Drone Swarms for Animal Monitoring: A Method for Collecting High-Quality Multi-Perspective Data

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ABSTRACT

Drone swarms offer great potential for wildlife monitoring, but their real-world use is still limited. This paper addresses the challenge of deploying drones to collect high-quality, multi-perspective data over herds of gregarious animals. We formalise this problem using the novel concept of *surface of interest*, combined with a Lambertian-inspired modelling approach. Together, these elements allow us to create an objective function for data quality that also considers the swarm's impact on animal welfare. Using a centralised controller and particle swarm optimisation, our approach determines the drone configurations that maximise this function. Experiments based on real-world animal spatial distributions show that our algorithm effectively identifies these configurations, paving the way for future field tests.

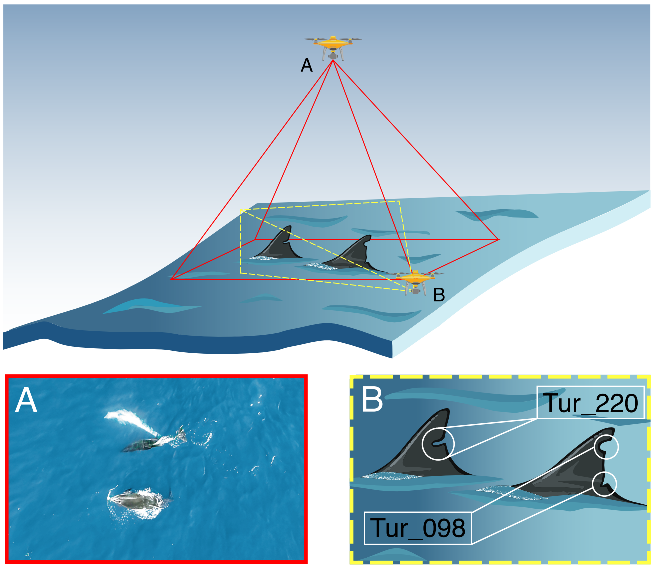

Figure 1: Drones performing (A) vertical and (B) horizontal monitoring of a pod of Tursiops

1 INTRODUCTION

Recently, the alarming decline in biodiversity has initiated the development of technological solutions for conservation efforts in nature [1, 2, 3]. Gathering biological data about endangered species is crucial for tracking the evolution of individuals and understanding how climate change and human activities affect their survival and reproduction. In this context, the recent democratisation of drones has transformed them into a versatile platform for wildlife monitoring surveys [4]. Their cost-effectiveness, time efficiency, and reduced labour demands have established drones as a preferred tool for such work. The literature already highlights numerous drone applications in this field, contributing to significant research output; see [5, 6] for examples.

Challenges persist in conducting effective data collection over large areas, particularly with animals that gather in large groups, commonly known as *gregarious species*. Biologists often rely on a single commercially available multi-rotor drone, operated manually [7]. However, this approach has several limitations. The restricted flight time of the UAV and the limitation of a single vantage point both constrain effectiveness. Additionally, when using non-nadir perspectives, the animals may occlude one another from the drone's view, compromising data collection. Thus, coordinating multiple drones to collect data simultaneously from different angles can address these limitations and introduces new possibilities for biological studies. As illustrated in Figure 1, vertical drone views and horizontal perspectives complement each other well in the context of wildlife monitoring. Vertical monitoring provides a contextual bird's-eye view that offers information about the group and its environment, making it particularly suitable for tasks such as wildlife censuses, movement analysis, and studies of social interactions [2, 8, 9]. In contrast, horizontal monitoring facilitates the integration of individual identification by recognising distinctive marks and patterns on animals [10, 11]. It has been demonstrated that utilising multiple viewpoints and oblique views is more effective for identification than relying solely on a single-view perspective [12]. Multi-perspective data allows for a comprehensive understanding of wildlife dynamics by integrating a

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broad ecological context with precise individual tracking [4].

