Combining Lévy Walks and Flocking for Cooperative Surveillance using Aerial Swarms

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Abstract. Continuous area coverage missions are a fundamental part of many swarm robotics applications. One of such missions is cooperative surveillance, where the main aim is to deploy a swarm for covering predefined areas of interest simultaneously by k robots, leading to better overall sensing accuracy. However, without prior knowledge of the location of these areas, robots need to continuously explore the domain, so that up-to-date data is gathered while maintaining the benefits of simultaneous observations. In this paper, we propose a model for a swarm of unmanned aerial vehicles to successfully achieve cooperative surveillance. Our model combines the concept of Lévy Walk for exploration and Reynolds' flocking rules for coordination. Simulation results clearly show that our model outperforms a simple collision avoidance mechanism, commonly found in Lévy-based multi-robot systems. Further preliminary experiments with real robots corroborate the idea.

Keywords: Lévy Walk · Swarm Intelligence · Reynolds' flocking · Surveillance Area Coverage · Swarm Robotics.

1 Introduction

The benefits of swarm intelligence techniques have been widely exploited in cooperative missions [1–7]. A particular advantage of these techniques is the focus on generating decentralized controllers, allowing for greater scalability in real-world applications. Such applications often require the swarm to deal with the lack of prior knowledge of the domain, as well as demanding reliable up-to-date information [8]. This is particularly true in surveillance and monitoring tasks in a variety of domains, such as: inspection and surveillance [9,10], search & rescue [8,11], and agriculture [12–14]. Both surveillance and monitoring tasks focus on developing control laws which enable groups of robots to transverse and observe a given domain, but with a slightly different focus. The goal of surveillance is to maximize some measure of coverage or information gathering, while monitoring focuses on ensuring that certain areas of the domain (usually predefined) are visited with a certain frequency. To tackle these tasks, aerial swarms have been widely employed as the preferred vehicle [15], due to their intrinsic ability to gather data over a wide field of the ground plane, for example, through a down facing camera. However, as their distance to the ground increases, the resolution of observations decreases [16]. Furthermore, the accuracy of these observations is also affected by the noisy characteristics inherent to any sensor leading to inaccuracies [17]. These factors have led researchers to propose that several simultaneous observations of the same point would yield a more accurate measurement [17,18]. This proposition is extremely useful when considering unmanned aerial vehicles (UAVs), since their overlapping sensing regions (or fields of view) on the ground plane, are the means by which these desired multiple simultaneous observations can be gathered. Figure 1 depicts an example where three quadcopters share points in their respective fields of view. This ability to maintain an overlap of sensing regions, naturally requires robots to be able to coordinate, while on the other hand, the very nature of the surveillance task, requires robots to continuously explore the domain [19].

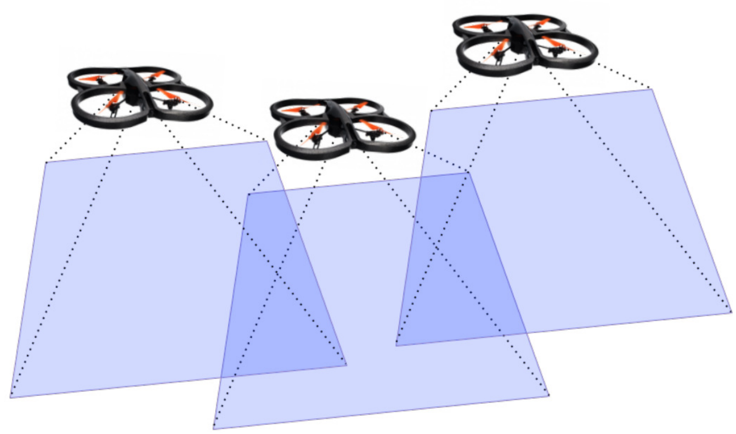


Fig. 1. Fields of view for 3 aerial vehicles, where the darker shades represent the areas sensed simultaneously by more than one UAV.

