Using Artificial Immune System to Prioritize Swarm Strategies for Environmental Monitoring

Manilo Monaco
Dept Information Engineering
University of Pisa
Pisa, Italy
manilo.monaco@dii.unipi.it

Giada Simionato
Dept Information Engineering
University of Pisa
Pisa, Italy
giada.simionato@phd.unipi.it

Mario G. C. A. Cimino
Dept Information Engineering
University of Pisa
Pisa, Italy
mario.cimino@unipi.it

Gigliola Vaglini
Dept Information Engineering
University of Pisa
Pisa, Italy
gigliola.vaglini@unipi.it

Sabrina Senatore
Dept Information Engineering,
Electrical Eng. & Applied Math
University of Salerno
Salerno, Italy
ssenatore@unisa.it

Gaetano Caricato
Regional Environment Protection
Agency of Basilicata (ARPAB)
Basilicata Region
Matera, Italy
gaetano.caricato@arpab.it

***Abstract*—Swarms of Unmanned Aerial Vehicles (UAVs) are increasingly adopted to provide early situational awareness in environmental monitoring missions. Currently, a challenging problem is to manage swarms via responsive and adaptive coordination mechanisms. This study considers a cutting-edge swarm coordination algorithm called SFE, based on three strategies: stigmergy, flocking and evolution. Stigmergy is the release of digital pheromone by drones to generate a potential field that influences the steering in the spatial-temporal proximity. Flocking is a formation mechanism to spatially organize drones into local groups. Evolution is the parametrical adaptation of Stigmergy and Flocking to a specific type of mission. A novel algorithm called P-SFE is proposed, to overcome the limit of SFE related to the static priority of the three strategies. This prioritization is managed through an Artificial Immune System. A simulation testbed is developed and publicly released, based on commercially available technology and real-world scenarios. Experimental results show that the proposed P-SFE extends and sensibly outperforms the SFE.**

Keywords—environmental monitoring, drones swarm, stigmergy, flocking, differential evolution, artificial immune system

I. INTRODUCTION AND BACKGROUND

Nowadays, air, water and soil are under observation for the long-term degradation processes and the destructive incidents often caused by human activities. It is essential to keep control of such processes and events before they become irreversible. In the last decade, environmental monitoring based on aerial survey has evolved in technological, economic and legislative aspects [1]. A variety of novel aerospace platforms have become available for environmental monitoring, such as satellites, aircraft, helicopters, and, more recently, unmanned aerial vehicles (UAVs). A single aerial platform cannot provide both high and low altitude, both broad coverage and high resolution. In addition, the capabilities of medium-high altitude and long endurance platforms are often limited "by design" from the on-board technology and from the need to assign human operators [2]. To match various environmental mission profiles, an aerial platform should consider requirements such as the morphology of near-ground and sub-urban flight areas, low velocity and high maneuverability, adaptability of on-board sensors and, above all, compact size. For this reason, small UAVs (sUAVs) are increasingly attracting body of research [1].

Due to its short endurance, an sUAV is designed for short mission profile surveillance. A promising solution for the acquisition of environmental information on large areas is an integrated multi-sUAV system, known as *swarm* in the literature. The shift from single to multiple sUAVs raises some fundamental issues: (i) the management of an array of onboard equipment distributed on several cooperating sUAVs; (ii) the adoption of swarm intelligence algorithms enabling a single operator to control several sUAVs; (iii) the development of a coping strategy for the loss of sUAVs, thus increasing the robustness of the swarm to harsh operating conditions [3]. In this work we have enhanced one of the cutting-edge algorithms for swarm intelligence thus addressing the above-mentioned issues in the context of environmental monitoring with swarms of sUAVs.

An environmental monitoring mission can be organized in two phases: (i) *environmental exploration*, i.e., to search targets, and (ii) *drones recruitment* for targets resolution, i.e., to collect sufficient situational information. Examples of targets are marine micro-plastics [4], illegal dumps [5], wild-land fires, gas leaks, and land mines [6].

In [5], the authors proposed SFE (Stigmergy Flocking Evolution), an algorithm for sUAVs swarm coordination based on three bio-inspired computational strategies: (i) *Stigmergy*, i.e., the ability of drones to release and sense attractive or repulsive potentials, according to the presence or absence of detected targets, respectively; (ii) *Flocking*, i.e., modeling the swarm formation on the basis of rules of cohesion, separation and alignment; (iii) *Evolution*, i.e., the usage of an evolutionary optimization algorithm for the calibration of both stigmergy and flocking parameters to the specific mission. In [5] the SFE algorithm was compared to the state-of-the-art of bio-inspired swarm algorithms for both exploration (ACO – Ant Colony Optimization) and recruitment (FTS – Firefly-based Team Strategy, PSO – Particle Swarm Optimization, ABC – Artificial Bee Colony). Experimental results on real-world scenarios shown that SFE significantly outperforms the state-of-the art.