To our knowledge, only a few studies have focused on the real-world deployment of autonomous drone swarms for wildlife monitoring. Developing such a system with an application-oriented design would enhance the data collection possibilities for biologists and transition drone swarms from simulations and laboratories to real-world applications. Our study consists of three contributions: Firstly, we create a methodology for assessing the quality of multi-perspective monitoring of gregarious animals, considering constraints to avoid disturbing wildlife [13]. Our methodology is inspired by the concept of *Lambertian surfaces*, commonly used in video games to model light reflection [14]. Secondly, we introduce a method for coordinating swarms of drones to maximise the quality of the data collected based on the concept of *surface of interest* (SI). Finally, we evaluate the performance of our solution using a custom-built 3D simulator. The relevance of the controller and its application to real-world scenarios are assessed using various spatial animal distributions based on real-world data.

2 Related Work

Common wildlife monitoring methods, such as GPS trackers, camera traps, and direct field observation, have long been the foundation of ecological research. While they provide valuable data on animal movement, population dynamics, and behaviour, they often struggle to capture comprehensive, multi-perspective data on animals in their natural habitats [7]. Recent advancements in remote sensing technology have introduced novel techniques for conducting animal ecology studies, including drones, acoustic sensors, and satellites [15, 16]. Simultaneously, advancements in machine learning have enabled the analysis of vast volumes of data generated by these remote sensing devices, allowing for the rapid production of ecological studies [17].

Drones are particularly well-suited for collecting ecological data on gregarious animals and have been employed to study a wide range of habitats across various animal species, including Plains and Grevy's zebras, gelada monkeys, giraffes, sheep, and horses [7, 18, 8]. Drones can rapidly traverse remote terrain to track groups of animals over time and offer capabilities often beyond those of camera traps or satellites [16]. Drones have the potential to provide detailed data on all individual animals in a group simultaneously, something that traditional methods cannot capture [19]. In addition to movement, behaviour, and identification in ecological studies, drones have been proposed for 3D pose estimation to evaluate the morphometric parameters of the animals [20, 21].

Techniques for gathering aerial imagery with drones in animal ecology studies vary widely depending on the species and the study's goals. However, they mostly involve collecting information about specific parts of the animals, referred to as SIs. Drones may be piloted to capture either oblique or nadir imagery. In vertical monitoring, the SI typically includes the animal's back. Horizontal monitoring focuses on surfaces where distinctive features for individual identification or fine-grained behaviours are visible, see Figure 2 for examples. Multi-perspective datasets containing both vertical and horizontal monitoring imagery are crucial for comprehensive studies, as they capture behaviour, movement, and identification [22, 8]. Currently, capturing both single- and multi-perspective drone imagery simultaneously is largely manual, requiring close coordination between expert drone pilots and biologists to collect the data while ensuring the animals are not disturbed. This manual approach involves logistical challenges, such as managing drone missions while capturing images [22] and synchronising efforts between operators and biologists [8]. Current protocols for conducting drone-based animal ecology missions are qualitative and largely involve executing missions manually. These protocols do not establish a standard procedure for positioning the drone relative to the SI being studied [22, 10]. Instead, the distance between the animals and the drone is chosen to ensure sufficient resolution for identifying physical characteristics while minimising impact on animal welfare [10].

Autonomous tracking methodologies have been proposed using single drones for cows [23] and yaks [24], and multi-drone swarms for zebras [25]. However, these approaches are typically not generalisable, as they focus on specific species or surfaces of interest and may not address the need to minimise disturbance to the animals. The potential of drone swarms for vertical animal observations has been explored with gregarious species in livestock monitoring [26]. For instance, Li et al. [27] employed density-based clustering to optimise drone deployment, maximising animal coverage while minimising the average distance between drones and animals to ensure high-quality imagery. More broadly, the challenge of covering the maximum number of targets with the minimum number of drones has been addressed using bio-inspired algorithms, for example, the elephant herding optimisation algorithm [28] and artificial bee colony algorithms [29].

