbol{M}^{-1} \begin{bmatrix} 0 \\ 0 \\ 0 \\ u_1 + u_2 \\ u_3 \\ \frac{Lu_3 + u_1 w - u_2 w}{4} \end{bmatrix} + \boldsymbol{M}^{-1}\left[\boldsymbol{\tau_{i2BD}} + \boldsymbol{\tau_{i2j}}\right] \tag{7}$$

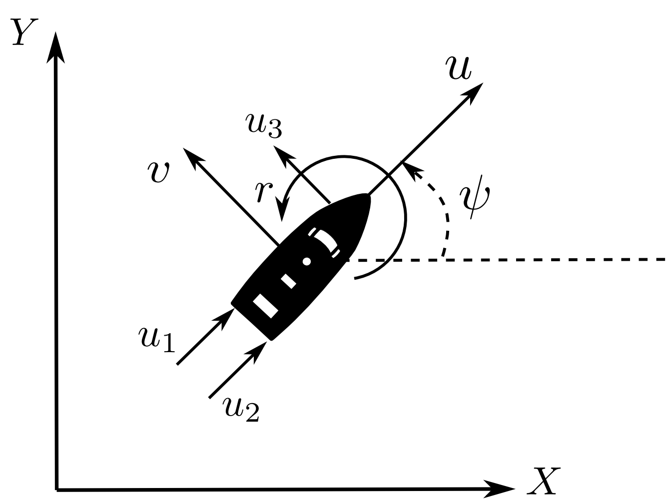

Fig. 1. Fixed and mobile reference system

where $\boldsymbol{M} = diag\,[1;1;1;m;m;I]$. The variables X, Y, ψ, u, v, r, m, I represent the coordinates in the $2D$ fixed reference, the heading orientation, the longitudinal and lateral speed, the rotational speed, the mass and the rotational inertia of the single agent, respectively. The symbols F_{drag_u}, F_{drag_v}, F_{drag_r} are drag resistances in the mobile reference frame. Each agent has two aft propellers and one lateral propeller, which produce u_1, u_2 and u_3 respectively. All boats are here supposed identical, with L, w, h to be the length, width and height of each boat respectively. Forces and torques $\boldsymbol{\tau_{i2BD}}$, $\boldsymbol{\tau_{i2j}}$ are between the $i-th$ agent of the swarm and the breakdown boat and between the $i-th$ and $j-th$ agents of the swarm, respectively. Both $\boldsymbol{\tau_{i2BD}}$ and $\boldsymbol{\tau_{i2j}}$ are intended of two types: crash forces and frictional forces. Fixed and mobile reference system are placed as depicted in Figure 1.

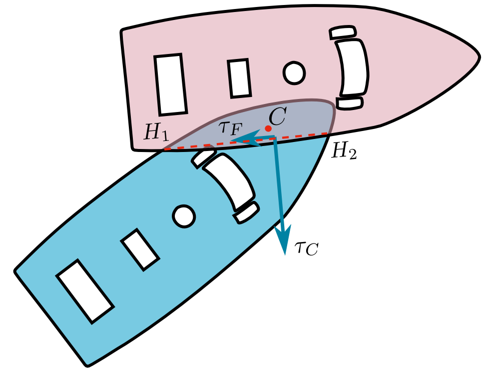

Fig. 2. Push and friction forces

In Figure 2 an emulation of the pushing phase is shown. In general, $\boldsymbol{\tau_{:}}$ is intended as a six rows vector written as: $\boldsymbol{\tau_{:}} = [0;0;0;\boldsymbol{\tau_{El}} + \boldsymbol{\tau_{Fric}}]$, where $\boldsymbol{\tau_{El}}$ and $\boldsymbol{\tau_{Fric}}$ represents the elastic and friction forces and torques along the longitudinal, lateral and height direction. Elastic force is evaluated as:

$$\boldsymbol{\tau_{El_{1:2}}} = K_{el}A\hat{\boldsymbol{n}} \tag{8}$$

where K_{el} depends on the soft material of which the agents are made, A is the contact area of which the centroid is individuated by point C, $\hat{n}$ is orthogonal to the two contact points H_1, H_2, which individuates the direction of the tangential versor $\hat{\tau}$. Friction force is evaluated as:

$$\boldsymbol{\tau_{Fric_{1:2}}} = \mu_d||(\boldsymbol{\tau_C})||sign(\boldsymbol{V_r})\hat{\boldsymbol{\tau}} \tag{9}$$

where μ_d is a friction coefficient of the chosen material, $||(\tau_C)||$ is the Euler-norm of τ_C and $sign(\boldsymbol{V_r})$is the sign of the relative velocity between the two colliding agents. Both torques due the elastic and friction forces are evaluated by using as a position vector the vector between the centroid of the boat and the centroid C of the contact area. According to (7), it is possible to write the state and control vector of the $i-th$ agent as $\boldsymbol{x_i} = [X_i,\ Y_i\ \psi_i, u_i,\ v_i,\ r_i]$ and $\boldsymbol{u_i} = [u_{i1},\ u_{i2},\ u_{i3}]$, respectively. In the case of N

agents in the swarm, state and control vector are defined as $\boldsymbol{x} = [\boldsymbol{x_1},\ \boldsymbol{x_2},\ \ldots,\ \boldsymbol{x_N},\ ]$ and $\boldsymbol{u} = [\boldsymbol{u_1}, \boldsymbol{u_2},\ \ldots, \boldsymbol{u_N}]$, so that the full nonlinear dynamic system can be written in the affine form:

$$\dot{\boldsymbol{x}} = \boldsymbol{\phi}\left(\boldsymbol{x}\right) + \boldsymbol{B}\boldsymbol{u} \tag{10}$$

The breakdown boat is intended as one of the agent of the swarm, but fully uncontrolled, so that the worst case scenario for rescuing is depicted. Its dynamical system is the same of the controlled boats in (7), with $\boldsymbol{u} = \boldsymbol{0}$, $\boldsymbol{\tau_{i2j}} = \boldsymbol{0}$. The breakdown boat and the rescue (target) state vector are introduced as $\boldsymbol{x_{BD}}$ and $\boldsymbol{x_{Tgt}}$.

4. TOWING MISSION STRATEGIES

In this section, different strategies for the towing assignment are discussed. Since the nature of the forces taken into account, the agents can only push the breakdown boat in the direction of the target, but they are not able to pull the vessel. Therefore, the environment is divided into a 'active area' and a 'non-active area'. First, the two areas are identified. Then, three strategies for towing the breakdown boat are discussed. The first one is the Individual Rescue Strategy or IRS, in which each agent must push the breakdown boat in the target direction. The second one is the Collective Rescue Strategy (CRS), in which a pushing formation is individuated. The third one is the Swarm Rescue Strategy (SRS), in which the entire swarm try to put the breakdown boat into the center of mass of the swarm and then to move as a unique group to the target area. It is reasonable to expect that the IRS should not be very effective, but it is here used as benchmark for the other strategies. The CRS would be very effective from a theoretical point of view, but from a practical point of view it would require to know a lot of *a priori* information, for example the size of the agents, their distance from the target, the number of agents that are coming etc. The SRS should work adaptively, regardless of the number of drones (as long as $N > 1$). It is reasonable to think that it could suffer from orientation problems, but it is equally reasonable that, with a fairly large number of drones, it can work ensuring the recovery of the damaged boat.