However, the most critical limitation of SFE is the static priority assigned by drones to attractive stigmergy (highest priority), flocking (intermediate priority) and repulsive stigmergy (lowest priority). To address this limitation, in this paper a novel variant called *Prioritized SFE* (P-SFE) is proposed, using the SFE algorithm as a reference. With P-SFE each drone can dynamically assign a different priority to the strategies according to the context. The local priority is assigned using the Artificial Immune System (AIS) algorithm: an adaptive method inspired by theoretical immunology [9].

The immune system response is carried out by *antibodies*: highly specialized cells manufactured by *B-lymphocytes*, able to detect foreign material, or *antigens*, and signal them for elimination. Each type of antibody can detect both other antibodies of the same category and a specific type of antigen. Upon detection, the lymphocyte is stimulated to clone itself, that is, to produce more antibodies of that specific type, to cope with the potential threat. The process of stimulating a lymphocyte to produce a number of antibodies proportional to the degree of matching between their receptors and the antigens is called *clonal selection* [10]. For a deeper overview, the reader is referred to [9][10]. The concentration of a particular type of antibody therefore depends on the times in which they are recognized by other antibodies, leading to its reduction, and the times in which they recognize other cells, leading to a stimulation, hence an increase in the concentration. The mathematical model representing this phenomenon was first presented in [10] and then adapted by [9] to swarm applications. Using this model, the priorities of the strategies of each drone in the swarm are updated and the one with the highest value is selected and executed by the agent. More details are discussed in Section II.

The coordination algorithms SFE and P-SFE have been experimented on two environmental monitoring scenarios: *illegal dump search* and *early fire detection-tracking*. For this purpose, a simulation testbed has been developed and publicly released [11], to foster its application on various environments. Experimental results show that the proposed P-SFE approach outperforms the SFE.

The paper is structured as follows. Section II illustrates the design and the test cases, while the experimental results are explained in Section III. Finally, in Section IV conclusions are drawn.

II. Materials and Methods

A. Pilot Scenarios and testbed

This section illustrates two missions of environmental monitoring that are used as pilots in the determination of problem requirements, in the formulation of the method, as well as in its experimentation.

Fig. 1a shows the area of *Illegal Dump* [12], which is a real-world abusive trash map of a 80,000 m^2 area near the town of Paternò (Italy). The mission consists in detecting illegal dumps in the region of interest. An illegal dump is modelled as a cluster of static targets. Fig. 1b shows a digital representation of an ongoing mission in the testbed environment, with all the available elements. In the map, 19 buildings of different size, and 140 trees have been modelled as obstacles, represented in grey color. Drones are depicted as small green triangles. Overall, the scenario is made by 11 cluster of targets with an average of 4 targets per group. In Fig. 1b, undetected/detected targets are represented as red/yellow points. Finally, attractive/repulsive stigmergy is represented as dynamic blue/pink continuous intensity, which disappears over time. The level of stigmergy is dynamic, and it is updated following the deposit and evaporation rules. A stigmergic mark is released by a drone when a target is found (*release rule*). A decisive aspect of the mission influencing the quality assessment of the solution is the mobility of targets. In the illegal dump scenario, targets are static; therefore, the quality measure employed is the time needed to find the 95% of targets. For a detailed formalization of all elements of the testbed, the reader is referred to [5][6].

A different scenario, characterized by dynamic targets, is *Wildfire* [6]. In this case, the purpose of the mission is to detect and track wildfire fronts, i.e., the portion sustaining continuous flaming combustion, where unburned material meets active flames [8]. Fig. 1c and Fig. 1d show the wildfire front in an ongoing mission of this type in the testbed environment, taken at 1022 and 1229 seconds after the start of the mission. For the sake of simplicity, only the attractive stigmergy is represented in figure, as a black-gray level. Targets dynamics is supplied to the testbed as a sequence of frames whose transition is ruled by a preset time frequency. For missions with dynamic targets, the quality measure is the average percentage of targets discovered in each frame.

B. Technical specifications

Overall, the swarm is controlled by a *cyber-physical system*, in which physical and software components are intertwined: for example, stigmergy is entirely maintained in a digital map, and made available at the ground station for sUAVs as to enable remote computations, whereas obstacle detection is based on physical sensors controlled by on-board logic [7]. The testbed considers the features of commercially available sUAVs in terms of sensing, actuation, and collision avoidance, by modeling drone size, battery duration, sensing radius, sensing angle, collision angle, collision vision angular speed, acceleration and cruise speed [6]. Table I and Table II show the technical specifications for the considered scenarios [3][6].

