

Adaptive exploration of a UAVs swarm for distributed targets detection and tracking

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Abstract: This paper focuses on the problem of coordinating multiple UAVs for distributed targets detection and tracking, in different technological and environmental settings. The proposed approach is founded on the concept of swarm behavior in multi-agent systems, i.e., a self-formed and self-coordinated team of UAVs which adapts itself to mission-specific environmental layouts. The swarm formation and coordination are inspired by biological mechanisms of flocking and stigmergy, respectively. These mechanisms, suitably combined, make it possible to strike the right balance between global search (exploration) and local search (exploitation) in the environment. The swarm adaptation is based on an evolutionary algorithm with the objective of maximizing the number of tracked targets during a mission or minimizing the time for target discovery. A simulation testbed has been developed and publicly released, on the basis of commercially available UAVs technology and real-world scenarios. Experimental results show that the proposed approach extends and sensibly outperforms a similar approach in the literature.

1 INTRODUCTION

In this paper we consider the problem of discovering and tracking static or dynamic targets in unstructured environments, with no prior knowledge about their location and about the obstacles layout (Senanayake *et al.* 2016). Examples of scenarios in this context are: (i) illegal dumps, in peri-urban and rural areas without waste/sanitation facilities (Persechino *et al.* 2010); (ii) anti-personnel landmines, left after a conflict in areas such as natural parks, agricultural and grazing lands (Rodriguez *et al.* 2014); (iii) early wildfire, intentionally or naturally lighted in large open areas, e.g., ecological habitats (Howden 2013); (iv) early toxic or dangerous gas dispersion, in industrial/urban areas characterized by large plants layouts (Qingchun *et al.* 2011). The quality of the process can be improved either by minimizing the time needed for discovering the given targets, or by maximizing the number of discovered targets in the given time.

In such type of missions, a promising approach is to employ small Unmanned Aerial Vehicles (UAVs) (Whitehead *et al.*, 2014). The current UAVs equipment and the available flight control logic offer

good solutions to the problem in a variety of fields. However, the current solutions for coordinating the exploration of UAVs swarms are not sufficiently mature: limited flexibility, complex management and application-dependent design are the main issues to solve (Senanayake *et al.* 2016).

Essentially, in environmental monitoring and surveillance one of the main requirements is to deal with circumstances where the target and the space of exploration are poorly specified. For this purpose, the UAVs coordination strategy should 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 (McCune *et al.*, 2013). In contrast, decentralized logic approaches can provide a UAVs swarm with a certain degree of autonomy (Meng *et al.*, 2014).

More specifically, a basic swarm of UAVs is characterized by a large number of homogeneous individuals, called *agents*, with local communication, sensing and actuation capabilities (Maza *et al.*, 2015). A multi-agent system presents a number of advantages: (i) it allows parallel/collective scan, according to the principles of self-organization; (ii) it

is scalable, since by increasing the number of agents in the swarm its effectiveness is poorly compromised; (iii) it is flexible, because the agent logic is simple and can be easily adapted to the scenario; (iv) it is robust, and then the task accomplishment is not affected by the fault of some agents (Aznar et al., 2014).

In general, a target search mission managed by a multi-agent system is characterized by (i) the number of targets and agents; (ii) the mobility of targets; (iii) the complexity of the environment; (iv) the prior knowledge about the target; (v) the type of swarm coordination. We propose an environment model to realistically represent the key characteristics of a mission, and to test the effectiveness of a given coordination logic. With regard to the swarm coordination logic, the approach proposed in this paper is based on three major aspects: (a) *spatial self-formation* in order to better explore the environment, i.e., the UAV movement is made according to a set of mutual spatial constraints of arrangement; (b) *collaboration* in order to exploit the knowledge already acquired, i.e., each UAV both contributes and is subject to some potential field influencing the steering; (c) *adaptation* in order to optimize the global behavior, i.e., the UAVs swarm adapts its behavioral parameters, considering also (a) and (b), to the specific type of mission.

In particular, the coordination logic is inspired by behavioral patterns of biological systems. The integration of biological patterns in a computational coordination logic has to consider the enhancements of the current UAVs information technology, such as instant communication, simultaneous localization and mapping, long-range sensing, etc. The final purpose is to verify on realistic settings whether the designed logic and the considered technological enhancements allow a reduction of complexity and a more effective optimization, keeping the essential benefits of the original biological models.

