# Swarm Intelligence based Approach for Real Time UAV Team Coordination in Search Operations

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*Abstract*—**This paper proposes swarm intelligence based approach for the real time coordination of groups of UAVs (Unmanned Aerial Vehicles) in tasks where values that are sensed from the aerial platform can be used to qualify the individuals. In particular, as an example application, here we consider environmental monitoring UAV teams. Their function is to monitor an area and when some undesired environmental condition arises, coordinate themselves to find the source as fast as possible. The swarm based algorithm has been extensively tested using a 3D simulation platform and validated with real UAVs flying over an industrial area.**

***Keywords-component; Unmanned Aerial Vehicles; Evolution; Robot Coordination***

## I. INTRODUCTION

In the last few years the interest in Unmanned Aerial Vehicles (UAVs) and their use for an ever increasing range of applications has grown tremendously. This type of aircrafts can be controlled remotely or programmed to fly in an autonomous way. They have been used for different types of applications as individual entities, both in military and civil tasks [1][2][3]. Research related to this type of systems is being undertaken in many areas going from the design of more efficient aircraft aimed at specific applications [4], to the development of improved control electronics that provide for better autonomous behaviors, to optimized path planning strategies [5][6], or to opening new application domains [7]. Currently, a whole new field of research is opening up in the area of coordinating UAV teams to cooperatively perform different missions. This field is still in its infancy and many exciting new approaches are being explored for different applications [8]. Examples of these are works related to trajectory planning in UAV teams [9][10], real time target tracking [3], and many others [11][12].

At the same time, environmental awareness is becoming ever more present in our societies. A need has arisen to evaluate and control the pollution levels in our lower atmosphere and, especially, to determine sources over which it would be important to act in order to reduce these levels when certain limits are surpassed. There has been a long tradition of systems developed to this end, from satellite based monitoring systems [13] to the typical local stations in cities or even approaches based on public transportation systems [14]. Most of these systems have been designed in order to map the pollution levels over extensive areas, but usually at ground level or integrating information from the whole air column as in the case of satellite based systems. However, for many applications it would also be very important to have information on air quality in different layers of the atmosphere. In fact, different sources of pollution such as forest fires or chimney plumes cannot be accurately detected by ground based systems. They are usually carried overhead and are often ignored. This is where monitoring systems based on UAVs really can come into play. Some authors have reported results on their use for monitoring pollution over different areas. An example is the work by Ramanathan et al. [15] who have used a set of UAVs with a combination of remotely controlled and preprogrammed strategies.

In this paper we propose an autonomous coordination strategy for UAV based systems that can be used for the detection of pollution emitting sources in the environment in an autonomous manner by teams of UAVs. The strategy is inspired on swarm based approaches to optimization but it has been adapted to its operation in real time using real UAVs. This use of real elements implies a set of constraints over where one of the UAVs can be and how fast they can move that are usually not contemplated by traditional optimization approaches and which are key for these types of systems to be able to operate.

The paper is structured as follows. Section II describes the set of aerial vehicles that were used for this work. Section III describes the distributed real time evolutionary coordination strategy used for the mission considered. Section IV provides information on the experiments that were carried out and on some of the results obtained. Finally, section V is devoted to the presentation of some conclusions.

## II. AERIAL VEHICLES

### *A. Basic Vehicle*

As an initial testing UAV platform we have opted for different models of electrically powered UAVs made of expanded polypropylene (EPP) having a wingspan of 180 cm, a length of 120 cm, a total weight without batteries of 1,5 kg, and a payload capability of 1,5 kg. Figure 1 shows pictures of some of the units in one of the teams. As these units where intended for sensing and visualization purposes, we chose to use mostly back propelled airplanes thus avoiding the problems for sensing and viewing of front propelled vehicles.

In terms of flight electronics (as shown in figure 2), to be able to generate autonomous flight modes, the units have been equipped with an autopilot based on a GPS, a miniature Inertial Measurement Unit (IMU) and an Attitude Heading Reference System (AHRS). Also a Long Range System (LRS) for UAVs has been installed. This system is able to provide telemetry, communications and video communications up to 170Km in the 869Mhz and 915Mhz ISM bands. The data from the different payload sensors, position, and other flight information is also transmitted through the video channel embedded within the teletext signal as shown in the picture of figure 3. All of these data are also recorded on-board using a data-logger and can be retrieved after landing. The LRS provides the possibility of manually controlling the UAVs if necessary by using a FPV (First Person View) system that is also incorporated.