C. The SFE coordination algorithm

This section briefly summarizes the SFE approach, for a more detailed explanation, the reader is referred to [5][6]. Each drone pose dynamics is governed by exploration and coordination rules. More formally, Fig. 2 shows an UML activity diagram with the workflow of an sUAV at each temporal step. The flow begins at the black circle on the left

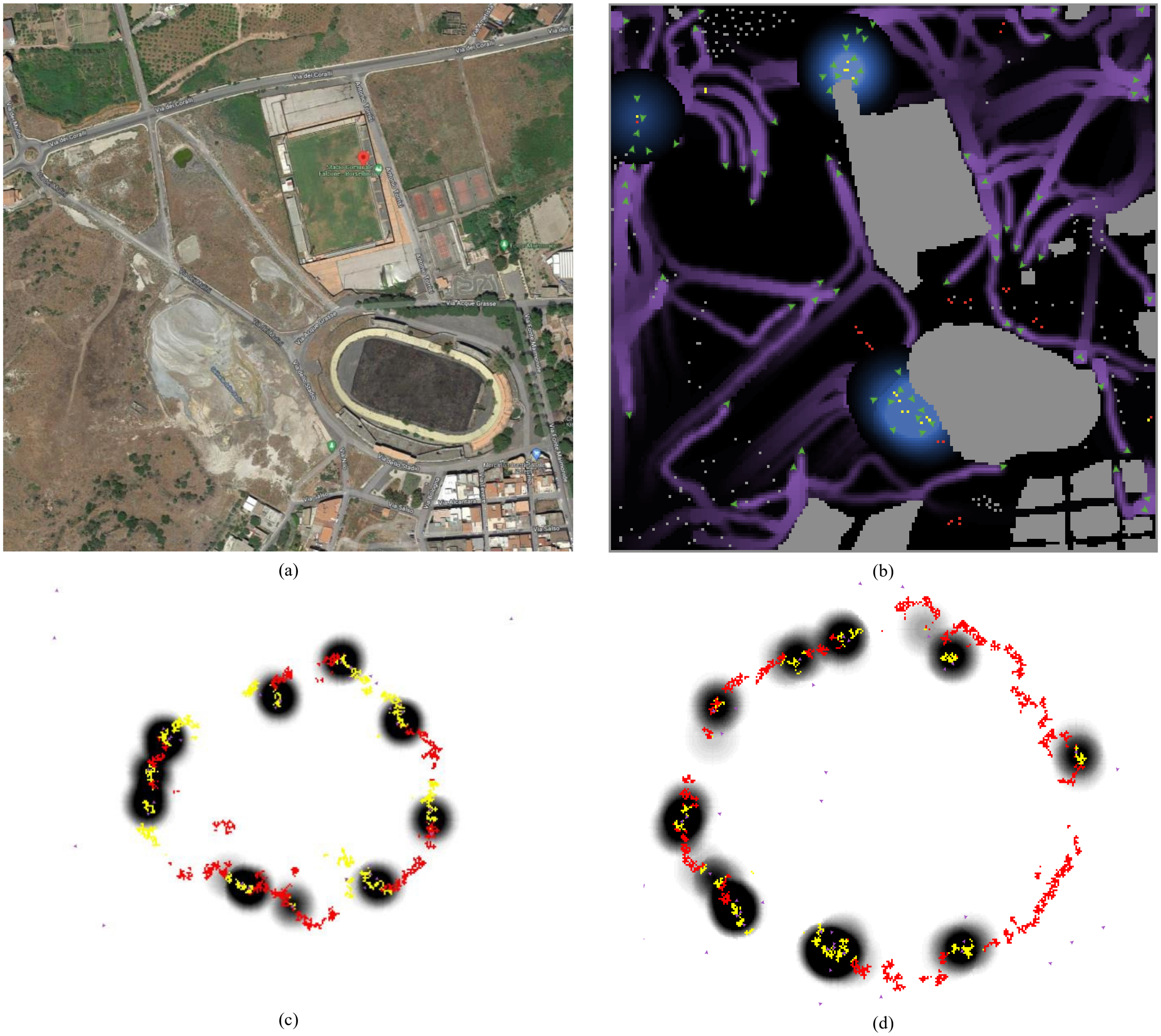


Fig. 1. (a) Illegal Dump Scenario (Google Maps ©); (b) testbed environment with drones, static targets, stigmergy and obstacles; (c) Wildfire scenario, with dynamic targets, after 1022s; (d) Wildfire scenario after 1229s.

