Flight Pattern and Experimental Flights of a Quadcopter Drone at the Edge of a Smoke Plume

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ABSTRACT

Measuring air quality is a burning challenge, and an increasing number of drones are now equipped with pollution sensors to detect airborne pollutants. This paper presents a trajectory tracking strategy that allows the drone to fly along the edge of the plume, preventing it from entering the plume where heat and gas concentrations are high. Algorithms developed in Python were tested in simulation with virtual plumes based on emulated GPS data, then validated experimentally in the field and during a real fire using an onboard particle sensor embedded on a quadcopter.

1 INTRODUCTION

One of the most significant industrial fires in France in recent years remains that of *the Lubrizol and Normandie Logistique* sites, which occurred on September 26, 2019, near Rouen. This large-scale disaster ignited a hydrocarbon pool covering more than 20,000 m^2, releasing a massive plume of black smoke over the city. More recently, on April 9, 2025, a battery recycling plant exploded in Kilwinning, Scotland. In the face of such events, understanding the composition of these plumes becomes a crucial issue: it is not only a matter of improving risk management, but also of informing and protecting populations.

When a fire breaks out, large quantities of fine particles (PM) and polluting gases – such as nitrogen dioxide (NO_2), sulphur dioxide (SO_2) and carbon dioxide (CO_2) – are released into the atmosphere [1]. Depending on the fire's origin, other gases like hydrogen fluoride (HF), hydrogen chloride (HCl), and similar compounds may also be emitted, particularly in the case of industrial fires. Exposure to these substances can have deleterious effects on the health of local populations, depending on the duration and concentration of exposure. Faced with these risks, the emergency services must rapidly assess the situation to establish a safety perimeter and, if necessary, organize the evacuation of areas at risk.

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In such contexts, drones have been extensively deployed to monitor smoke plumes and the dispersion of pollutants. The analysis of fire-related smoke, however, raises two major challenges: should the measurements be conducted indoors, as in the case of an apartment fire, or outdoors? In the former case, the drone must operate directly within the smoke and therefore requires an architecture capable of withstanding extreme temperatures. The FireDrone project [2] addressed this issue by introducing a thermally resistant UAV, equipped with insulating materials and a biologically inspired phase-change cooling system, enabling safe operation under harsh conditions.

For outdoor smoke analysis, such as in wildfires or large-scale industrial accidents, plumes can be transported over several kilometers. To tackle these challenges, numerous research initiatives—supported in France in particular by the French National Research Agency (ANR) [3, 4]—have focused on developing innovative approaches for measuring and mapping air pollution using fleets of drones. [5] proposed a ConvLSTM-based model coupled with data assimilation to map smoke dynamics in real time, with adaptive recalculation of drone fleet trajectories. Similarly, [6] developed a cooperative reinforcement learning approach to optimize multi-drone coordination and produce reliable plume maps.

In this article, we focus on large-scale industrial fires, for which the development of effective plume-mapping strategies is essential. In the literature, two main classes of strategies for mapping pollutant clouds can be identified: those in which the drone penetrates the cloud, and those in which it navigates along its boundary.

The first family consists of flying the drone inside the cloud to collect measurements at the heart of the plume. For example, [7] proposes strategies such as the rosette trajectory, which involves 2D exploration by several internal passes, and the oblique cone spiral, characterized by a helical movement within the cloud. Other works, such as [8], use swarms of drones to detect, explore, and map the boundaries of the cloud using coordinated dispersion.

However, in the specific case of fire plumes, the high heat and high concentrations of pollutants make it risky to fly directly through the cloud, both for the drone and its sensors, that risk being saturated or damaged. Rather than using reinforced UAVs and sensors [2], a parsimonious approach is favored by limiting flight to the periphery of the plume.

We are interested in the second family of cartography

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strategies, in which the drone evolves only on the border of the cloud. In [7] notably, two approaches are distinguished: the "Trinity" strategy, which consists of loop trajectories around the periphery of the cloud ; and the "Lace" strategy, where the drone follows arcs along the border of the cloud (see Figure 2) similar to the methods presented in [8, 9]. The adopted strategy is derived from the latter.