Figure 1: Some of the UAVs that make up the team.

### *B. Mission Sensors*

In terms of mission sensing, as the task to be performed is related to pollutant measurements, a sensing ensemble has been developed that includes the capability of measuring amounts of the most common pollutants such as NOx, CO, CO2, and SO2, as well as temperature and humidity. The unit is open to the addition of more sensors as needed with the only limitation of the actual payload the UAV can carry. In the current experiments we will not use more than two or three of these pollutant sensors at a time, but this is more than enough at present for the type of problem that is being considered here.

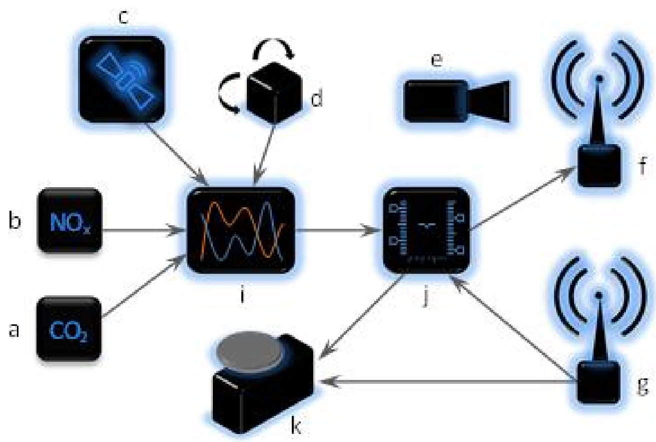


Figure 2: Schematic diagram of the electronics within each airplane

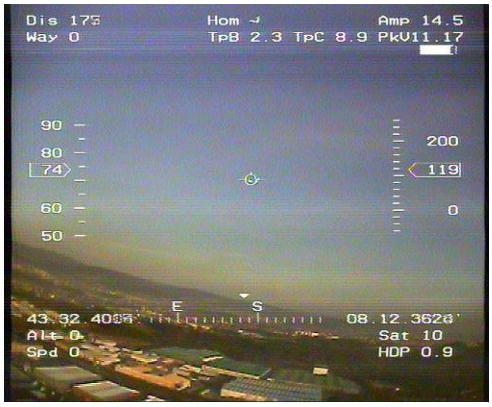


Figure 3: Sensing and flight information transmitted using the video signal from the front facing camera of the UAV

## III. Coordination Approach

The swarm intelligence based strategy uses a completely distributed approach where every airplane operates autonomously and collaborates with surrounding airplanes to explore the environment and find pollution sources.

In this strategy the airplanes have three phases of operation. A flow diagram of the behavior of the planes can be seen in Figure 4. After take-off, they start a spread out phase for a fixed period of time. This first stage is used to place the planes in a good positions to start exploring the environment. This spread out of the planes in the environment is achieved by maximizing the minimum distance between them while at the same time flying within a fixed radius of the take-off area, it can obviously be implemented in a distributed and local way.

Once the spread out stage finishes, the planes start the monitoring phase. The behavior of the planes continues to be the same as in the spread-out phase, they try to maximize the minimum distance between them while moving, but in this state they are also sensing the environment seeking pollution values above a fixed alarm threshold. Also during this stage, the planes start broadcasting their sensed data through the communications channel so other agents of the system can receive it (at least those that are close enough to it).

As soon as one of the planes detects a pollution value above the threshold it enters the search stage. In this stage the plane starts collaborating with surrounding planes in order to find the pollution source. As each plane is receiving the data sensed and broadcast by others surrounding it, it uses the data coming from the *N* nearest neighbors and its own sensing data to select a promising direction for continuing its search.