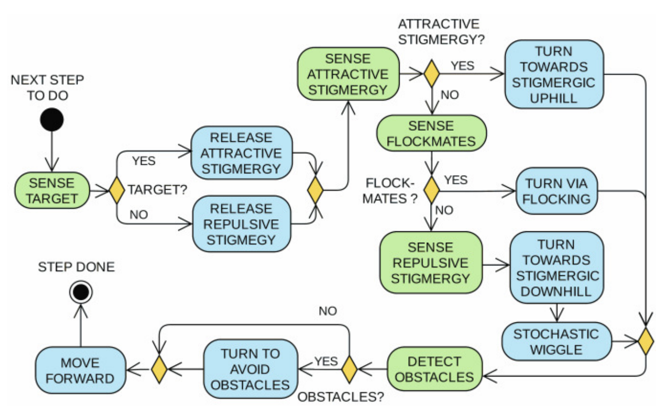


Fig. 2. UML activity diagram of the behavior of the drone in the SFE method.

(labelled as "next step to do") and ends at the black circle with white border ("step done"). A rounded-corner box represents an activity (a *procedure*). Green activities relate to sensing/ detection, whereas azure activities relate to actuation. Finally, a yellow diamond or activity represents decision logic.

TABLE I. TECHNICAL SPECIFICATIONS OF THE COMMERCIAL DRONE "DJI MATRICE 200"

Parameter	***Value***
Radius	0.3 m
Max speed	17 m/s
Max acceleration	4.4 m/s^2
Max angular speed	2.6 rad/s
Max angular acceleration	6.9 rad/s^2
Battery duration	24-38 min
Obstacle vision distance	3-30 m
Obstacle vision angle	60°

TABLE II. TECHNICAL SPECIFICATIONS OF THE SENSING EQUIPMENT, FOR EACH SCENARIO

	Illegal Dump	***Wildfire***
Cruise speed (m/s)	4	12
Sensing technology	Visual + Thermal	Visual
Sensor model	Dji Zenmuse XT2	Dji Zenmuse XT2
Sensing radius (m)	5	36

More precisely, for each temporal step, first the sUAV *senses for targets* and, if detected/not detected, *releases attractive/repulsive stigmergy*. Second, it *senses for attractive stigmergy* and, if detected, points towards the direction of its maximum intensity. If no attractive stigmergy is recognized, it *senses for flockmates* (surrounding drones) and, if detected, points towards the flock. Otherwise, it *senses for repulsive stigmergy* and, if detected, points towards the direction of its minimum intensity and *applies a stochastic wiggle* to its orientation. This wiggle, a key feature of bio-inspired approaches, allows escaping the determinism inherent to P-SFE. By perturbing the computed orientation with a small random component, it is possible to let the agents following the selected behavior while preventing the saturation of the area and exploiting the potential of the swarm. Finally, if it *detects obstacles* (or drones), it finds a free trajectory or slows down before moving.

In addition, for a given type of mission, the parameters of the stigmergic and flocking behaviors are adapted offline by the Differential Evolution (DE): an evolutionary algorithm which improves the overall quality of the search process before the mission [5]. Table III summarizes the space of parameters taken into consideration. Distance measurements are expressed in *patches*, i.e., squares having side of 2m or 4m for the Illegal Dump and Wildfire scenarios, respectively.

An example of improvement resulting from the parametric optimization is shown in Fig. 3, where the tracks left by the swarm before (a) and after (b) the application of DE are reported. For reducing the sources of non-determinism, the initial swarm position is fixed: they are located at the corners, facing the area center. In the figure, a higher green intensity corresponds to a more visited area. Clearly, the optimization leads to an effective exploration, focusing the mission on regions of interest rather than on the initial positions. It is worth to observe that the number of hyperparameters and the complexity of the parametric space makes manual tuning often infeasible. In most cases, human knowledge allows to determine only parametric intervals (Table III), because of the inherent complexity of the mission. Therefore, it is highly desirable to develop a method for semi-automatic hyperparameter tuning. Over the years, this problem has attracted a lot of research interests. It is known in the literature that interval data are suitable for managing situations characterized by excess or a lack of data. The proposed method, including what-if simulation analysis, supported by genetic optimization, and taking human qualitative assessments, is efficient for both workflows and systems parameterization [13][14]. Indeed, interval-valued data is easy to comprehend and express by a domain expert, and simple to process when there is a great variability depending on the available domain knowledge.