Examples of such exploratory behaviours are widely found in natural societies, such as in honeybees [20], sharks [21] and primates [22]. In fact, foraging individuals in these societies have been noted to explore an environment by coupling periods of localized random walks with periods of ballistic relocation across the domain [23]. This exploratory behaviour is known as *Lévy Walk* (LW) [24] and has been successfully used as an exploratory behavior for single-agent systems [25], as well as in swarm-based systems [26]. In contrast to previous works, we focus on studying the ability of robots within swarm, not only to coordinate in order to maintain the aforementioned overlapping sensing regions, but to do so while preforming LWs, leveraging exploration. We propose that this can be accomplished by merging a biologically-inspired coordination strategy and a LW controller, in a decentralized manner. Such coordination strategies have long drawn inspiration also from natural agents' inherent ability to coordinate using only simple and local control rules [27]. The most popular of such frameworks was introduced by Reynolds in [28], where the rules to generate *flocking* behaviours were proposed. In our work, we bringing together the *flocking* rules proposed by Reynolds, and the LW motion model, effectively creating a system that seamlessly integrates both coordination and exploration.

1.1 Contribution

The main contribution of this paper is the development of a decentralized model, integrating the coordination mechanism based on Reynolds' rules, with and an exploratory behaviour based on *Lévy Walk*. We test our model in a simulated environment on a cooperative surveillance task. The aim is to explore a given domain, while maintaining an overlap between the regions sensed by robots of the swarm. We also demonstrate our controller with proof-of-concept experiments with two drones.

2 Swarm Systems

2.1 Surveillance in Swarm Systems

Surveillance tasks in multi robot systems have been long addressed by the research community [9]. Some of the initial works in this area focused on optimizing policies, considering trajectory planning, energy consumption and dynamic constraints for a single robot, which were later extrapolated into the multi-robot scenario [29]. Other works developed model-based strategies to determine feasible trajectories in real time while also considering detailed sensing models [30], or considering the task routing problem with a set of predefined locations that need to be visited [31]. More recently authors also applied the *flocking* strategy proposed by Reynolds to address coordination [32], using a pheromone map to guide the swarm to explore new regions. While control actions were computed in a decentralized manner, the pheromone map is treated as a central shared resource, of which every robot is assumed to have knowledge at any point in time. We should highlight that, even if these works focus on the surveillance task by employing an aerial swarm, neither of them address the extra constraint of having overlapping sensing regions.

Another approach to surveillance using aerial swarms was proposed by Saska in [9]. In this work a Particle Swarm Optimization (PSO) based method was used to derive individual robot trajectories before deployment, with prior knowledge of areas of interest to be visited, therefore centralising the method on the planning level. However, authors demonstrate that, after deployment, on-board sensing can be used in a distributed fashion to adjust trajectories using relative-localization methods between UAVs, in cases where external localization is non-existent or lacks the desired precision. Even though this work mentions the benefits that multiple simultaneous observations can bring, the metrics presented focus mainly on the output of their proposed PSO in regards to the areas visited and accuracy of individual pose estimation.

Interestingly, the topic of overlapping sensing regions has been given more attention in the field of Wireless Sensing Networks (WSNs) [33] [34]. However, works in this field usually assume that a predefined set of areas exist such that each point needs to be observed by k sensors simultaneously, a task known as k-coverage [35]. Approaches to k-coverage using robots mainly focus on: optimizing the number of robots to be deployed for the desired coverage constraints [36]; optimizing energy efficiency [19], or optimizing network connectivity [37], which tend to require prior knowledge of the set of areas of interest. Nevertheless, k-coverage is a topic relevant to this work and as such we will use this concept as a metric to show that our proposed model enables the swarm to achieve simultaneous observations while exploring the domain.

2.2 Lévy Walks in Swarm Systems

Sutantyo *et al.* introduced the *Lévy Walk* (LW) into swarm applications [38], using the notion of artificial potential fields, as a means of collision avoidance between robots preforming LWs, for a target search task. Later, that work was extended to consider an adaptation of the Lévy parameter (μ) based on the density of targets found [26]. Another work that deals with underwater multi-robot search using LW is presented in [39]. However, contrary to what we will assume, authors consider the scenario where regions of the environment are divided and each robot explores its own assigned region. Suarez and Murphy in their survey [40] also suggest that robots should divide the environment into individual search areas. Nevertheless, they also point out that regions of interest might not clear at the start, and might even change over time, making it it difficult to subdivide an environment prior to the mission. However, all the aforementioned works focus on a slightly different problem, since they consider targets in the domain and study their impact on each robot's behaviour. Our approach focuses on a more fundamental aspect of the swarm's behaviour, namely, how can robots both coordinate and explore, while maintaining overlapping sensing regions.