4.1 Initialization of the rescue

The problem starts by assigning random initial positions to all agents, the breakdown boat and the target position. First, the environment is divided into two different areas:

- Active area
- Non-active area

The non-active area is an arc of a circle of angle $\beta_{NA} = 2\hat{\beta}$, centered on the angle between the breakdown boat and the target position ψ_{BD2Tgt}. This area, depicted in Figure 3, represents the zone in which agents can not push the breakdown boat to the target. If any robot find itself in this area at any point of the simulation, it is forced to go at a chosen checkpoint location $\boldsymbol{\xi_{CP}}$ evaluated as follows:

$$\boldsymbol{\xi_{CP}} = \begin{bmatrix} X_{BD} \\ Y_{BD} \end{bmatrix} + R\left(\psi_{BD2Tgt} + \pi\right) \begin{bmatrix} -k_{CP}L \\ 0 \end{bmatrix} \tag{11}$$

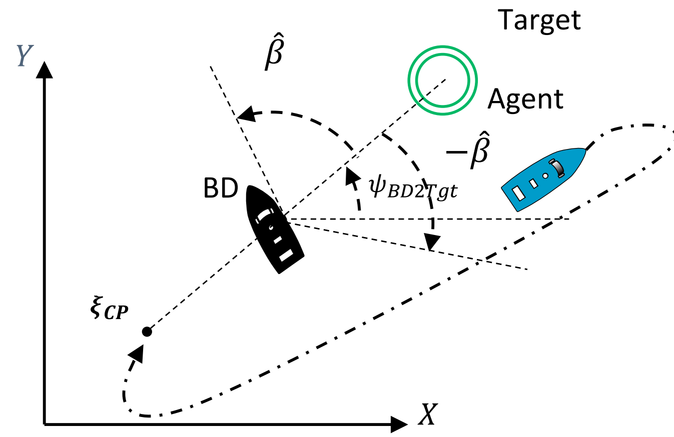

Fig. 3. Study case environment

Anytime an agent is in the towing area, must try to rescue the breakdown boat. To this aim, three different towing strategies are illustrated:

- the *Individual Rescue Strategy* (IRS)
- the *Collective Rescue Strategy* (CRS)
- the *Swarm Rescue Strategy* (SRS)

In the IRS each agent has the individual task to reach the breakdown boat and to push it by orienting itself in the direction of the target. In the CRS, it is asked to all agents to keep a chosen formation and to pursuit the individual task given in the IRS. In the SRS, all agents must reach the breakdown boat (IRS) and simultaneously they must go to the center of mass of the swarm. When the mean distance of all agents from the center of mass is lower than a chosen threshold, the center of mass is attracted to the target position. In each strategy, two different phases can be described:

- The approach phase
- The pushing phase

4.2 Individual Rescue Strategy

In the approach phase, each agent try to reach a determined approach point $\boldsymbol{\xi_A} = [X_A,\ Y_A]$ near the breakdown boat. The approach point is determined starting from the coordinates in the fixed reference of the breakdown boat, using the angle ψ_{BD2Tgt} in the fixed reference between the breakdown boat and the target, so that

$$\boldsymbol{\xi_A} = \begin{bmatrix} X_{BD} \\ Y_{BD} \end{bmatrix} + R\left(\psi_{BD2Tgt} + \pi\right) \begin{bmatrix} -k_A L \\ 0 \end{bmatrix} \tag{12}$$

where $k_A \in (0,\ 1)$ and the following notation is assumed: $R\left(\alpha\right) = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}$. Example of the placement of approach point $\boldsymbol{\xi_A}$ is illustrated in Figure 4.

The cost function related to the approach phase of each agent $g_A\left(\boldsymbol{x_i}\right)$ is represented as it follows:

$$g_A\left(\boldsymbol{x_i}\right) = \left(\boldsymbol{x_i} - \boldsymbol{x_A}\right)^T \boldsymbol{Q}_A \left(\boldsymbol{x_i} - \boldsymbol{x_A}\right) \tag{13}$$

where $\boldsymbol{x_A} = [\boldsymbol{\xi_A};\ \psi_{BD2Tgt};\ 0,\ 0;\ 0]$ and $\boldsymbol{Q_A}$ is an appropriate gain matrix. Following phase differs from strategy to strategy. The first approach is intended as an individual try of each agent to pursue the final objective to move the vessel in distress to the desired target. Therefore, each