D. The P-SFE coordination algorithm

The most critical limitation of SFE is the static priority assigned by drones to the different strategies: the highest priority is given to attractive stigmergy, the intermediate priority to flocking, and, finally, repulsive stigmergy has the lowest priority. In this paper an enhancement of SFE, i.e., P-SFE, is proposed. P-SFE allows for dynamic assignment of strategies priority to better adapt the behavior of each drone to the current scenario.

The priorities are dynamically computed using an artificial immune system. Inspired by the concepts of the AIS presented in Section I, in this work the following analogies hold: each strategy represents a specific kind of antibody, the concentration of an antibody type is the priority of the strategy, and the antigen is represented by a detected target. Each drone accounts for a selection of B-lymphocytes, in the number of strategies available. Given a swarm $\mathcal{S}$, for each drone k with $\mathrm{k} = 1, \dots, |\mathcal{S}|$ and for each strategy i with $i = 1, \dots, N$, the priority of the strategy i for the drone k at time t, is denoted by $s_i^k(t)$ and computed according to Eq. (1), taking into account the discrete nature of the simulation.

$$s_i^k(t) = \frac{\alpha}{N}\sum_j^N \sum_{l \in I^{C(k)}} m_{ij} c_j^l(t-1) c_i^k(t-1) + \beta \sum_{l \in I^{D(k)}} \varphi_{i,l}^k c_i^k(t-1) - \mu c_i^k(t-1) \quad (1)$$

Eq. (1) reports the adaptation of the model of the immune system proposed in [9], where m_{ij} is the matrix of matching specificities, that is, a coefficient encoding the degree of matching between priorities of strategies i and j [10]. α, β and μ are coefficients taking values in $(0,1]$, where the first two are *mass* coefficients [9] and the last represents the natural decay rate. $\varphi_{i,l}^k$ are the coefficients of the interaction between strategy i onboard agent k and target l, while $c_i^k(t)$ is a version of $s_i^k(t)$ restricted to $[0,1]$. The deflection of the priority of a strategy i

onboard agent k for the time t is computed according to Eq. (2), where the parameter σ is the rate of compression.

$$c_i^k(t) = \frac{1}{1+e^{-\sigma s_i^k(t)}} \quad (2)$$

The parameters $\alpha, \beta, \mu, \sigma, m_{ij}$ and $\varphi_{i,l}^k$ are included in the parametric space optimized with the Differential Evolution algorithm. $I^C(k)$ and $I^D(k)$ are the sets of drones within the range of communication and detection of drone k, respectively. More details on the additional parameters provided by P-SFE are collected in Table IV.

The first term of Eq. (1) is the analogue of the variation in the concentration of an antibody type considering the stimulus that a B-lymphocyte would receive to produce that specific type upon detection of other matching antibodies and the suppression caused by the recognition of that type by other antibodies. This represents the impact of mutual interaction among agents [9]. The second term accounts for the variation induced by the presence of antigens (i.e., targets) while the third models the tendency of antibodies to die, reflected by the decrease of a strategy priority when it cannot undergo proper stimulation.

After having computed the updated priorities for all the strategies using Eq. (1), the one with the highest priority is chosen as the preferred strategy $i_k^\star$, i.e., $i_k^\star(t) = \underset{i=1,\dots,N}{\operatorname{argmax}}\ s_i^k(t)$.

However, the selection of the same strategy by a group of neighboring drones could lead to conflictual situations. For this reason, the AIS additionally limits the number of agents performing the same strategy, preventing from crowding specific areas, and acting therefore as a "critic" [9]. Fig. 4 shows an UML activity diagram with the behavior of each drone in the P-SFE method. The initial and final part of the workflow, which are related to the stigmergic release and to the obstacle detection, respectively, do not change. In the middle, additional logic related to the AIS is represented in yellow, together with a more flexible sensing/actuation. In particular, the agent *identifies drones within communication range* and *known targets within detection range* to *evaluate the strategies strengths*. If the *strongest strategy is crowded*, it is weakened, to allow the selection of different strategies. Finally, as before, the strongest strategy is selected.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The testbed has been implemented on *NetLogo* (ccl.northwestern.edu/netlogo/) a leading platform for swarm intelligence, using *NL4Py* as a controller interface to NetLogo, and *Scipy*, a Python library providing the implementation of the DE algorithm. To guarantee the repeatability of experiments and to foster the scientific collaboration, the source code and the scenarios have been publicly released [11].

The Differential Evolution is a stochastic algorithm that does not use gradient methods to find the minimum. It can search large areas of candidate space, but often requires larger numbers of function evaluations than conventional gradient-based techniques. For this purpose, the implementation has been engineered for parallel computing. This work has been carried out on a CPU Intel(R) Xeon(R) Gold 6140M working at 2.2-2.3 GHz and using Linux as operating system. In addition, Python has been used for optimization and Java/NetLogo for mission simulation purposes.