More specifically, this study presents the development of an autonomous system built around a quadcopter drone equipped with a particle sensor, designed for real-time mapping of smoke plumes and for monitoring pollutants along the plume boundary. Following the description of the drone prototype and its onboard detection system (Section 2), the article examines the proposed flight control strategy (Section 3), details the experimental campaigns (Section 4), and discusses the results obtained (Section 5).

2 Architecture

2.1 Drone Prototype

The prototype used in this study is a quadcopter based on the X500 kit from Holybro. The carbon fiber frame adopts an X configuration. It measures 50 cm in diameter and has an empty weight of 978 g. The kit includes all the components necessary for assembly: a Pixhawk 4 autopilot, four brushless motors, four electronic speed controllers (ESCs), a PM07 power distribution board, a GPS module, propellers, a radio telemetry module, a FrSky XR8 receiver, as well as power and communication cables. Manual control of the drone is provided by a FrSky Taranis X7ACCESS remote controller, which transmits instructions to the Pixhawk 4. To enable autonomous missions, a Raspberry Pi 3B+ mini-computer is also onboard. It communicates with the Pixhawk via a USB connection and hosts the adaptive flight algorithms. Additionally, the Raspberry Pi receives sensor data through an SPI connection with an Arduino Mega, which serves as an interface for collecting environmental measurements.

2.2 Onboard Measurement System

The measurement module mounted on the drone integrates the following components:

- An OPC-R2 20 particle sensor,
- A GSM communication module,
- A GPS module,
- A SD card reader,
- An Arduino Mega.

The OPC-R2 sensor, which operates based on light diffraction principles, enables the detection and classification of airborne particles. The data collected by the sensor are processed by the Arduino Mega, and then transmitted to an online database via a 2G connection provided by the GSM module. In parallel, the measurements are geolocated using the GPS module and stored locally on an SD card.

The collected data are also sent to the onboard Raspberry Pi for further processing via an SPI connection. The entire system is powered by a 4S 3700 mAh Tattu LiPo battery. An overview diagram of the system is presented in Figure 1.

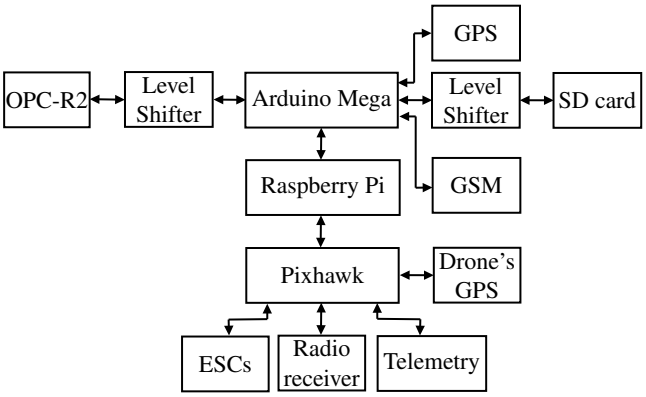

Figure 1: Architecture of the measurement system.

3 Plume-Edge Tracking Strategy

3.1 Navigation Strategy: the 'Lace' Approach

As part of our application, the adopted navigation strategy is inspired by the 'Lace' method described in the paper [7] and illustrated in Figure 2. This strategy is based on a trajectory pattern composed of successive circular or elliptical arcs, alternating inside and outside the area to be mapped. When a particle concentration threshold is exceeded, the drone initiates a trajectory along the boundary of the cloud, alternating between approach and bypass phases.

This strategy can be innovatively reimagined by redefining its core approach. For example, one novel adaptation involves exclusively performing exterior trajectories, see Figure 3, thereby circumventing sensor saturation that would otherwise result from the high particle concentrations found at the core of the cloud. Similarly, the shape of the trajectories can be adapted: instead of following a perfect circle, an ellipse or a polynomial curve can be used to better match the actual shape of the cloud.

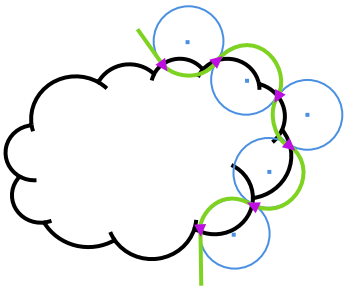

Figure 2: Lace adaptive flight pattern derived from [7].

