

Bioinspired Approaches for Coordination and Behaviour Adaptation of Aerial Robot Swarms

Hugo Ricardo Meireles Sardinha

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Abstract

Behavioural adaptation is a pervasive component in a myriad of animal societies. A well-known strategy, known as Lévy Walk, has been commonly linked to such adaptation in foraging animals, where the motion of individuals couples periods of localized search and long straight forward motions. Despite the vast number of studies on Lévy Walks in computational ecology, it was only in the past decade that the first studies applied this concept to robotics tasks. Therefore, this Thesis draws inspiration from the Lévy Walk behaviour, and its recent applications to robotics, to design biologically inspired models for two swarm robotics tasks, aiming at increasing the performance with respect to the state of the art.

The first task is cooperative surveillance, where the aim is to deploy a swarm so that at any point in time regions of the domain are observed by multiple robots simultaneously. One of the contributions of this Thesis, is the Lévy Swarm Algorithm that augments the concept of Lévy Walk to include the Reynolds' flocking rules and achieve both exploration and coordination in a swarm of unmanned aerial vehicles.

The second task is adaptive foraging in environments of clustered rewards. In such environments behavioural adaptation is of paramount importance to modulate the transition between exploitation and exploration. Nature enables these adaptive changes by coupling the behaviour to the fluctuation of hormones that are mostly regulated by the endocrine system. This Thesis draws further inspiration from Nature and proposes a second model, the Endocrine Lévy Walk, that employs an Artificial Endocrine System as a modulating mechanism of Lévy Walk behaviour. The Endocrine Lévy Walk is compared with the Yuragi model (Nurzaman et al., 2010), in both simulated and physical experiments where it shows its increased performance in terms of search efficiency, energy efficiency and number of rewards found. The Endocrine Lévy Walk is then augmented to consider social interactions between members of the swarm by mimicking the behaviour of fireflies, where individuals attract others when finding suitable environmental conditions. This extended model, the Endocrine Lévy Firefly, is compared to the Lévy+ model (Sutantyo et al., 2013) and the Adaptive Collective Lévy Walk Nauta et al. (2020). This comparison is also

made both in simulated and physical experiments and assessed in terms of search efficiency, number of rewards found and cluster search efficiency, strengthening the argument in favour of the Endocrine Lévy Firefly as a promising approach to tackle collaborative foraging

To all and to a few in particular.

“It is the long history of humankind (and animal kind, too) that those who learned to collaborate and improvise most effectively have prevailed.”

Charles Darwin

“Ser emigrante não deixar a terra, é levar a terra consigo”

José Saramago

“Science, for me, gives a partial explanation for life. In so far as it goes, it is based on fact, experience and experiment.”

Rosalind Franklin

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To all,

Bem hajam

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List of Acronyms

AES Artificial Endocrine System.

AF Adaptive Foraging.

CBW Composite Brownian Walk.

CPF Central Place Foraging.

CRW Correlated Random Walk.

DFA Discrete Firefly Algorithm.

EAHS Evolutionary Artificial Homeostatic System.

ELF Endocrine Lévy Firefly.

ELW Endocrine Lévy Walk.

ES Endocrine System.

FA Firefly Algorithm.

FC Foraging and Collection.

FSM Finite State Machines.

GA Genetic Algorithm.

LFFA Lévy Walk Firefly Algorithm.

LSA Lévy Swarm Algorithm.

LW Lévy Walk.

RCGA Real-Coded Genetic Algorithm.

UAV Unmanned Aerial Vehicle.

Notation

θ_i	Orientation of agent i
v_x, v_y	Linear components of the agent's velocity in local frame
δ	distance threshold
Φ_i	Velocity command for agent i based on the Flocking rules
Θ	Average heading of neighbours considered for the flocking rules
\mathbf{N}	Set of neighbours considered for in the flocking rules
\mathbf{p}_i	Position of agent i
\mathbf{P}	Centroid of the neighbours' positions used in flocking rules
μ	Lévy parameter
ω	Angular velocity
\bar{L}	Long walk threshold
l	Length of generated walk
ι	Weights considered for the flocking rules
Λ_i	Velocity command for agent i based on the Lévy process
\mathbf{x}	Internal state
∇U	Dynamics of the attractor model
$\vec{\mathbf{u}}$	Velocity command
β	Attractiveness in the firefly model
η	Efficiency definition
λ	Hormonal modulation of the desire to interrupt a current walk
\mathcal{A}, \mathcal{S}	Sets of agents relevant to collective adaptive foraging tasks
ρ	Correlation between consecutive walks
τ	Target orientation for a agent performing Lévy Walks
ζ, C	Parameters of the ACLW model
$\mathbf{a}, \mathbf{b}, \mathbf{c}$	Weights considered for Artificial Endocrine System

NOTATION

$H(t)$ Hormone level at time t

$S(t)$ Hormonal stimulus at time t

Chapter 1

Introduction

In recent times, societies have witnessed the increased pervasiveness of robotics applications. While at the beginning of the 21st century robots outside research laboratories were mostly exclusive industrial automation tools, today they are expected to take on tasks in our agricultural fields, oceans and skies while being able to sense, communicate and act collaboratively, in increasingly unconstrained environments and with minimal or no human supervision (Schranz et al., 2020).

With increased task complexity, specially in unconstrained environments, it became apparent that some of such tasks would not be accomplished by a single robot and would be carried out more effectively by several robots as a coordinated group (Bayındır, 2016). Nevertheless the control of a group of robots poses its own challenges regarding communication and coordination, which has led researchers to turn to Nature for inspiration on how to address such challenges (Bonabeau et al., 1999). By observing natural societies such as insects, birds or fish, researchers noted that by leveraging local interactions and simple individual behaviours, these societies were capable of tackling incredibly more complex tasks than a single individual would ever do (Dorigo and Sahin, 2004). As a consequence, a new field of study in robotics started to emerge and the term *Swarm Robotics* was coined by Şahin (2004) as “(...) *the study of how large number of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment*”. From this definition Şahin (2004) highlights three distinct inherent (and desirable) characteristics that also serve as the motivation behind the Swarm Robotics approach, namely:

- **Robustness:** Through the homogeneity of a group of robots performing simple behaviours, either in reaction to the environment or to each other, the *swarm* is able to continue its task despite the failure of individual agents or environmental disturbances.
- **Flexibility:** Simple individual behaviours that are sensitive to the environment tend to generate different emergent behaviours.
- **Scalability:** Local communication is, in principle, unaffected by the size of the swarm since each individual robot only communicates to others in its vicinity. In practice a truly scalable system would be that with only indirect communication.

In order to fully exploit the inherent advantages of Swarm Robotics to decentralised control problems, synthesising individual behaviours is paramount, and is in fact a continuously open issue, as new approaches are developed that outperform the state-of-art (Brambilla et al., 2013; Şahin et al., 2008). The deployment of even the simplest behaviours can have have significant impact in a robot’s behaviour as shown by Braitenberg (1986), but, as this work will propose, it is in *how* these systems react to change, or *adapt*, where lies one of the biggest opportunities for intelligent robots to unlock improved levels of performance.

Adaptation itself is a universal constant in the animal kingdom, and this work will mimic such natural mechanisms and embody the resulting controllers in robots to tackle one of the central tasks in Swarm Robotics.

1.1 Adaptation: from Natural to Synthetic

Adaptation in the animal kingdom is often observed through a set of different behaviours as a response to environmental changes, which is considered to be among the most notable examples of evolutionary biology (Darwin, 1859). It has been postulated that such behavioural responses, are intimately related to a set of underlying neural-chemical mechanisms, perfected over the course of natural evolution (Zera et al., 2007), and what one perceives as *adaptation* is, in actuality, the visible manifestation of how these mechanisms affect an animal’s physical behaviour in response to environmental conditions.

Ashby (1960) characterized a behaviour as adaptive if *it maintains the essential variables within physiological limits*, thus linking observable physical behaviour to how internal variables are kept in an equilibrium, later defined by Pfeifer and Scheier (2001) as *homeostasis*. According to Ashby’s definition, one ubiquitous component of adaptive natural systems where this principle is particularly evident is the *Endocrine System* (ES) (Bonier and Martin, 2016). The ES is responsible for the production or inhibition of hormones in response to external stimuli captured by the immune and nervous system (Besedovsky and del Rey, 1996; Vargas et al., 2002, 2005a), and responsible for behaviours and bodily functions such as temperature, heart rate and the desire to sleep, hunt, or the fight-or-flight instinct (Jansen et al., 1995).

Due to the unquestionable relation between hormone-based regulation and a system’s ability to adapt its behaviour to external stimuli, researches in the field of mobile robotics have been, for over two decades, synthesising Artificial Endocrine Systems (AES) that mimic the behaviour of their natural counterpart. Adaptive (and therefore) robust controllers were developed for several behaviours such as phototaxis (Dyke and Harvey, 2005) and obstacle avoidance (Timmis and Neal, 2003), but also for tasks with increased complexity where competition between robots for the same resource is considered (Di Paolo, 2000) or even scenarios where multiple conflicting behaviours exist within the same robot (Vargas et al., 2009).

A particularly recent and interesting modelling of an AES is proposed by Wilson et al. (2018), for the problem of efficient foraging employing a robot swarm where the fluctuation of artificial hormones models the transition between finite machine states such as: collision avoidance, search, or homing behaviours. Foraging can be a particularly complex problem for robot swarms due to the aspects it entails: search strategy, collision avoidance and collaboration strategy among the group. As in many foraging scenarios in robotics, a previously unknown scenario exists where clustered rewards need to be discovered or collected. Due to this cluster-based environment, an effective adaptation strategy is paramount, and is therefore the main focus of study in this thesis.

1.2 Optimal Foraging Strategies: The Lévy Walk Paradigm

An animal's ability to forage in an unknown environments in search for resources, such as water or food, has been noted to be strongly entwined with their success in evolving adaptive strategies (Bartumeus, 2007). It has also been observed that such search strategies, not only exhibit a random motion component (Jandhyala and Fotopoulos, 2018), but tend to be very similar across quite different animal populations such as: honeybees (Reynolds et al., 2007), sharks (Sims et al., 2008) and primates (Raichlen et al., 2014; Sun et al., 2014). All seem to perform searches that couple periods of localized search, with periods of ballistic relocation across the domain (Bénichou et al., 2011), a pattern known as Lévy Walk (LW) (Zaburdaev et al., 2015) and depicted in Figure 1.1.

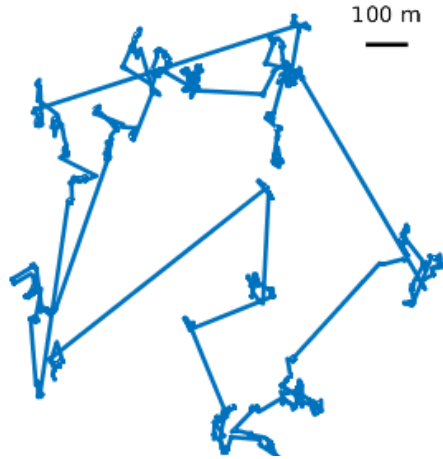


Figure 1.1: Example of a Lévy Walk motion

The Lévy Walk paradigm, rests on the idea that the length of consecutive forward motions can be approximated by a heavy-tail distribution, or power law, rather than a Gaussian distribution as proposed by the Brownian motion model (Viswanathan et al., 1999). Indeed Viswanathan was the first to compare Lévy and Gaussian distribution to fit empirical data collected from animals in the wild, to highlight the advantage of the former in doing so (Viswanathan et al., 1996). This advantage stems from the fact that the power-law approximation, due its long tail, provides a tool to generate localized searches interspersed with long relocations across a given domain (Reynolds and Rhodes, 2009; Viswanathan et al., 1996), potentiating

a behaviour that, natively, couples exploitation and exploration.

Nevertheless, the Lévy Walk hypothesis has not been without criticism, namely by authors such as Benhamou (2007) who have noted, one should not confuse the observed motion *pattern*, with the underlying *process* that gives rise to an animal's motion. To make this point clear Benhamou (2007) has proposed the Composite Brownian Walk (CBW), for foraging in patchy environments. In this model foragers switch between Brownian walks with different means, effectively modulating the average step length depending on the density of rewards. The result is what appears to be a more efficient model than the simple “*blind*” Lévy process proposed before. However, as walk length distributions are analysed, it is concluded that they also fit a power law which can approximate the Lévy Walk. In other words, if animals in the wild perform search in a manner fitting with a Lévy distribution, it is expected that an environmental stimulus is the origin of the of such behaviour (Bartumeus et al., 2005).

Similar arguments were also echoed in subsequent works in computational ecology, namely by Plank and James (2008) where a continuous model is proposed (rather the traditional step-by-step random walk approach) and by Gautestad and Mysterud (2013) where a memory-based model is derived to better reflect that characteristic of animals. These works have focused on scenarios where rewards are also clustered in patches, and attempt to modulate transitions from reward-dense regions reward-sparse ones. Despite the interesting result that an explicit Lévy process is not needed to achieve this adaptation, these works, invariantly achieve a motion pattern that fits a power law distribution which in turn is consistent with the Lévy Walk approximation. This conclusion shows that the Lévy Walk hypothesis indeed offers a solid basic behaviour, upon which one can employ some modulation to reflect the forager's interaction with its environment, a result that has inspired roboticists to adopt the Lévy Walk approach when designing their respective controllers (Fricke et al., 2013, 2016; Nauta et al., 2020; Sutantyo et al., 2010, 2013), and is therefore the nuclear premise for the work developed in this Thesis.

These works also highlight the critical reason to study the design of adaptation mechanisms, especially in environments where desirable conditions are cluster in patches, that is that motion patterns and adaptation in such environments are

intimately linked. By defining a *cluster* in the same manner as Danchin et al. (2008) —“*an homogeneous resource containing area (or part of habitat) separated from others by areas containing little or no resources*”—the necessity for behavioural adaptation in foraging becomes evident ~~in the~~ as agents aim to switch their behaviour from exploration in empty areas, to exploitation in resource rich ones.

Therefore, it is a major aim of this work to establish a connection between the underlying Lévy process and a modulation strategy based on artificial endocrine systems that will allow robots to efficiently explore a domain where rewards are grouped in clusters.