For this purpose, we (i) propose a swarm coordination algorithm that is adaptive to heterogeneous scenarios with either static or dynamic targets, (ii) develop and publicly release a simulation testbed on which the commercially available UAVs technology and real-world scenarios can be considered.

The paper is structured as follows. The swarm coordination logic and the operating environment is presented in Section 2. In Section 3, the real-world scenarios and the related UAV technologies are detailed. Experimental results are presented and discussed in Section 4. Finally, Section 5 summarizes conclusions and future work.

2 ENVIRONMENT FOR SWARM COORDINATION LOGIC

In the design of the testbed, an important distinction is between *flight* simulator and *exploration* simulator. A flight simulator focuses on control logic: it recreates the equations that govern UAV fly, how it reacts to external factors such as air density, turbulence, wind shear, cloud, precipitation, etc. In contrast, an exploration simulator focuses on coordination logic, assuming that external factors are already managed. It represents the exploration at a different scale, which depends on the spatial and temporal resolution needed to detect the target, and recreates at that scale obstacles and target distribution. Consequently, in the environment the basic UAV movements and collision avoidance are simulated for the specific purpose of exploration.

Figure 1 shows a simplified representation of the environment with the available elements. For a better granularity and without loss of generality, the search problem is formulated by discretizing the environment into a lattice of cells. In the environment, a single UAV, or *drone*, is represented by a disc with an inner arrowhead. An obstacle or a target usually covers many cells. In figure, each obstacle-cell is black, whereas each targeted cell is colored. A targeted cell can either be discovered, i.e., yellow cell, or undiscovered, i.e. red cell. The color intensity of a targeted cell represents the quantity/presence of target, when applicable (e.g., fire, gas, etc.). Finally, a pheromone mark is represented as a cluster of grey cells. The grey level represents the pheromone intensity.

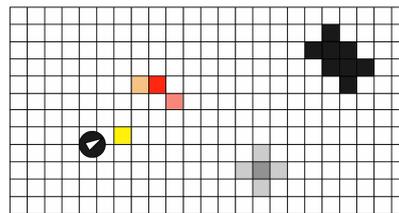


Figure 1: Environment and its elements: (from left to right) drone, target, pheromone, and obstacle.

The temporal unit (tick) of the simulation environment is set to a given number of seconds, depending on the type of mission. On every tick, the environment changes its current state to the next state, according to the following rules. An obstacle-cell is static. A targeted-cell can either be static (e.g. landmine or dump) or dynamic (e.g., fire or gas). The target dynamics is supplied as a sequence of frames whose transition is ruled by a preset time frequency.

This both avoid the effort of coding the equations underlying the dynamics of targets and allows to use real available frames to recreate a new scenario. The grey level of a pheromone cell is dynamic, and it is updated following an evaporation rule. A pheromone mark is released by a drone when a target is found (release rule). The drone position and direction is dynamic and set according to exploration and coordination rules. For a given type of mission, all rules can be parametrically adapted by an evolutionary algorithm which improves the overall quality of the search process.

Specifically, Figure 2 shows a drone model with the related parameters. The simulator takes into account the drone *cruise speed*, *acceleration*, *angular speed*, *battery duration*, *drone size*, *sensing angle* and *sensing radius*.

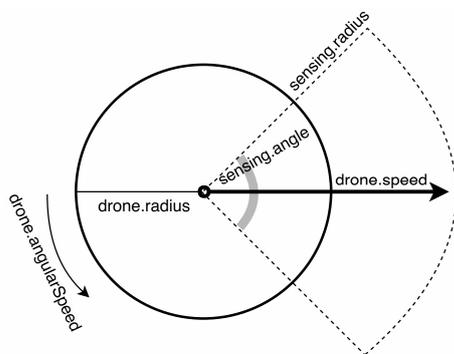


Figure 2: Drone model with parameters.

Figure 3 shows the formation rules, based on Reynolds' flocking (1987): rules of *alignment*, *separation*, and *cohesion*. Alignment aligns the drones heading to the average heading of nearby agents (flock mates). Separation keeps a large formation by maintaining a minimum distance among flock mates. Cohesion directs each agent towards the center of the flock mates. A global *angle of vision* and different *ranges of radius* characterize the three areas of influence.