To highlight the benefits of LW in surveillance or coverage tasks, authors in [41] have compared analytical results, considering strategies based on LW and other random walk-based methods to show the clear advantage of the former, in terms of overall robots' displacement. More recent papers on Lévy Walks for swarm systems have also focused primarily on math-based models [42], which tend to abstract real constraints such as robots' dynamics, communication and sensing capabilities, as well as ability to maintain overlapping observations.

In summary, our proposed model differs from the any of the above, in two key aspects: i) absence of predefined search regions for each robot and ii) fully decentralized control of UAVs.

3 Proposed Model

In our model, robots use a behaviour-based controller divided into two components: *Flocking:Interaction*, dealing with the coordination behaviour, and *Lévy Walk*, introducing the exploratory behaviour, each outputting a velocity vector.

3.1 Flocking:Interaction

This component, based on [28], consists of three rules: separation; cohesion; and alignment, defined below.

Separation: Consider the i^{th} robot, with a neighbourhood $\mathbf{N_s}$ of all the j robots below a distance δ_s whose positions $\mathbf{p_j}$ have their centroid at $\mathbf{P_s}$ defined as:

$$\mathbf{P_s} = \left(\sum_{j \in N_s} \mathbf{p_j} \Big/ N_s \right) - \mathbf{p_i} \tag{1}$$

Based on the relative orientation of $\mathbf{P_s}$ to the position of the i^{th} robot (ρ_s^θ) we compute the *separation* contribution, in form of an angular velocity, as:

$$\mathbf{w_s} = \beta \left[0\ 0\ w_s^z\right]^T = \beta \left[0\ 0\ (\rho_s^\theta + \pi) - \theta_i\right]^T \tag{2}$$

Where θ_i is the orientation of the i^{th} robot. Note that we add π to the computation so that we consider a vector *away* from the geometric center $\mathbf{P_s}$.

Cohesion: Consider the i^{th} robot, with a neighbourhood $\mathbf{N_c}$ of all the j robots below a distance δ_c whose positions $\mathbf{p_j}$ have their centroid at $\mathbf{P_c}$ defined as:

$$\mathbf{P_c} = \left(\sum_{j \in N_c} \mathbf{p_j} \Big/ N_c \right) - \mathbf{p_i} \tag{3}$$

Based on the relative orientation of $\mathbf{P_c}$ to the position of the i^{th} robot (ρ_c^θ) we compute the *cohesion* contribution, in form of an angular velocity, as:

$$\mathbf{w_c} = \gamma \left[0\ 0\ w_c^z\right]^T = \gamma \left[0\ 0\ \rho_c^\theta - \theta_i\right]^T \tag{4}$$

where θ_i is the orientation of the i^{th} robot. Note that we *do not* add π to the computation so that we consider a vector *towards* the geometric center $\mathbf{P_c}$.

Alignment: Consider i^{th} robot, and the average heading $\mathbf{\Theta}$ of the j robots in a neighbourhood $\mathbf{N_a}$ within distance $\delta_a > \delta_s$.

$$\mathbf{\Theta} = \sum_{j \in \mathbf{N_a}} \theta_{\mathbf{j}} \Big/ \mathbf{N_a} \tag{5}$$

where $\theta_{\mathbf{j}}$ is the orientation of robot j in $(r\ p\ y)$ coordinates. The *alignment* contribution, in the form of angular velocity $\mathbf{w_a}$, is computed as:

$$\mathbf{w_a} = \alpha \left[0\ 0\ \omega_a^z\right]^T = \alpha \left[0\ 0\ (\mathbf{\Theta} - \theta_i)\right]^T \tag{6}$$

The contribution from the *interaction* block, for the i^{th} robot in the swarm, is given by eq (8), where α, β and γ are weights between 0 and 1:

$$\mathbf{\Phi_i} = \begin{bmatrix} \mathbf{v} \\ \mathbf{w_s} + \mathbf{w_a} + \mathbf{w_c} \end{bmatrix} \tag{7}$$

$$= \begin{bmatrix} v_x \; 0 \; 0 \; 0 \; 0 \; \beta\omega_s^z + \gamma\omega_c^z + \alpha\omega_a^z \end{bmatrix}^T \tag{8}$$