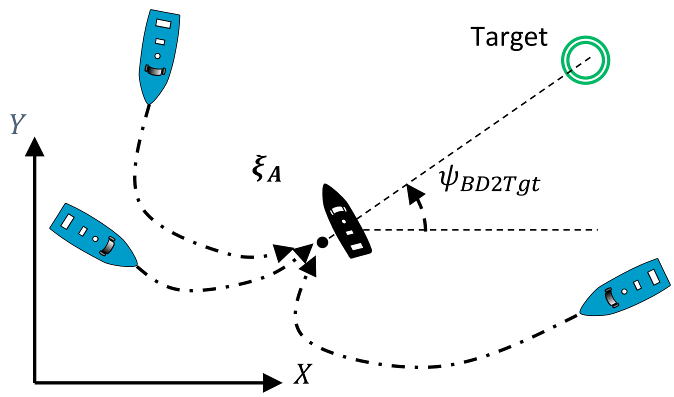

Fig. 4. Approach phase for IRS

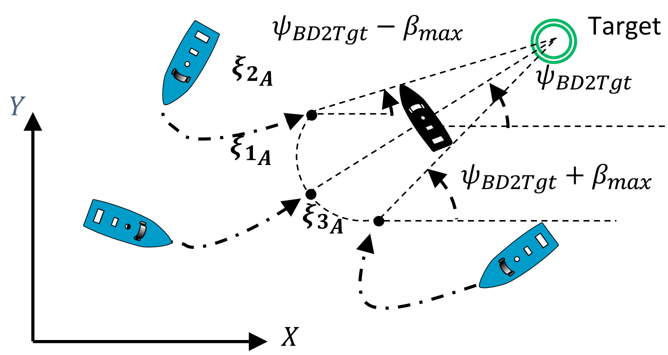

Fig. 5. Approach phase for CRS

agent has the individual objective to push the breakdown boat in the direction of the target. To perform this purpose, each agent receives two tasks:

- to orient its heading in the direction of the target
- to impose $k_A = 0$

This can be written as a general cost function for the individual rescue strategy $g_{IRS}(\boldsymbol{x_i})$, so that it is the sum of the approach phase cost function $g_A(\boldsymbol{x_i})$ and the pushing phases one, $\boldsymbol{g}_{i2Tgt}(\boldsymbol{x_i})$.

$$\begin{aligned} g_{IRS(\boldsymbol{x_i})} &= \boldsymbol{g}_A(\boldsymbol{x_i}) + \boldsymbol{g}_{i2Tgt}(\boldsymbol{x_i}) = \\ &= (\boldsymbol{x_i} - \boldsymbol{x_A})^T \boldsymbol{Q}_A (\boldsymbol{x_i} - \boldsymbol{x_A}) + \\ &+ (\boldsymbol{x_i} - \boldsymbol{x_{Tgt}})^T \boldsymbol{Q}_{2Tgt} (\boldsymbol{x_i} - \boldsymbol{x_{Tgt}}) \end{aligned} \tag{14}$$

where $\boldsymbol{x_{Tgt}} = [0;\ 0;\ \psi_{i2Tgt};\ 0,\ 0;\ 0]$ and $\boldsymbol{Q_{2Tgt}}$ is an appropriate gain matrix.

4.3 Collective Rescue Strategy

Here, each drone takes into account also the position of other agents and tries to establish a given position in a designed formation. The required formation is designed with similar idea respect to the one for the design of the approach phase of the IRS. The approach point for each drone $\boldsymbol{\xi_{iA}}$ is written as:

$$\boldsymbol{\xi_{iA}} = \begin{bmatrix} X_{BD} \\ Y_{BD} \end{bmatrix} + R(\psi_{BD2Tgt} + \beta_i) \begin{bmatrix} -k_A L \\ 0 \end{bmatrix} \tag{15}$$

where β_i is designed so that: $\sum_{i=1}^{N} \beta_i = 0$ and $\beta_i \leq \beta_{max}$, with β_{max} previously decided. Example of of the approach phase for CRS is illustrated in Figure 5.