The sensed data is averaged by each plane before it is broadcast by using only the last sensed values, in order to avoid peaks and noise. For the tests included in this paper, a simple statistical average is performed using the last five sensed values. The planes use a one second period for sensing. Therefore, the data received by each plane is already averaged. The plane uses those data to seek the surrounding plane with the maximum pollution value. If it is larger than its own pollution value, the plane changes its flight direction towards the current position of the airplane that provides the maximum value in its surroundings. Otherwise the plane continues

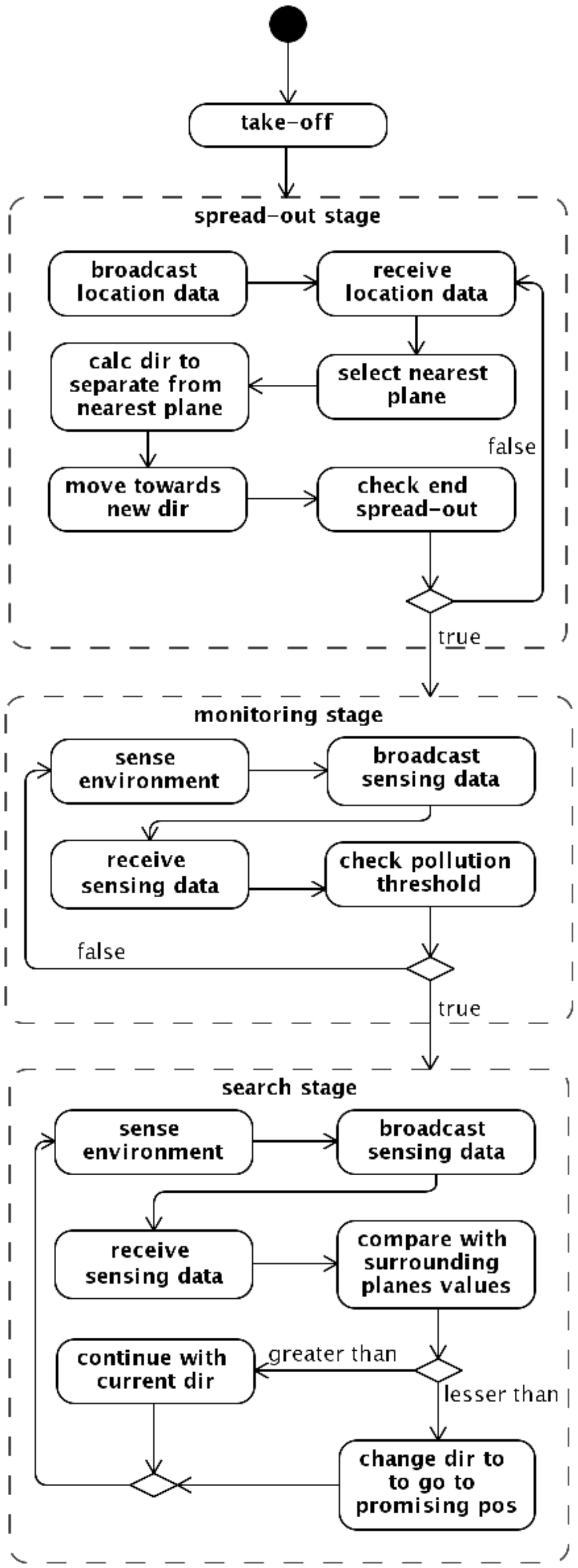


Figure 4: Block diagram of the three operation modes of the UAVs using swarm intelligence.

moving in its current course. This decision about which direction to follow is taken every *D* seconds (a parameter of the plane that we call 'decision gap'). Therefore, the plane will follow a given direction for at least as long the length of the decision gap, and then it will decide if it continues to be promising or not.

When each plane starts detecting a pollution value above the threshold and starts collaborating with surrounding planes, it is like the plane has become a member of a virtual team that is exploring a particular promising area of the environment. Therefore this strategy leads to the autonomous emergence of different teams of cooperating planes. A team is created when a plane starts following other surrounding planes because they are reporting positions that are more promising in terms of finding a maximum sensed value than its current one. Obviously, any plane can leave a team any moment, as long as it finds itself a more promising pollution value, thus creating a new possible group, or it detects a different surrounding plane that has a more promising pollution value.

The group behavior is controlled, to some extent, by the decision gap parameter, which can be said to control the exploration exploitation ratio of the search strategy. If this parameter is low, the displacements of the plane between direction changes will be small, making its behavior much more dependent on other planes in its team (increased exploitation). However, as the decision gap is increased, the displacements of the planes between direction changes will be larger, thus increasing the exploration capacity of the strategy and, therefore, increasing the probability of finding new promising areas. Consequently, as parameter D represents to some extent the exploration/exploitation ratio, the algorithm can benefit from an increment in the D parameter when the number of UAVs is low, as it will increase its exploration capabilities and prevent premature convergences to suboptima.