The runtime of the DE depends linearly on the population size and on the number of generations, which has been fixed to 20 for all algorithms. The most sensitive hyper-parameters of the DE are the differential weight, the crossover rate, the population size, and the mutation strategy [5][15]. The optimal values of hyperparameters have been determined through grid search.

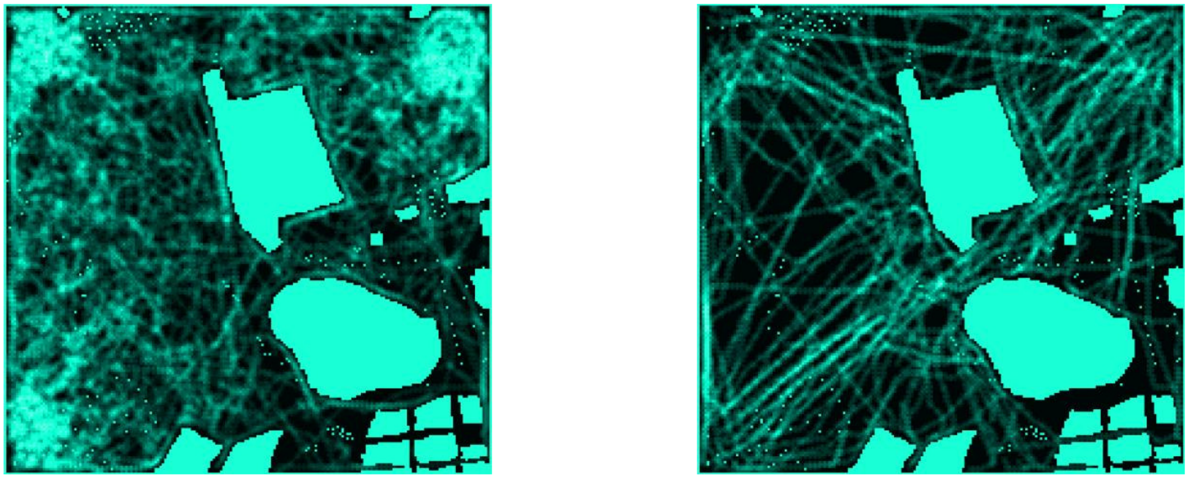
TABLE III. PARAMETER SPACE OF THE SFE COORDINATION

Parameter	*Range*	*Description*
radius-top	[0.1, 10]	Upper base radius of the truncated cone modelling the attractive pheromone trial
radius-down	[0.1, 20]	Lower base radius of the truncated cone modelling the attractive pheromone trial
evaporation-rate	[0.01, 1]	Evaporation rate of the trail of attractive pheromone
olfactory-habituation	[1, 60]	Time required to reach olfactory habituation
repulsive-radius	[0.1, 10]	Base radius of the cone modelling the repulsive pheromone trial
repulsive-evaporation-rate	[0.01, 1]	Evaporation rate of the trail of repulsive pheromone
wiggle-angle	[0, 30]°	Maximum angle of random perturbation (applied to repulsive stigmergy)
flock-angle	[90, 360]°	Field of view for detection of flock members
separate-radius	[5, 10]	Radius of separation area
max-separate-turn	[0, 30] °	Maximum angle of rotation during separation
align-radius	[5, 15]	Radius of alignment area
max-align-turn	[0, 30]°	Maximum angle of rotation during alignment
cohere-radius	[5, 20]	Radius of cohesion area
max-cohere-turn	[0, 30]°	Maximum angle of rotation during cohesion

TABLE IV. MAIN ADDITIONAL PARAMETERS OF THE P-SFE COORDINATION

Parameter	*Symbol*	*Range*	*Description*
Detection range	r_D	[0.1, 20]	Sensing range for already detected targets
Communication range	r_C	[5, 20]	Communication range among flockmates
Agent-to-agent coefficient	α	[0.01, 1]	Ratio between the strength of the interaction among agents over the total strenght of the strategy
Agent-to-target coefficient	β	[0.01, 1]	Ratio between the effect of an already detected target over the total strenght of the strategy
Decay rate	μ	[0.01, 1]	Natural decay rate
Strategy deflection rate	σ	[0.01, 1]	Rate controlling the deflection of strategy concentration

A comparative analysis of SFE and P-SFE for both Illegal Dump and Wildfire scenarios has been carried out. For each scenario and for each algorithm, the DE optimization has been performed



(a) (b)

Fig. 3. Illegal Dump, trails of drones before (a) and after (b) the evolutionary optimization.