In a similar way to (13), the cost function for the approach phase in the CRS is:

$$g_{A_i}(\boldsymbol{x_i}) = (\boldsymbol{x_i} - \boldsymbol{x_{i_A}})^T \boldsymbol{Q}_A (\boldsymbol{x_i} - \boldsymbol{x_{i_A}}) \tag{16}$$

where this time $\boldsymbol{x_{i_A}} = [\boldsymbol{\xi_{i_A}};\ \psi_{BD2Tgt} + \beta_i;\ 0,\ 0;\ 0]$ so that each agent has an individual approach point. The pushing phase in the CRS follows the same methodology of the IRS case, so the cost function of the CRS can be directly written as:

$$\begin{aligned} g_{CRS}(\boldsymbol{x_i}) &= g_{A_i}(\boldsymbol{x_i}) + \boldsymbol{g}_{i2Tgt}(\boldsymbol{x_i}) = \\ &= (\boldsymbol{x_i} - \boldsymbol{x_{i_A}})^T \boldsymbol{Q}_A (\boldsymbol{x_i} - \boldsymbol{x_{i_A}}) + \\ &+ (\boldsymbol{x_i} - \boldsymbol{x_{Tgt}})^T \boldsymbol{Q}_{2Tgt} (\boldsymbol{x_i} - \boldsymbol{x_{Tgt}}) \end{aligned} \tag{17}$$

4.4 Swarm Rescue Strategy

In the last strategy each agent has both individual and collective tasks, which can be summarized as it follows:

- approach phase (as in the IRS);
- minimization of the distance from itself and the center of mass of the swarm;
- following the center of mass which is asked to go in the direction of the target.

The first task is taken from the IRS without any difference. As supplementary request, to each agent is asked to minimize the distance between itself and the center of mass of the swarm. When the variance of all the distances between agents and the center of mass is lower than a given threshold, it is asked to the center of mass to reach the desired target. This last requirement represents the pushing phase for the SRS. First, the center of mass of the swarm is evaluated as

$$\boldsymbol{\xi_{CM}} = \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{\xi_i} \tag{18}$$

where $\boldsymbol{\xi_i} = [X_i;\ Y_i]$, and a vector for the center of mass is defined as: $\boldsymbol{x_{CM}} = [\boldsymbol{\xi_{CM}};\ \boldsymbol{0};\ \boldsymbol{0};\ \boldsymbol{0};\ \boldsymbol{0};\ Y_i]$. A quadratic cost function for the attraction to the center of mass $g_{CM}(\boldsymbol{x_i})$ is evaluated as:

$$g_{CM}(\boldsymbol{x_i}) = (\boldsymbol{x_i} - \boldsymbol{x_{CM}})^T \boldsymbol{Q}_{CM} (\boldsymbol{x_i} - \boldsymbol{x_{CM}}) \tag{19}$$

The variance of relative distances between agents and the center of mass is:

$$\sigma = \sum_{i=1}^{N} \sqrt{\frac{(X_i - X_{CM})^2 + (Y_i - Y_{CM})^2}{N}} \tag{20}$$

The cost function for the movement of the center of mass in the direction of the target is

$$g_{2Tgt}(\sigma) = (\boldsymbol{x_{CM}} - \boldsymbol{x_{Tgt}})^T \boldsymbol{Q}(\sigma) (\boldsymbol{x_{CM}} - \boldsymbol{x_{Tgt}}) \tag{21}$$

where $\boldsymbol{Q}(\sigma) = [q_1(\sigma);\ q_2(\sigma);\ 0;\ ;\ 0;\ 0]$ and $q(\sigma) = \frac{\hat{q}}{\sigma}$. All considered, the SRS cost function is written as:

$$g_{SRS}(\boldsymbol{x_i}) = g_{IRS}(\boldsymbol{x_i}) + g_{CM}(\boldsymbol{x_i}) + g_{2Tgt}(\sigma) \tag{22}$$