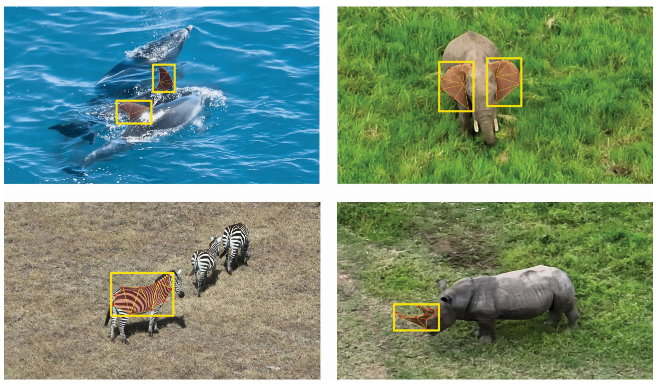


Figure 2: Examples of SIs

The lack of uniformity in mission planning for animal ecology studies highlights the need for a general method to assess the quality of data collected regarding the different SIs to be monitored. The autonomous coordination of multiple drones for aerial imagery collection could address these challenges, significantly enhancing both the efficiency and quality of wildlife studies. Both centralised and decentralised computing approaches can be employed to address this challenge. In this study, we focus on a centralised method, which is sufficient for this setting and more feasible to implement for real-world field tests. In the future, we will consider a decentralised approach for surveying multiple herds, as proposed in [25]. These challenges motivate the need for an adaptive, non-invasive approach that can be customised to various drone swarm sizes and SIs.

3 PROBLEM STATEMENT

Our drone swarm deployment problem resembles the *art gallery problem* [30], which focuses on optimising the placement of cameras to cover as much ground area as possible. To address this, we explore solutions from the camera placement literature. Strategies, including the utilisation of a dedicated objective function coupled with bio-inspired algorithms such as Particle Swarm Optimisation (PSO) [31, 32], have been employed to find optimal camera configurations. We base our methodology on this approach and thus need to define an objective function for assessing the monitoring quality of a herd of gregarious animals using the concept of SIs.

Given a set $\mathcal{A}$ of N_a animals distributed across a 2D plane, each animal defined by its position $p_i = (x_i, y_i)$ and its heading θ_i. We define our drone swarm as a set of M agents, represented as $\mathcal{D}$. We aim to find a configuration for the swarm in which the configuration of each drone π_j leads to the maximisation of the value of the objective function. Assuming our drones are stabilised, the camera frustum is determined by the following parameters: drone position in 3D space (u_j), yaw angle (Ψ_j), camera tilt (τ_j), and the horizontal field of view (FoV_j). We define a drone configuration tuple as $s_j = (u_j, \Psi_j, \tau_j, FoV_j)$, and $\mathcal{S} = \{s_1, s_2, \dots, s_M\}$ as the parameters of the swarm. We also introduce $\overrightarrow{v_j}$, which defines the view direction of the drone. Figure 3 illustrates all the parameters for an animal i and a drone j.

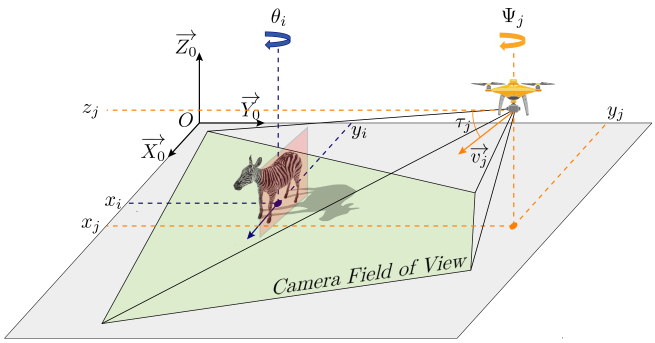


Figure 3: Illustration of parameters for an animal i and a drone j

3.1 *Design Criteria*

We want to construct an objective function, $\Omega(S) \in [0, 1]$, representing the monitoring quality: the closer the value is to 1, the higher the quality. To achieve this, we must define the monitoring objectives and constraints for effective non-intrusive data collection.