It is important to note that the current swarm strategy has very low synchronization requirements. In fact, the airplanes can even operate in a completely disconnected fashion. The messages broadcast by the planes include the sent date and time and the receiver airplanes use this information to check if the data is still valid. For the current tests we are considering as valid those message sent in the previous thirty seconds.

## IV. SOME EXPERIMENTS

To test the proposed strategies we have performed a series of tests, both on the real planes and on simulations. In fact, simulations were used in order to be able to extensively test the strategy under different controlled conditions. These results were validated by means of real flights.

### *A. Simulator*

We developed a 3D simulator that could mimic the behavior of the airplanes in a reasonably realistic manner. It allows us to easily test different exploration and search algorithms, as well as different configurations of plane teams, without the high costs and difficulties of testing every configuration in the real world.

The simulator is implemented as a multi-agent system in which the planes are agents interacting in a simulated 3D world populated by pollution sources. Figure 5 displays a diagram of its components, which are:

- *Pollution functions*. There are simulated sources of pollution in the virtual world and different types of functions for the spatial and temporal evolution of pollution are supported. In the work presented here, the simulated functions use a Gaussian distribution. The capability of reading data from the log files of the real planes is included in order to be able to run simulations using real pollution distributions.
- *World.* It is used as an aggregator of the pollution functions. When an agent senses a point in the environment, the world requests the pollution contributions from the different pollution functions and mixes each different pollutant, returning a list of pollutants and values to the agent.
- *Airplanes.* The airplanes are the main agents in the multi-agent system of the simulator. They have access to the world in order to sense it, and they are associated to a communications channel to be able to talk with other agents of the system.
- *Controller.* The controller is an optional agent that can be used in some configurations where a central point is required. This is not the case here and, thus, it just contains a simple controller that only logs the sensing information coming from the airplanes.
- *Communications channel*. It allows the interchange of messages between the different agents that populate the simulator. It can have many implementations but, currently, we have an implementation that simulates a radio communications channel in which every agent that shares the communications channel receives every message posted on the channel. It can have range coverage limitations.

The simulator software has been implemented using JAVA and the jMonkey 3 OpenGL Game Engine for the 3D environment as a single threaded process that executes a continuous loop. All the airplanes in the simulations contain a set of common behaviors that provide them with abilities to avoid collisions with other planes or the environment, to take off and to move to a goal direction. This motion is constrained both in terms of speed and heading changes to values that are compatible with the way real planes move. That is, an instantaneous 180 degree turn is not possible for a real plane.

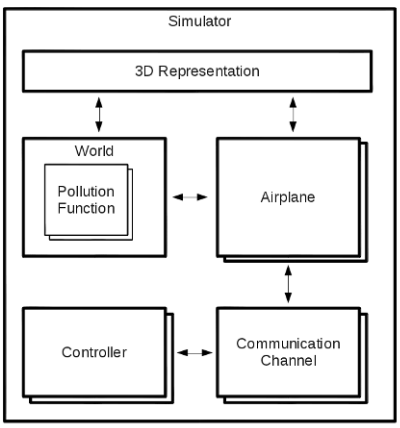


Figure 5: Block diagram of the multiagent based 3D simulator.

