MANAGING THE OCEANS CLEANUP VIA SEA CURRENT ANALYSIS AND BIO-INSPIRED COORDINATION OF USV SWARMS

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ABSTRACT

This work presents the results of a simulated analysis concerning algorithms of self-coordination of a swarm of Unmanned Surface Vehicles (USV) for the mitigation of plastic pollution in oceans. The analysis is based on real scenarios provided by the Copernicus Marine Service. The scenario includes the localization of plastics on the sea surface and their movement in time based on the sea surface currents. A swarm intelligence algorithm is used for the de-centralized coordination of the USV swarm. Results are presented on a study area located in the northern Tyrrhenian sea between Corsica and the Tuscan coast, in the period of July 2016.

Index Terms— Swarm intelligence, evolutionary optimization, Unmanned Surface Vehicles, plastic pollution, sea.

1. INTRODUCTION

Plastic pollution is a major source of marine debris. Many plastics – including polypropylene, polyethylene, nylon, polystyrene, polycarbonate and polyvinyl chloride (PVC) – are very durable; some are predicted to persist in the marine environment for many years. The wind and ocean current can bring to the accumulation over time of buoyant plastic in specific geographical areas so inducing serious pollution problems, also related to the degradation of plastic materials and the formation of sea-slicks and bio-films. Europe is the second largest producer of plastic (after China). The major plastic-consuming countries in the EU are Germany and Italy [1][2].

Observation and mitigation represent a fundamental step to marine plastics reduction. Among the most common mitigation techniques we mention those based on a removing/cleaning-up and biotechnology strategies.

This paper focuses on the perspective use of the Albatross Unmanned Surface Vehicle (USV) prototype which was designed and presented in 2019 at the NASA Space Apps Challenge. In the literature, swarms of robots are increasingly proposed as a viable solution to mitigate the problem of plastic pollution in oceans. The cooperation of a USV swarm can sensibly increase the performances of cleaning dirty oceanic zones. The USV is assumed to be equipped with on-board sensors that allow it to identify the plastic debris [3].

In general, the cooperation of USVs can be coordinated either in a centralized or a de-centralized way. The centralized coordination asks for a human operator who analyses and collects information about dirty zones and updates the environment map of USVs. As a result, the swarm navigates to a new assigned dirty zone and cleans it.

The main characteristic of a USV coordination strategy is its capability to be autonomous, robust, resilient, and adaptive. Centralized logic solutions are not effective for this purpose, due to the high level of complexity, design and management effort. In contrast, decentralized logic approaches can provide a USV swarm with a certain degree of autonomy [4].

This work focuses on a de-centralized coordination of the swarm, for investigating the use of swarm intelligence techniques. More specifically, two swarm intelligence algorithms are compared, i.e., Ant Colony Optimization (ACO) [5] with Evolution (ACO-E), and Stigmergy Flocking Evolution (SFE) [7]. ACO is a biologically inspired algorithm, based on ant colonies behavior. In contrast, SFE includes different biological cooperation models, inspired by chemical pheromone, olfactory and visual perception. Both algorithms are parametrically adaptive with respect to the layout, thanks to the use of Evolutionary Optimization. Simulation results show that the SFE algorithms sensibly overcomes the ACO in terms of amount of collected debris per month.

A key point of the USV swarm coordination is the capability to provide a dynamic update of the environment map, according to the sea current moving the plastic debris. To this end, in this work the model of the Copernicus

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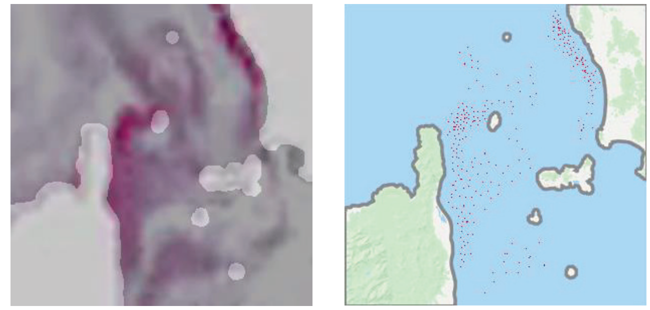
Marine Service is used [5]. The model provides a stream of frames with the spatial distribution of floating plastics, based on the pattern of ocean currents. The model has been created from Earth Observation data in a Numerical Weather Prediction (NWP).
The paper is organized as follows. Section 2 presents the coordination methodology based on ACO and SFE [7][9][10]. The study area, the dataset of the Copernicus Marine Service, and the experimental results are presented in Section 3. Finally, conclusions are drawn in Section 4.