Relative angle of the drone view and the animal: The relative angle should be optimised to maximise the visibility of the different SIs on the animal. The drone's view direction $\overrightarrow{v_j}$ should be as close to collinear as possible with the surface normal of these SIs for effective monitoring. Camera traps, which usually capture images from a near-horizontal angle, have shown that individual identification is easier when the images provide a clear, perpendicular view of the relevant characteristics [33].

FoV centring: In the captured images, the animals should be centred in the camera frame. Placing the animals away from the edge of the frame helps prevent distortion and chromatic aberration in the collected data.

Maximising the coverage of the different SIs: The configurations should minimise redundancy by ensuring that different SIs are being monitored by different drones. This means that a solution where multiple drones monitor the same SI provides less information than one where more SIs are covered.

Non-intrusive monitoring: The quality of the collected data should be sufficient in terms of the pixel-to-meter ratio to enable biological studies. However, this must be balanced against the negative impact of wildlife disturbance, as the noise generated by drones poses a potential threat to the well-being of wildlife [13]. Thus, we assume that our drones should not be closer than d_{min} to avoid introducing any disturbances, and not farther than d_{max} to prevent low-quality data collection [10].

3.2 *An Analogy with Lambertian Surfaces*

To construct our optimisation function, Ω, we drew inspiration from *Lambert's cosine law*. This law states that the intensity reflected by a surface I is proportional to the cosine of the angle θ between the surface normal and the observer's line of sight, as expressed by the equation $I = I_0 \cos\theta$ [14]. By analogy, we relate surface reflectivity to monitoring quality, as this equation, specifically the cosine term, allows us to model the relative angle criterion. For an animal i, our goal is to maximise the overall 'reflectivity' of its SIs, where I_0 in our solution should be extended to take into account the other criteria of Section 3.1.

3.3 *Monitoring Quality of a Surface of Interest*

For each animal i, we associate a set of $N_{L,i}$ SIs, denoted as $\mathcal{T}_i = \{SI_{i,1}, SI_{i,2}, \ldots, SI_{i,N_{L,i}}\}$. Each SI k is associated with a surface centre $O_{i,k}$ and a normal vector $\overrightarrow{n_{i,k}}$. For a SI we want to evaluate the monitoring quality provided by a drone π_j. This assessment involves quantifying the quality of the FoV centring, modelled by the function $\alpha(SI_{i,k}, \pi_j)$, and the pixel-to-meter ratio of the images, modelled by the function $\beta(SI_{i,k}, \pi_j)$. As defined in equations (1) and (2), these functions judge the quality of centring and the distance to the surface through piece-wise continuous functions that yield output values between 0 and 1, indicating how well the quality criteria are met. We define $\mathcal{H} = \{\alpha, \beta\}$ as the set containing these functions, and let N_H denote the number of functions in $\mathcal{H}$.

$$\alpha(SI_{j,k}, \pi_j) = \begin{cases} 1 - \frac{l_{j,k}}{d_{max}} & \text{if } l_{j,k} \leq d_{\text{max}} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$\beta(SI_{i,k}, \pi_j) = \begin{cases} \frac{d_{max} - d_{j,k}}{d_{\text{max}} - d_{\text{min}}} & \text{if } d_{\text{min}} \leq d_{j,k} \leq d_{\text{max}} \\ \frac{1}{d_{j,k}} & \text{if } d_{j,k} < d_{\text{min}} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