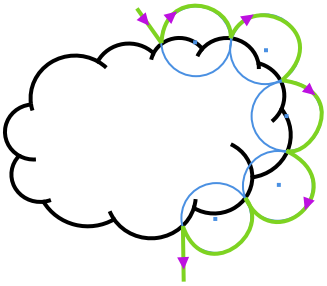

Figure 3: The 'Petals' strategy used in this work.

3.2 *Strategy Process*

The Lace strategy is divided into several steps:

1. Initial Approach: the drone flies in a straight line toward the estimated position of the cloud.
2. Boundary Detection: as the drone enters the cloud (defined by a particle concentration threshold), it stops its forward movement.
3. Looped Trajectories: the drone then performs circular or elliptical trajectories around the concentration zone each time it detects the cloud boundary.
4. Mission Completion: Once the mission-ending conditions are met (e.g., low battery), the drone autonomously concludes the tracking of the cloud.

Simulations were conducted using the QGroundControl software, which allows for aerial visualization of the drone's trajectory.

3.3 *Algorithmic Architecture*

The proposed control algorithm is represented by the flowchart in Figure 4. The adapted 'Lace' strategy – afterwards called 'Petals' – workflow is as follows:

- Takeoff preparation: switch to "STABILIZE" mode while awaiting user instruction.
- Takeoff: Switch to "GUIDED" mode, arm the drone, and ascend to the target altitude.
- Navigation toward the cloud: fly toward the predefined GPS coordinates corresponding to the suspected area.
- Position hold and trajectory calculation: In "LOITER" mode, the drone holds its position and computes the GPS waypoints forming the elliptical trajectory.
- Trajectory execution: move in straight lines between the GPS waypoints of the ellipse.
- Boundary loss: if the cloud boundary is lost, adjust the ellipse parameters to relocate it. Loss of boundary is detected when the drone has traveled through all the GPS points of the current ellipse. At that point, its axes are multiplied by 1,3 for the next ellipse, and this process repeats as long as the boundary remains undetected. As soon as the boundary is found, the ellipse returns to its original size. Additionally, with each iteration, the ellipse's angle is shifted by 0,7 radians to improve the search for the cloud's boundary.
- End of mission: once the mission-ending conditions are met, the drone executes an exit procedure.