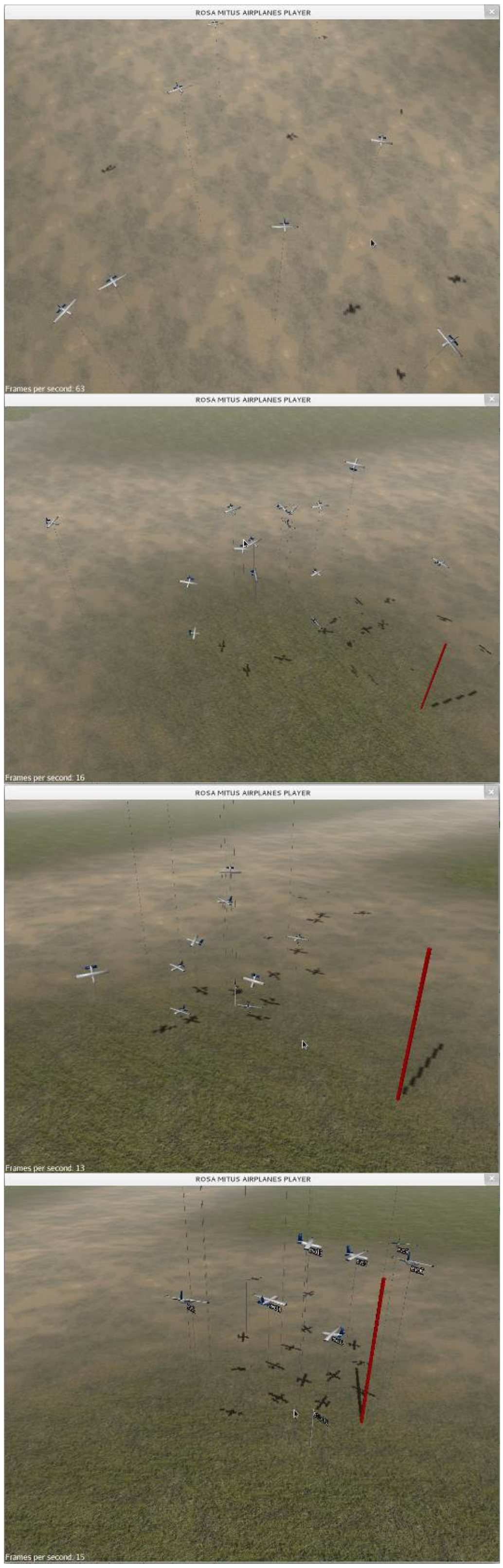


Figure 6: Four instants in the process of finding a source. From top to bottom: initial monitoring stage, two intermediate instants of the approach to the source and source found.

In fact it usually requires quite a large turn radius. This is taken into account within the simulation environment.

*B. Tests*

To test the efficiency of the algorithm we have performed a series of tests. As the objective was to locate pollution sources, we created a series of environments with up to three pollution sources and ran experiments with the planes taking off from points at different distances from the pollution sources and with different numbers of planes forming the teams. In terms of the the value for the decision gap, which to some extent determines the exploration/exploitation ratio, in the current examples it was set to a small value, five seconds. The reason is that given the relatively small size of the exploration area, the nature of the pollution function used, and the existence of a spread out stage, once the airplanes are searching for the source it is more useful to rely on exploitation.

In order to provide values for the quality of each run three time related measures were created. They correspond to points in time determined by the spatial positions of the planes. These spatial criteria are:

- Near area criterion: This spatial condition is activated when one of the planes is within a radius of 100 meters from the pollution source. It reflects how fast the algorithm converges to the interesting area of the environment.
- Lucky plane criterion: It is activated when at least one of the planes fly within a radius of 25 meters from the pollution source. To a certain extent it reflects the ability of the algorithm to explore the interesting area once they have found it.
- And finally, an 'end' criterion is activated when the maximum value detected by the team is inside a radius of 40 meters from the pollution source for 15 seconds. It is useful to measure the stability of the solution found and how fast the algorithm finds the solution.

Table 1 shows the results obtained in an environment with one pollution source. The pollution sources are situated 600 meters and 1000m from the take-off area and the planes are limited in their flying area to a radius of 1200 meters and 1500 meters respectively. In order to reduce the effects of the randomness in the approach we have executed each test 10 times and averaged the results. The table shows the comparison of times to achieve the different conditions in the two cases. The data in the tables is normalized to the reference of the averaged time to detect a pollution source with 15 planes taking off 600 meters from the source. That is, the values shown in the table are all relative to that reference. It is important to note that the time it took the team to find the source in this reference case assuming 12m/s speed for the planes, a value that was obtained from the motion of the real planes, was about 98 seconds.

Two results can be extracted from the table. On one hand it can be seen that the effectiveness of the strategy highly depends on the number of airplanes used. For 15 and 8 planes the swarm approach always finds the source. While in the case of 5 planes, the source is found only 80% and 60% of the runs, depending on the distance from the take-off point to the source. On the other, it can be clearly seen that the total time for finding the source increases in a very contained manner both, with a decreasing number of planes and with distance to the source of the takeoff point. It must be taken into account that the area to be explored increases with this distance and the area per plane increases with decreasing number of planes. Figure 6 displays a sequence of images corresponding to four instants of one of the search processes with a single pollution source: from the initial monitoring stage to the final concentration of the team over the source.