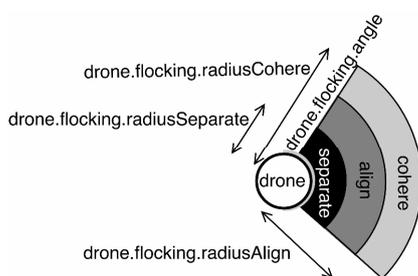


Figure 3: Formation rules (flocking).

Figure 4 shows a 3D shape of a single pheromone mark, where (x,y) is the environment and z is the pheromone intensity. A mark is modelled as a truncated cone determined by the parameters *radiusTop*, *radiusDown*, initial *pheromone intensity*. When overlapping, pheromone marks can aggregate in pheromone tracks. The track evaporates over the time: every tick, its intensity is linearly reduced by a given amount (*deltaEvaporate*).

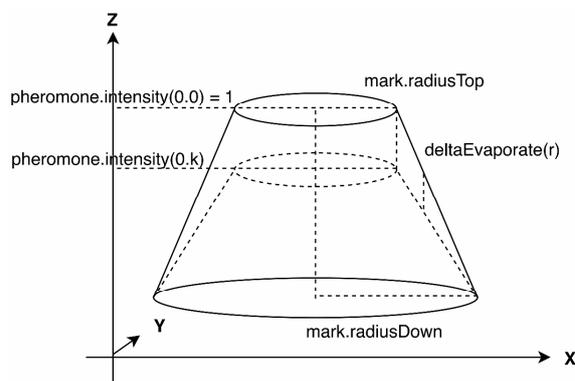


Figure 4: pheromone mark (stigmergy).

In the literature, the indirect communication mechanism based on pheromone is called *stigmergy* (Cimino *et al.* 2015a): an agent's action produces a mark which, in turn, incites another action, which produces another mark, and so on. In the proposed stigmergy, when a drone detects a new targeted cell, the drone releases a pheromone mark on the location of the sensed target. Pheromone acts as an attractive potential on neighboring drones. While unknown targets are sensed, additional pheromone marks are released by flock members, thus enabling an incremental positive feedback up to completion of all targets in the proximity of the initial target. After a certain time, the pheromone intensity cannot be reinforced, and in practice disappears.

Figure 5 shows the collision avoidance model.

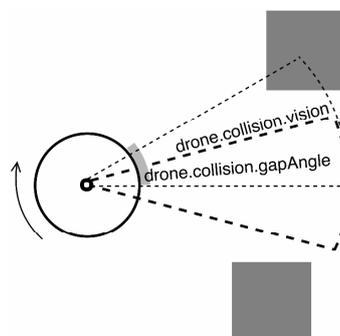


Figure 5: Collision avoidance.

The drone obstacle vision is set via two parameters, i.e., *collision.vision* and *collision.angle*, creating a circular sector area, whose vertex is centered on the drone. When an obstacle or another drone is detected in the collision area, the drone changes its heading and speed to avoid the obstacle. The area that will be occupied by the drone in the next tick can be easily calculated via its velocity and its possible headings. Thus, the multiple drones can be accordingly organized in the current instant so as to avoid overlapping with drones and obstacles at the next temporal tick.

Overall, the swarm logic at each tick can be summarized by the following pseudocode:

```

function SwarmSearch(environment)
tick = 0; targetsFound = 0;
do
evaporate(pheromone);
foreach drone d in swarm
  if targets in d.sensing then
    markTargetsFound(targets);
    releasePheromone(targets.position);
    targetsFound = targetsFound + 1;
  endif
  if obstacles in d.vision then
    turnAway(d.heading, obstacles);
  elseif pheromone in d.sensing then
    turnTowards(d.heading, pheromone);
  elseif flockmates in d.flock then
    turnForFlocking(d.heading, d.flock);
  else
    turnForRandomWalk(d.heading, wiggle);
  endif
  moveForward(drone);
endfor
tick = tick + 1;
while (targetsFound < targetsThreshold)
  or (tick = maxSearchTime);
return {tick, targetsFound};

function QualityMeasure(environment)
if targets.dynamic then
  totTargets = 0;
  foreach frame in environment
    targets = SwarmSearch(environment);
    totTargets += targets/targetsFrame;
  endfor
  return totTargets/numFrame;
else
  tick = SwarmSearch(environment);
  return tick;
endif

```

To adapt the swarm behavior to the environment, the quality of the process is measured and optimized by using the Differential Evolution (DE) algorithm (Cimino *et al.* 2015b). Specifically, let K be the number of adaptive parameters of the mission. In DE

a solution is represented by a real K -dimensional vector. The overall quality of the process is optimized either by minimizing the time needed for discovering the given targets (static targets), or by maximizing the average number of discovered targets in the overall search time (dynamic targets). The adaptation process is an intrinsic part of the swarm: in some sense only after the optimization the initial set of UAVs becomes a swarm, i.e., an effective organism specialized for the type of mission.