5. RESULTS

In this section, first results for IRS, CRS and SRS strategies are illustrated. For all strategies, the study case scenario is as it follows: the breakdown boat is positioned at

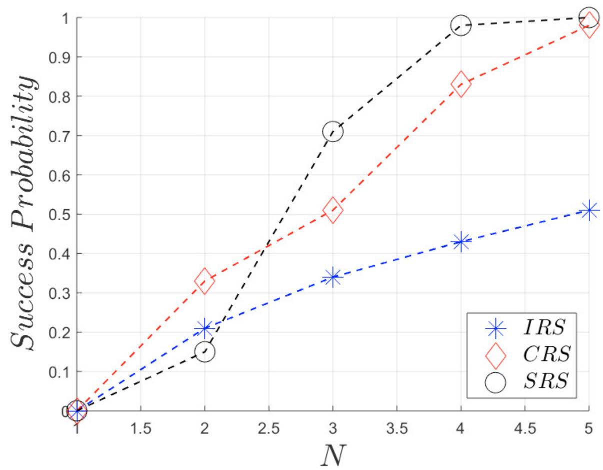

Fig. 6. Success Probability

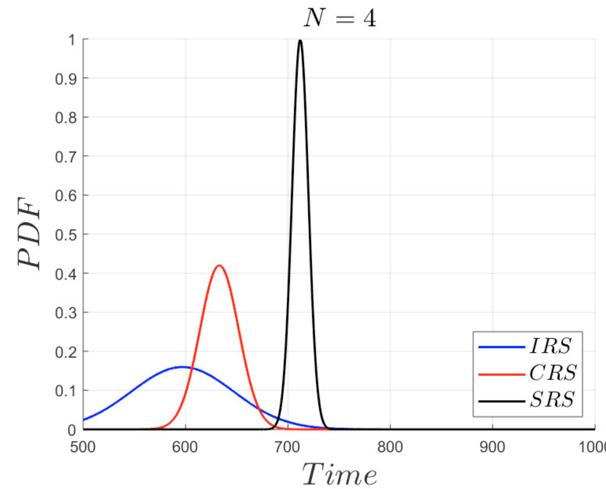

Fig. 7. Probability Density Function for $N = 4$

a distance of around 300 meters from the target position, with random initial heading. The swarm boats are placed in random positions in a 'box' around the breakdown boat of approximately 100 meters, with random heading as well. All vessels are identical. For each random initial conditions, all three strategies are performed and around 100 simulations with different initial conditions are performed. Since the equal dimensions of the breakdown boat and the agents, maximum number of agents considered is $N = 5$. Each simulation is considered successful if the breakdown boat arrives in proximity of the target, with a circular threshold with radius is L . In Fig. 6 the success rate of each strategy in the performed simulations is shown, while in Fig. 7 the probability density function of the arrival time at the target with $N = 4$ is depicted. As it can be seen, CRS and SRS are not performed for $N = 1$, because they required at least $N = 2$ agents. All three strategies gave promising results, with a minimum success probability around the 80% in correspondence of the maximum number of agents. As it was expected, the SRS had best results in terms of success probability, but as it can be seen in , it is slower both than the CRS and the IRS. However, the IRS is quicker of the other two strategies, but it is the one with the lower success probability. This was addressed to the lack of control in the heading variable during the SRS strategy, which is very robust in term of results but slower than the CRS.

6. CONCLUSION

In this paper, a new feedback control named Feedback Local Optimality Principle, or FLOP, was applied in the towing of a breakdown boat by a swarm of marine drones. The FLOP method provides the possibility to control each agent of the swarm with individual task, and to give a collective task to the entire swarm. Different towing strategies were illustrated, and some preliminary results for each strategy has been given. Although the initial state of the project, FLOP method succeeds in rescuing the breakdown boat with all three tested strategies. Further developments will comprehend a more complex dynamics for both agents and the breakdown boat, different sizes and shapes for each agent. The chance to have different size between agents and the breakdown boat will give the possibility to use larger numbers of agents for the swarm. Nevertheless, showed results give a first insight of the capability of the FLOP control to manage the cooperation between agents with different tasks assigned.