1.3 Contributions of the Thesis

The previous section highlighted how the Lévy Walk paradigm has, in recent years, become central in tackling exploration and foraging tasks. In this Thesis the LW model will play a central part in devising models to study aspects of these two different tasks. The first objective is to study the effect of Lévy Walks in an exploration problem and assess its impact in a swarm’s ability to perform collective surveillance. As it will be detailed in the next Chapter, cooperative surveillance approaches often rely on either global knowledge of the domain or centralized control strategies. To overcome these limitations the first proposed model leverages both a LW component for exploration and the flocking model proposed by Reynolds (1987) for coordination. By addressing this problem we aim to question if a behaviour-based approach to the design of Lévy controllers has any applicability, thus highlighting the intrinsic benefits of the Lévy process itself to swarm robotics tasks.

Secondly we aim to develop a method that endows a robot with the appropriate behavioral response to changing environmental conditions, namely by triggering transitions between local and global search, according to the density of rewards found in cluster-based scenarios. To such an end this Thesis proposes a modulation strategy of the Lévy Walk parameters based on the modelling of Artificial Endocrine Systems envisioned to increase its efficiency given the compounded biological inspiration. In order to better distinguish the effect between the influence of individual and emergent collective behaviours, this Thesis will present results in both single-robot and

swarm scenarios.

In the swarm scenario, this thesis will also address the topic of how each robot interacts to those in its vicinity, and in that regard draw inspiration from recent works, and use such as benchmark. By employing the same swarm level cooperation strategy as other works, while overlaying it on a different individual adaptation strategy based on AES, this thesis aims to show the importance of a more biological plausible adaptation mechanism. The different proposed across this Thesis aim to validate the following hypothesis:

Behaviour Adaptation can modulate and improve the efficiency of Lévy Walks for cooperative and collective tasks in aerial swarm robotics.

Acceptance of the hypothesis will then be subject to a series of incrementally more complex approaches and is conditional to the answering the following research questions:

1. Can Lévy Walk, in conjunction with flocking strategies, be used to tackle cooperative surveillance?
2. Can an Artificial Endocrine System, be used to model adaptive Lévy Walks while maintaining inherent properties of exploitation and exploration, for a single agent performing foraging?
3. Is such a model, able to outperform other strategies aimed at the same foraging task?
4. Can this model be extended to a robotic swarm, and still be able to deliver an increased performance in comparison to other swarm strategies which tackle foraging in the similar manner?

Being able to answer these four questions will prove that the increased biologically plausibility of adaptation mechanisms is paramount to the successful deployment of a system that is able to outperform alternative approaches to the same tasks.

1.4 Publications

Over the course of this work three main publications were made that pertain directly to the research questions, namely:

1. Research Question 1

Sardinha, H., Dragone, M., and Vargas, P. A. (2020). Combining Lévy Walks and Flocking for Cooperative Surveillance Using Aerial Swarms. *In Multi-Agent Systems and Agreement Technologies* (pp. 226-242). Springer, Cham.

2. Research Question 2 & 3

Sardinha, H., Dragone, M., and Vargas, P. A. (2020, October). Towards an Adaptive Lévy Walk Using Artificial Endocrine Systems. *In 12th International Conference on Adaptive and Self-Adaptive Systems and Applications 2020* (pp. 116-121). IARIA.

3. Research Question 4

Sardinha, H., Dragone, M., and Vargas, P. A. (2021, August). Endocrine Lévy Firefly Model for Swarm Robot Foraging. *Submitted to Swarm Intelligence*. Springer.

Other publications were also made in the field of swarm robotics, albeit related to the purposed hypothesis or research questions, which spawned from international collaboration namely:

1. **Sardinha, H.R.**, Dragone, M. and Vargas, P.A., 2018. Closing the gap in swarm robotics simulations: An extended ardupilot/gazebo plugin. *arXiv preprint arXiv: 1811.06948*.
2. Artaxo, P. G., **Sardinha, H.**, de Paiva, E. C., Bourgois, A., Fioravanti, A. R., Vieira, H. D. S., and Vargas, P. A. (2017). Control of multiple airships for autonomous surveillance and target tracking. *In XIII Brazilian International Symposium in Intelligent Automation* (pp. 771-778).
3. Artaxo, P. G., Bourgois, A., **Sardinha, H.**, Vieira, H., de Paiva, E. C., Fioravanti, A. R., and Vargas, P. A. (2020). Autonomous cooperative flight control for airship swarms. *arXiv preprint arXiv:2004.07665*.

1.5 Outline of this Thesis

This thesis is divided into seven chapters. Chapter 1 has given an overview of the main concepts this thesis addresses, the Hypothesis it aims to validate and which research questions are asked in order to do so.

Chapter 2 provides a the necessary background on the several disciplines pertaining to the contributions of this Thesis, and presents the most relevant works in each field as as well as their connection to the overall objectives. Chapters 3, 4 and 5 present successive contributions to answer the research questions posed in Section 1.3.

In particular, Chapter 3 presents a model for coordination in a swarm approach to collective surveillance employing Lévy Walks. Chapter 4 exploits the usage of Artificial Endocrine Systems as a adaptation mechanism for Lévy Walks performed by a single agent, and compares the results with a long-standing solution to the same problem. Chapter 5 presents a comprehensive adaptive strategy for collective foraging in swarm robotics, also in a comparative manner with other purposed solutions in the literature.

Chapter 6 will discuss results on all main contributions and how these relate the hypothesis put forth as well as the research questions, and finally, Chapter 7 concludes this thesis and provides an outlook into the future of the field.

Chapter 2

Biologically Inspired Principles

This Chapter gives an overview of the distinct fields of scientific enquiry that are related to the main contributions of this Thesis, namely: Lévy Walks, Artificial Endocrine Systems, Evolutionary Robotics, Firefly inspired techniques and Swarm Robotics. This overview aims to provide a solid background on how concepts from different fields can coalesce to tackle a specific challenge in adaptive collective foraging, and therefore highlight the synergies that can be achieved from pursuing a multi-disciplinary approach.

2.1 Lévy Walks: Principles & Applications

Random Walks have been for some decades at the core of modelling empirical data from foraging strategies employed by animals in the wild (Gautestad and Mysterud, 1993). Existing processes arise from the intuitive idea of taking successive steps, each in an uniformly random direction and of a random length. Therefore, they consist of displacement events (i.e., walk lengths) interspersed by reorientation events (Bartumeus, 2007), and the study of which distribution of walk lengths better fits the observed animal behaviour has been a core interest of computational ecologists (Jandhyala and Fotopoulos, 2017).

To describe these natural motions, computational ecologists firstly attempted to use Brownian models to fit empirical data, over large spatial scales and long temporal scales, with relative success (Berg, 93). Later however, and due to collection of more comprehensive data, it has become evident that Brownian models did not

account for the tendency that animals show for maintaining *directional persistence*. To address this shortcoming of the Brownian motion, Bovet and Benhamou (1988) proposed the employment of Correlated Random Walk (CRW) models to fit animal behavioural data, where the reorientation step does not follow an uniform distribution but instead is biased towards the current direction of motion. Notwithstanding the better fit of the CRW to model directional persistence, it has subsequently been shown to lack scale invariance. Therefore as movement scales increase, so does the error due to the many successive small changes of direction, ultimately converging to a Brownian pattern (Raposo et al., 2009; Viswanathan et al., 2000).

An alternative to describe directional persistence, and in a scale free manner, was subsequently presented by Viswanathan et al. (1996), to describe the movement of flying albatrosses, i.e., the Lévy Walk. Contrarily to previous studies on animal motion, the Lévy Walk model draws length walks from a power law distribution described by equation (2.1):

$$P(l) \sim l^{-\mu}, \quad 1 < \mu \leq 3 \quad (2.1)$$

where the parameter μ controls the shape of the distribution converging to Brownian motion for $\mu > 3$ (Reynolds, 2010b), l stands for the length of each step (in meters) and $P(l)$ denotes the probability distribution function of a power law. Since power laws are heavy tailed (see Figure 2.1), this leads to occasional *long* walks being generated, effectively coupling periods of localized search with periods of directional persistent motion across the domain (Bénichou et al., 2011; Reynolds and Rhodes, 2009). A comparison between motions is depicted in Figure 2.2.

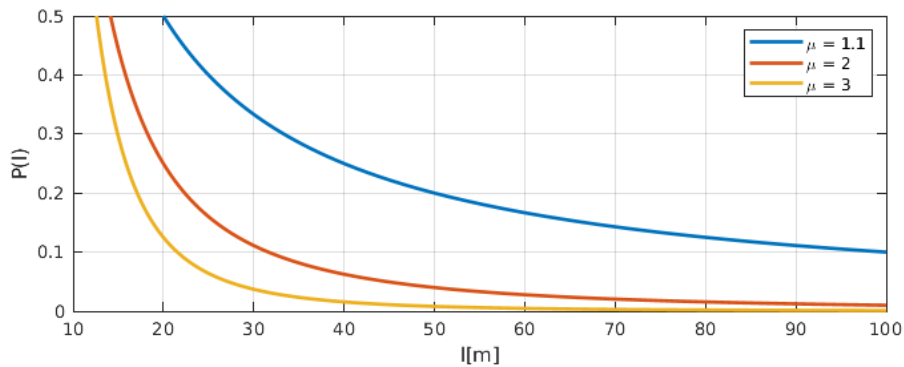


Figure 2.1: Power law distributions with varying values of μ

The importance of the scale invariant property of Lévy Walks in modelling biological motion behaviour is such (Bartumeus et al., 2005), that a series of studies have successfully observed Lévy motion in the most varied life forms, such as: cellular structures (Reynolds, 2010a); microzooplankton (Bartumeus et al., 2003), fruitflies (Reynolds and Frye, 2007), honeybees (Reynolds et al., 2007), marine predators, (Sims et al., 2008), bumblebees and deer (Edwards et al., 2007).

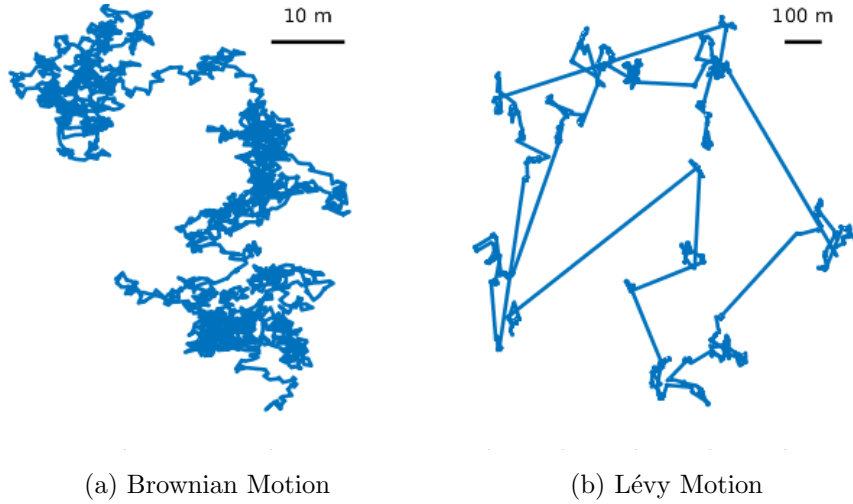


Figure 2.2: Examples of trajectories generated by Brownian and Lévy motions

However, despite the success of LWs in explaining observed behaviours, the question still remained on how to deploy them in artificial foragers in order to maximize the finding of rewards with respect to the total distance travelled. Viswanathan et al. (2000) and Bartumeus (2007) have shown that in environments where rewards are sparse and uniformly distributed, Lévy processes constitute a robust solution to the generic search problem, where $\mu = 2$ tends to maximize the number of encounters between forager and rewards, such as depicted in Figure 2.3.

Nevertheless, as it was pointed out by Benhamou (2007), simply using a Lévy process to generate successive walks from a power law (2.1), may not provide insight on why these observed patterns occur in Nature. To make this point clear Benhamou (2007) has proposed the Composite Brownian Walk (CBW), for foraging in patchy environments. In this model foragers switch between Brownian walks with different means, effectively modulating the average step length depending on the density of rewards. The result is what appears to be a more efficient model than the simple “*blind*” Lévy process proposed before. However, as walk length distri-

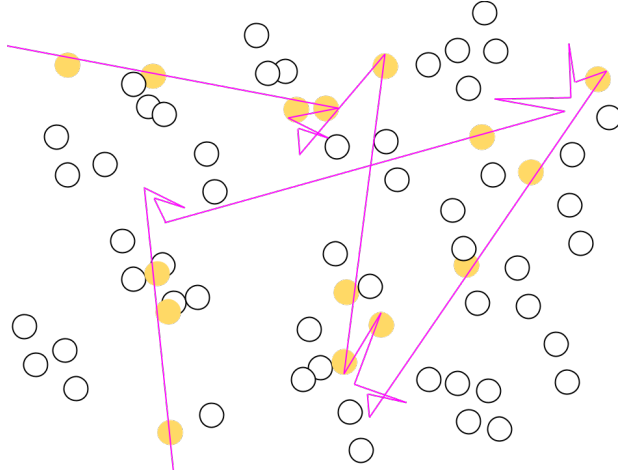


Figure 2.3: Example of Lévy process ability to find sparsely distributed rewards

butions are analysed it is concluded that, due to the different means, they also fit a power law. Benhamou’s work clearly shows that the environment plays a crucial role in how a forager behaves, and by considering interactions with the environment, search efficiency can be greatly improved, highlighting that even without an explicit Lévy Process, a Lévy pattern can still be observed. Similar arguments were echoed in subsequent works, namely by Plank and James (2008) where a continuous model is proposed (rather the traditional step-by-step random walk approach) and by Gautestad and Myrsetrud (2013) where a memory-based model is derived to better reflect that characteristic of animals. One notices that a underlying focus of these works is on modulating transitions from reward-dense regions of the search space to reward-sparse ones. Recalling the properties of Lévy process, one can observe that these transitions are inherent, leading to the notion that Lévy processes can still be used to explore patchy environments if a meaningful modulation of μ is employed that also reflects the forager’s interaction with its environment.

2.1.1 Synthesising Lévy Walks

The large evidence of LWs found in Nature has invariantly led researchers to realize the potential of LW-based controllers for robotics tasks where a parallel with nature is observed, such as: foraging, search or exploration. Across these fields several works demonstrated the ability of simple controllers designed for autonomous robots to replicate LW patterns described by computational ecologists such as Bartumeus or Viswanathan (Krivonosov et al., 2016). The first step before such a controller

can be deployed depends on generating a random variable that is Lévy distributed. Generating such a random variable is accomplished by employing the method proposed by Harris et al. (2012), and summarized in Algorithm 1 which starts by fixing the value of μ , then drawing uniformly distributed variables U_1, U_2 and use these to compute the target distance (l) and finally also drawing a uniformly distributed orientations (τ).