3 SCENARIOS AND RELATED TECHNOLOGICAL SETTINGS

In this section, the scenarios used and the various quality measurements are illustrated. Table 1 summarizes the main features of each scenario. The first three scenarios are static: *Illegal Dump* is based on the abusive trash map in Paternò, Italy (Trashout 2018); *Rural Mine* and *Urban Mine* are based on publicly available data of landmines in areas near Sarajevo, in Bosnia-Herzegovina (See-demining, 2018). The remaining scenarios are dynamic: *Fire Tracking* comes by a propagation model developed by the Northwestern University (Wilensky, 2018); *H₂S Leak* is based on a sour gas accident occurred in December 2003, in Chongqing City, northeastern Sichuan Gas Field, China (Ma Q.C. *et al.* 2011); *LPG Leak*, is based on an accident occurred in June 2009 in Viareggio, Italy, and involving an LPG railcar rupture in a congested urban area (Pontiggia *et al.* 2011).

Table 1: Characteristics of each scenario.

Scenario	Area size (m × m)	Targets Animation	No of frames
Illegal Dump	400 × 400	0 min.	1
Rural Mine	400 × 400	0 min.	1
Urban Mine	400 × 400	0 min.	1
Fire Tracking	1400 × 1400	20 min.	5
H ₂ S Leak	4816 × 4400	48 min.	4
LPG Leak	500 × 300	4 min.	4

To show the environmental complexity, Figure 6 and Figure 7 show the satellite map used for *Illegal Dump*, and the corresponding initial vector image represented in the simulation environment, respectively. Here, obstacles (buildings and trees) are represented in black, whereas targets are represented as red points. Drones, represented as purple triangles, are placed at the corners and are oriented towards the center of the area. Figure 8 shows another scenario, *Urban Mine*, during the search process. Here, the

targets found are represented in yellow. A large pheromone cloud is clearly visible in the center of the area, where a higher concentration of targets has attracted a relevant number of drones.



Figure 6: Illegal Dump, satellite image (Google Maps ©)

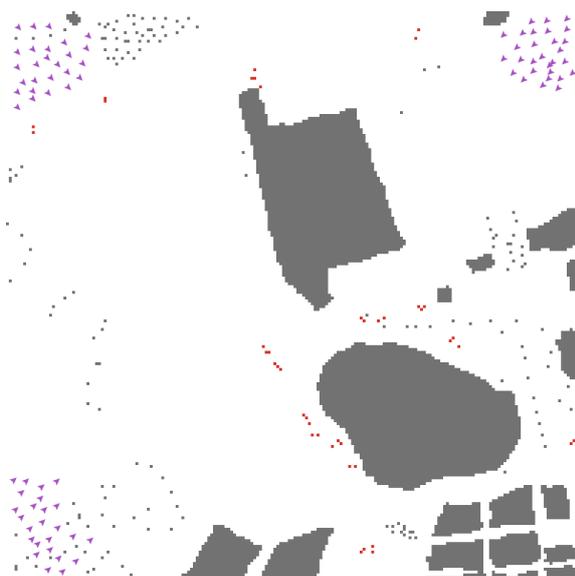


Figure 7: Illegal Dump, vector image

The environmental characteristics have been considered for the technical specifications of the commercially available UAV. Table 2 and Table 3 show, respectively, the technical specifications of the drone “Dji Matrice 200” (www.dji.com/matrice-200-series), and the sensing equipment for each scenario. Such technology has been selected on the basis of gained knowledge and skill over a number of projects

using UAV technology for environmental monitoring and surveillance.