REFERENCES

Antonelli, D., Nesi, L., Pepe, G., and Carcaterra, A. (2018). Mechatronic control of the car response based on vfc. In *ISMA2018, Leuven, Belgium (2018)*.

Arbanas, B., Ivanovic, A., Car, M., Haus, T., Orsag, M., Petrovic, T., and Bogdan, S. (2016). Aerial-ground robotic system for autonomous delivery tasks. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. doi: 10.1109/ICRA.2016.7487759.

Bibuli, M., Bruzzone, G., Caccia, M., Gasparri, A., Priolo, A., and Zereik, E. (2014). Swarm-based path-following for cooperative unmanned surface vehicles. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, 228(2), 192–207. doi:10.1177/1475090213516108.

Bibuli, M., Singh, Y., SharmaS., Sutton, R., Hatton, D., and Khan, A. (2018). A two layered optimal approach towards cooperative motion planning of unmanned surface vehicles in a constrained maritime environment. In *11th IFAC Conference on Control Applications in Marine Systems, Robotics, and Vehicles CAMS 2018*. doi:https://doi.org/10.1016/j.ifacol.2018.09.458.

Braganza, D., Feemster, M., and Dawson, D. (2007). Positioning of large surface vessels using multiple tugboats. In *2007 American Control Conference*. doi: 10.1109/ACC.2007.4282954.

Bui, V.P., Ji, S.W., Choi, K.H., and Kim, Y.B. (2012). Nonlinear observer and sliding mode control design for dynamic positioning of a surface vessel. In *12th International Conference on Control, Automation and Systems*.

Esposito, J., Feemster, M., and Smith, E. (2008). Cooperative manipulation on the water using a swarm of autonomous tugboats. In *2008 IEEE International Conference on Robotics and Automation*. doi: 10.1109/ROBOT.2008.4543414.

Matos, A., Martins, A., Dias, A., Ferreira, B., Almeida, J.M., Ferreira, H., Amaral, G., Figueiredo, A., Almeida, R., and Silva, F. (2016). Multiple robot operations for maritime search and rescue in eurathlon 2015 competition. In *OCEANS 2016-Shanghai*, 1–7. IEEE.

Mohan, Y. and Ponnambalam, S. (2019). An extensive review of research in swarm robotics. In *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*. IEEE. doi:10.1109/NABIC.2009.5393617.

Murphy, A., Landamore, M., and Birmingham, R. (2008). The role of autonomous underwater vehicles for marine search and rescue operations. *Underwater Technology*, 27(4), 195–205.

Murphy, R.R. (2012). A decade of rescue robots. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 5448–5449. IEEE.

Naveh, Y., Bar-Yoseph, P.Z., and Halevi, Y. (1999). Nonlinear modeling and control of a unicycle. *Dynamics and Control*, 9(4), 279–296.

Nesi, L., Antonelli, D., Pepe, G., and Carcaterra, A. (2019). Fast moving of a population of robots through a complex scenario. In *Nodycon 2019, Roma, Italy.*

Paifelman, E., Pepe, G., and Carcaterra, A. (2019). An optimal indirect control of underwater vehicle. *International Journal of Control 2019.* doi: 10.1080/00207179.2019.1590737.

Pepe, G., Antonelli, D., Nesi, L., and Carcaterra, A. (2018). Flop: feedback local optimality control of the inverse pendulum oscillations. In *ISMA2018, Leuven, Belgium.*

Varughese, J., Thenius, R., Schmickl, T., and Wotawa, F. (2017). Quantification and analysis of the resilience of two swarm intelligent algorithms. In *3rd Global Conference on Artificial Intelligence*. doi:10.29007/5fhn.