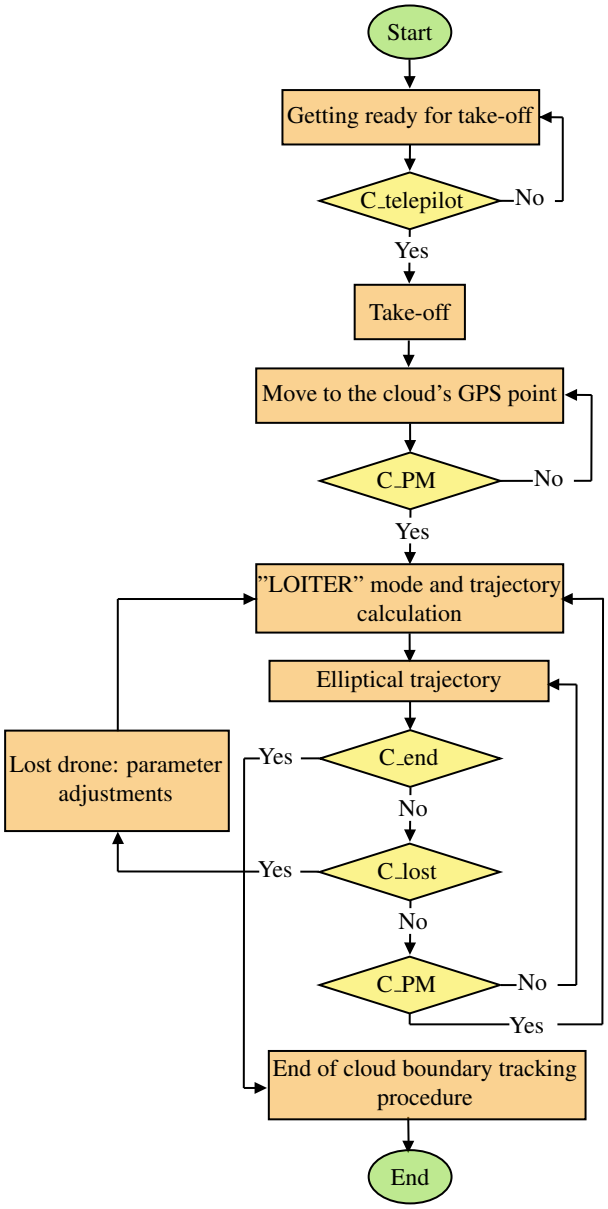

Figure 4: Flowchart of the adaptive flight pattern algorithm (Processes are shown as orange rectangles, and transition conditions as yellow diamonds).

The transition conditions between each of these steps are as follows:

- C_pilot: the drone takes off once the user activates "AUTO" mode.
- C_PM: when the particle concentration (PM1 or PM2.5) exceeds 70 μg/m^3, the drone considers that it has entered the cloud.
- C_end: if the battery level becomes critical, the mission is interrupted to ensure the drone's safety.
- C_lost: this condition is triggered if the drone completes an elliptical trajectory without detecting any variation in the C_PM condition, indicating a loss of the cloud boundary.

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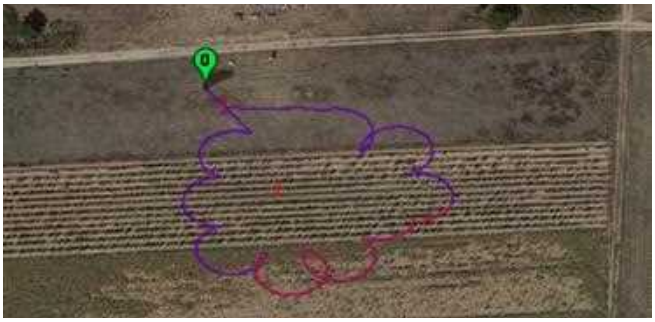
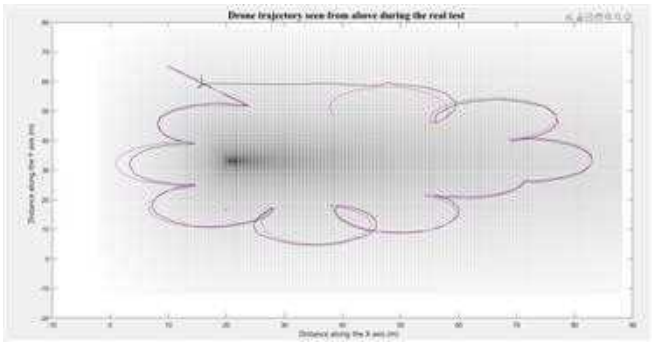
4 EXPERIMENTS AND RESULTS WITH THE PARTICLE SENSOR

4.1 Simulations and Experiments on an Emulated Sensor

In order to validate the flight strategy, initial tests were conducted using a simulated sensor. This device emulates the concentration measurements of the artificial cloud based on the drone's GPS position. The main objective of this first flight test campaign was to evaluate the "Petals" flight strategy without using the actual particle sensor, by following the planned trajectory along the boundary of a cloud artificially



(a) GPS position: comparison of the theoretical trajectory of the drone obtained through simulation (in purple) with the trajectory measured during the flight test (in black).



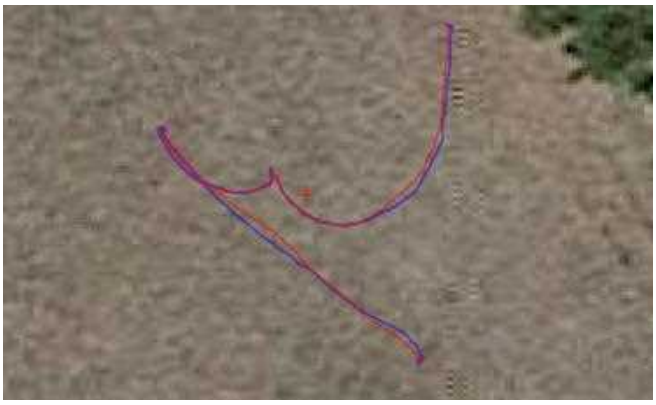
(b) 2D trajectory of the drone around the cloud generated during the mission.