Algorithm 1: Generate Lévy distributed random variable

Set the value of μ ;

Draw U_1, U_2 where $U_1, U_2 \sim \mathcal{U}(0, 1)$;

Compute $\widetilde{U}_1 = U_1\pi/2$, $\widetilde{U}_2 = (U_2 + 1)/2$;

Compute target distance $l = \frac{\sin((\mu-1)*\widetilde{U}_1)}{\cos(\widetilde{U}_1)^{\frac{1}{1-\mu}}} \left(\frac{\cos((2-\mu)*\widetilde{U}_1)}{\widetilde{U}_2} \right)^{\frac{2-\mu}{\mu-1}}$;

Draw random orientation τ where $\tau \sim \mathcal{U}(-\pi, \pi)$;

For autonomous mobile robots, generating a trajectory that achieves forward motions and reorientation steps can be implemented by imposing a series of velocity commands, $\vec{\mathbf{u}}$ consisting of a linear (v) and angular (w) components. A generic LW controller can be summarizing by the following steps:

- Define the value of μ
- Generate tuple (τ, l) , from Algorithm 1
- Move in straight line while the distance travelled is smaller than l
- When l is reached, generate another tuple (τ, l) and rotate towards the new angle τ until the agent's heading is within a small tolerance.

These steps are formalised below in Algorithm 2.

Algorithm 2: Generic LW Controller

```

Set  $\mu$ ;
Generate tuple  $(\tau, l)$  ; // From Algorithm 1
Set  $d = 0$  ; // Initialize distance travelled
if  $d \leq l$  then
     $\vec{u} = [v, 0]^T$  ; // Move forward
    Update  $d$ ;
else
    Generate tuple  $(\tau, l)$ ;
    while  $|\theta - \tau| \geq \epsilon$  do // until  $\theta$  is within a small error of the target  $\tau$ 
         $\vec{u} = [0, \omega]^T$  ; // Rotate
    end
    Set  $l = 0$ ;
end

```

As it will be highlighted in the course of this Thesis, this simple control approach lays the ground work to enable the design of LW-based strategies to tackle several tasks withing the robotics domain.

2.1.2 Lévy Walks in Robotics

The ability of the LW model to maximize the probability of encounter with sparsely distributed targets, or rewards, demonstrated by Viswanathan et al. (1999) has been a fundamental motivation for roboticists to apply approaches based on Algorithm 2 to artificial agents (Flenner et al., 2012). Indeed, autonomous search in unknown domains is a critical task where LWs have demonstrated their increased reliability and efficiency when comparing to other random walk methods (Bekey, 2005; Zhu et al., 2017), even in dynamic scenarios (Fioriti et al., 2015).

As LWs became a subject of greater interest within the robotics community, several other uses of LW based strategies were adopted. Stevens and Chung (2013) have proposed the use of LWs in an autonomous agent searching for a single stationary target, while also avoiding being targeted by an adversary agent throughout the operation. Frasheri et al. (2018) proposed a framework for multi-robot collaboration in a fire rescue scenario, where each robot performs LWs to search either

for fire fronts, other agents already engaged in fire extinguishing or even individuals that need rescuing. Pang et al. (2019) also proposed an improved LW for area coverage where the step length generated depends on robot density so that repeated searches are minimized. Area coverage is also addressed by Deshpande et al. (2017) who propose an adaptive LW in which agents use artificial pheromones to trigger a switch between Lévy and Brownian motions depending on the level of coverage at their current location. Multi-robot mapping is also studied by employing LW-based random strategies in grid domains while exploiting map sharing to inform walk directions and lengths (Kegeleirs et al., 2019; Ramachandran et al., 2020). Fricke et al. (2016) also employ LW models for the Central Point Foraging problem, where agents forage an unknown environment, from a central position, or nest, and performs sensitivity analysis on the μ parameter for different swarm sizes and reward configurations. Indeed, LWs have become a frequent aspect of methodologies that deal with exploratory motions of autonomous robots, especially where no concrete prior knowledge exists, and some form of search or foraging task is required. As it will be highlighted in the next section, LWs are also a pervasive and frequent component in many Swarm Robotics applications.

An alternative to distribution-based random walk models was proposed by Nurzaman et al. (2010), where the transition between local searches and ballistic motions happens based on the concept of *yuragi* or biological fluctuation. This mechanism is one by which certain bacteria are able to alter their behaviour in the presence, or absence, of nutrients. A formal description of such behaviour is given by the attractor selection model, represented by the Langevin equation:

$$\dot{\mathbf{x}}(t) = -\nabla U(\mathbf{x}(t))A(t) + \epsilon(t) \quad (2.2)$$

where \mathbf{x} and $-\nabla U(\mathbf{x}(t))$ are respectively the state and dynamics of the attractor model, $\epsilon(t)$ is a noise term, and $A(t)$ represents a variable *activity* which indicates how well the current state fits the environment, chosen in Nurzaman’s work to be respectively:

$$U(\mathbf{x}(t)) = (\mathbf{x}(t) - h)^2 \quad (2.3)$$

$$A(t) = R \cdot A(t-1) + f(t) \quad (2.4)$$

where $f(t)$ represents the number of resources sensed, and R is a decaying coefficient with respect the previous value of $A(t)$. An example of the temporal evolution of the system's state $\mathbf{x}(t)$ is depicted in Figure 2.4.

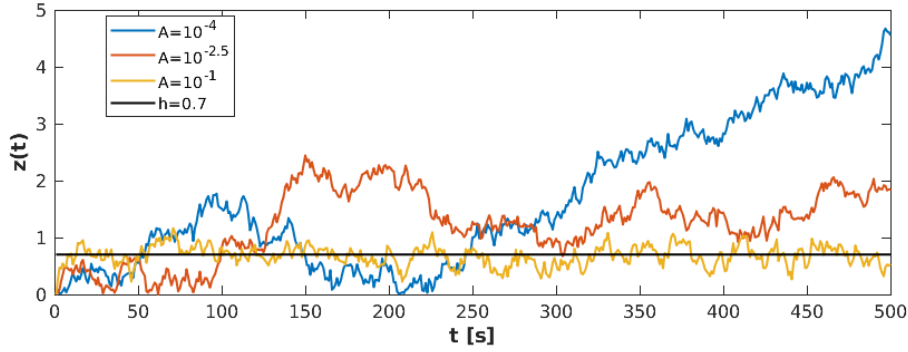


Figure 2.4: Fluctuation of $z(t)$ around the attractor $h = 0.7$

The way the system changes from continuously straight motions to local search is modeled by a finite state machine with two states: *swimming* or *gliding*, which corresponds to a forward motion, and *tumbling* which corresponds to a reorientation. One can observe, from the depiction of in Figure 2.5, that the transition from the *gliding* state \mathcal{G} , to the *tumbling* state \mathcal{T} depends on a probability $P(t)$. On one hand, if $P(t)$ is small the gliding motion continues and long relocations are expected, whereas on the other hand, for high values $P(t)$ a *tumbling* step is more likely to occur, immediately followed by another *gliding* step leading to a local search behaviour.

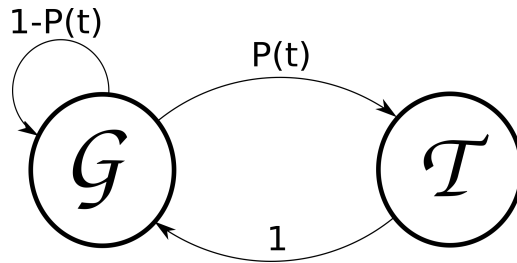


Figure 2.5: Finite state machine for behaviour

Based on the state of the system, the probability of transitioning between states

Citation	Comments
Bovet and Benhamou (1988)	Proposes the CRW to account for directional persistence lacking in Brownian models.
Viswanathan et al. (1996)	Original proposition of using Lévy Walks to modulate empirical data.
Viswanathan et al. (2000)	Shows the CRW lacks scale invariance, which in large scale environments converges to a Brownian motion
Nurzaman et al. (2010)	Proposes the Yuragi model to achieve a Lévy Walk pattern of motion, without an explicit Lévy process
Harris et al. (2012)	Describes Algorithm 2 as a generalized tool to generate LWs.
Benhamou (2007)	Proposes the CBW to generate Lévy Walk patterns, without an explicit Lévy distributed variable
Krivososov et al. (2016)	Reviews LW-based robotics applications. Establishes the term Lévy Robotics
Jandhyala and Fotopoulos (2018)	Reviews and compares random walk methods in computational ecology. Highlights the LW as the one that better fits empirical data

Table 2.1: List of relevant citations regarding the principles of Lévy Walks.

is computed using (2.5). One can see, from (2.2), that when $A(t)$ increases, the first term becomes dominant and the value of the system's state \mathbf{x} decreases towards attractor h (with $0 < h < 1$), therefore leading to a high probability transitioning from \mathcal{G} to \mathcal{T} .

$$P(t) = e^{-\mathbf{x}(t)} \quad (2.5)$$

On the other hand, when $A(t)$ is very small, the dominant term of (2.2) is the noise term $\epsilon(t)$, which, due to being applied to $\dot{\mathbf{x}}$, gradually makes the state \mathbf{x} diverge from the attractor (as shown by Figure 2.4) leading to small value of $P(t)$, and therefore a continued gliding motion.

The importance of Nurzaman's work lies in the fact that it is one of the few works that proposes an adaptive model for foraging where the interspersation of local searches with large relocations is achieved, without explicitly recurring to a LW-based model. Thus it will be used as a benchmark for one of the models proposed in this Thesis,

namely the one in Chapter 4. Finally, a list of the most relevant works for this Thesis, with regards to Lévy Walks principles can be consulted in Table 2.1.

2.2 Mimicking Fireflies

Even though the LW motion pattern appears to materialise in several foraging animals, one should not assume this is the only mechanism at play, in particular when such animals tend to live cohesively in large societies. In fact, it has also been highlighted that even though the LW model is successful at describing natural motions, and improving the performance of artificial ones, the manner in which agents in these societies interact with each other is no less important (Dorigo et al., 2007). Computational ecologists have pointed out that, the simple individual behaviours observed in members of animal societies, are inherently overlaid by a social behavioural response enabling the emergence of complexity in the observed behaviour (Sumpter, 2006).

This is particularly true in the case of foraging agents (either natural or artificial) which act upon the exchange of limited local information, to optimize the collective discovery of some objective environmental condition. In the natural world these conditions can mean water, food or prey, whereas in the robotics domain it can mean the characterization of pollution sources, or mapping weed density in agricultural applications. Regardless of the target application, the challenge of emulating the social aspects of natural societies, invariantly falls on how to synthesize these collective behaviours to achieve the desired behaviour in an efficient manner. In this regard, one particular source of inspiration has been the Firefly Algorithm (FA) proposed by Yang, initially as an optimization tool (Yang, 2009). As the name suggests, the FA mimics the behaviour of fireflies, where each agent emits a bio-luminescent light with intensity proportional to how desirable the environmental conditions are at its locations. Other agents in the vicinity are therefore more or less attracted depending on their own intensity and the distance to the observed light source.

The FA is designed upon two main concepts: Brightness (I), and Attractiveness (β). Brightness, refers to the actual intensity of light of a single firefly. From an optimization perspective this is interpreted as value of the fitness function at a

particular position \mathbf{p} , $I(\mathbf{p}) \propto f(\mathbf{p})$. Attractiveness on the other hand, is considered from the perspective of another agent, and can be viewed as the perceived intensity at its position. Naturally, the further an agent i is from an agent j the weaker attraction is between them. This relationship is given by (2.6), where r is the Cartesian distance between agents, β_0 is the attractiveness at $r = 0$ and γ emulates the light absorption coefficient by the environment, i.e., the higher the value of γ is the closer agents need to come to be attracted to brighter neighbours.

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (2.6)$$

In particle-based numerical experiments, where there are no real world constraints of actuation, Yang describes the movement of and agent i attracted to another (brighter) agent j as follows:

$$\mathbf{p}_i = \mathbf{p}_i + \beta_0 e^{-\gamma r^2} (\mathbf{p}_j - \mathbf{p}_i) + \alpha(\epsilon - 1/2) \quad (2.7)$$

where the third term represents a randomization, predominant when there are no brighter agents. In this term, α is a weight of the importance of the randomization, and ϵ is a random number such that $\epsilon \sim \mathcal{U}(0, 1)$. In sum the FA can be summarized in the following steps:

- Fix the light absorption parameter γ
- Place n agents in the domain
- Compute the brightness for each agent
- Update the position of each agent based on the relative brightness and distance to its neighbours
- Repeat while the termination condition is not met.

These steps are formalised in Algorithm 3.

Algorithm 3: Original firefly algorithm

```

Define  $\gamma$ ;
Generate  $n$  initial population of agents  $\mathbf{x}_i$  ( $i = 1, 2, \dots, n$ );
while  $t \leq T$  do
    Compute brightness  $I_i$ ;
    for  $i=1:n$  do
        for  $j \neq i$  do
            if  $I_j > I_i$  then
                 $\mathbf{p}_i = \mathbf{p}_i + \beta_0 e^{-\gamma r^2} (\mathbf{p}_j - \mathbf{p}_i) + \alpha(\epsilon - 1/2)$ ;
            end
        end
    end
end

```

Building on the foundations laid by Yang (2009) other researchers have augmented the original FA to tackle challenges in the field of robotics by making real-world considerations such as communication constraints and collision avoidance mechanisms. De Rango et al. (2015) studied the problem of collective mine disarmament, where several mines exist in an previously unknown scenario, and each mine needs to be disarmed by several robots simultaneously. Therefore, once a robot finds a mine to be disarmed it will attract others based on the FA principles. Palmieri and Marano (2016) studies a similar problem and proposes a Discrete Firefly Algorithm (DFA) for robots moving in a grid domain. More recently, the work by Zedadra et al. (2019) describes a Lévy Walk and Firefly Algorithm (LFFA) to tackle the Forage & Collection problem, where sparsely distributed rewards need to be collected by several robots in order to be returned to the base. Robots explore the domain executing a Lévy search and once rewards are found, attract their neighbours based on the FA principles. Finally, a contribution that is particular relevant to this Thesis is the approach proposed by Sutanty et al. (2013). In their work authors propose a method for Adaptive Foraging, that integrates an Adaptive Lévy model with a collective behaviour based on firefly attraction laws, named Lévy+. According to the Lévy+ model agents slow down as they enter a cluster of rewards, making it

Citation	Comments
Yang (2009)	Proposes the FA as an optimization method
Sutantyo et al. (2013)	One of the first to transpose the FA to a robotics problem namely collective foraging
De Rango et al. (2015)	Applied the FA to collective mine disarmament employing a robotic swarm
Zedadra et al. (2019)	Proposes the LFFA to tackle collaborative foraging and transport of uniformly distributed rewards

Table 2.2: List of relevant citations regarding the principles and applications of the Firefly Algorithm (FA).

more likely to finish their walk within a cluster, and attract other agents in the neighbourhood depending on the frequency with which they find new rewards. The Lévy+ model constitutes one important benchmark for our work, and therefore it is one of the models that we describe more detail in Section 2.5. A non-exhaustive list of the most relevant works in robotics that applied the principles of FA is given in Table 2.2.