2. METHODOLOGY

The methodology is developed in an exploration simulator which focuses on the coordination logic, assuming that control aspects are managed by the on-board technology. The obstacles and target distribution are recreated at a given scale, allowing the simulation of USV movement and collision avoidance in the environment.
The exploration problem is modelled by discretizing the environment into a lattice of cells. Each cell has an area of 0.25 Km^2. The temporal unit (tick) of the simulation environment is set to 5 minutes. The duration of the mission is statically specified and corresponds to one month of floating plastic movement. The target dynamics is reproduced by using a sequence of frames with daily transition. The USV position and direction is dynamic and set according to exploration and coordination rules, which can be parametrically adapted by an evolutionary algorithm. In particular, the Differential Evolution (DE) is used as the evolutionary algorithm because it is more suitable for this class of problems (see [10] and references therein).
Figure 1 summarizes the main steps of the procedure used to model the daily spatial distribution of plastics within the study area. The starting point of the procedure is given by a frame providing spatial density of plastics over sea. This frame is used to estimate the 2D probability density function to find plastics at a location (latitude, longitude) over the sea. A Montecarlo technique is then used to sample the location of plastics over sea, to generate the map with the target to collect, represented as red points in Figure 1-(b).

2.1. Modelling of USV swarm dynamics

Since the ACO algorithm is well-known in the literature, this section focuses on the SFE algorithm. SFE is based on two fundamental swarm cooperation models: stigmergy and flocking [6][7]. Stigmergy is used to release an attractive (or repulsive) stimulus while collecting (not collecting) targets. In the proposed computational model, a digital stigmergic mark is released by the drones in the environment. Figure 2 illustrates the model of a stigmergic mark: it is a truncated cone with unit height, radius top and down [9].



(a) **(b)**

Fig. 1 - Procedure to determine the daily distribution of plastics: **(a)** spatial density of plastic provided by the Copernicus Marine Service; **(b)** vectorial map generated for the exploration simulator.

Multiple stigmergic marks can overlap, creating a stigmergic trail. Stigmergic trail evaporates over time. Since the stigmergic trail is maintained in a digital environment, it is instantly diffused, to immediately propagate information to nearby drones.

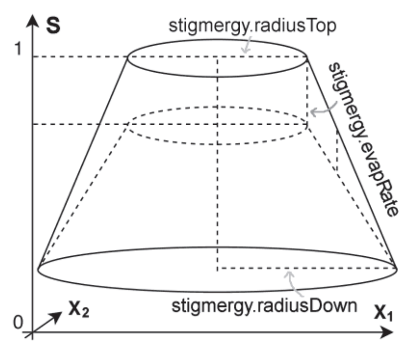


Fig. 2 - Model of stigmergic mark [9].

Flocking is used to model a robust and flexible swarm formation. It is based on the rules of cohesion, separation and alignment, illustrated in Figure 3. The different rules are activated on disjoint regions (Figure 3a). The separation rule (Figure 3b) maintains a distance among flock mates for a better scan of the area. The cohesion rule (Figure 3c) directs the drone to the flock center, to avoid dispersion. Finally, the alignment rule (Figure 3d) keeps the drone's heading aligned to the average flock mates heading.
The DE logic is summarized by the pseudocode presented in Algorithm 1. In the simulated scenario, the swarm S_i explores the environment where the targets are dynamically specified. Let K be the number of aggregated parameters. In DE, S_i is a solution represented by a real K-dimensional vector called genotype $\boldsymbol{p_i}$. The overall collected plastic by the swarm is returned by the simulated mission and is used as a fitness of the solution, f_i.