3.2 Lévy Walk

To introduce a *Lévy*-based velocity command into the algorithm, we first generate the appropriate variables, i.e., target orientation ψ and walk length L. For that we use the *Lévy Generator* proposed by [43] to randomly draw a Lévy distributed variable r:

$$r = \frac{\sin\left((\mu - 1) * \widetilde{U_1}\right)}{\cos(\widetilde{U_1})^{\frac{1}{1-\mu}}} \left(\frac{\cos\left((2-\mu) * \widetilde{U_1}\right)}{\widetilde{U_2}} \right)^{\frac{2-\mu}{\mu-1}} \tag{9}$$

where $\widetilde{U_1} = U_1\pi/2$, $\widetilde{U_2} = (U_2 + 1)/2$, and a random orientation being given by $\psi = U_3\pi$ with U_1 U_2 U_3 being uniformly distributed random variables between 0 and 1 and μ the Lévy parameter that influences the length of the jump. Fig. 2 illustrates this influence.

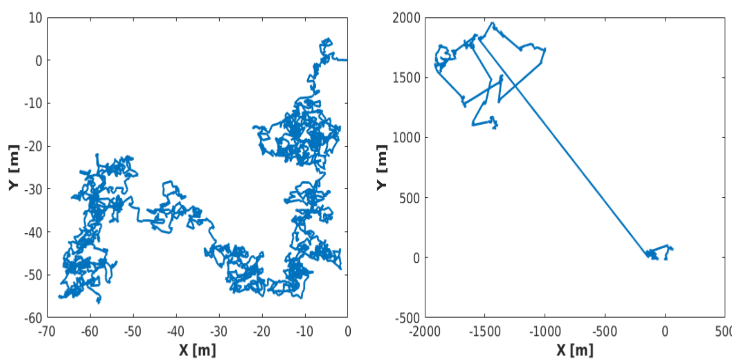


Fig. 2. Trajectories of one robot with different μ values. On the left $\mu = 3$ and on the right $mu = 2$, showing how higher values o μ lead to smaller walks and hence more frequent change of orientation.

Having selected r, we draw an uniformly distributed value of ψ and compute:

$$x = r \cdot \cos(\psi) \tag{10}$$

$$y = r \cdot \sin(\psi) \tag{11}$$

$$L = \sqrt{x^2 + y^2} \tag{12}$$

As robots transverse space, the distance each one travels d is calculated and updated. When this distance reaches L, a new L is generated as well as a new ψ.

As this happens and a robot finishes its walk, it starts updating its orientation making its neighbours react to this change and continue their trajectory in a different direction. Similarly to before this change is forced upon a robot through a velocity command:

$$\mathbf{w_l} = \eta \left[0\ 0\ \omega_l^z\right]^T = \left[0\ 0\ \eta\big(\psi - \theta\big)\right]^T \tag{13}$$

where η is a scaling factor and θ is the yaw angle of a robot in the swarm. This angular velocity command overrides both *alignment* and *separation* rules in order to achieve the desired orientation. In this case linear velocity command assumes the type of $\mathbf{v_l} = \left[v_x, v_y, 0\right]$ with orientation $(\rho_s^\theta + \pi)$ and therefore the Lévy based contribution to a robot's velocity is given by eq(14). Tables 1 and 2 summarize, respectively, the notation used in our proposed model and the fixed parameters used in the interaction component of our model.

$$\mathbf{\Lambda_i} = \left[\mathbf{v_l}\ \mathbf{w_l}\right]^T = \left[v_x\ v_y\ 0\ 0\ 0\ \omega_l\right]^T \tag{14}$$

Table 1. Notation

$\mathbf{P_s}$	Centroid of the neighbours' positions considered for the Separation rule.
$\mathbf{P_c}$	Centroid of the neighbours' positions considered for the Cohesion rule.
$\mathbf{\Theta}$	Average heading of neighbours considered for the Alignment rule.
δ_s	Threshold below which neighbours are considered for the Separation rule.
δ_c	Threshold below which neighbours are considered for the Cohesion rule.
δ_a	Threshold below which neighbours are considered for the Alignment rule.
$\mathbf{N_s}$	Set of neighbours considered for the Separation rule.
$\mathbf{N_c}$	Set of neighbours considered for the Cohesion rule.
$\mathbf{N_a}$	Set of neighbours considered for the Alignment rule.
μ	Lévy parameter.
L	Length of generated walk.
$\mathbf{w_s}$	Angular velocity component output by the Separation rule.
$\mathbf{w_c}$	Angular velocity component output by the Cohesion rule.
$\mathbf{w_a}$	Angular velocity component output by the Alignment rule.
$\mathbf{w_l}$	Angular velocity component output by the Lévy generator.
$\mathbf{\Phi_i}$	Velocity command for agent i based on the Interaction rules.
$\mathbf{\Lambda_i}$	Velocity command for agent i based on the Lévy process.
$\mathbf{p_i}$	Position of agent i.
v_x, v_y	Linear components of the agent's velocity in local frame.
θ_i	Orientation of agent i.
β, γ, α	Weights for Separation, Cohesion and Alignment rules respectively.