2.3 Artificial Endocrine Systems

In the previous section it was established that observed behaviours that fit the Lévy Walk pattern may exist as a consequence of the interaction of a forager with its environment. It is clear then, that it is of paramount importance to address what structures can, effectively and robustly, model the change in behaviour and therefore improved foraging efficiency. An example of such was purposed by Nurzaman et al. (2010), where a model based on the concept of biologically fluctuation through the Langevin equation is derived. Following the argument of *Lévy Process* versus *Lévy Pattern* Nurzaman corroborates previous results, namely the ones from Benhamou (2007); Gautestad and Mysterud (2013); Plank and James (2008) in showing that a Lévy Pattern can occur without the existence of an underlying and explicit Lévy Process. On the topic of adaptation, a key component that biologists have identified to be intrinsically linked with behavioural adaption is the endocrine system (McEwen, 2012).

A remarkable structure of the endocrine system is the pituitary gland, present in all vertebrates, which serves as a central point for *feedback* between the neural and

endocrine systems, effectively regulating hormone production (Schreibman, 1986; Scully and Rosenfeld, 2002; Widmaier et al., 2008). For an illustrative reference, Figure 2.6 shows the location of the pituitary gland within the human brain structure.

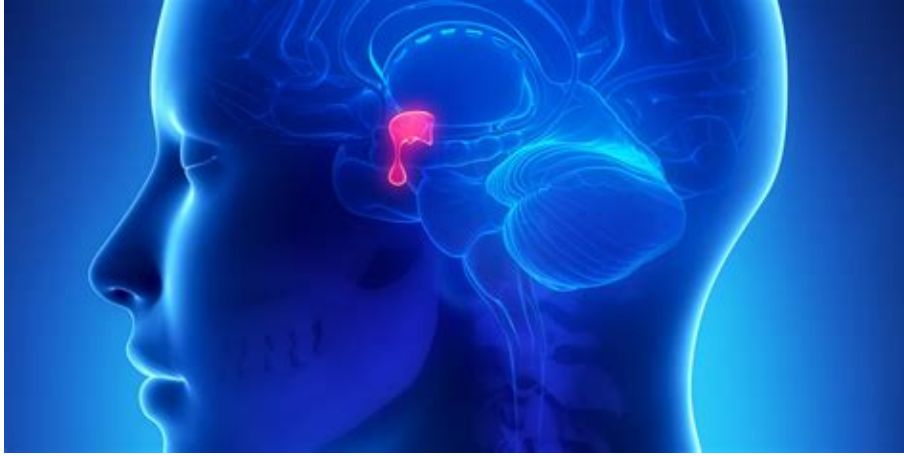


Figure 2.6: Location of the pituitary gland in the human endocrine-neural system ¹

Even though it is not the purpose of this Thesis to create realistic models of the pituitary gland, it is however important to highlight its importance within natural endocrine systems, and the longstanding understanding that hormone regulation is intimately linked to animal behaviour (Clotfelter et al., 2004).

Since it is also well established that Lévy patterns arise from interactions between foragers and their surrounding environment this Thesis sets out to propose a model through which these interactions may be modelled in a novel manner through an Artificial Endocrine Systems (AES), effectively creating an adaptive Lévy Walk model.

A first instance of an AES was proposed by Timmis and Neal (2003) that together with an Artificial Neural Network showed how an artificial agent could display behaviours which could be classified as “emotive”, namely by approaching unknown objects in the test environment more carefully, or retreating more expeditiously. Shortly thereafter a more comprehensive overview was presented on how the natural endocrine, neural and immune systems interact to achieve the so-called “homeostatic” behaviour (Neal and Timmis, 2005). In fact this shows how the concept of AES exists as a subset of a broader discipline studying artificial homeostasis similarly

¹Image publicly available at hormone.org

defined by several authors as “*the ability of an organism to achieve a steady state of internal body function in a varying environment*” (Besedovsky and del Rey, 1996; deFur, 2004; Varela et al., 1988). Having this ability to adjust internal variables depending on sensory input, aligns neatly with the definition of adaptive behaviour by Ashby (1960), and is crucial to the development of artificial adaptive systems. In the context of an artificial forager one may interpret this *varying environment* from the agent’s perspective as it is stimulated when entering and exploring a cluster of rewards.

More recently, models that focused exclusively on modulating hormone variation have been able to tackle tasks such as simple obstacle avoidance through an evolved AES (Stradner et al., 2009), or more complex ones such as competing behaviours in foraging namely: collision avoidance, search and recharge (Wilson et al., 2018). The model proposed by Stradner et al. (2009), and lately applied by Wilson et al. (2018) captures the variation of a given hormone level over time according to the following expression:

$$H(t) = c_0 + c_1H(t-1) + c_2S(t) \quad (2.8)$$

where $H(t)$ is the level of hormone H at time t c_0, c_1, c_2 are constant coefficients, $H(t-1)$ represents the previous hormone level and $S(t)$ is the stimulus received from sensory input. The first term, c_0 , represents a base increment simulating a default and constant hormone production, the second term $c_1H(t-1)$ acts as decay over time, and $c_2S(t)$ represents the contribution from the sensory stimulus to the overall level of $H(t)$. Furthermore, Wilson et al. (2018) also highlights that one could calculate the settling point of $H(t)$, when no stimulus is received (2.9) as

$$H_s = c_0/(1 - c_1) \quad (2.9)$$

In their work, Stradner et al. (2009) employed evolutionary computation to tackle the problem of obstacle avoidance in single robot systems as a test of the capabilities of an AES. Vargas et al. (2005a) also drew inspiration from the concepts put forth

Citation	Comments
Ashby (1960)	Establishes the principles to describe a behaviour as adaptive
Schreibman (1986)	Highlights changes in animal behaviour as a consequence of hormonal regulation
Timmis and Neal (2003)	Proposes an AES to modulate the parameters of an Artificial Neural Network.
Neal and Timmis (2005)	Reviews the shared influence of the immune, neural and endocrine systems in animal behaviour
Stradner et al. (2009)	Proposes fluctuation model to describe artificial hormones in robots for collision avoidance
Wilson et al. (2018)	Expands Strander's work to model the transition between different behaviours namely: collision avoidance, search and homing

Table 2.3: List of relevant citations regarding the principles and applications of the Firefly Algorithm (FA).

by Neal and Timmis (2005) to proposed an AES for obstacle avoidance and phototaxis for a single robot. However, for the sake of completeness, one should observe that not only AES can be viewed as homeostatic. Neal and Timmis (2005) highlight that in complex biological systems, homeostasis is achieved by the interactions of the endocrine, neural and immune systems. In fact, some works have embraced this overarching view of homeostasis. Moiola et al. (2009) and Vargas et al. (2009) propose an Evolutionary Artificial Homeostatic System (EAHS) to manage conflicting behaviours, where the AES modulates the the behaviour of a neural controller, to achieve obstacle avoidance, phototaxis and line-following. Nevertheless we should note that in the field swarm robotics Wilson's work is, to the best of our knowledge, one of the latest works to employ AES in the context of collective foraging tasks. The most relevant works to this Thesis, in what concerns Artificial Endocrine Systems is presented in Table 2.3.

2.4 Evolutionary Robotics

In the previous sections of this chapter it became apparent that many approaches to the design of controllers in the context of autonomous robots, rely on a strong natural inspiration. As it has been proposed by many roboticists, a path to achieve an emulation of natural behaviours in robots is also to mimic Nature's ability to

evolve such behaviours (Nolfi et al., 2016; Nolfi and Floreano, 2000).

Inspired by Darwinian theory of evolution and *survival of the fittest* concept, a first family of algorithms developed for such a purpose, known as *genetic algorithm* (GA), was developed by Holland (1975). In typical implementations, these algorithms operate on randomly generated *genotypes* constituted by vectors of binary values, select the reproducing genotypes (or parents) stochastically with a probability proportional to their performance in a given environment (*fitness*), and generate variations through recombination and mutation. Recombination, or crossover, is usually realized by dividing the genotype of two reproducing individuals in k parts and by pasting (crossing over) some of the parts copied from the first genotype with the complementary parts copied from the second genotype (k -point crossover). Alternatively, crossover can also be achieved by randomly selecting each entry of the genotype from either parent with equally probability, and do so for every such entry, in which case, is referred to as *uniform crossover* (Pereira et al., 2005). Mutations are usually realized by flipping each bit with a low probability, e.g. 1%. New generations are formed by offspring of these reproducing parents. Eventually, a non-varied copy of the best genotype of the previous generation can be included in the new generation (elitism). A second family of algorithm known as evolutionary strategies was developed by Rechenberg (1978) and Schwefel (1981, 1993). In typical implementations, these algorithms operate on genotypes formed by vectors of real coded numbers and generates mutations by perturbing the numbers with small randomly generated values. Crossover in this case can be implemented by picking a random value for each entry of the genotype, in between the values of each parent in that same position, a method named *arithmetic crossover* (Herrera et al., 2003). The most common crossover operators are depicted below in Figure 2.7.

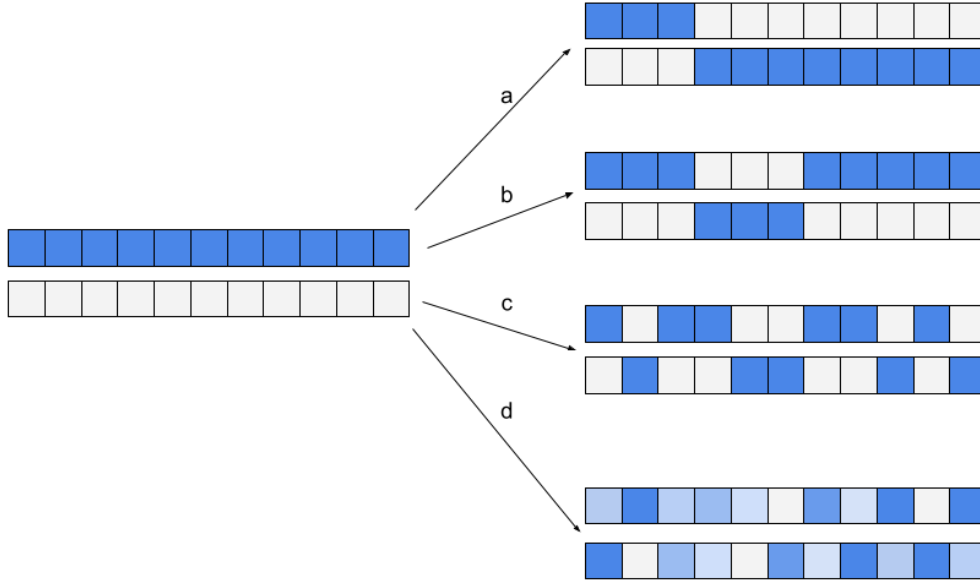


Figure 2.7: Crossover operators: a) 1-point crossover; b) 2-point crossover; c) Uniform crossover; d) Arithmetic Crossover

With the above principles in mind, simulating natural evolution for robot behaviour consists on creating an artificial population of genotypes that encode the robot behaviour, or *phenotype*, deploying them in a simulated environment for evaluation through a *fitness function*, and iteratively applying the genetic operators of selection, crossover and mutation.

The evolutionary robotics (ER) approach has in fact proven its feasibility to generate a series of behaviours from obstacle avoidance (Jakobi et al., 1995) to phototaxis (Francesca et al., 2014; Watson et al., 2002), to both behaviours in a single robot (Vargas et al., 2005a) and even bipedal locomotion in humanoid robots (Eaton, 2015). Also in the swarm robotics domain, the concept of evolution has been employed to perform a variety of behaviours (Trianni, 2008) such as self-assembly Mondada et al. (2002), path following (Sperati et al., 2011), aggregation (Gauci, Chen, Dodd and Groß, 2014; Gauci, Chen, Li, Dodd and Groß, 2014) or information gathering (Khaluf and Simoens, 2019).

In this Thesis a Real-Coded Genetic Algorithm (RCGA) is employed in Chapter 4 to evolve the parameters of the proposed model for adaptive foraging. Similarly

Citation	Comments
Holland (1975)	Seminal work introducing the principles of Genetic Algorithms
Herrera et al. (2003)	Taxonomy study on crossover operators
Nolfi (2021)	Recent compendium of evolutionary-based methods applied to behaviour-based robotics

Table 2.4: List of relevant citations regarding the principles of evolutionary robotics.

to the previous sections, Table 2.4, presents a list of the most relevant literature regarding the concepts of Evolutionary Robotics employed over the course of this Thesis.

2.5 Swarm Robotics

As it was briefly discussed in section 2.2, synthesizing decentralized controllers, for groups of autonomous artificial agents, has long drawn inspiration from interactions observed in the natural world (Bayındır, 2016; Brambilla et al., 2013; Şahin et al., 2008).

One of the earlier examples of how empirical rules observed in the animal kingdom can be derived to successfully coordinate a group of agents was established by Reynolds (1987) when the rules for *flocking* were purposed, which can be summarized as follows:

- Collision Avoidance - A minimum distance is maintained between an individual and others in its neighbourhood
- Velocity Alignment - The velocity of an individual is aligned with those of agents in its neighbourhood
- Flock Cohesion - The velocity of an individual is also weighted towards the geometric centre formed by its neighbours positions.