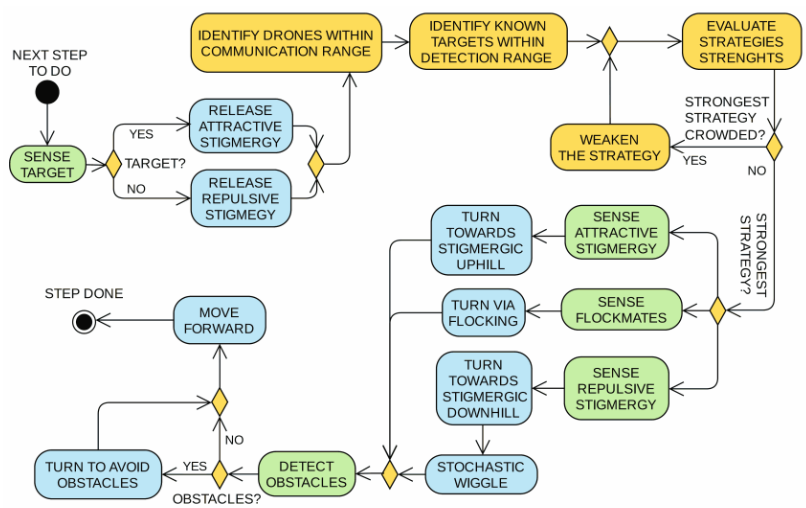


Fig. 4. UML activity diagram of the behavior of the drone in the P-SFE method.

TABLE V. PERFORMANCE EVALUATION FOR SCENARIOS AND METHODS

Scenario	*Method*	*Performance*
Illegal Dump	SFE	292.58 ± 11.94 s
Illegal Dump	P-SFE	**235.27 ± 17.05 s**
Wildfire	SFE	64.19 ± 3.34 %
Wildfire	P-SFE	**73.91 ± 5.11 %**

for 10 times, determining via a graphical normality test that the resulting mission duration is well modelled by a normal distribution. Finally, the 95% confidence intervals have been calculated. Table V reports the performance evaluation, showing that the P-SFE sensibly outperforms plain SFE.

To emphasize the effectiveness of the proposed approach, Fig. 5 and Fig. 6 show the trend of the fitness metric of the population, averaged over 10 trials, versus the number of generations of the DE. As it can be seen, the P-SFE achieves better performance over generations with respect to plain SFE.

IV. CONCLUSIONS

This paper introduces a novel approach to manage the priority of multiple strategies coordinating swarm of drones for environmental monitoring. For this purpose, the Stigmergy-Flocking-Evolution (SFE) algorithm is considered as a reference, proposing a more adaptive strategy based on Artificial Immune System, called Prioritized SFE. The workflow design of the proposed approach is first discussed, and then experimented on a testbed. The comparative analysis shows that the proposed P-SFE achieves 19.5% of improvement in the mission time and 15.6% of improvement in the number of found targets for an Illegal Dump and a Wildfire missions, respectively. The improvements made by the adaptive evolution are also remarkable. Although a more in-depth exploration of the technique and an enrichment of the experiments are needed, the promising results achieved show the potential of the proposed method.

Acknowledgment

This work has been supported by the Italian Ministry of University and Research (MUR), formerly Ministry of Education, University and Research (MIUR), in the framework of the CrossLab project (Departments of Excellence), and under the National Operational Programme on Research and Innovation 2014-2020.

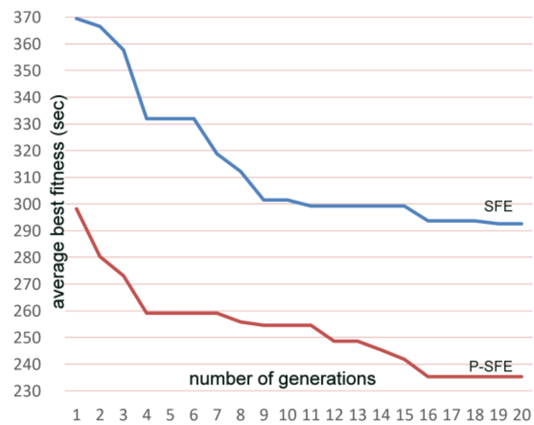


Fig. 5. Results of the DE optimization process on the Illegal Dump scenario [5]. Both algorithms improve their average fitness over the number of generations, but P-SFE strongly outperforms plain SFE.