TABLE I. RESULTS FROM EXPERIMENTS (NORMALIZED TIMES)

| | Take off 600m from source | | | Take off 1km from source | | |
|---|---|---|---|---|---|---|
| Nº planes | Near area | Lucky plane | End condition | Near area | Lucky plane | End condition |
| 15 | 0.755 | 0.892 | 1 | 1.59 | 2.12 | 2.028 |
| 8 | 1.018 | 1.327 | 1.53 | 1.698 | 1.969 | 2.242 |
| 5 | 0.782 | 1.547 | 1.559 | 1.576 | 1.99 | 2.406 |

Finally we have tested the strategy with two and three pollution sources. Here the swarm team strategy, thanks to its ability to divide the team into multiple subteams that explore locally interesting areas, was able to detect multiple sources in an effective and repeatable fashion. Figure 7 shows the final situation achieved by the teams when two and three sources were present in the environment. The way the swarm algorithm works leads to an autonomous division of the planes into teams that concentrate on each one of the sources.

The tests have shown that there are parameters that determine the performance of the strategy when detecting multiple sources. In fact, the size of the team and the minimum

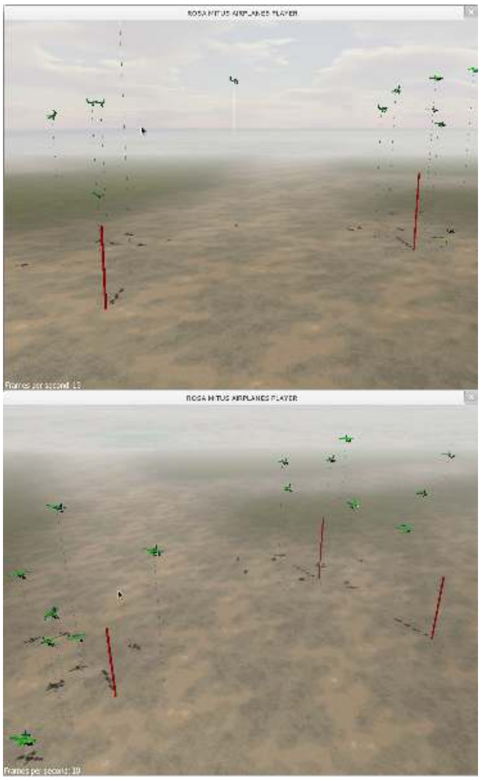

Figure 7: UAVs dividing into teams and finding the pollution sources when two and three pollution sources are present.

number of planes within a subteam that are necessary to be able to detect a source are the most important ones. These two parameters are related, as the team size must be large enough to allow the planes to build at least one minimum sized team per pollution source. Therefore, to detect multiple sources, larger teams are required. In the tests we have seen that a minimum team size of three planes per pollution source was required. With a team of 8 planes they were able to find two pollution sources, and with 10 they were able to find three pollution sources. Nevertheless, to increase the effectiveness of the strategy it is a good idea to increase the team size, as with more planes multiple sources are found in a much faster and easier manner.

To ensure the correctness of the approach and the validity of the conclusions obtained in the simulations some experimental flights were carried out over an industrial area in the northwest of Spain. Figure 8 displays a picture of one of the UAVs flying over the main pollution source in this area as well as the trajectories followed in one of the experiments. The results produced in these real flights have qualitatively supported the data produced using the simulator. However, it must also be said that being reality real, discrepancies in the average times obtained were observed without implying any change in the conclusions.

Figure 8: One of the UAVs flying over one of the test zones that includes industrial installations (left) and trajectory followed by a team.

## V. CONCLUSIONS

In this paper we have presented a swarm based approach for the coordination of UAV teams that are being used for environmental monitoring and pollution source detection. The swarm approach is based on a fitness value for each aircraft each moment in time given by the pollution sensors they carry. Thus, at predefined intervals, each UAV broadcasts its sensed values to its surrounding UAVs and from the values it receives from the others determines which is the most promising direction to move in and takes it.