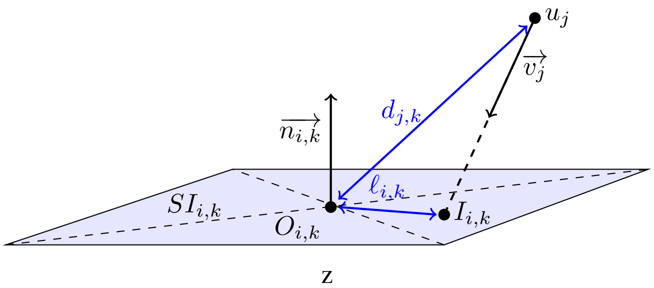


Figure 4: Illustration of parameters for a $SI_{i,k}$ and a drone j

Figure 4 illustrates the parameters of the quality functions, where $l_{j,k}$ represents the distance between $O_{i,k}$ and the intersection point of the ray passing through $\overrightarrow{v_j}$ with $SI_{i,k}$. $d_{j,k}$ represents the distance between the drone and the centre of the surface considered. Thus, we use the Lambertian analogy to construct our monitoring quality function, as presented in equation (3). We calculate the mean of the quality functions to ensure that the output remains between 0 and 1. In this study, we assume that FoV centring and distance have equal importance. Consequently, our model can be expanded if more quality functions are introduced to the set $\mathcal{H}$.

$$\Gamma(SI_{i,k}, \pi_j) = \frac{1}{N_H} \sum_{f \in \mathcal{H}} f(SI_{i,k}, \pi_j) \cdot |\langle \overrightarrow{n_{i,k}}, \overrightarrow{v_j} \rangle| \tag{3}$$

3.4 *Generalisation to the Drone Swarm and the Herd*

We express our monitoring quality $\Omega(\mathcal{S})$ given a drone swarm configuration $\mathcal{S}$ in equation (4), which we aim to maximise based on the drones' configuration. This Lambertian-inspired approach allows us to define a generic method for assessing the monitoring quality provided by a drone swarm, regardless of the number of animals and their associated surfaces of interest to be monitored. Equation (4) defines the objective function as a product of the monitoring quality $\Delta(S)$ and the penalty $\Lambda(S)$ based on the criteria in Section 3.1.

$$\max_{s_1, s_2, \ldots, s_M} \quad \Omega(\mathcal{S}) = \Delta(\mathcal{S}) \cdot \Lambda(\mathcal{S}) \tag{4}$$

We can compute the *monitoring quality* Δ over the entire herd of animals using equation (5). $\mathcal{D}_{i,k}$ is a subset of the drones in $\mathcal{D}$ representing the drones that can view the k-th surface of interest belonging to the animal i in their camera's field of view. If different drones monitor the same surface, the contribution retained will be that of the drone with the highest individual monitoring quality value, rendering the others redundant.

$$\Delta(\mathcal{S}) = \frac{1}{N_a} \sum_{i=1}^{N_a} \sum_{k=1}^{N_{L,i}} \frac{1}{N_{L,i}} \max_{\pi_j \in \mathcal{D}_{i,k}} \Gamma(SI_{i,k}, \pi_j) \tag{5}$$

Finally, the criteria for developing a *non-intrusive* system is defined as a penalty Λ to our objective function Ω. We apply the penalty Λ to solutions where a drone in the swarm is too close to one of the animals or if a drone is not monitoring any animal, and is presented in equation (6). $\delta_j \in [0, 1]$ applies a possibly non-linear penalty if the drone does not monitor any animal, as seen in equation (7). The subset $\mathcal{A}_j$ of $\mathcal{A}$ represents the animals seen by drone j. The further the drone is from the centre of the herd (represented by the drone's distance to the centroid of the herd, $d_{j,c}$), the greater the penalty. $\phi_{i,j} \in [0, 1]$ applies a linear penalty if drone j is too close to animal i, and can be seen in equation (8).

$$\Lambda(\mathcal{S}, \mathcal{A}) = \prod_{i=1}^{N_a} \prod_{j=1}^{M} \delta_j \phi_{i,j} \tag{6}$$

$$\delta_j = \begin{cases} 1 & \text{if } |\mathcal{A}_j| \neq 0 \\ 1 - \frac{d_{j,c}}{d_{max}} & \text{otherwise} \end{cases} \tag{7}$$

$$\phi_{i,j} = \begin{cases} 1 & \text{if } d_{i,j} > d_{min} \\ \frac{d_{i,j}}{d_{min}} & \text{otherwise} \end{cases} \tag{8}$$