Table 2. Values of fixed parameters used in the interaction component.

δ_s[m]	δ_c[m]	δ_a[m]	β	γ	α
1.5	2.5	2.5	5	0.2	1

Having set the components of our proposed model, we present below the algorithm for a seamless integration of *Lévy Walks* and coordination rules which runs in a decentralized manner, for each separate UAV. Algorithm 1 shows the conditional relationships between commands ($C(t)$) sent to each agent. While time t is smaller than the total time of the experiment T, each agent computes the interaction rules according to their respective neighbourhoods and check if their walk is completed. The action of each agent is then conditional on its own walk being completed or not.

Algorithm 1 Lévy Swarm Algorithm (LSA)

```
Initialize distance d = 0.
Assign L
Initialize control action C(t_0) = [0 0 0 0 0 0]
while t ≤ T do
    Compute Interaction rules
    if d ≥ L then                                  ▷ Completed Walk
        Compute new ψ and L
        d = 0
        C(t) = Λ                                   ▷ Lévy Command
    else
        C(t) = Φ                                   ▷ Interaction Command
    end if
    Get pose
    Update distance d
end while
```

4 Experiments and Results

In this section, we illustrate the effectiveness of the proposed model in a number of simulated experiments. We also present a preliminary real robot experiment that was designed to test the main components of our model using 2 Parrot drones. A video demonstrating the results accompanies this paper[1].

4.1 Simulation Experiments

Simulations were conducted on 20m by 20m grid sub-divided into tiles of 0.5m, for evaluation, and run in `GAZEBO-ROS` framework. The size of the swarm was set to 15 Parrot `ar-drones`, to sufficiently large for the interaction rules to have an effect, but not excessively so, to avoid covering the domain without the need for a strategy. A ROS-based framework was chosen due to its wide adoption in both academia and industry, and the recognition it receives as being the *de-facto* operating system for the development of applications in robotics.

[1] https://youtu.be/KvEs7wQ0Ti4.

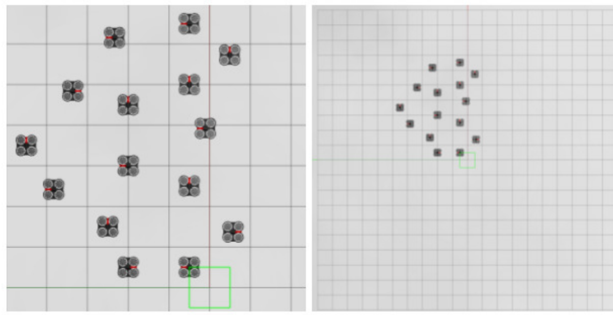


Fig. 3. Initial position of 15 UAVs in an empty arena, for the simulation experiments

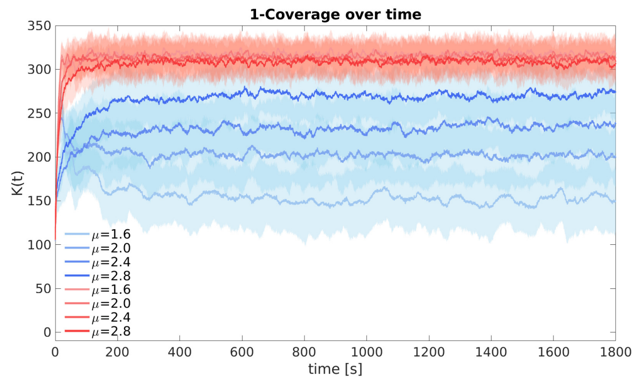
Each robot, i.e. Parrot `ar-drone`, has a down-facing camera capable of sensing an area of 2.5m by 2.5m. Each robot is assumed to have an accurate estimation of its pose (through GPS in simulation, and through the VICON mocap system in the real experiments) which is communicated directly to its neighbourhood. Such neighbourhood is limited by the robot's communication range considered to be the same as δ_a. Fig. 3 shows the initial positions of the UAVs in the simulated area. These simulations considered a varying Lévy parameter (μ) with values $\mu \in]1, 3[$. Each parameter (μ) was run 60 times, for a period of 1,800 seconds. Simulations were run with $\mu = [1.6, 2.0, 2.4, 2.8]$ to show differences in the behaviour of the swarm, at low, medium and high values of μ. In this work we quantify how many tiles of the grid-domain the swarm is able to maintain under a certain k coverage level over time, defined as $K(t)$. Our metric is defined by, firstly, considering the subset of tiles sensed by UAV i at time t, i.e. $A_i(t)$, and define a set $\Omega(t)$ that contains all these subsets as:

$$\Omega(t) = \{A_i(t)\} \quad \forall i \leq N \tag{15}$$

where N is the number of UAVs. Through set Ω we can enumerate all the combinations of k A subsets and create set S^k, of size $\binom{N}{k}$, where each member is one of said combinations. Therefore, $K(t)$ is the total size of intersections between the A subsets within the elements of S^k, and defined as:

$$K(t) = \sum_{\forall j} |\cap \{S_j^k\}_{j \subset J}| \tag{16}$$

where J is the index set of S. Results of our simulations are depicted in Fig. 4 and show our proposed model (blue) and a simpler one with only the avoidance rule (red), hereafter addressed as the baseline, for $k \in [1, 2]$. Our results for $k = 1$, show that it is the baseline case which performs the best. Since robots only interact to avoid each other, this creates a diffusive behaviour, that naturally increases the number of cells sensed only by one UAV. However, in the context of our problem we are mainly interested in the scenario where k =2.



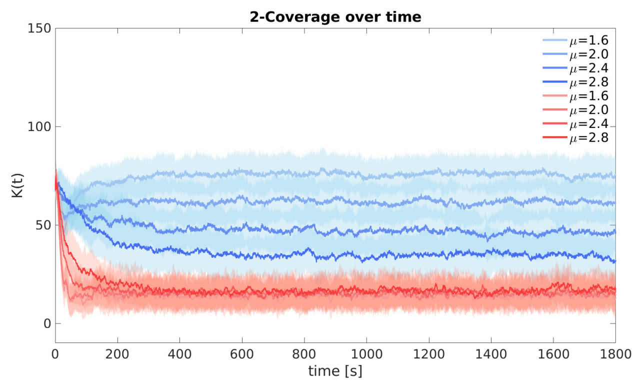


Fig. 4. Number of cells under k-coverage over time for $k \in [1, 2]$, with our model (blue) and the baseline (red).

Figures 4.1 and 4.1 both show how much merging the *flocking* rules with the LW component impacts the results. In qualitative terms the results are completely the opposite, showing how this merging of techniques leads to a significant outperforming behaviour when $k = 2$.
It is also interesting to highlight that as the value of μ increases, the performance of the system tends to the baseline case, showing that as μ approaches its maximum value, the local exploratory component of the system dominates the coordination mechanism. However, by observing Fig. 4 alone one cannot assess about the effectiveness of exploration, since there is no indication if the cells sensed at a given point in time are the same, or not, than the cells sensed at a later stage. To assess this, we introduce a random variable $\mathscr{X}_k$, that represents *the total number of different cells sensed by k UAVs* and whose probability distribution, $P(\mathscr{X}_k)$, is shown in Fig. 5.

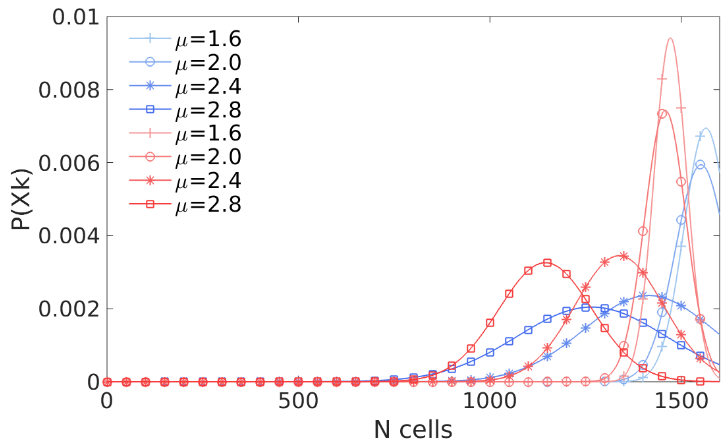


Fig. 5. Simulated $P(\mathscr{X}_k)$ for k=2, with our model (blue) and the baseline (red).