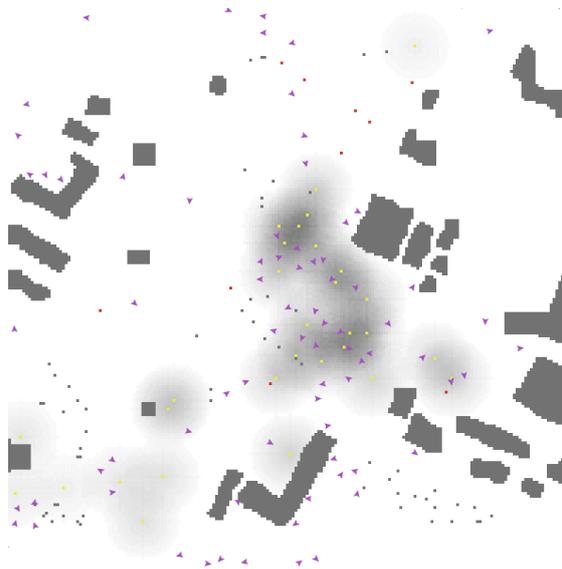


Figure 8: Urban Mine, simulator image with pheromone

Table 2: 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 3: Technical specifications of the sensing equipment, for each scenario.

Scenario	Cruise speed (m/s)	Sensing technology	Sensor model	Sensing radius
Illegal Dump	4	Visual + Thermal	Dji Zenmuse XT2	5 m
Rural Mine	4	Visual + Thermal	Dji Zenmuse XT2	5 m
Urban Mine	4	Visual + Thermal	Dji Zenmuse XT2	5 m
Fire Tracking	12	Visual	Dji Zenmuse XT2	36 m
H ₂ S Leak	8	Electro-chemical	Dräger X-am 5600	0 m
LPG Leak	4	Resistive	NiTiO ₃	0 m

Specifically, the sensing technology proposed for:
 (i) Illegal Dump, is based on (Persechino *et al.* 2010)

and (Lega *et al.* 2012); (ii) Rural and Urban Mine, is based on (Rodriguez *et al.* 2014); (iii) Fire Tracking, is based on (Cruz *et al.* 2016). The Sensor proposed for H2S Leak and LPG Leak is based on (Neumann *et al.* 2013) and (Chaudhari, 2018), respectively.

4 EXPERIMENTAL RESULTS

The environment and the coordination logic are implemented on *NetLogo*, a leading simulation platform for swarm intelligence (ccl.northwestern.edu/netlogo). The adaptation module is implemented on *MATLAB* ©, a numerical optimization framework (www.mathworks.com). The source code of the integrated system, called *Sciadro 3.1*, together with the scenarios, has been publicly released on the Github platform (Cimino *et al.* 2018).

As a pilot example, Figure 9 and Figure 10 show two frames of the Fire Tracking scenario. Here, the pheromone clouds clearly show that the swarm is tracking the fire evolutions.

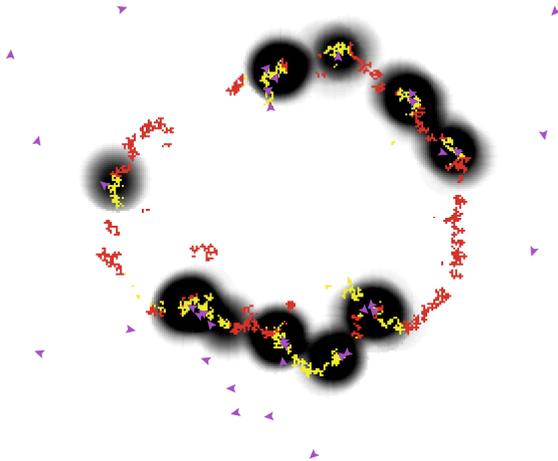


Figure 9: Fire Tracking, simulation frame, tick = 1013.

Figure 11 shows the number of targeted cells found (%) against time (sec). The plot indicates a constant trend of targets found per second, up to about 95%. Since this is commonly a point of trend variation, to shorten the simulation duration the *targetThreshold* value is set to 95% in the function *SwarmSearch*, for static scenarios. For a dynamic scenario, the *maxSearchTime*, i.e., the frame period, can be calculated as the ratio between *targets animation* and *number of frames*. For example, in the Fire Tracking scenario, it is set to $20 \cdot 60 / 5 = 240$ sec.

