# Detection and mapping of a toxic cloud using UAVs and emergent techniques

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**Abstract.** Unmanned aerial vehicles have gained a lot of interest in recent times, due to their potential use in several civil applications. This paper focuses on the use of an autonomous swarm of drones to detect and map a toxic cloud. A possible real-world scenario is the accidental release of hazardous gases into the air, resulting from fire or an explosion at an industrial site. The proposed method is based on the concept of swarm intelligence: each drone (agent) performs basic interactions with the environment and with other drones, without need for a centralized coordination technique. More precisely, the method combines collision avoidance, flocking, stigmergy-based communication, and a cloud exploration behavior called inside-outside. For the experiments we developed a simulator using the NetLogo environment, and tested different combinations of these emergent behaviors on two scenarios. Parameters were tuned using differential evolution and separate scenarios. Results show that the combined use of different emergent techniques is beneficial, as the proposed method outperformed random flight as well as an exhaustive search throughout the explored area. In addition, results show little variance considering two different cloud shapes.

**Keywords:** differential evolution, drone, fractals, mapping, NetLogo, quadcopter, stigmergy, swarm intelligence, toxic cloud, unmanned aerial vehicle

## 1 Introduction

Over the last few decades, unmanned aerial vehicles (UAVs), also known as drones, have become extremely accessible thanks to the advancement in different technological areas, and their use has been proposed in an increasing number of applications [3, 8]. In particular, drones can replace traditional human-operated vehicles in dangerous missions, such as monitoring a wildfire and exploring unknown or highly polluted environments.

The use of multiple low-cost drones is particularly effective in these scenarios, as it ensures better fault tolerance and timely accomplishment of missions. However, the simultaneous use of multiple drones also poses the challenge of finding a proper coordination strategy. In this context, approaches inspired by natural swarms (swarm intelligence) have been investigated [1, 4, 2]. In a swarm, each agent's behavior is characterized by simple interactions with the environment, without full awareness of the overall aim of the mission: the aim is achieved as a result of these simple behaviors (emergence of global behavior in swarm intelligence). This approach proved effective in different applications, and strongly reduces the requirements in terms of drone's processing capabilities and duration of operation.

One interesting application for UAV swarms is represented by the exploration of the environment after a disaster, such as the accidental release of toxic gases in the atmosphere from an industrial site [7, 13, 17]. In this scenario, a swarm could be immediately deployed to quickly detect and map the toxic cloud. This information could be paramount to take prompt measures in order to preserve public safety in the area nearby the industrial site. Recent works have proposed and evaluated different approaches, in terms of drone and sensor characteristics, to monitor the presence of chemical substances in the air [16]. These systems are also known as eNose applications [11]. A commonly used sensing technology is represented by MOSFET (chemoresistive) sensors, which offer long-term stability and fast response [18, 15]. The response is caused by direct interaction with the volatile chemical, hence the use of stationary measurement systems is not a viable solution in most cases.

The swarm should adopt an effective strategy to quickly detect the presence of the pollutant in the air and then determine the area occupied by the toxic cloud. A relevant work in this field was presented in [9], which proposed a decentralized approach for a UAV swarm. This approach relied on constrained randomized behavior, and took into account restrictions regarding sensors, processing capabilities, and flight envelope. The mapping procedure was based on the inside-outside strategy: drones move straight across the cloud and then turn to repeat the procedure. A somehow similar study was presented in [10], which considered different mapping strategies (including inside-outside) to determine the contour of a toxic cloud. Both studies considered fixed-wing drones for their simulations.

In this work, we propose and evaluate a method for detecting and mapping a cloud using a swarm of quadcopters. The contribution can be summarized as follows:

- The proposed method is based on the combined use of different emergent techniques, namely flocking, stigmergy, and inside-outside cloud exploration. Drone behavior logic also includes an obstacle avoidance strategy to avoid collisions with other drones as well as with obstacles (e.g., buildings).
- The method was evaluated by means of two scenarios built in the Netlogo simulation environment. The scenarios were created using the areal view of a real incinerator and two different cloud shapes inspired by real life examples. Clouds were represented in two dimensions for the sake of simplicity (the same approach can be easily extended to study clouds in 3D).
- The parameters of the emergent techniques were tuned using differential evolution and artificial cloud shapes, which were generated using fractals.