Figure 5: Flight carried out during the mission at the model aircraft field in Brumath, Alsace, France.

generated by the Raspberry Pi. This approach aimed to identify any weaknesses in the strategy and suggest areas for improvement before deploying it with an operational particle sensor. During the mission, the drone followed the trajectory shown in Figure 5 at the model aircraft field, under favorable weather conditions (sunny weather and no wind). A good fit between the two curves can be observed when comparing the simulated and experimental trajectories (Figure 5a). This closeness indicates that the simulation results accurately reflect the drone's actual behavior during real-world testing.

This test made it possible to validate, through field experiments, the proper functioning of the adaptive flight scheme by demonstrating its ability to accurately reproduce the expected trajectory as simulated. The main issues identified and resolved during this phase concerned sudden altitude variations as well as an irregular drone trajectory, particularly during elliptical paths. In conclusion, these experimental tests confirmed the effectiveness and robustness of the 'Petals' adaptive flight algorithm, developed in Python. The autonomous strategy for tracking pollutants at the edge of a smoke plume was thus validated in a real environment using a simulated sensor. The next step involved testing this approach on a real smoke plume, using a drone prototype equipped with an onboard particle sensor.

(a) Smoke cloud produced by the smoke bomb.



(b) Trajectory during a smoke bomb test.

Figure 6: Experimental test on smoke bombs in a field.

4.2 Experimental Results on a Smoke Bomb

Before performing a test on an actual fire, an initial way to ensure that the adaptive flight strategy works with the particle sensor is to first test it on smoke puffs generated by a smoke bomb. The smoke bomb generated a small cloud (Figure 6a) lasting only about 2 minutes. This is too short to fully map and follow the boundary, but sufficient to verify the correct triggering of the program's different processes.

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The threshold set for the smoke plume boundary is 70 μg/m^3 for PM1 and PM2.5. PM1 and PM2 are particulate matter sizes, with PM1 being particles smaller than 1 micrometer and PM2.5 being particles smaller than 2.5 micrometers. This choice was made from experiments conducted using smoke from a barbecue and a smoke bomb. The trajectory followed by the drone during the test with a smoke bomb is shown in Figure 6b. During this experimental test, the weather was sunny with a northwest wind at 10 km/h and occasional gusts. This test with a smoke bomb confirmed that the program was functioning correctly, enabling subsequent testing on the smoke plume from a controlled fire chamber. Indeed, the drone stops and switches to "LOITER" mode when the threshold is exceeded, then performs elliptical trajectories along the edge of the smoke puffs.

4.3 Experimental Results on a Fire Training Container

The final experimental test was in sunny weather with a East/Northeast wind. The objective of this test was to evaluate the adaptive flight pattern over a smoke plume originating from a fire training container. For this purpose, a member of The Bas-Rhin Fire and Rescue Service (SIS67) ignited a fire using wooden pallets inside a container, as shown in Figure 7a. A GPS point at the center of the plume was defined, and the input parameters for the algorithm were as follows:

- An ellipse radius of 5 meters: a major axis of 6 m (1.2 × 5 m) and a minor axis of 4 m (0.8 × 5 m)
- A flight altitude of 10 meters
- 35 GPS waypoints generated for each ellipse
- An angle between successive ellipses of 85 °C
- A maximum flight speed of 1.4 m/s during the elliptical path
- A GPS point distance factor of 2 during the elliptical trajectory
- Ellipse orientation set at 45 °C, given the wind from the East/Northeast
- PM1 and PM2.5 entries threshold into the plume: 70 $\mu g/m^3$
- PM1 and PM2.5 exits threshold from the plume: 70 μg/m^3