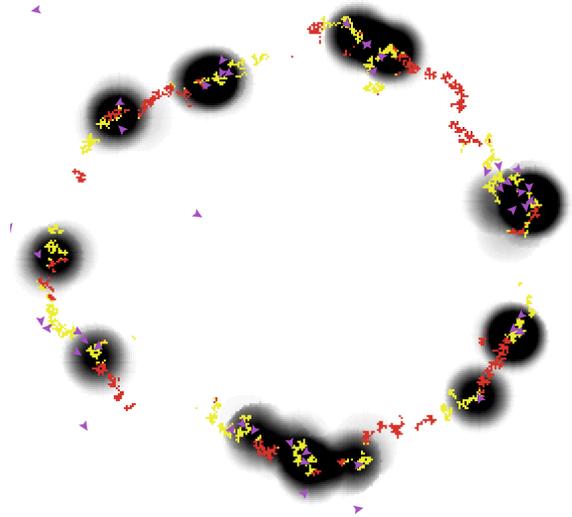


Figure 10: Fire Tracking, simulation frame, tick = 1277.

Thus, for static scenarios the quality measure is the time needed for the target threshold, whereas for dynamic scenarios it is the average percentage of targets discovered in each frame. The purpose of the DE is to find the parameters minimizing the quality measure, namely the fitness.

More formally, given a simulated scenario Ω , made of: (i) simulation instants of time $t \in \mathbb{N}^+$; (ii) a set of drones $\{D\}$, each drone having a dynamic position $(x_t, y_t)_D$; (iii) a set of targets $\tau \in T$, each target having a fixed position $(x, y)_\tau$. The set of targets already found $T_F(t) \subseteq T$, at a given instant of time t , is the set of targets for which it exists a time $t' \leq t$ and a drone D such that the drone's position allows the detection of the target's position (relationship denoted as " \sim "):

$$T_F(t) = \{\tau \mid \exists D, \exists t' \leq t: (x_{t'}, y_{t'})_D \sim (x, y)_\tau\} \quad (1)$$

The fitness of the static simulated scenario Ω is then defined as the minimum instant of time for which $T_F(t)$ has cardinality greater than or equal to $0.95 |T|$:

$$fitness(\Omega) = \min_{t \in \mathbb{N}^+} \{t : |T_F(t)| \geq .95 \cdot |T|\} \quad (2)$$

In case of dynamic scenarios, the targets can change every frame transition period P , i.e., $(x, y)_{\tau(\varphi)}$, $\varphi = 0, P, 2P, \dots, t \cdot P, \dots, \Phi$, where Φ is the predefined final instant of the simulation. The fitness of the dynamic simulated scenario Ω is then defined as the average percentage of targets discovered in all frames:

$$fitness(\Omega) = \frac{P}{\Phi} \sum_{\varphi=1}^{\Phi} \frac{|T_F(\varphi)|}{|T(\varphi)|} \quad (3)$$

Figure 12 shows the average best fitness, over 10 trials, against the number of generations, for the Rural Mine scenario.

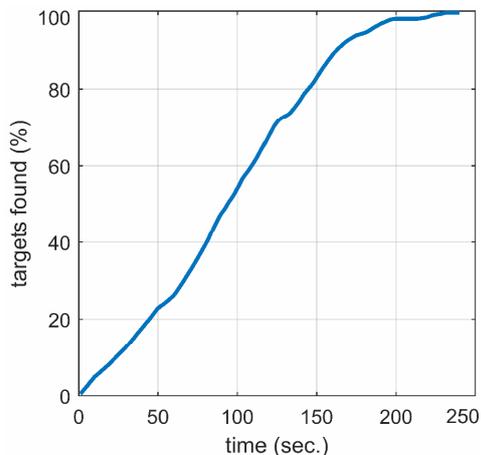


Figure 11: Percentage of targets found against time.

The figure clearly shows the structural importance of DE adaptation, since it improves the performance by 27%. Table 4 shows the performance of 80 UAVs swarm, adapted for each scenario, in terms of the 95% confidence interval over 10 repeated trials. The number of UAVs has been determined by setting incremental values and assessing the impact on performance. For example, table 5 shows the performance of 20, 40, 60, 80 UAVs for Fire Tracking, in terms of 95% confidence interval over 10 repeated trials.