This procedure has been shown to be quite effective for finding sources of pollution and its parameters can be regulated so as to just find the source that produces the highest pollution value or to find all the sources in a given area. A UAV team has been developed with the appropriate characteristics to be able to perform the task in real time. The approach has been validated over different scenarios, both in simulation and using a real UAV team.

We are now working on the introduction of new, more effective algorithms that improve the speed at which the sources are found and that, at the same time, require a smaller number of planes.

## ACKNOWLEDGMENTS

This work was partially funded by the Xunta de Galicia and European Regional Development Funds through projects 09DPI012166PR and 10DPI005CT.

## REFERENCES

[1] T. Samad, J. S. Bay, and D. Godbole, "Network-centric systems for military operations in urban terrain: The role of UAVs," in *Proc. IEEE*, Jan. 2007, vol. 95, no. 1, pp. 92–107.

[2] R. Sengupta and J. K. Hedrick, "Strategies of path planning for a UAV to track a ground vehicle," in *Proc. 2nd Annu. Symp. Auton. Intell.Netw. Syst.*, Menlo Park, CA, 2003, CD-ROM.

[3] U. Zengin and A. Dogan, "Real-Time Target Tracking for Autonomous UAVs in Adversarial Environments: A Gradient Search Algorithm," in *IEEE Trans. Robot.*, vol. 23, no. 2, pp. 294–307, Apr. 2007.

[4] A. Feshchenko, "Bird's-eye perspective. A review of indigenous UAV designs", Defense Express. English Version, No. 1-2, February 2007, page(s): 52-59.

[5] Y. Qu, Q. Pan, and J. Yan, "Flight path planning of UAV based on heuristically search and genetic algorithms," in *Proc. 31st Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2005, p. 5.

[6] C. Zheng, L. Li, F. Xu, F. Sun, and M. Ding, "Evolutionary route planner for unmanned air vehicles," *IEEE Trans. Robot.*, vol. 21, no. 4, pp. 609–620, Aug. 2005.

[7] Zhou Chuan-xiang, Yan Jian-guo, Hu Shan, Qu Yao-hong "Navigation/Flight control system design of a UAV based on DSP and CPLD[";Manufacturing Automation;2006-09

[8] M. Quaritsch, R. Kuschnig, H. Hellwagner, B. Rinner, "Fast Aerial Image Acquisition and Mosaicking for Emergency Response Operations by Collaborative UAVs, Proceedings of the 8th International ISCRAM Conference – Lisbon, Portugal, May 2011.

[9] E. Besada-Portas, L. de la Torre, J. M. de la Cruz, and B. de Andres-Toro, "Evolutionary Trajectory Planner for Multiple UAVs in Realistic Scenarios" *IEEE Trans. Robot.*, vol. 26, no. 4, pp. 619–634, Aug. 2010.

[10] S. Mittal and K. Deb, "Three-dimensional offline path planning for UAVs usingmultiobjective evolutionary algorithms," in *Proc. IEEE Congr. Evol. Comput.*, 2007, vol. 7, pp. 3195–3202.

[11] Z. Jin, T. Shima, and C. J. Schumacher, "Optimal scheduling for refueling multiple autonomous aerial vehicles," *IEEE Trans. Robot. Autom.*, vol. 22, no. 4, pp. 682–693, Aug. 2006.

[12] D. Howden and T. Hendtlass, "Collective intelligence and bush fire spotting," in *Proc. Genet. Evol. Comput. Conf.*, 2008, pp. 41–48.

[13] K. D. Hutchinson. "Applications of MODIS satellite data and products for monitoring air quality in the state of Texas" Atmospheric Environment, Volume 37, Issue 17, June 2003, Pages 2403-2412.

[14] F. Lopez-Pena, G. Varela, A. Paz-Lopez, R.J. Duro and F. J. Gonzalez Castaño "Public Transportation Based Dynamic Urban Pollution Monitoring System". Sensors & Transducers Journal, V. 8, 2010, pp 13-25.

[15] Ramanathan, V., G. Roberts, M. Ramana, C. Corrigan, and H. Nguyen, Modulation of Albedo and Solar Absorption by Aerosols and Clouds: First Observations with a New Observing System of Stacked Multiple UAVs and Ground Based Observatory, in Invited Paper for the Western Pacific Geophysics Meeting (WPGM), http://www-abcasia.ucsd.edu/MAC/RamanathanWPGMAbstract2006.pdf, Beijing, China, 2006.