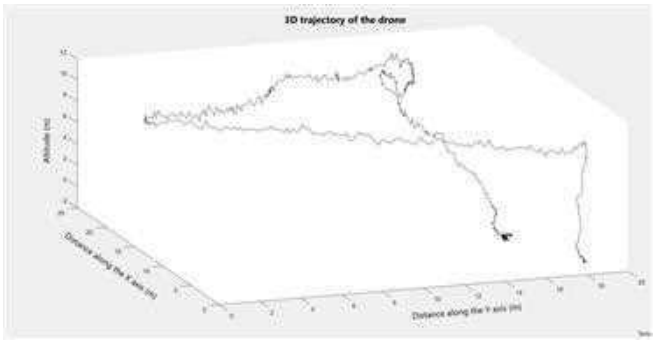
In Figure 7b, the drone's flight path over the fire training container area is shown. Figure 7c shows the drone's trajectory re-plotted in MATLAB, both in a 3D perspective. The drone initiates its strategy approximately 25 meters from the fire source.

5 ANALYSIS OF THE RESULTS

Several test campaigns were conducted using the OPC-R2 particle sensor to monitor real smoke plumes, with continuous readings of PM concentrations. Preliminary trials with smoke bombs were instrumental in calibrating the detection threshold and resolving issues related to particle concentration readings. As detailed in Section 4.2, these tests led to a functional integration of the sensor with the adaptive flight algorithm: the drone successfully followed an adaptive flight pattern around the smoke generated by the bombs. However, smoke bombs present certain limitations – their plumes are low, not very dense, and short-lived (less than two minutes). These constraints make it difficult to fully evaluate the flight strategy in such conditions.

(a) Smoke plume from the fire training container.

(b) GPS drone trajectory during the fire training container test (the drone trajectory is marked in yellow, the green arrow indicates wind direction, and the red cross marks the fire source).



(c) 3D trajectory flown by the drone around the smoke plume.

Figure 7: Experimental test on a fire training container in the industrial zone of Drulingen, Alsace, France.

To overcome these limitations, a final test on a real fire-generated smoke plume was carried out, as described in Section 4.3. The results were promising: the drone correctly identified and tracked the edge of the plume using the adaptive trajectory. Nonetheless, the flight was brief, as the drone had to be retrieved early due to collision risks.

One challenge encountered was the drone's ability to locate the plume at the start of the mission. The predefined GPS point, intended to lie within the plume, was sometimes

outside the actual smoke zone due to inaccurate positioning, overly strict PM detection thresholds, or suboptimal flight altitude. These three parameters – initial GPS point, PM threshold, and flight altitude – require fine-tuning to ensure proper activation of the adaptive strategy. Future trials are needed in safer environments with fewer obstacles, along with better control over parameter settings. Overall, these tests confirm the functionality of the adaptive flight algorithm for mapping and tracking pollutants along smoke plume boundaries.

6 CONCLUSION

This work develops and evaluates an autonomous drone system for tracking airborne pollutants along smoke plume edges. A trajectory-following strategy, based on adaptive path planning, was developed, simulated, and experimentally validated through a series of tests using both smoke bombs and a controlled fire training container. A total of 27 test flights were conducted over 9 days, amounting to 1 hour and 5 minutes of total flight time with the prototype. The result is a first operational prototype of an autonomous quadcopter equipped with a functional OPC-R2 particle sensor. The drone is capable of detecting variations in PM1 and PM2.5 concentrations and autonomously adapting its trajectory to follow the boundaries of a smoke plume.

However, this prototype remains an initial proof of concept, and multiple avenues for improvement are identified for future development. Algorithmically, enhancements could include replacing elliptical trajectories with polynomial path generation for better adherence to irregular plume shapes, implementing more robust boundary-loss recovery strategies, and enabling 3D mapping of the smoke plume. The implementation of performance criteria for flight paths is also part of the ongoing work.

To date, testing has been limited to small-scale conditions, covering distances of approximately 100 meters, whereas the ultimate objective is to map large-scale smoke plumes extending over several kilometers. To achieve this goal, flight endurance will need to be improved through higher-capacity UAV platforms and more robust, integrated electronic architecture. Our team is currently developing a VTOL-type drone designed to enable longer flight durations, thereby improving flight performance while reducing battery consumption. Future sensor integration could also involve the addition of gas sensors, humidity sensors, and temperature probes to enrich the environmental data collected. The long-term goal is to develop a deployable system that could assist firefighting units in real-time plume tracking and pollutant monitoring during active fire events.

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