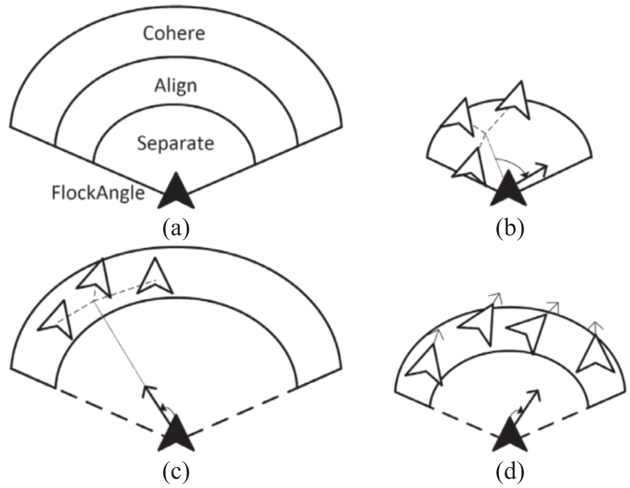


Fig. 3 - Model of flocking behavior

DE starts with a population $P^{(0)}$, made by N candidate solutions, $\boldsymbol{p}_i^{(0)}$, randomly generated under user-specified parametric constraints. At each iteration t, and for each genotype $\boldsymbol{p}_i^{(t)}$ of the current population $P^{(t)}$, a mutant vector m is created by applying the mutation of randomly selected members. Then, a trial vector $\boldsymbol{p}_i^*$ is created by crossover of m and $\boldsymbol{p}_i^{(t)}$. Subsequently, the population is modified selecting the best fitting vector between the fitness of the trial vector f_i^* and the fitness of the initial genotype ($f_i^{(t)}$).

Algorithm 1: Differential Evolution algorithm

function differentialEvolution(*USVs*, *Obstacles*, *Targets*)
$t = 0$;
$P^{(0)}$ = initializePopulation();
for each genotype $\boldsymbol{p}_i^{(0)}$ **in** $P^{(0)}$ **do**
  $S_i^{(0)}$ = genotypeToSwarm($\boldsymbol{p}_i^{(0)}$);
  $f_i^{(0)}$ = simulateMission($S_i^{(0)}$, *USVs*, *Obstacles*, *Targets*);
do
  for each genotype $\boldsymbol{p}_i^{(t)}$ **in** $P^{(t)}$ **do**
    $\boldsymbol{m}$ = generateMutant($P^{(t)}$, $\boldsymbol{p}_i^{(t)}$);
    $\boldsymbol{p}_i^*$ = binomialCrossover($\boldsymbol{p}_i^{(t)}$, $\boldsymbol{m}$);
    S_i^* = genotypeToSwarm($\boldsymbol{p}_i^*$);
    f_i^* = simulateMission(S_i^*, *USVs*, *Obstacles*, *Targets*);
  for each genotype $\boldsymbol{p}_i^{(t)}$ **in** $P^{(t)}$ **do**
    if ($f_i^* > f_i^{(t)}$) **then**
      $\boldsymbol{p}_i^{(t+1)} = \boldsymbol{p}_i^*$ **;** $f_i^{(t+1)} = f_i^*$ **;**
    else
      $\boldsymbol{p}_i^{(t+1)} = \boldsymbol{p}_i^{(t)}$ **;** $f_i^{(t+1)} = f_i^{(t)}$ **;**
  $f_{max}^{(t+1)} = \max\{ f_1^{(t+1)},\dots, f_N^{(t+1)} \}$;
  $t = t + 1$;
while (terminationCriterion($f_{max}^{(t)}$, t) = **false**);
return genotypeToSwarm($\boldsymbol{p}_{max}^{(t)}$);

When the termination criterion is true, i.e., the monthly evolution of the floating plastic is finished, the vector characterizing the swarm with the best fitness (i.e. the maximum overall collected plastic) in the current population is considered as the optimal swarm parameterization. The DE algorithm has at least two hyper-parameters: the scaling factor F∈ [0,2] from which results the mutant vector, and the crossover probability CR. The smaller CR the higher probability to produce a vector that is more similar to the target vector rather than to the mutant vector.

3. EXPERIMENTAL RESULTS

The study area covers the portion of the Tyrrhenian Sea between northeastern Corsica and Tuscany. Specifically, it is a 150.5×150.5 Km^2 area, with an overall navigable surface of 16235 Km^2. This area is often affected by the formation of non-permanent floating plastic islands, due to the characteristic sea currents [11][12]. A realistic scenario is simulated by using a video animation of the sea plastic pollution made available by the Copernicus Marine Service [5]. For this study, the period from 01/07/2016 till 30/07/2016 has been selected.