This result also highlights the benefit of our model, which invariably leads to a higher mean of different cells sensed, leading to a higher probability of sensing all the cells of the domain with $k = 2$ robots . This advantage is evident in the results obtained with our model, always outperforming its baseline counterpart for each value of μ.

4.2 Preliminary Real Experiments

In order to further investigate the role of k in the simulation, some preliminary experiments were conducted with two real Parrot `ar-drones` in a 3x3m arena. To consider a similar ratio between the size of the arena domain and the size of each tile of the grid, tiles are considered to be 0.05x0.05m. Fig. 6 shows this domain as well as the initial positions of the two UAVs.

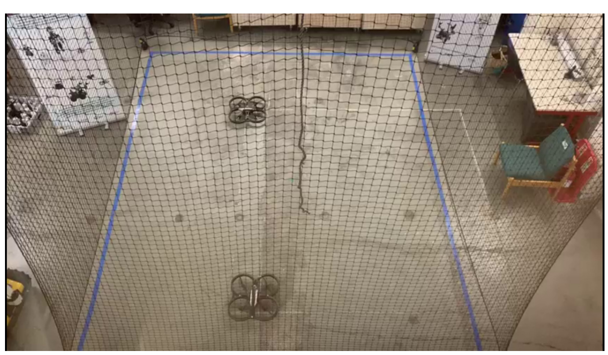


Fig. 6. Initial positions of 2 `ar-drones`

Similarly to the simulated experiments, we first plot the total number of cells sensed by k UAVs over time t. Figures 4.2 and 4.2 show these results.

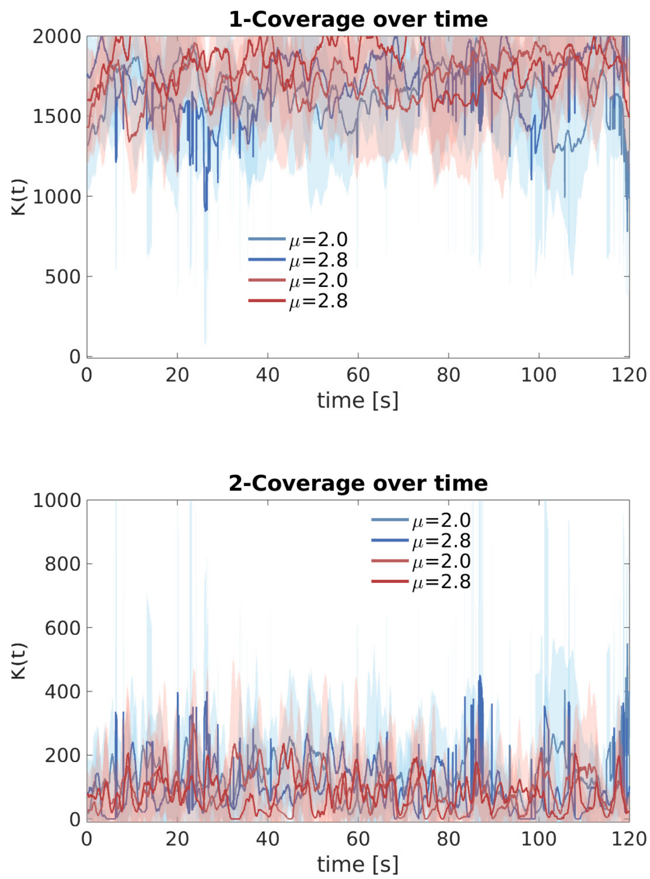


Fig. 7. Experimental number of cells under k-coverage for $k = [1, 2]$ with our model (blue) and the baseline (red).

The first noticeable difference between simulated and real results is the apparent lack of effect of μ in both cases. In fact, since Lévy processes tend to occur over long distances, the preliminary scenario used is too small for such investigation. Nevertheless one can still draw a parallel with simulated results where values for k are concerned. On one hand, for $k = 1$, the baseline always yields a higher value, as expected since $k = 1$ favours a diffusion behaviour, rather than a coordinated one. On the other hand, for $k = 2$, the results are again reversed, being our model able to outperform the baseline.