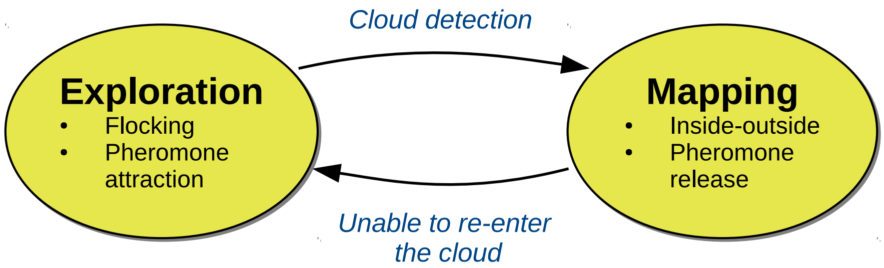


**Fig. 1.** Drone behavior as a finite state machine.

– The contribution of each emergent technique was evaluated in terms of time required to fulfill the mission (i.e., detect at least 95% of the cloud area).
– Results show that the adoption of each emergent technique in the combined approach is beneficial to reduce the average exploration and mapping times, as well as to reduce variance between different repetitions of the experiment. The proposed method outperforms random flight and exhaustive exploration.

The following Section presents the proposed strategy. Section 3 describes the evaluation procedure based on Netlogo. Finally, results are presented and discussed in Section 4.

## 2 Method

The behavior of a drone in the proposed method is shown in Figure 1. At the beginning of a mission, each drone is in the *exploration* state, and its aim is to explore the environment in order to find the toxic cloud. In exploration, drone behavior is characterized by flocking and stigmergy (pheromone attraction). There is an emergent formation of groups of drones (flocks), which start moving randomly throughout the environment. Drones follow the rules of flocking and random flight when no pheromone is sensed, whereas they follow a pheromone trace when present. As soon as a drone detects the toxic cloud, its state changes from exploration to *mapping*. At this point, drone behavior is characterized by the inside-outside mapping strategy and stigmergy (pheromone release). The drone starts mapping the cloud without following flocks or pheromone traces released by other drones. Instead, the drone releases pheromone while inside the cloud, so as to attract other drones towards the target. Finally, a transition from mapping to exploration may occur if the drone exits the cloud as part of the mapping strategy and it is not able to re-enter the cloud within a predefined time interval.

Throughout the mission drones also observe basic rules to prevent collisions (collision avoidance). In particular, we developed a simple approach based on two parameters – obstacle vision and obstacle vision angle – which are used to define an obstacle vision area. This is the area where the drone is capable of sensing the presence of obstacles (e.g., another drone, a tree, a building, etc.). When a drone detects an obstacle in its vision area, it reduces its speed and changes its heading to prevent a collision. It should be highlighted that this work is not focused on flight simulation, but on exploration and target discovery.

The following subsections describe flocking, stigmergy, and inside-outside mapping.

### 2.1 Flocking

Flocking is used to coordinate the movement of drones in the exploration phase and keep them in communication range. As defined in the best known work presented in [14], flocking is based on the rules of alignment, separation, and cohesion. Alignment consists in aligning the heading according to the average heading of nearby drones (flock mates). Separation ensures that a minimum distance is maintained between flock mates, so as to prevent collision and ensure effective sensing. Finally, cohesion directs each drone towards the center of the flock. These three rules are combined using specific parameters.

### 2.2 Stigmergy (pheromone attraction and pheromone release)

Digital stigmergy is a form of communication between agents, based on the release of a digital pheromone. This digital mark is characterized by radius, intensity, and linear evaporation dynamics. In our implementation, drones in the exploration state are attracted by the pheromone released by other drones (pheromone attraction): pheromone is sensed according to an olfaction radius parameter. Pheromone release is performed during the mapping phase, when a drone senses the presence of the toxic cloud.

### 2.3 Inside-outside mapping strategy

After entering the cloud for the first time, the drone changes its state from exploration to mapping. In mapping, the drone keeps a constant heading to quickly move across the cloud, according to the inside-outside strategy described in [9]. As soon as the volatile chemical is not sensed anymore (i.e., the drone has exited the cloud), the drone starts turning in order to re-enter the cloud. This maneuver is based on a return heading angle, which is chosen randomly in a predefined range of angles. For example, if the return heading is set to 180 degrees the drone stops turning when its heading is equal to $fixed\_heading+180$, where $fixed\_heading$ was the heading of the drone when it entered and exited the cloud. When the drone stops turning, it then proceeds with constant heading and must re-enter the cloud within a specified time – if this succeeds, the procedure is repeated. Conversely, if the drone is unable to find the cloud again within the specified time, it returns to the exploration state.