Reynolds' flocking model has indeed become a seminal work, and over the past three decades has been a constant inspiration for several studies and tools, spanning from optimization, where the Particle Swarm Optimization (Eberhart and Kennedy, 1995) is the most notable example, to philosophical enquiry on consciousness (Chalmers, 1996), and naturally becoming an unavoidable reference in robotics (Dudek and Jenkin, 2010). To this day Reynolds' work continues to be a major

reference in various studies in the field of robotics pertaining to, for example, aerial traffic management of autonomous drones (Balázs and Vásárhelyi, 2018), multi-robot navigation (Asiain and Godoy, 2020) or underwater coordination (Berlinger et al., 2021). However, despite the flocking of birds being Reynold’s major inspiration, other behaviours, such as the foraging of ant colonies or the aforementioned swarms of fireflies have also inspired collaborative strategies for multi-robot interaction, coordination and cooperation, examples of which are depicted in Figure 2.8.



(a) Flock of birds ²



(b) School of fish³



(c) Colony of ants⁴



(d) Swarm of fireflies⁵

Figure 2.8: Examples of collective behaviours in Nature

By emulating the behaviour of other natural decentralized systems such as cellular structures (Beni and Wang, 1993) or social insects (Şahin, 2004), biologically inspired control techniques have provided reliable approaches to standing challenges in swarm robotics such as: collaborative transport (Kube and Bonabeau, 2000); mapping of hazardous environments (Cui et al., 2004); task allocation (Brutschy et al., 2014), self-assembly (O’Grady et al., 2009) or even astrophysical studies (Macktoobian et al., 2021). As it will be discussed in the next subsection, making the transition from idealized emulators of natural societies into the embodied world of robotics, is often an arduous task, which presents its own challenges mainly

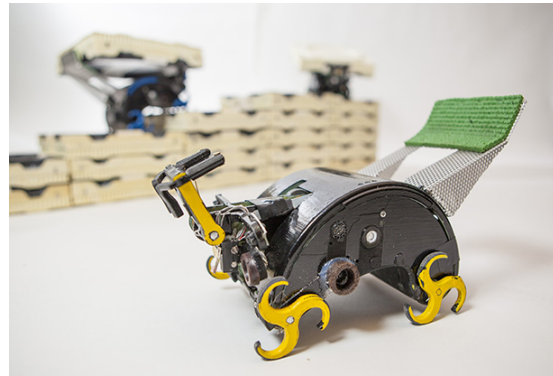
relating to the large-scale production of simple, cheap and yet reliable robots that can be employed to tackle the desired application.

2.5.1 Development platforms

Indeed, despite the envisioned applicability of biologically inspired controllers to tackle complex tasks in a decentralized manner, a large effort still resides in the development of robotic platforms onto which these controllers can be deployed, making the journey from theory to simulation and finally to a robust deployment a quite complex and time consuming one (Jiménez-González et al., 2013). Examples of such successes include the Termes project for Harvard University (Werfel et al., 2014) where a decentralized controller for collaborative construction was developed based on the behaviour of termites, and the seaswarm project from MIT (2010) to clean oil spills, whose platforms are depicted in Figure 2.9.



(a) Seaswarm robot - slides through the water surface using strap inspired by conveyor belts made of an oil-absorbent material ⁶



(b) Termes robot - capable of lifting, carrying and stacking 3D-printed tiles and build complex structures (Werfel et al., 2014).

Figure 2.9: Example of platforms created for collective oil-spill cleaning and construction

One common characteristic that several swarm robotics approaches share is that these swarms are *homogeneous*, i.e., every agent in the swarm is identical in terms of computing power, sensing, actuation and behaviour. However, this does not

²Image publicly available at Fox-actors blogspot

³Image publicly available at European Economic Area natural capital report

⁴Image publicly available at Zerone Magazine

⁵Image publicly available at National Geographic Photo of the Day

⁶Image publicly available at MIT

need to be the case as it was demonstrated in the Swarmanoid heterogeneous swarm project (Dorigo et al., 2013). Robots belonging to the swarmanoid depicted in Figure 2.10, were designed to perform different functions: the foot robot - able to navigate autonomously in the ground plane; the hand robot, that is carried collectively by multiple foot robots and is capable of reaching objects above ground floor by using its grippers to climb; and the eye robot capable of flight like a regular drone, and attaching itself to the ceiling and transmitting information to the robots on the ground.

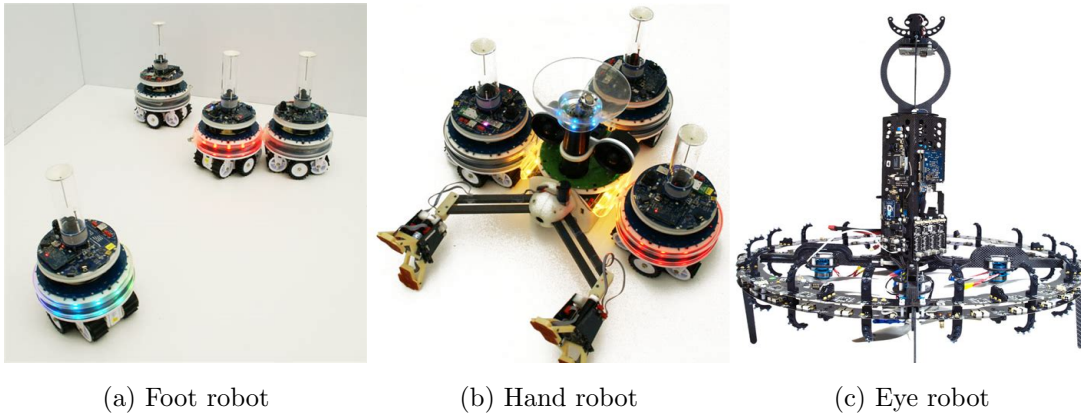


Figure 2.10: Swarmanoid Robots (available video at <http://www.swarmanoid.org/>)

The increased interest from the research community in swarm robotics, has spawned the commercialization of small and accessible robotic platforms for swarm experiments. A notable example of such is the e-puck robot (Figure 2.11a), equipped with distance sensors for collision avoidance, a small forward-facing camera, accelerometer, loudspeaker, a microphone and extension boards for wireless communication. Another, and more recent example, is the Crazyflie drone by Bitcraze (Figure 2.11b).

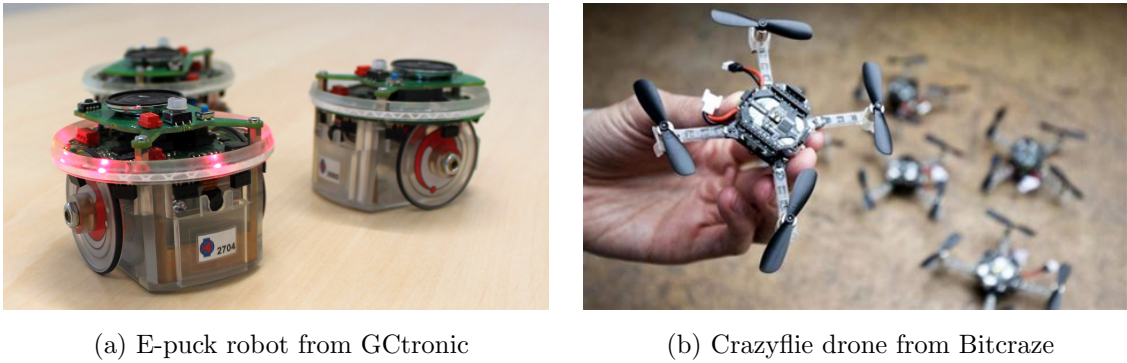
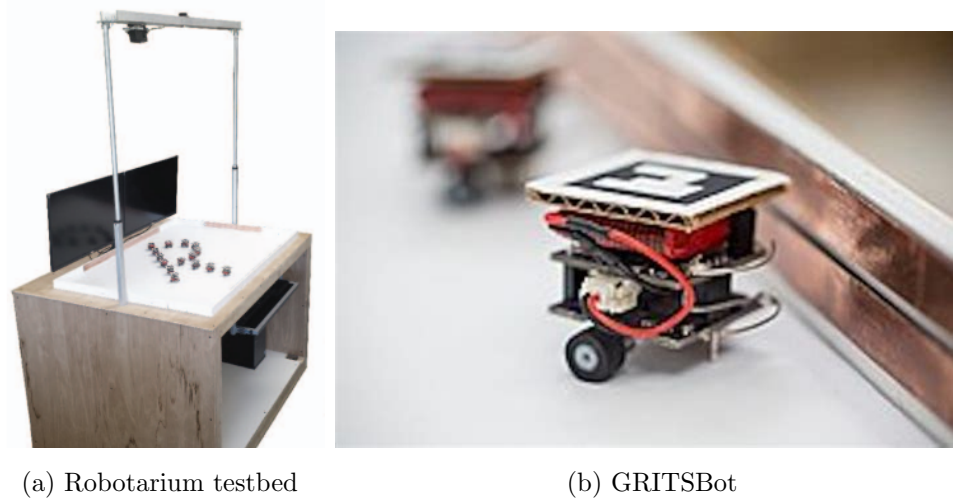


Figure 2.11: Examples of commercially available swarm robotics platforms

The Crazyflie is quite a versatile platform that through its various extension boards can be configured to suit the needs of the user. Apart from the on-board radio for communication, gyroscope, accelerometer and controller it can be upgraded to carry a distance sensor and optical flow sensor for ground referencing, camera and LED ring. Moreover, its firmware is designed for seamless integration with motion capture systems for increased stability.

Despite the great progress that has been made in achieving commercial solutions for swarm robotics research work, acquiring large numbers of such systems might still be prohibitive. Due to this increasing interest in the field of swarm robotics, others have purposed a different approach to the dissemination of swarm robotics research by creating a state-of-the-art multi-robot test facility, i.e., the Robotarium (Pickem et al., 2017). Accessing this platform one is able to deploy their developed applications remotely and test using the GRITSBot (Pickem et al., 2015), which is then tracked by an overhead tracking system, and is able to navigate towards wireless charging points when need.



(a) Robotarium testbed

(b) GRITSBot

Figure 2.12: Robotarium: a testbed for development in swarm robotics (Pickem et al., 2015)

Despite the small footprint of the Robotarium platform, limiting the size of the swarm, access to remote testbeds has the potential to significantly democratize the development of swarm robotics as a field, as more researchers access these testbeds and lower the unitary cost of their usage.

Besides the existence of suitable platforms that allow for the efficiency of swarm-based control strategies to be demonstrated, the applicability of such strategies still depends strongly on the problem one wishes to address. In the remaining of this Chapter, two problems are highlighted where swarm-based strategies have proven to be an effective approach.

2.5.2 Applications of Lévy Walks in Swarm Robotics

Over this chapter several swarm robotics applications were mentioned in order to highlight the applicability to real-world problems of decentralized, robust and scalable approaches as well as what such approaches may deliver in the future. This Thesis will focus on two such tasks more precisely where the inherent exploratory capabilities of LWs are envisioned to be advantageous.

Cooperative Surveillance

Several swarm robotics 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

(Couceiro et al., 2014). This is particularly true in surveillance and monitoring tasks in a variety of domains, such as: inspection (Artaxo et al., 2017; Saska et al., 2014), search & rescue (Couceiro et al., 2014; Din et al., 2018), and agriculture (Albani et al., 2017; Costa, Ueyama, Braun, Pessin, Osório and Vargas, 2012; Faïçal et al., 2014).

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, due to their intrinsic ability to gather data over a wide field of the ground plane, for example, through a down facing camera (Chung et al., 2018). However, as their distance to the ground increases, the resolution of observations decreases (Albani et al., 2018). Furthermore, the accuracy of these observations is also affected by the noisy characteristics inherent to any sensor leading to inaccuracies (Petrлік et al., 2019). These factors have led researchers to propose that several simultaneous observations of the same point would yield a more accurate measurement (Petrлік et al., 2019; Yu et al., 2017). 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 2.13 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 (Zam et al., 2019).

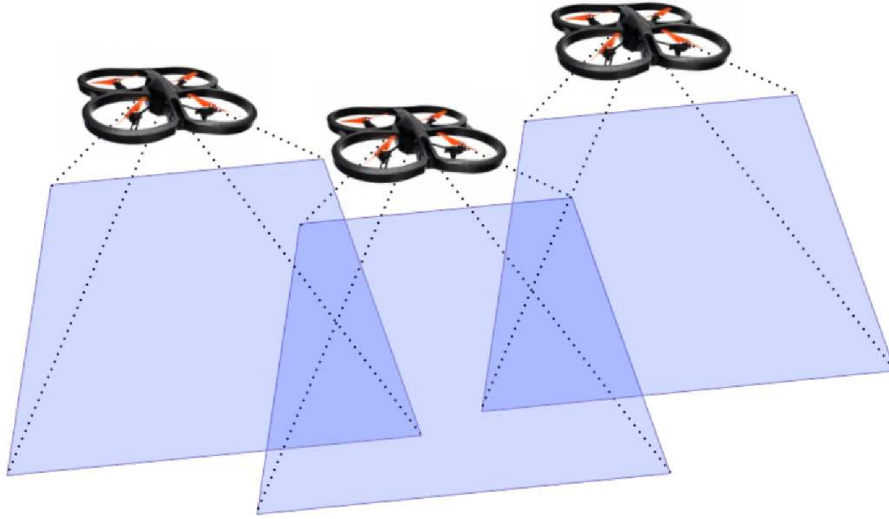


Figure 2.13: Fields of view for 3 aerial vehicles, where the darker shades represent the areas sensed simultaneously by more than one UAV.

Works on surveillance, have 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 (Nigam et al., 2011). Other works developed model-based strategies to determine feasible trajectories in real time while also considering detailed sensing models (Keller et al., 2016), or considering the task routing problem with a set of predefined locations that need to be visited (Michael et al., 2011). More recently authors also applied the flocking strategy proposed by Reynolds to address coordination (Li, 2015), 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. Cooperative surveillance has also been studied in an underwater scenario using LWs (Keeter et al., 2012). However, contrary to what will be assumed in the course of this Thesis, authors consider a scenario where regions of the environment are divided and each robot explores its own assigned region. Suarez and Murphy (2011) have also suggested 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 of the mission, and might even change over time, making it difficult to subdivide an environment without prior knowledge.

Another approach to surveillance, this time using aerial swarms, was proposed

by Saska et al. (2014). 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. This work also highlights the benefits of having multiple simultaneous observations of the same area of the domain and stresses the importance of this feature to measurement accuracy of perceived phenomena.

Interestingly, the topic of overlapping sensing regions has been given more attention in the field of Wireless Sensing Networks (WSNs) (Costa, Ueyama, Braun, Pessin, Osório and Vargas, 2012; Faïçal et al., 2014). However, works in this field tend to 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 (Elhoseny et al., 2017). Approaches to k -coverage using robots mainly focus on: optimizing the number of robots to be deployed for the desired coverage constraints (Kumar et al., 2004); optimizing energy efficiency (Elhoseny et al., 2018), or optimizing network connectivity (Khoufi et al., 2017), which tend to require prior knowledge of the set of areas of interest. The concept of k -coverage is of significant relevance to this Thesis, and will be further addressed in Chapter 3, where a novel LW-based model for cooperative surveillance is proposed.