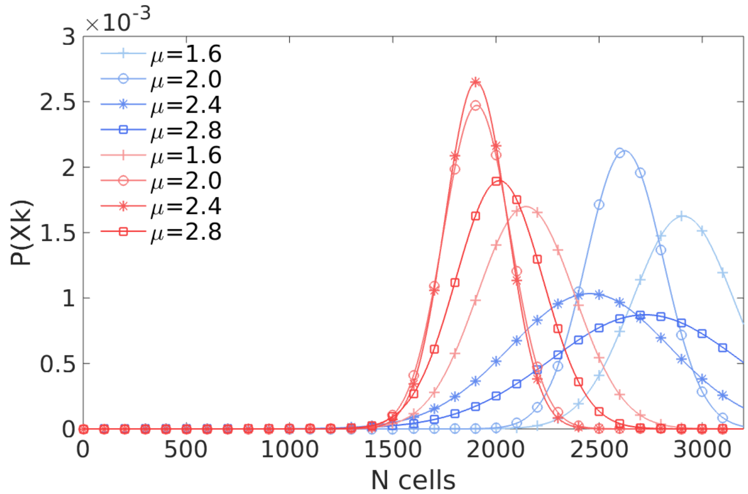


Fig. 8. Experimental $P(\mathscr{X}_k)$ for k=2, for our model (blue) and the baseline (red).

The same is true for the probability distributions of $\mathscr{X}$, depicted in Fig. 8, where our model continues to show a higher average number of cells being sensed by k UAVs simultaneously.

5 Conclusions and Future Work

This paper presented a swarm model that combines coordination and exploration strategies using UAVs for collaborative surveillance. Our model is fully decentralized, with minimal direct communication between robots [44] and does not require global knowledge or partitioning of the domain. This model is, to the best of our knowledge, the first to merge the Reynolds *flocking* rules and the *Lévy Walk* exploration strategy.

Simulation results were assessed based on two metrics. The first, $K(t)$, represents the total number of tiles, in a grid domain, sensed by k UAVs at time t. The second, $P(\mathscr{X}_k)$, represents the distribution of the *number of different cells sensed by k UAVs* over the course of the experiment. Both metrics have shown the advantage of the proposed model for k-coverage when = 2. Merging the *flocking* rules with the LW strategy, always increased the performance of the system, when compared to the baseline case where only collision avoidance exists. Our results show that, choosing lower values of μ is preferential when our model is adopted. On the other hand, in the baseline case, the performance of the system, in respect to $K(t)$, seems to be independent of μ. Since the only interaction between agents is collision avoidance, we infer that this aspect, rather than the LW, is the predominant behaviour, pointing towards the need for future work on the study of interference among agents in a swarm.

The effect of μ, in both our model and the baseline, is evident in the second metric, $P(\mathscr{X}_k)$. The results show that higher values of μ tend to lead to a lower mean of (N) different cells being discovered, reflecting the expected behaviour of the LW for values of μ in this range. Noticeably, when comparing the distributions $P(\mathscr{X}_k)$ between our model and the baseline, the mean value of $P(\mathscr{X}_k)$ is always higher in our model, than the respective baseline result. This shows that, for the same mission time, the baseline approach restricts the swarm from sensing a higher number of different cells simultaneously with k UAVs. These results corroborate the hypothesis that merging both behaviours ensures that a larger portion of the domain is covered, maintaining the desired overlapping sensing regions. Despite the positive results favouring our model, the difference between probability distributions is less evident in simulation than in real experiments.

Future work will focus on studying the behaviour of our coordination algorithm with more realistic sensing and communication models as well as performing a sensitivity analysis regarding the swarm size and flocking parameters. We aim to assess the performance of our approach applied to a larger swarms of flying drones, in terms of k-coverage but also in terms of its ability to deal with robots' failures and other unexpected events.

We also would like to conduct experiments on variations of the *Lévy Walk* concept. For instance, by including inertial motion, making the change of orientation not uniformly random but biased towards the current heading. This way we could maximize the crossing of the entire domain. Another example, would be to explore other *Lévy Walk* parameters using machine learning techniques, more specifically, artificial homeostatic systems [45–47], evolutionary approaches [48] [49] or a combination of both [50, 51].

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