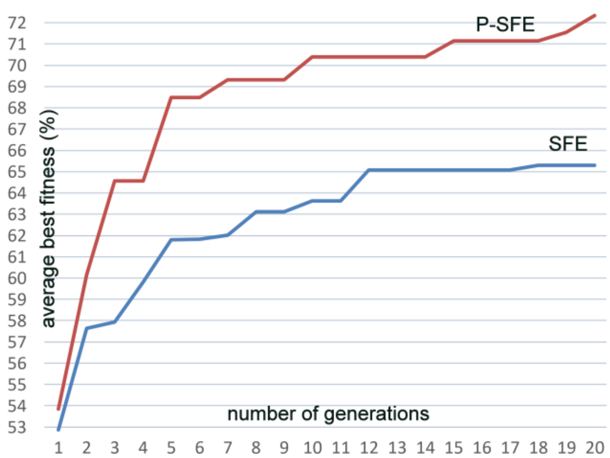


Fig. 6. Results of the DE optimization process on the Wildfire scenario [6] showing P-SFE achieving better performances with respect to SFE.

References

[1] Tmušić, G., Manfreda, S., Aasen, H., James, M. R., Gonçalves, G., Ben-Dor, E., …, McCabe, M. F. (2020). Current practices in UAS-based environmental monitoring. Remote Sensing, 12(6), 1001.

[2] Watts, A.C.; Ambrosia, V.G.; Hinkley, E.A (2012). Unmanned Aircraft Systems in Remote Sensing and Scientific Research: Classification and Considerations of Use. Remote Sens. 2012, 4, 1671-1692. https://doi.org/10.3390/rs4061671.

[3] Persechino, G., Schiano, P., Lega, M., Napoli, R. M. A., Ferrara, C., Kosmatka, J. (2010). Aerospace-based support systems and interoperability: the solution to fight illegal dumping. WIT Transactions on Ecology and the Environment, 140, 203-214. https://doi.org/10.2495/WM100191.

[4] Monaco M., Cimino M.G.C.A., Vaglini G., Fusai F., Nico G. (2021), Managing the oceans cleanup via sea current analysis and bio-inspired coordination of USV swarms, Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS 2021), 1-4.

[5] Cimino M.G.C.A., Minici D., Monaco M., Petrocchi S., Vaglini G. (2021). A hyper-heuristic methodology for coordinating swarms of robots in target search", Computers & Electrical Engineering, 95:1-19 (2021), doi: 10.1016/j.compeleceng.2021.107420.

[6] Cimino M.G.C.A., Lega M., Monaco M., Vaglini G. (2019). Adaptive exploration of a UAVs swarm for distributed targets detection and tracking. Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods, 1:837-844 (2019), doi: 10.5220/0007581708370844.

[7] Cimino M.G.C.A., Lazzeri A., Vaglini G. (2015), Combining stigmergic and flocking behaviors to coordinate swarms of drones performing target search, Proceedings of The Sixth International Conference on Information, Intelligence, Systems and Applications (IISA 2015), 1-6 (2015), doi: 10.1109/IISA.2015.7387990

[8] Pham H. X., La H. M., Feil-Seifer D., Deans M. C. (2020). A Distributed Control Framework of Multiple Unmanned Aerial Vehicles for Dynamic Wildfire Tracking. in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 50, no. 4, pp. 1537-1548, April 2020, doi: 10.1109/TSMC.2018.2815988.

[9] Weng L.,Liu Q., Xia M., Song Y.D. (2014) Immune network-based swarm intelligence and its application to unmanned aerial vehicle (UAV) swarm coordination. Neurocomputing 125 (2014) 134-141.

[10] Farmer, J. D., Packard, N. H., & Perelson, A. S. (1986). The immune system, adaptation, and machine learning. Physica D: Nonlinear Phenomena, 22(1-3), 187-204.

[11] Monaco, M. (2022). Github repository, https://github.com/mlpi-unipi/sfe

[12] TrashOut, www.trashout.me, accessed on March 2022.

[13] Cimino, M G C A, Vaglini G., "An Interval-Valued Approach to Business Process Simulation Based on Genetic Algorithms and the BPMN", Information, 5:319-356 (2014), doi: 10.3390/info5020319.

[14] Cimino, M.G.C.A., Lazzerini B., Marcelloni F., Pedrycz W., "Genetic interval neural networks for granular data regression", Information Sciences, 257:313-330 (2014), doi: 10.1016/j.ins.2012.12.049

[15] Cimino, M. G. C. A.; Lazzeri; A.; Vaglini, G. (2016), Using Differential Evolution to Improve Pheromone-based Coordination of Swarms of Drones for Collaborative Target Detection, Proceedings of The 5th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2016), 605-610 (2016), doi: 10.5220/0005732606050610.