Cooperative Adaptive Foraging

The second application where this Thesis proposes a LW-based model is collective adaptive foraging. However, a distinction ought to be made between two types of tasks, which despite their differences, are often referred to in the literature as *foraging*. The first, is concerned with the discovery of rewards in an unknown environment, and their transport back to a central base or *nest*, known as Central Place Foraging (CPF) (Olsson and Bolin, 2014). Typically, to tackle this task, researchers focus on the use of Finite State Machines (FSMs), whose states describe some predefined behaviours such as (but not limited to): exploration, collision avoidance and homing. In these works the focus is on how to tune the transition between states so

that some measure of efficiency is optimized (Castello et al., 2016). In this Thesis this problem will be referred to as Foraging and Collection (FC). The second task, and the one this Thesis aims to tackle, focuses on scenarios where rewards need to be discovered but cannot be collected, such as the aerial weed mapping in agricultural settings. In such scenarios, researchers focus mainly on designing search strategies that will efficiently maximize the number of rewards found, specially when they might be clustered together in patches. Here we will refer to this task as Adaptive Foraging (AF), and present two separate approaches that will be used to benchmark our model described in Chapter 5, namely those proposed by Sutantyo et al. (2013) and Nauta et al. (2020), both of which proposed adaptive versions of the LW model. As it is described by Algorithm 2, synthesising a LW for the i agent can be achieved by computing a combination of linear and angular velocities such as:

$$\vec{\mathbf{u}} = [v, w]^T = [v_x, 0, 0, 0, 0, \omega_z]^T \quad (2.10)$$

Nevertheless, in a swarm of robots, collision avoidance must also be taken into consideration. Throughout this Thesis, and across methods we will employ the following method.

We consider each agent, i , computes an angular velocity for collision avoidance by considering the positions \mathbf{p} of j agents which are within a collision avoidance radius δ_c and define a set of such agents as:

$$\mathcal{A}_i = \{j : \|\mathbf{p}_j - \mathbf{p}_i\| < \delta_c, \forall j \neq i\} \quad (2.11)$$

Having \mathcal{A} we compute the geometric centre formed by the positions of its members using (2.12), where n_j is the number of j agents in set \mathcal{A}_i .

$$\bar{\mathbf{p}}_j = \frac{1}{n_j} \sum_{\forall j \in \mathcal{A}_i} \mathbf{p}_j \quad (2.12)$$

Knowing $\bar{\mathbf{p}}_j$, computed in the fixed global frame O , we derive its value with respect

to the local frame of agent i by using (2.13), where $\mathbf{R}^{O \rightarrow i}$ represents the rotation matrix from the fixed frame O to the i^{th} local frame.

$$\bar{\mathbf{p}}_j^{(i)} = \mathbf{R}^{O \rightarrow i}(\mathbf{p}_j - \mathbf{p}_i) \quad (2.13)$$

Consequently we can extract the relative orientation of $\bar{\mathbf{p}}_j^{(i)}$ with respect to the i^{th} frame, $\theta^{(i)}$, through (2.14), where atan2 is the numeric arc-tangent function, where $\bar{\mathbf{p}}_{jy}^{(i)}$ and $\bar{\mathbf{p}}_{jx}^{(i)}$ are respectively the x and y components of $\bar{\mathbf{p}}_j^{(i)}$.

$$\theta^{(i)} = \text{atan2}(\bar{\mathbf{p}}_{jy}^{(i)}, \bar{\mathbf{p}}_{jx}^{(i)}) \quad (2.14)$$

Since this angle represents the direction *towards* $\bar{\mathbf{p}}_j^{(i)}$ the subsequent angular velocity command, needs to be such that the agent i moves *away* from this position. We compute it using (2.15), where ω_c^i represents the contribution of the collision avoidance mechanism to the angular velocity of agent i , and K is a simple proportional gain. We can then define the velocity command component from the collision avoidance mechanism for agent i , in (2.16).

$$\omega_c^i = K \times (\theta' - \pi) \quad (2.15)$$

$$\vec{\mathbf{u}}_c^i = [v, \omega_c^i]^T \quad (2.16)$$

In summary the output velocity command, $\vec{\mathbf{u}}^i$, for every agent i becomes a conditional value, subject to the conditions of the generic LW controller, and collision avoidance. Therefore the velocity command in the simplest scenario where individual agents perform LW and collision avoidance is defined by (2.17).

$$\vec{\mathbf{u}}_0^i = \begin{cases} \vec{\mathbf{u}}_c^i, & \mathcal{A}_i \neq \emptyset \\ \vec{\mathbf{u}}^i, & \text{otherwise} \end{cases} \quad (2.17)$$

Even though this combination of Lévy Walks has been employed to the foraging problem by Sutanty et al. (2010), it still lacks adaptation components, that empower agents to seamlessly change their behaviour when environmental conditions change. In the remaining of this section, two strategies to achieve such an adaptive behaviour are reviewed.

Adaptive Collaborative Lévy Walk model

The Adaptive Collaborative Lévy Walk model (ACLW) proposed by Nauta *et al.* Nauta et al. (2020) stems from the intuition that, in a swarm of robots where each individual performs LWs and collision avoidance, long walks that allow for a ballistic relocation, are cut short by collision avoidance mechanisms as these become more frequent with larger swarm sizes. To address this issue Nauta defines a threshold, \bar{L} , above which the generated walk lengths L are considered to be “*long walks*”. One of the purposes of the ACLW is therefore to steer agents away from those who are performing a so called “*long walks*” while these maintain their direction. Figure 2.14 shows how this behaviour compares to the generic collision avoidance mechanism, where δ_r stands for the communication range and $\delta_r > \delta_c$. To formalize it in terms of the velocity command control, we start by defining set \mathcal{S} , consisting of k agents within communication range of the i^{th} agent, whose current walk L is larger than \bar{L} :

$$\mathcal{S}_i = \{k : \|\mathbf{p}_k - \mathbf{p}_i\| < \delta_r \wedge L_k > \bar{L}, \forall k \neq i\} \quad (2.18)$$

Knowing \mathcal{S} we employ (2.12)-(2.15) to calculate an angular velocity ω_a^i , and can establish the velocity command control as:

$$\vec{\mathbf{u}}_a^i = [v, \omega_a^i]^T \quad (2.19)$$

By introducing this additional avoidance component, Nauta et al. (2020) allow agents to still perform long relocations across the domain, increasing the foraging efficiency of the swarm. Moreover they have shown that the collection of all walks performed by the agents in the swarm follow a power law of the type of eq. (2.1), as opposed to when only collision avoidance is present, in which case long walks are truncated upon collision avoidance, and the actual pattern of executed walks resemble those of a local search.

However, this mechanism is not the only novelty proposed by the ACLW. Authors also consider an adaptation mechanism of the parameter μ . This adaptation mechanism reflects the need for agents to switch from Lévy search to local search when entering a cluster of rewards. In their work, authors assume that when a reward is found other rewards will be nearby due to the cluster-based configuration of the environment.

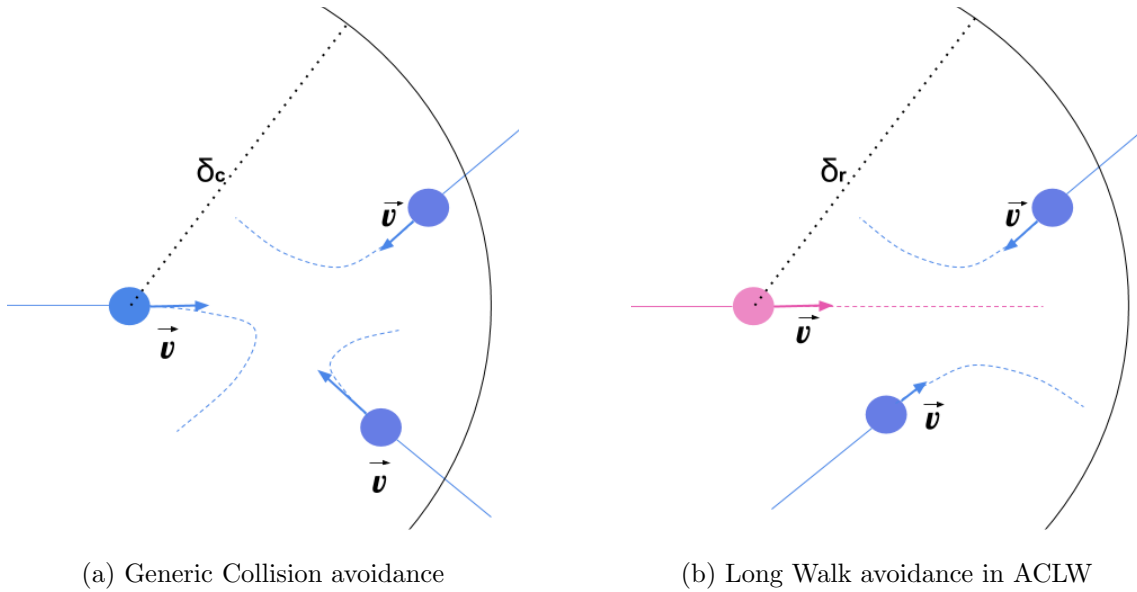


Figure 2.14: Different concepts of avoidance in ACLW

Since Brownian motion is optimal in the presence of high density of targets (Bartumeus et al., 2002; Wang et al., 2009), the value of μ changes when entering a patch, from its initial value ($\mu = 2$) to 3, and decreases over time if no rewards are found. Nauta *et al.* model this decrease by using the complementary error function,

$\text{erfc}(x)$, and define the value of μ at time t as:

$$\mu(t) = 1 + \max(1, \text{erfc}[\zeta(\delta t - C)]) \quad (2.20)$$

where ζ and C are constants ($\zeta = 0.04$, $C = 50$) and δt represents the time since the last reward detection, resulting in a function that is limited between 2 and 3 as depicted in Figure 2.15.

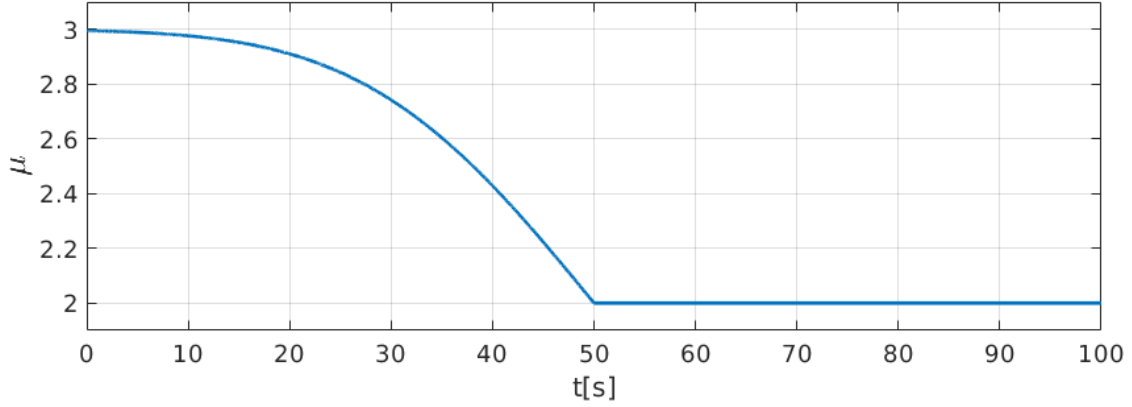


Figure 2.15: Decrease of μ in the ACLW

Consequently Algorithm 2 is updated to include an extra step, the variation of μ and is summarized below.

Algorithm 4: LW Controller with ACLW adaption of μ

```

Set  $\mu = 2$ ;   Generate tuple  $(\tau, l)$ ;   Set  $l = 0$ ;
if  $l \leq L$  then
     $\vec{u}_l = [v, 0]^T$ ;
    Compute current  $l$ ;
    Update  $\mu$  according to (2.20) ;           // Additional step
else
    Generate tuple  $(\tau, L)$ ;
    while  $|\theta - \tau| \geq \epsilon$  do
         $\vec{u}_l = [0, \omega]^T$ 
    end
    Set  $l = 0$ 
end

```

Finally the specific velocity command, resulting from the previous considerations is provided in (2.21).

$$\vec{\mathbf{u}}_{aclw}^i = \begin{cases} \vec{\mathbf{u}}_a^i, & \mathcal{S}_i \neq \emptyset \\ \vec{\mathbf{u}}_0^i, & \text{otherwise} \end{cases} \quad (2.21)$$

We should note that Nauta *et al.* do not make any considerations about truncating flights as rewards are discovered. One assumes that upon the discovery of such rewards only μ is updated, and when the current walk is completed the subsequent walk is generated considering the value of μ at such a time. In fact, this seems to be a more sensible approach than simply truncating a walk upon discovery of one reward. Doing so could lead to a local search starting at the edge of the clusters where the portion of empty space would increase δt and trigger the motion back to Lévy search. However, since the ACLW adaptation does not guarantee that walks are finished within a cluster, it is possible for some agent, executing a long walk, to transverse an entire cluster without actually switching to a local search.

Lévy+ model

Another work that proposes a method for adaptive LWs in the context of collective adaptive foraging is presented by Sutantyo et al. (2013). In this work, authors have considered that agents performing LWs and collision avoidance, are also attracted to others within their communication range, thus mimicking the FA in an embodied swarm. This implies that for each agent there will be an extra contribution to the angular velocity. To compute such contribution we start by defining the set \mathcal{B} containing the agents within the communication range δ_r that have a brightness β larger than the i^{th} the agent's own brightness β_0 .

$$\mathcal{B}_i = \{k : \|\mathbf{p}_k - \mathbf{p}_i\| < \delta_r \wedge \beta_k > \beta_0, \forall k \neq i\} \quad (2.22)$$

From set \mathcal{B} we select the member k with the highest brightness and use its position, $\hat{\mathbf{p}}$, to compute a angular velocity using a similar approach to collision

avoidance, only this time the agent i will be rotating *towards* agent k , such as depicted in Figure 2.16.