The environment and the coordination logic are implemented on *NetLogo*, a leading simulation platform for swarm intelligence (ccl.northwestern.edu/netlogo). The optimization module is implemented in Python, exploiting *NL4Py*, which is a NetLogo controller software for Python, for the rapid and parallel execution of NetLogo models [13]. Figure 4-(a) shows the pheromone clouds and the USV swarm tracking the floating plastic movements.

In our study, we have set the simulator with the physical and technological parameters of the USV prototype designed in the ALBATROSS project [14]. The main characteristics of this drone are summarized in Table 1.

The performances of the swarm coordination algorithm have been assessed by considering both ACO and SFE algorithms.

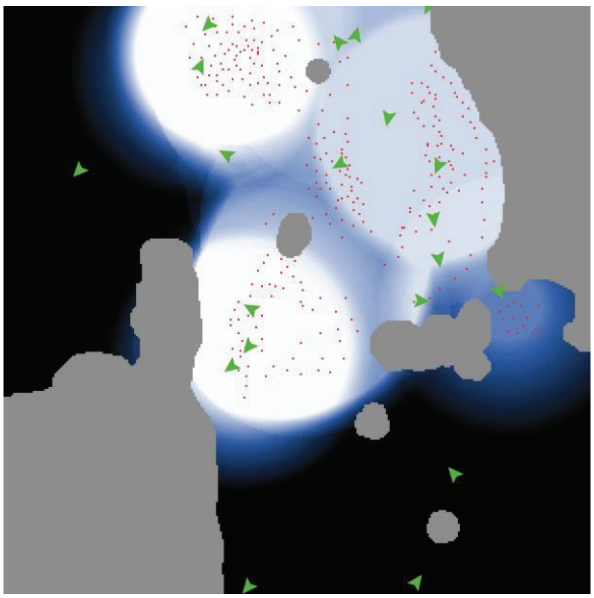
Figure 4-(b) shows the performance of 20 USVs swarm, obtained with the two coordination strategies in the same simulation configurations. For each strategy, the DE optimization is carried out 5 times, to calculate the 95% confidence intervals. The results show that the SFE algorithm clearly outperforms the ACO strategy.

4. CONCLUSIONS

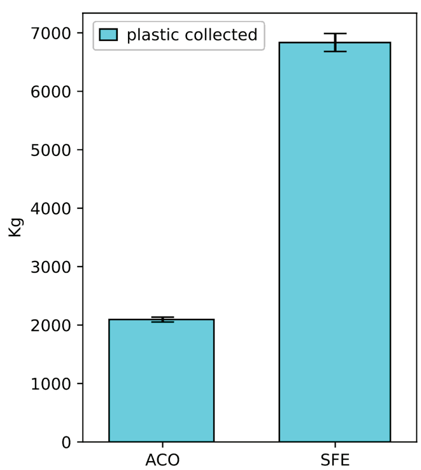
This paper focuses on the problem of mitigation of plastic pollution in oceans via a swarm of USVs. A realistic scenario has been simulated considering a dataset provided by the Copernicus Marine Service. The swarm coordination logic, namely SFE, is based on stigmergy and flocking, two bio-inspired behavioral models that steer the USVs for plastic collection. Moreover, the exploration and coordination rules has been parametrically adapted by the Differential Evolution algorithm in order to maximize the amount of plastic collected. A simulation testbed has been developed, using the technical specification of a USV prototype designed in the ALBATROSS project. Comparative results with the ACO algorithm clearly show that the SFE algorithm is more suitable for plastic collection task.

Table 1 - Technical specification of the ALBATROSS trimaran

USV Parameter	**Real value**	**Simulated value**
cruising speed	6 Km/h	1 patch/tick
maximum payload	6000 Kg	6000 Kg
net capacity	33.3 Kg	33.3 Kg
size	25 x 13 m	0.05 x 0.026 patches



(a)



(b)

Fig. 4 – **(a)** Simulation of plastic collection; **(b)** amount of plastic collected by the USV swarm after the DE adaptation.

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