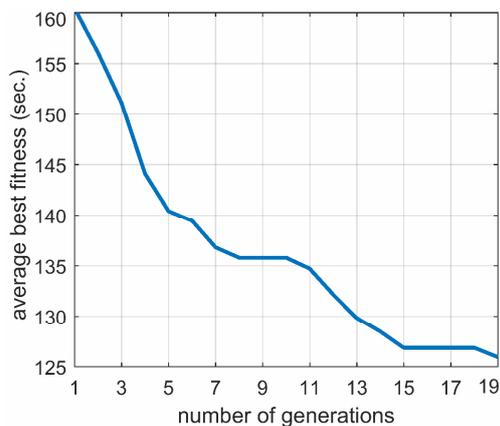


Figure 12: DE-based adaptation, average best fitness against number of generations.

Finally, to better show the effectiveness of the proposed approach, the same parameters have been set in the previous version, valid for static scenarios only, published in (Alfeo *et al.* 2018), hereafter called *Sciadro 2.0*. For this purpose, the sensing radius has

been set to 4. The results, in Table 6, clearly show that the proposed version sensibly outperforms *Sciadro 2.0*.

Table 4: 80 UAVs swarm performance adapted for each scenario.

Scenario	Performance
Illegal Dump	121.70 ± 4.75 sec.
Rural Mine	125.96 ± 8.90 sec.
Urban Mine	152.38 ± 5.25 sec.
Fire Tracking	99.88 ± 0.06 %.
H ₂ S Leak	98.78 ± 0.17 %
LPG Leak	93.88 ± 0.28 %

Table 5: Fire Tracking: swarm performance for a different number of adapted UAV.

No of UAVs	Performance
20	60.64 ± 2.06 %
40	90.36 ± 0.54 %.
60	98.43 ± 0.25 %
80	99.88 ± 0.06 %

5 CONCLUSIONS

The paper summarizes the design of a bio-inspired approach for the coordination of UAVs swarm involved in distributed targets detection and tracking. The coordination logic includes a spatial self-formation and a collaboration based on dynamic potential field. Moreover, the swarm adapts its parameters to the specific mission by using an optimization algorithm. A simulation testbed has been developed and publicly released, using real-world UAV technology and scenarios. Experiments are encouraging, since the proposed approach extends and sensibly outperforms a similar approach in the literature. To provide comparative results with other approaches is considered a key investigation task for future work.

Table 6: Comparative analysis of performance (sec.)

Scenario	Sciadro 2.0	Sciadro 3.1
Illegal Dump	363.20 ± 102.6	159.03 ± 5.35
Rural Mine	195.80 ± 49.60	193.43 ± 6.79
Urban Mine	303.00 ± 85.70	208.76 ± 5.27