4 EXPERIMENTAL SETUP

Given a swarm of M drones, we aim to find the set of drone configurations $\mathcal{S}$ that maximises our objective function Ω. The optimisation involves $M \times N_S$ parameters. We choose to decrease the degrees of freedom by limiting the number of parameters. We assume that the FoV of the onboard cameras is the same for all drones. For the remainder of this paper, we will use a FoV of $40°$. The drone swarm is divided into two types of roles: one for vertical monitoring and the other for horizontal monitoring. The altitude and camera tilt for these drones will be kept constant. For the vertical monitoring drones, the chosen altitude is d_{min} with a camera tilt of $90°$. For the horizontal monitoring drones, the altitude is $d_{\text{min}}/2$ with a camera tilt of $30°$. Therefore, for each drone j, the parameters to optimise are x_j, y_j, and Ψ_j thus reducing the search space dimension of our optimisation problem.

We assume that the positions and orientations of the animals, as well as the locations of their associated SIs, are known. In this initial approach, the animals are considered static and we do not consider potential environmental obstacles that the drones might encounter in the real world.

4.1 *Simulation Platform*

We developed a 3D simulator based on the RayLib framework[1] in Python. This open-source tool, designed for creating video games and graphical applications, provides a flexible and highly customisable platform for visualising our studied species, their associated SIs, and their positions on the ground. Furthermore, it allows us to define camera views associated with different drone parameters, as demonstrated in the dedicated YouTube video[2].

In this paper, we concentrate on a case study involving zebras and define three SIs for our analysis. Firstly, we examine the back of the animal, which facilitates behavioural analysis and census tracking. Secondly, we focus on the zebra's left and right longitudinal sides. By monitoring these two surfaces, we can identify individual zebras through side views, which reveal their unique features. To simplify the development, we consider the surfaces that belong to a rectangular prism encompassing the zebra.

4.2 *Evaluation Methodology*

We implement a centralised controller based on the PSO algorithm and then assess the relevance of our methodology across different herd configurations from real-world data. To build our validation set and draw performance conclusions, we have used Koger's dataset [7], which includes labelled vertical-view pictures of various animal species, including Grevy's zebras. The dataset also provides the drone's telemetry data, allowing us to deduce the animals' planar coordinates. Additionally, we labelled the pictures to retrieve the heading of each animal. The 10 studied herd configurations consist of a mean size of 19.70 animals, with an associated standard deviation of ± 11.02. The standard deviation of the herds' heading varies: in the worst case when the zebras are grazing, it can reach as much as $\pm 140.35°$. Otherwise, when the animals are moving, the standard deviation is smaller, with the smallest being $\pm 19.00°$.

[1] `https://github.com/raysan5/raylib`
[2] `https://www.youtube.com/watch?v=A_eDvyo_bb4`

Figure 5: Example of a studied herd configuration

The performance of our approach is assessed using three different drone swarm configurations to evaluate how well it generalises to various setups (# vertical-view drones $\times$ # horizontal-view drones): 1×1, 2×2, and 3×3. These configurations are tested across 10 different animal scenarios. Due to the stochastic nature of the PSO, each experiment is repeated 10 times with different random seeds to assess overall performance, resulting in a total of $10 \times 10 \times 3$ experiments. We retrieve the value of our objective function Ω from these experiments.

5 Implementation of a Centralised Controller

We implement a centralised controller to solve the optimisation problem with the objective function Ω and determine the drone configurations $\mathcal{S}$ for deploying them over the zebra herd. This controller calculates a configuration for each drone based on the zebras' spatial distribution and their respective SIs. As detailed in Section 2, we use PSO to determine the (x_j, y_j) coordinates and the yaw Ψ_j for each drone j in the swarm.