As previously mentioned, in the mapping state the drone is not attracted by digital pheromone and it does not follow flocking rules. On the other hand, while mapping the cloud a drone is responsible for releasing pheromone to attract other drones towards the target.

**Table 1.** Evaluated approaches.

| **Approach** | **Description** |
|---|---|
| Random | Random flight. |
| Stigmergy only | Drones are attracted by digital pheromone; pheromone is released by drones inside the cloud. Random flight when no pheromone is sensed. |
| Stig. & Flocking (SF) | Stigmergic attraction and release; drones also follow the rules of flocking. |
| Inside-outside only | Random flight outside the cloud; each drone, after detecting the cloud, performs mapping according to the inside-outside strategy. |
| Combined | Proposed approach described in Section 2. Drones behave according to SF when outside the cloud. As soon as a drone finds the cloud it starts performing inside-outside mapping and it also releases pheromone while inside the cloud. |

## 3 Experimental setting

We implemented all the aspects of drone behavior using Netlogo, which is a leading platform for multi-agent simulation [12]. Flight parameters were chosen according to the characteristics of common quadcopters, like the DJI Phantom 4. A relatively slow cruising speed of $\sim$ 4 m/s was chosen – slow speed better suits the considered scenario, as MOSFET sensors have a typical delay of a few seconds before responding to the toxic chemical.

As previously mentioned, our approach to detect and map a toxic cloud is based on flocking, stigmergy, and inside-outside mapping. Hereafter, we refer to the proposed approach as Combined, as it combines several emergent techniques. For our evaluation, we compared Combined with simpler approaches, based on a reduced subset of the emergent techniques. Considered approaches are listed and described in Table 1. This allowed us to evaluate the contribution of each technique.

Two scenarios were created for the evaluation, shown in Figure 2b and Figure 2c. Both scenarios are based on the same aerial view of an incinerator, shown in Figure 2a. The simulation environment is divided into patches: the two scenarios are made of 200x200 patches: each patch represents a squared area of 4x4 meters in the corresponding real-world scenario. As a result, the search field corresponds to an area of 640,000 m$^2$. The above mentioned speed of 4 m/s means that a drone is capable of visiting a patch per second. Buildings and trees are represented in gray, whereas the patches containing the toxic cloud (target) are red. The two scenarios differ for the cloud shape, which was inspired by real aerial views of toxic volatile chemicals. The number of drones used in each simulation is 20 – at the beginning of the mission drones are deployed from the bottom-left corner of the scenario.

(a) Aerial view of the incinerator (source Google Earth)

(b) Scenario 1 (c) Scenario 2

**Fig. 2.** Aerial view and Netlogo scenarios.

Adaptation of parameters related to flocking, stigmergy, and inside-outside emergent techniques was achieved using differential evolution [5]. In practice, it is not possible to tune the techniques to the exact cloud to be detected and mapped, but artificial cloud shapes can be used to adapt the techniques to the problem at hand as much as possible. In this study, optimization was done on separate artificial scenarios, created using fractals and shown in Figure 3. Fractals were created using the Fractint software [6].

The performance of a specific approach, among the ones listed in Table 1, was measured in terms of the time required to map 95% of the cloud area. Since all experiments were partially characterized by random behavior, each experiment

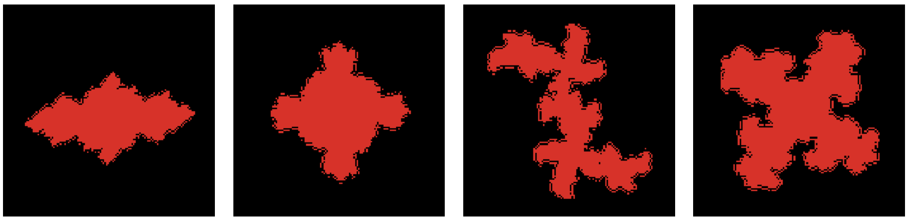

**Fig. 3.** Artificial cloud shapes used to tune parameters with differential evolution.

**Table 2.** Results – mission duration in seconds with the different approaches.

| **Approach** | **Scenario 1** | | **Scenario 2** | |
|---|---|---|---|---|
| | **Mean time** | **CI 95%** | **Mean time** | **CI 95%** |
| R | 4665 ± 526 | 104 | 4560 ± 370 | 73 |
| S | 1756 ± 280 | 55 | 1634 ± 308 | 61 |
| SF | 1638 ± 242 | 48 | 1523 ± 230 | 46 |
| IO | 1892 ± 343 | 68 | 1552 ± 182 | 36 |
| CO | 1017 ± 98 | 19 | 1014 ± 57 | 11 |

was repeated 100 times to determine the average time to fulfill the mission and the respective 95% confidence interval.