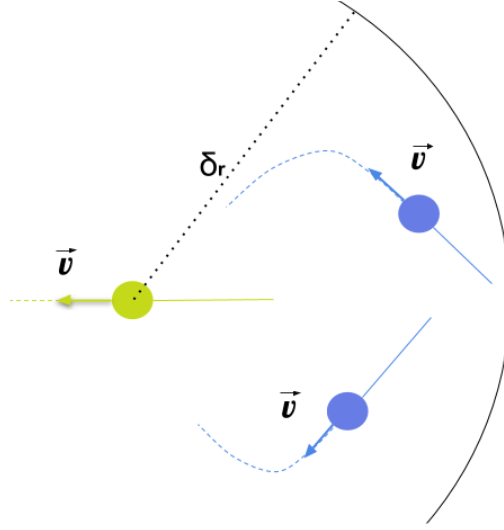


Figure 2.16: Depiction of the firefly attraction behaviour.

Knowing $\hat{\mathbf{p}}$, and employing (2.13)-(2.14), we compute its relative position to agent i , extract the relative direction $\hat{\theta}$, and compute the angular velocity component of the Lévy+ as:

$$\omega_+ = K \cdot \hat{\theta} \quad (2.23)$$

To calculate β_0 , Sutantyo *et al.* consider that attractiveness is measured as the frequency of reward detection and decays linearly (with gradient m) when rewards are not found (2.24).

$$\beta_0(t) = \begin{cases} \delta t^{-1} & , f > 0 \\ \min(0, \beta_0(t-1) - m) & , f = 0 \end{cases} \quad (2.24)$$

Furthermore, rather than updating the μ parameter in order to modulate the length of walks according to reward density, authors propose to decrease the agent's forward velocity (v_x) when entering a patch. The velocity update can be described by (2.25), where $\underline{v_x}$ and $\overline{v_x}$ represent respectively the minimum and maximum admissible values of v_x . One can see that as $\Delta\beta_0$ is a positive value, i.e., brightness is increasing, then the $v_x(t)$ will decrease until it is cutoff by the *max* function not allow-

ing it to be lower than the minimum value. In a similar fashion, if $\Delta\beta_0$ is negative, i.e., brightness is decreasing, the computed value within the *min* function increases, this time being cutoff at the value of $\overline{v_x}$. Dividing the value of $\Delta\beta_0$ by β_0 maintains dimensional consistency.

$$v_x(t) = \begin{cases} \max\left(\frac{v_x}{\beta_0}, \min\left(v_x(t-1) - \frac{\Delta\beta_0}{\beta_0}v_x(t-1), \overline{v_x}\right)\right) & , \beta_0 \neq 0 \\ \overline{v_x} & , \beta_0 = 0 \end{cases} \quad (2.25)$$

This change in velocity is coupled with another design strategy by Sutantyo *et al.*, where the Lévy variable employed does not signify a target distance L but instead represents the time \bar{t} that an agent will move in an uniformly generated direction τ . These steps are taken while maintaining a constant value of $\mu = 2$.

By slowing down agents as they enter clusters, since time is linear, there is an increased probability that a walk will be completed within the cluster. Since the velocities will be slower at this point, even if the value of μ used to generate \bar{t} is fixed, such a search will be more localized. Algorithm 5 describes this behaviour in every agent of the swarm.

Algorithm 5: LW Controller with Lévy+ adaption

```

Set  $\mu = 2$ ;   Generate tuple  $(\tau, \bar{t})$ ;   Set  $l = 0$ ;
if  $(t - t_0) \leq \bar{t}$  then
    |   Update  $\omega_+$  and  $\mathbf{v}_x(\mathbf{t})$  according to (2.23) and (2.25);
else
    |   Generate tuple  $(\tau, \bar{t})$ ;
    |   while  $|\theta - \tau| \geq \epsilon$  do
    |   |    $\vec{\mathbf{u}}_t = [0, \omega]^T$ ;
    |   end
    |   Set  $l = 0$ ;
end

```

We can now express the resulting Levy+ velocity update as :

$$\vec{\mathbf{u}}_+^i = \begin{cases} [v_x, 0, 0, 0, 0, \omega_+]^T, & \mathcal{B}_i \neq \emptyset \\ \vec{\mathbf{u}}_0^i, & \text{otherwise} \end{cases} \quad (2.26)$$

Citation	Comments
Reynolds (1987)	Seminal work introducing the concept and rules of flocking.
Beni and Wang (1993)	Coined the term <i>Swarm Intelligence</i> and advocates a nature-based approach to distributed control.
Michael et al. (2011)	Studies coverage in aerial swarms, depending on predefined regions of interest.
Dorigo et al. (2013)	Developed the swarmanoid project featuring a heterogeneous swarm leveraging a symbiotic approach between ground and aerial robotics.
Sutantyo et al. (2013)	Applies the principles of the FA and Lévy Walks to tackle collaborative foraging. Does not provide a mechanism to modulate the underlying Lévy process. Instead focuses on modulating speed depending on reward density.
Keeter et al. (2012)	Studies coverage based on individual Lévy process. Still relies on prior knowledge of the domain before deployment.
Yu et al. (2017)	Studies coverage in aerial multi-robot systems. Highlights the necessity of aerial agents to maintain overlapping sensing regions.
Nauta et al. (2020)	Studies collective foraging in clustered environments. Considers a social component based on collision avoidance in two levels. One based on immediate avoidance, and a second one based on the communication radius to allow agents performing long relocations to do so uninterrupted. Modulates the Lévy parameter based on the complementary error function.

Table 2.5: List of relevant citations regarding the principles and applications of Swarm Robotics.

where in the case there are no brighter neighbours, i.e., $\mathcal{B} = \emptyset$, the velocity command $\vec{\mathbf{u}}_0^i$ still considers the updated forward velocity v_x computed by eq.(2.25). Similarly to the summary tables that were presented in the previous sections, Table 2.5 summarizes the most relevant works for this thesis with respect to Swarm Robotics and its applications.

2.6 Summary

This Chapter introduced the main concepts which underlie the contributions made by this Thesis. It started by introducing the concept of Lévy Walks in detail, its most relevant mathematical and algorithmic aspects as well as the applications for the field of robotics in general.

Secondly it examined the mimicking of the social behaviour of fireflies, highlighting how this approach transitioned from an optimization algorithm to robotic control. Thirdly the development of Artificial Endocrine systems was also reviewed, detailing the generic mathematical formulation and most relevant works of its employment in the field of robotics.

Indeed, since most of the models discussed in this Chapter, and indeed proposed throughout this Thesis, are parametric models which require parameters to be selected, or optimised, evolutionary approaches to optimization were also discussed with particular focus on evolutionary robotics.

Lastly, a review of swarm robotics is presented. This review describes the field itself, detailing its inspirations from Nature, the more common platforms employed as well as the two main applications to which this Thesis contributes, as well as alternative models which will be used as benchmark.

In sum, by encompassing detailed information about several relevant aspects of this Thesis, this Chapter functions as theoretical anchor for the work presented in subsequent ones.

Chapter 3

A Lévy Swarm Algorithm for Cooperative Surveillance

This Chapter will follow-up on one of the main applications highlighted in Section 2.5.2 namely, cooperative surveillance, and in doing so answering the first research question, namely:

- Can Lévy Walk strategies be used to tackle cooperative surveillance?

As pointed out in Section 2.5.2 typical strategies to tackle cooperative surveillance have depended on prior knowledge of the domain (Keeter et al., 2012; Li, 2015; Suarez and Murphy, 2011) or centralized control strategies (Saska et al., 2014). Relaxing these constraints, especially prior knowledge, means that an exploratory component must be included in the model to ensure that a given domain is widely explored. In this regard, this Chapter will claim that the LW approach presents a suitable choice to achieve such an exploratory feature. Furthermore, the cooperative surveillance task also requires coordination among agents of the swarm so that multiple and simultaneous observations are achieved by agents in the swarm.

The detailed model for cooperative surveillance here presented, proposes an augmentation of the Reynolds' flocking model through the inclusion of a LW-based component. By integrating these two components our model exploits the synergy brought from two separate characteristics: the inherent coordination mechanisms of the Reynolds flocking model, and the exploratory behaviour of LW-based motions.

To define cooperative surveillance one should recall the benefit, and even the necessity, of maintaining overlapping sensing regions highlighted by Zam et al. (2019),

which is central to our approach. Therefore, the main goal of our model is to provide a reliable behaviour-based strategy which endows a swarm of drones to thoroughly explore a given domain. It builds on the LW properties, and is simultaneously able to maintain the observed regions of the domain under coverage by multiple drones. This Chapter is divided into three sections: Section 3.1 provides the formal description of our model is presented; Section 3.2 details the metrics used to assess the model, the setup of simulated and real experiments, as well as the characteristics of the robots deployed; Section 3.3 displays and evaluates the obtained results and finally Section 3.4 summarizes and discusses our findings.

3.1 Model Description

The model proposed in this Chapter rests on a behaviour based approach that merges two distinctive components: a swarm coordination based on Reynold's flocking rules, and a *Lévy Walk* based component, introducing the exploratory component. The output of our model is a velocity command, with both linear and angular components. Since the LW component of the model presented in this Chapter is based on Algorithm 1, at the end of each walk the agent re-orientates itself in place, and therefore the only suitable UAVs are rotary wing, which have the ability to hover while changing direction.

This coordination component, based on the model put forth by Reynolds (1987), consists of three rules: separation; cohesion; and alignment, as depicted below in Figure 3.1.

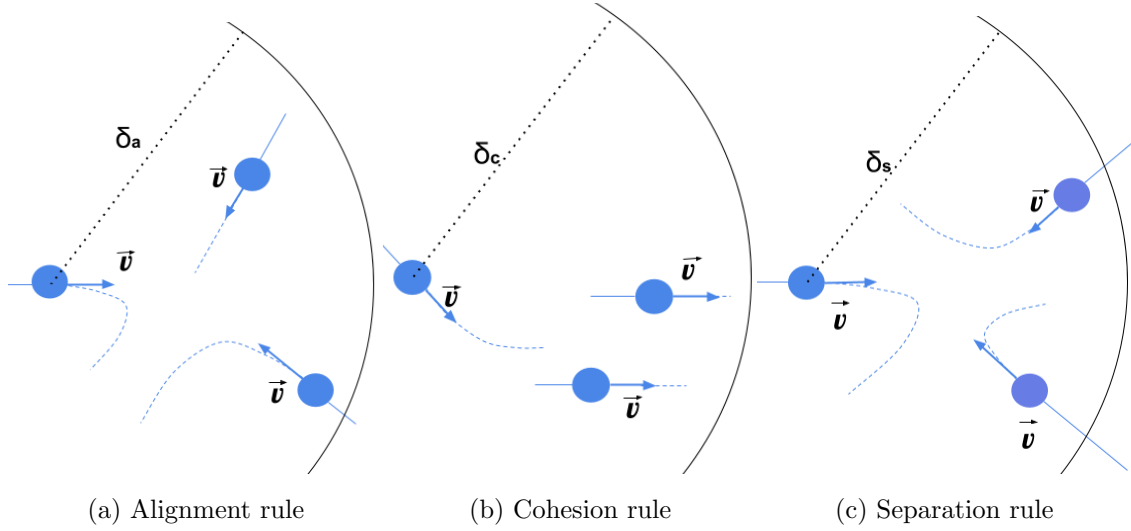


Figure 3.1: Depiction of the flocking rules proposed by Reynolds (1987)

Separation Rule: Introduces collision avoidance between agents, by being activated when agents are below a certain distance from each other. To compute this rule one considers the i^{th} robot, with a neighbourhood \mathbf{N}_s of all the j robots positioned at a distance smaller than δ_s whose positions \mathbf{p}_j have their centroid at \mathbf{P}_s defined as:

$$\mathbf{P}_s = \left(\sum_{j \in \mathbf{N}_s} \mathbf{p}_j / N_s \right) - \mathbf{p}_i \quad (3.1)$$

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:

$$\mathbf{w}_s = \iota_s \begin{bmatrix} 0 & 0 & w_s^z \end{bmatrix}^T = \iota_s \begin{bmatrix} 0 & 0 & (\rho_s^\theta + \pi) - \theta_i \end{bmatrix}^T \quad (3.2)$$

Where θ_i is the orientation of the i^{th} robot. Note that by adding π to the computation one considers this velocity command to *away* from the geometric center \mathbf{P}_s .

Cohesion Rule: Aims to maintain a maximum distance between agents, to maintain agents in each other's radius of communication. This rule is computed by con-

sidering 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:

$$\mathbf{P}_c = \left(\sum_{j \in \mathbf{N}_c} \mathbf{p}_j / N_c \right) - \mathbf{p}_i \quad (3.3)$$

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:

$$\mathbf{w}_c = \iota_c \begin{bmatrix} 0 & 0 & w_c^z \end{bmatrix}^T = \iota_c \begin{bmatrix} 0 & 0 & \rho_c^\theta - \theta_i \end{bmatrix}^T \quad (3.4)$$

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 velocity command that changes the agent's pose *towards* the geometric center \mathbf{P}_c .

Alignment Rule: Maintains consistent velocity directions between an agent and another agent in its vicinity. This rule is computed by considering the i^{th} robot, and the average heading Θ of the j robots in a neighbourhood \mathbf{N}_a within distance $\delta_a > \delta_s$.

$$\Theta = \sum_{j \in \mathbf{N}_a} \theta_j / N_a \quad (3.5)$$

where θ_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:

$$\mathbf{w}_a = \iota_a \begin{bmatrix} 0 & 0 & \omega_a^z \end{bmatrix}^T = \iota_a \begin{bmatrix} 0 & 0 & (\Theta - \theta_i) \end{bmatrix}^T \quad (3.6)$$

Therefore, the cooperation aspect of our model, for the i^{th} agent in the swarm, is given by eq (3.7), where ι_a , ι_c and ι_s are weights between 0 and 1:

$$\Phi_{\mathbf{i}} = \begin{bmatrix} \mathbf{v} \\ \mathbf{w}_s + \mathbf{w}_a + \mathbf{w}_c \end{bmatrix} = \begin{bmatrix} v_x & 0 & 0 & 0 & 0 & \iota_s \omega_s^z + \iota_c \omega_c^z + \iota_a \omega_a^z \end{bmatrix}^T \quad (3.7)$$

3.1.1 A Transition to a Lévy Component

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:

$$\mathbf{w}_1 = \eta \begin{bmatrix} 0 & 0 & \omega_l^z \end{bmatrix}^T = \begin{bmatrix} 0 & 0 & \eta(\psi - \theta) \end{bmatrix}^T \quad (3.8)$$

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 $\mathbf{v}_1 = [v_x, v_y, 0]$ with orientation $(\rho_s^\theta + \pi)$ and therefore the Lévy based contribution to a robot's velocity is given by eq(3.9). Table 3.1 summarizes the values fixed parameters used in the interaction component of our model, respectively.

$$\Lambda_{\mathbf{i}} = \begin{bmatrix} \mathbf{v}_1 & \mathbf{w}_1 \end{bmatrix}^T = \begin{bmatrix} v_x & v_y & 0 & 0 & 0 & \omega_l \end{bmatrix}^T \quad (3.9)$$

Table 3.1: Values of fixed parameters used in the interaction component.