5.1 *Particle Swarm Optimisation: Bio-Inspired Algorithm*

The PSO algorithm [34] is a biologically inspired population-based stochastic optimisation algorithm that explores a search space to find the best solution. In PSO, each particle represents a candidate solution and adjusts its position based on both its own experience and that of the group. The goal is for all particles to converge to an optimal solution by balancing exploration with refinement. Like most optimisation algorithms, PSO has hyperparameters that must be tuned to maximise performance. For PSO, these hyperparameters are defined as follows [34]:

Swarm Size (n): The number of particles exploring the search space. This value balances computational complexity (larger swarms) with solution quality (smaller swarms may lead to premature convergence on local minima).

Inertia Weight (w): Controls the evolution of particle speed at each iteration. A high inertia weight encourages exploration, while a low value promotes the exploitation of local minima.

Cognitive Coefficient (c_1): Reflects a particle's tendency to return to its personal best position.

Social Coefficient (c_2): Represents the influence of the swarm's best-known position on each particle, promoting collaboration.

5.2 *Hyperparameter Tuning*

To tune the hyperparameters, we follow the recommendations suggested by Robison et al.[34]. We use a swarm size of 100 particles and set the PSO algorithm to 100 iterations. For the remaining parameters w, c_1, and c_2—we employ Bayesian optimisation [35]. In each Bayesian optimisation iteration, we aim to maximise Ω using two vertical and two horizontal drones across 16 herd configurations, ranging from compact to sparse herds. To carry out the tuning, we model the spatial distribution of zebras with a simplified approach, assuming normal distributions for planar positions and headings to ensure the PSO's general applicability. For the 16 synthetic herds, we define a fixed herd size of 30 zebras, in line with the literature [36], and use normal distributions with standard deviations of 10, 20, 30, and 40 metres for planar coordinates, and 0, $\frac{\pi}{4}$, $\frac{\pi}{2}$, and π for headings. The optimisation process, set for 500 iterations, converged by the 21st iteration, resulting in optimal values of $w = 0.53$, $c_1 = 2.27$, and $c_2 = 0.99$.

6 Results and Discussion

Using the hyperparameters identified in Section 5.2, we validate our approach on the 10 different real-world herd configurations described in Section 4.2. For all the spatial distributions, we observe the same trend: having more drones resulted in a higher objective value than having fewer drones, as the drones could cover more SIs. Moreover, the PSO-based approach is stable in solving the optimisation problem regardless of the number of drones in the swarm. The highest observed standard deviation of the objective function Ω was 0.07. Table 1 details our algorithm's performance for a representative herd configuration consisting of 48 animals. The $\overline{\Omega}$ values presented are the mean values from the 10 experiments conducted.

Swarm Configuration	1x1	2x2	3x3
Objective Function Value $\overline{\Omega}$	0.43	0.66	0.76
Ω Standard Deviation	0.00	0.02	0.01
Top SIs Monitored (%)	83.33	100.00	100.00
Left SIs Monitored (%)	24.58	89.58	98.75
Right SIs Monitored (%)	68.13	91.46	99.17

Table 1: Monitoring results for a herd of 48 animals

A single horizontal drone cannot effectively monitor both sides of an animal simultaneously. As illustrated in the 1×1 column of Table 1, this limitation results in lower monitoring quality for the horizontally observed SIs. Moreover, a vertical drone might struggle to cover an entire herd, affecting the overall monitoring quality. When adding more vertical and horizontal monitoring drones, the generated drone configurations achieve significantly better results, as seen in Table 1.