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REFERENCES

- Alfeo, A.L., Cimino, M.G.C.A., De Francesco, N., Lega, M., Vaglini, G. "Design and simulation of the emergent behavior of small drones swarming for distributed target localization", *Journal of Computational Science*, Elsevier Science, Vol. 29, Pages 19-33, 2018, (ISSN 1877-7503).
- Aznar, F., Sempere, M., Pujol, M., Rizo, R., and Pujol, M. (2014). Modelling oil spill detection with swarm drones. In *Abstract and Applied Analysis*, volume 2014. Hindawi.
- Chaudhari, P. and Mishra, S., 2018. Ilmenite phase nickel titanate nanowhiskers as highly sensitive LPG sensor at room temperature. *Journal of Materials Science: Materials in Electronics*, 29(1), pp.117-123.
- Cimino, M.G.C.A., Lazzeri, A., Vaglini, G. "Combining stigmergic and flocking behaviors to coordinate swarms of drones performing target search", in *The Sixth International Conference on Information, Intelligence, Systems and Applications (IISA)*, pp. 1-6, IEEE, 2015.
- Cimino, M.G.C.A., Lazzeri, A., Vaglini, G. "Improving the analysis of context-aware information via marker-based stigmergy and differential evolution." *International Conference on Artificial Intelligence and Soft Computing (ICAISC)*. Springer, Cham, 2015.
- Cimino, Mario G.C.A., Monaco M., Piscione P., Alfeo L. (2018). Github platform, Sciadro 3.1 repository, (<https://github.com/mlpi-unipi/drones-swarm>). Accessed November 10, 2018.
- Cruz, H., Eckert, M., Meneses, J., Martínez, J.-F. "Efficient forest fire detection index for application in unmanned aerial systems (UASs)." *Sensors* 16, no. 6 (2016): 893.
- Howden, D. J., "Fire tracking with collective intelligence using dynamic priority map", in *IEEE Congress on Evolutionary Computation (CEC)*, 2013. IEEE, 2013, pp. 2610-2617.
- Lega, M., J. Kosmatka, C. Ferrara, F. Russo, R. M. A. Napoli, and G. Persechino. "Using advanced aerial platforms and infrared thermography to track environmental contamination." *Environmental Forensics* 13, no. 4 (2012): 332-338.
- Ma Q.C., Zhou L.B. "CFD simulation study on gas dispersion for risk assessment: a case study of sour gas well blowout". *Safety Science* 2011;49(8):1289-95.
- Maza, I., Ollero, A., Casado, E., and Scarlatti, D. (2015). Classification of multi-UAV architectures. In *Handbook of unmanned aerial vehicles*, pages 953-975. Springer.
- McCune, R., Purta, R., Dobski, M., Jaworski, A., Madey, G., Madey, A., Wei, Y., and Blake, M. B. (2013). Investigations of dddas for command and control of uav swarms with agent-based modeling. In *Simulation Conference (WSC)*, 2013 Winter, pages 1467-1478. IEEE.
- Meng, W., He, Z., Su, R., Shehabinia, A. R., Lin, L., Teo, R., and Xie, L. (2014). Decentralized control of multi-UAVs for target search, tasking and tracking. *IFAC Proceedings Volumes*, 47(3):10048{10053.
- Neumann, P.P., Asadi, S., Bennetts, V.H., Lilienthal, A.J. and Bartholmai, M., 2013. Monitoring of CCS areas using micro unmanned aerial vehicles (MUAVs).
- Persechino, G., P. Schiano, M. Lega, R. M. A. Napoli, C. Ferrara, and J. Kosmatka. "Aerospace-based support systems and interoperability: The solution to fight illegal dumping." *WIT Transactions on Ecology and the Environment* 140 (2010): 203-214.
- Persechino, G., P. Schiano, M. Lega, R. M. A. Napoli, C. Ferrara, and J. Kosmatka. "Aerospace-based support systems and interoperability: The solution to fight illegal dumping." *WIT Transactions on Ecology and the Environment* 140 (2010): 203-214.
- Pontiggia, M., Landucci, G., Busini, V., Derudi, M., Alba, M., Scaioni, M., Bonvicini, S., Cozzani, V., Rota, R., 2011. "CFD model simulation of LPG dispersion in urban areas". *Atmospheric Environment* 45, 3913e3923.
- Qingchun, Ma, Laibin, Zhang, "CFD simulation study on gas dispersion for risk assessment: a case study of sour gas well blowout", *Safety Science*, 2011; 49(8):1289-95.
- Reynolds, C. W. "Flocks, herds and schools: A distributed behavioral model". In *ACM SIGGRAPH computer graphics*, volume 21, pages 25-34 (1987), ACM.
- Rodriguez, J., C. Castiblanco, I. Mondragon, and J. Colorado. "Low-cost quadrotor applied for visual detection of landmine-like objects." In *Unmanned Aircraft Systems (ICUAS)*, 2014 International Conference on, pp. 83-88. IEEE, 2014.
- Rodriguez, J., Castiblanco, C., Mondragon, I., Colorado, J.: Low-cost quadrotor applied for visual detection of landmine-like objects. In: *International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 83-88. IEEE (2014).
- See-demining, Mine detection Center for the Region of South-Eastern Europe, accessed February 2018, <http://www.see-demining.org/main.htm>,
- Senanayake, M., Senthoooran, I, Barca, J. C., Chung, H., Kamruzzaman, J., Murshed, M., "Search and tracking algorithms for swarms of robots: A survey", *Robotics and Autonomous Systems* 75 (2016) 422-434.
- Trashout, Trash Maps Data, accessed February 2018, <https://www.trashout.ngo/trashmap/?ref=trashout.me>.
- Whitehead, K., Hugenholtz, C. H., Myshak, S., Brown, O., LeClair, A., Tamminga, A., Barchyn, T. E., Moorman, B., and Eaton, B. (2014). Remote sensing of the environment with small unmanned aircraft systems (uass), part 2: Scientific and commercial applications. *Journal of unmanned vehicle systems*, 2(3):86-102.
- Wilensky, U. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. NetLogo Fire models library, November 2018, <http://ccl.northwestern.edu/netlogo/models/Fire>.