For the sake of simplicity, in this preliminary study we did not consider diffusion and dispersion dynamics, as well as the effect of the wind. It was supposed that these dynamics do not affect the cloud shape significantly during the mission, which lasts less than 30 minutes.

## 4 Results and Discussion

The results obtained by the evaluated approaches are shown in Table 2. More precisely, for each approach it is shown: the average time ± the standard deviation of the time required to find 95% of the toxic cloud patches; the respective 95% confidence interval (CI). Times are expressed in simulation ticks, which correspond to seconds.

As expected, the behavior based entirely on random flight obtained the worst result, with more than 4000 s required on average to fulfill the mission in both the considered scenarios. In this simple approach, drones tend to scatter throughout the map and do not exploit any kind of communication when the cloud is found. This does not enable prompt mapping of the cloud. Moreover, in the considered scenarios this approach would require to replace the drones during the mission, as battery duration is typically in the order of 30 minutes.

The use of stigmergy alone drastically improves the performance in both scenarios, with a mean time of about 1700 s. As soon as a drone finds a target (i.e., a patch containing the toxic cloud), it leaves a digital mark with specific diffusion and evaporation characteristics, which are defined by the parameters tuned with differential evolution. This digital mark attracts the drones nearby towards the cloud. As more drones reach the target, there is a substantial increase in the amount of released pheromone – this leads to a stronger and more diffused digital mark, which is capable of attracting more drones. As such, most of the drones quickly converge towards the target and explore the relevant patches.

Previous works, like [4], showed that combining stigmergy and flocking further increases the performance of a swarm of drones in target discovery. This result is confirmed by our study, as the SF approach obtains slightly better results than stigmergy alone. One possible interpretation of this result is that with flocking rules drones tend to be closer to each other, which in turn facilitates stigmergy-based communication. When a drone finds the target, thanks to flocking rules it is ensured that other drones (flock mates) are close enough to immediately sense the pheromone mark and move towards the cloud.

Before testing the approach proposed in this study, we evaluated the use of the inside-outside mapping strategy alone, without stigmergy-based communication and flocking rules. Hence, drones move randomly while searching for the cloud and do not communicate to each other when the cloud is found. Results were slightly worse than SF, especially in the first scenario, where the peculiar cloud shape increases the probability of being unable to re-enter the cloud while performing the mapping strategy. In fact, this strategy is very efficient when the drone is actually mapping the cloud, but it is clear that it must be combined with proper techniques to also deal efficiently with cloud detection and to attract drones towards the target once it has been detected.

To this end, we proposed a method that combines all of these emergent techniques. Drones exploit stigmergy and flocking to explore the environment and to quickly move towards the target when is found. At the same time, the inside-outside strategy is used by drones that have found the cloud to efficiently perform mapping. The combined approach obtained substantially better results in terms of mean time, standard deviation, and 95% CI. Notably, despite the different cloud shape, the result was very similar for both scenarios (about 1000 seconds), with a 95% CI below 20 seconds. In terms of average time, it showed a reduction of 78% if compared to the random approach, and a reduction of 36% compared to SF. Another way to evaluate this result consists in considering the time required to exhaustively explore all the patches in the scenario, without taking into account the presence of obstacles. As our scenarios are made of 40,000 patches and each of the 20 drones can visit one patch per second, the time to exhaustively visit all the patches would be 2000 ticks or seconds. That would be two times longer than the time achieved by the proposed approach.

In future work we plan to extend the promising results of this preliminary study and address its main limitations. To obtain a more realistic scenario, gas dispersion and diffusion dynamics will be considered, as well as the effect of the wind. Another important aspect to be considered, is the choice of the optimal number of drones to be deployed. To this end, we will carry out an evaluation as the number of drones is varied and consider more scenarios. In addition, we will evaluate how the discovery process evolves over time for each technique, by measuring the time required to map different percentages of the cloud area.

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