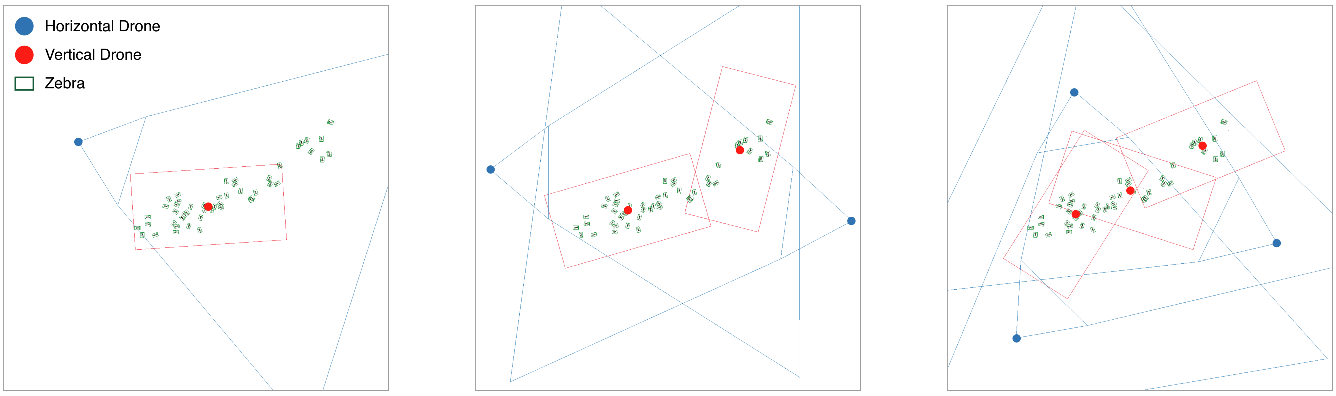
Moreover, as illustrated in Figure 6, we can qualitatively assess whether the swarm configuration is coherent. In Figure 6a, the number of drones performing the vertical and horizontal views is not sufficient to cover the entire herd; as a result, the drones are monitoring the part of the herd with the highest density, thus maximising the number of SIs covered. In Figure 6b, the vertical drones monitor the two clusters of animals, while the horizontal drones provide complementary views by facing each other. In Figure 6c, the swarm configuration is more complex and allows for an increased monitoring quality value.

Our approach is based on strong assumptions: the animals are static, and the positions of their SIs are known. To apply this approach in the real world with moving animals, we need to investigate the performance of the PSO in terms of convergence time. If the computation speed is sufficiently high, it might be feasible to run the PSO at a frequency high enough to update the positions of the drones while the animals are moving.

Further work is required to integrate machine vision for detecting and localising the animals. In our centralised approach for real-world deployment, we envision locating the animals using either a coverage algorithm or a drone flying high above the herd [37]. Subsequently, This drone would retrieve the animals' positions and orientations, as well as estimate their SIs. This data would be then processed by a ground station using the PSO algorithm, which updates the drones' positions based on its solution.

7 Conclusion

In this paper, we described and formalised a general approach for performing gregarious animal monitoring with a drone swarm based on the concept of surfaces of interest (SI) with Lambertian properties. The results show that our PSO centralised controller can find a drone configuration that maximises the quality of monitoring the herd, for different swarm size. In addition, we evaluated the performance of the PSO by analysing the drone configurations obtained using a real-world dataset of zebra distributions. Our algorithm was able to generate satisfactory configurations that met the criteria outlined in Section 3.1, using as few as two drones and up to six drones. As part of the WildDrone Project [38], we plan to test our approach in Kenya in January 2025. To achieve this goal, further work is needed to quantify the performance of our method in terms of computing speed and to enable animal localisation through machine vision.



(a) 1x1 (b) 2x2 (c) 3x3

Figure 6: Drone configurations for 1x1, 2x2, and 3x3 vertical and horizontal monitoring setups

ACKNOWLEDGEMENTS

This work is supported by the WildDrone MSCA Doctoral Network funded by EU Horizon Europe under grant agreement no. 101071224, the Innovation Fund Denmark for the project DIREC (9142-00001B), the Imageomics Institute, funded by the US National Science Foundation (2118240), and the ICICLE Institute funded by the National Science Foundation (OAC-2112606).

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