$\delta_s[\text{m}]$	$\delta_c[\text{m}]$	$\delta_a[\text{m}]$	ι_s	ι_c	ι_a
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 6, translates our proposed model and 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 6: Lévy Swarm Algorithm (LSA)

```

Initialize distance  $d = 0$ ;
Assign  $L$ ;
Initialize control action  $\mathbf{C}(t_0) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ ;
while  $t \leq T$  do
    Compute Interaction rules;
    if  $d \geq L$  then
        Compute new  $\psi$  and  $L$ ;
         $d = 0$  ;
         $\mathbf{C}(t) = \mathbf{\Lambda}$ 
    else
         $\mathbf{C}(t) = \mathbf{\Phi}$ 
    end
    Get pose;
    Update distance  $d$ ;
end

```

3.2 Methodology

To test the viability of the LSA model, a series of experiments were conducted both in simulation and in physical setups. This section provides a formal description of such experiments, as well as of the metrics employed.

3.2.1 Metrics

To successfully deploy and assess Algorithm 6 for cooperative surveillance, appropriate metrics ought to be established. To target this particular application specially where overlapping sensing areas are achieved and maintained throughout the mis-

sion, two main metrics are considered that capture this particular aspect of the proposed model. Following the approach from Elhoseny et al. (2017) that employs methods for k -coverage, testing of our model is carried out in a grid-like environment, as illustrated in Figure 3.3, both in simulation and in a real setup.

In this work, and in a similar manner to what was proposed by Esterle and Lewis (2017, 2020), 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 $K(t)$. This metric is computed 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:

$$\Omega(t) = \{A_i(t)\} \quad \forall i \leq N \quad (3.10)$$

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:

$$K(t) = \sum_{\forall j} |\cap \{S_j^k\}_{j \in J}| \quad (3.11)$$

where J is the index set of S . This metric provides, at any given time t , the number of cells of the domain that are sensed by k agents.

However, it does not give any indication of how many *different* cells have been sensed by k agents throughout the domain and over the course of experiments. To assess this, we introduce a random variable \mathcal{X}_k , that represents *the total number of different cells sensed by k agents*, over several runs, and compute its average and standard deviation. Since each experiment is independent the random variable \mathcal{X}_k is plotted as an approximation to a normal distribution.

3.2.2 Experimental Setup

As it was previously mentioned, experiments were conducted both in simulation in a physical setting. In simulation, runs were conducted on 20X20m grid sub-

divided into tiles of 0.5m, for evaluation, and deployed in ROS-Kinetic for the robot control and using Gazebo 8 as a physics simulator, since this is the latest supported configuration at the time of these experiments. The size of the swarm was set to 15 Parrot AR-drones (depicted in Figure 3.2), to be sufficiently large for the interaction rules to have an effect, but not excessively so, to avoid covering the domain without the need for a particular 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 (Couceiro et al., 2014). Each robot, i.e., Parrot ar-drone, has a down-facing camera capable of sensing an area of 2.5m by 2.5m.

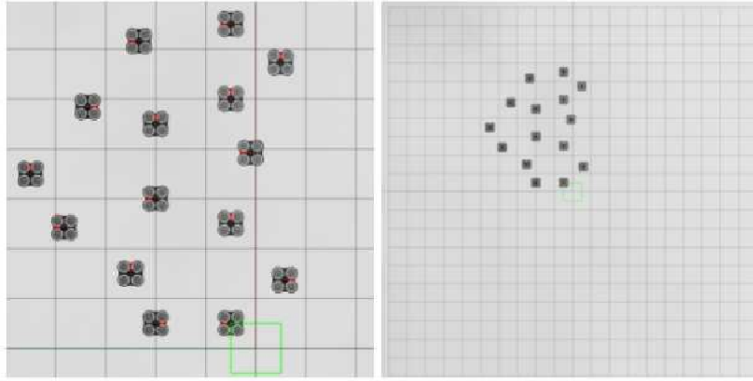


Figure 3.2: Initial position of 15 UAVs in the simulation arena.

As opposed to the GAZEBO physics engine, where ground truth regarding the pose of each Parrot drone is available, in an indoor experimental setup, where GPS positioning is not available, each robot's pose can be accurately estimated by a VICON motion capture system (mocap)¹. In our setup there are nine infrared cameras that detect the position of each tracked object, by the positioning of spherical reflective markers which is communicated directly to its neighbourhood. Such neighbourhood is limited by the robot's communication range considered to be the same as $\delta_a(2.5\text{m})$. Embodied experiments were performed in a Precision 5520 Dell Laptop with Ubuntu 16.04 and ROS Kinetic. Each Parrot drone is mounted with four reflective markers and is connected to the laptop via wireless network. All Parrot drones use the same network and are set with individual IPs. A list of available resources is given by Table 3.2. Vicon cameras are connected to the workstation

via a dedicated Ethernet network as per the default setup. Even though only four cameras are needed to track an object, in experimental work nine Vicon cameras are used to ensure there is redundancy in motion capture according to the official documentations².

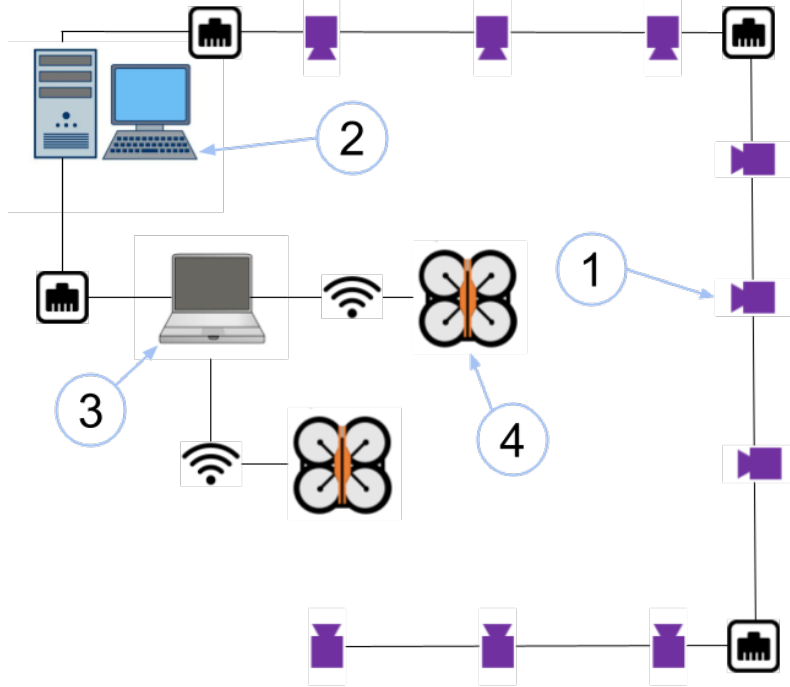


Figure 3.3: Schematic of the experimental setup. 1-Position of the VICON infrared cameras where each camera is connected via Ethernet. 2-Desktop station that collects individual detections from each camera and outputs the final detection through the VICON-licensed software. 3-Laptop where Algorithm 6 is implemented, receiving as input the VICON detection and outputting the velocity commands to each Parrot AR 2. 4-Parraot AR 2 drone connected to ROS laptop via wireless network.

Installing ROS	http://wiki.ros.org/kinetic
Gazebo Parrot model	https://github.com/vislab-tecnico-lisboa/ardrone_gazebo
Parrot ROS driver	https://github.com/AutonomyLab/ardrone_autonomy
Acquiring Vicon data in ROS node	http://wiki.ros.org/vicon_bridge
Configuring Wireless connection	https://github.com/daraosn/ardrone-wpa2
LSA source code	https://github.com/Hurisa/multi_uav

Table 3.2: Resources for Parrot AR drone embodied experiments.

¹<https://www.vicon.com/>

²Vicon documentation: <https://docs.vicon.com/display/Tracker39>

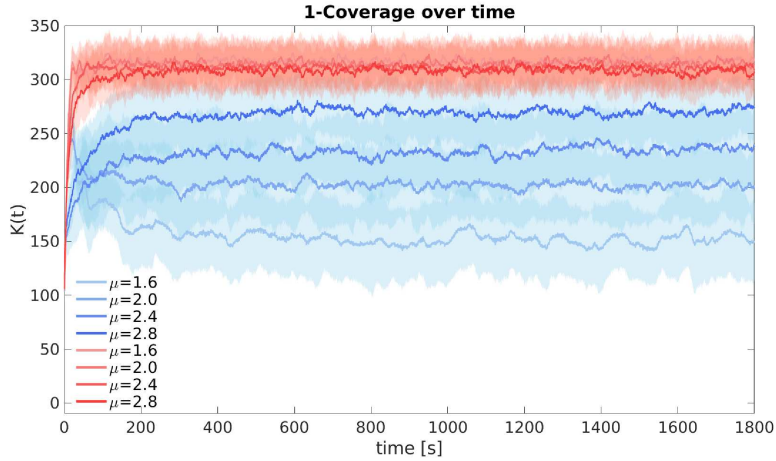
3.3 Results

In this section, we illustrate the feasibility 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 Parrot AR 2 drones.

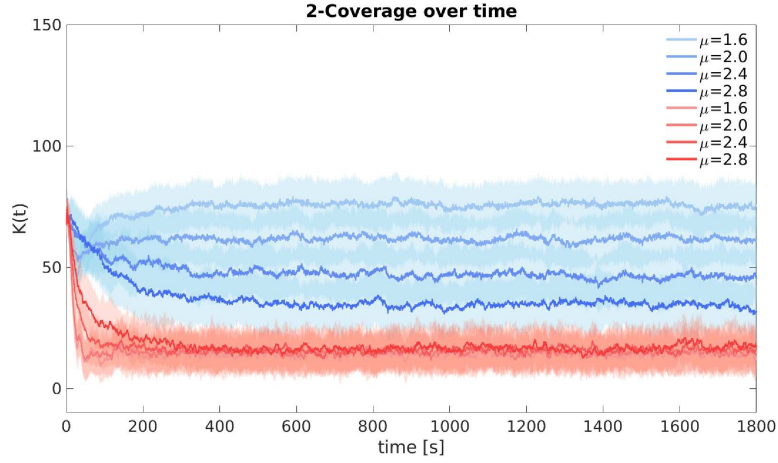
3.3.1 Simulation Experiments

The 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 .

Results of our simulations are depicted in Fig. 3.4 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 $k = 2$.



(a) Temporal evolution of the number of different cells sensed by each drone individually



(b) Temporal evolution of the number of different cells sensed by 2 drones simultaneously.

Figure 3.4: Number of cells under k -coverage over time for $k \in [1, 2]$, with our model (blue) and the baseline (red). These temporal trends show how for $k=1$ (3.4a) introducing a simple mechanism of collision avoidance leads to a higher number of cells being sensed by each drone. However, since the goal is to achieve simultaneous sensing by more than one drone, i.e., $k=2$, the more significant result is shown in 3.4b where one sees the proposed model (in blue) outperforming a simple collision avoidance mechanism in achieving this simultaneous sensing of the environment

Figures 3.4a and 3.4b 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 Fig3.4 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 \mathcal{X}_k , that represents *the total number of different cells sensed by k UAVs* and whose probability distribution, $P(\mathcal{X}_k)$, is shown in Fig. 3.5.

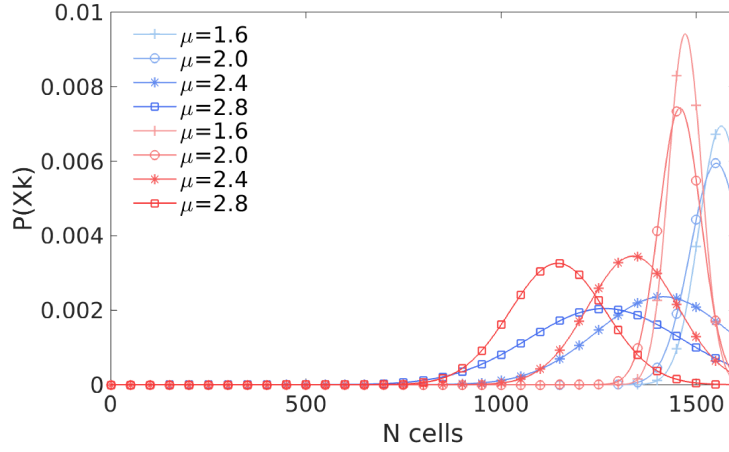


Figure 3.5: Simulated $P(\mathcal{X}_k)$ for $k=2$, with our model (blue) and the baseline (red).

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 .

3.3.2 Real Experiments to Investigate the Role of k

In order to further investigate the role of k in the simulation, some real experiments were conducted with two real Parrot AR-drones in a 4x3m 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. 3.7 shows this domain as well as the initial positions of the two UAVs.

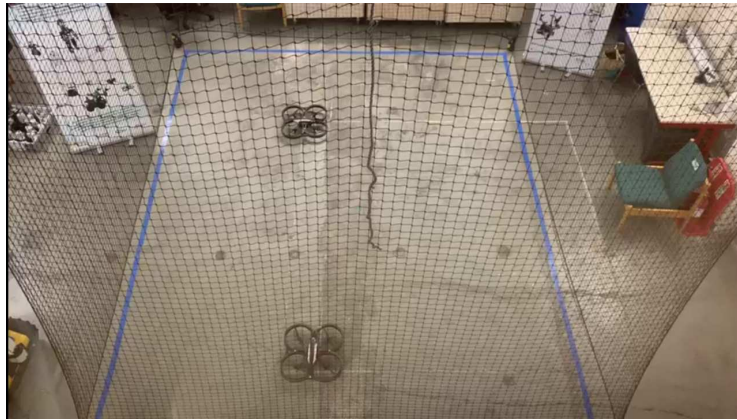


Figure 3.7: Initial positions of 2 ar-drones

³Available video of the experiments at: <https://youtu.be/KvEs7wQ0Ti4>.

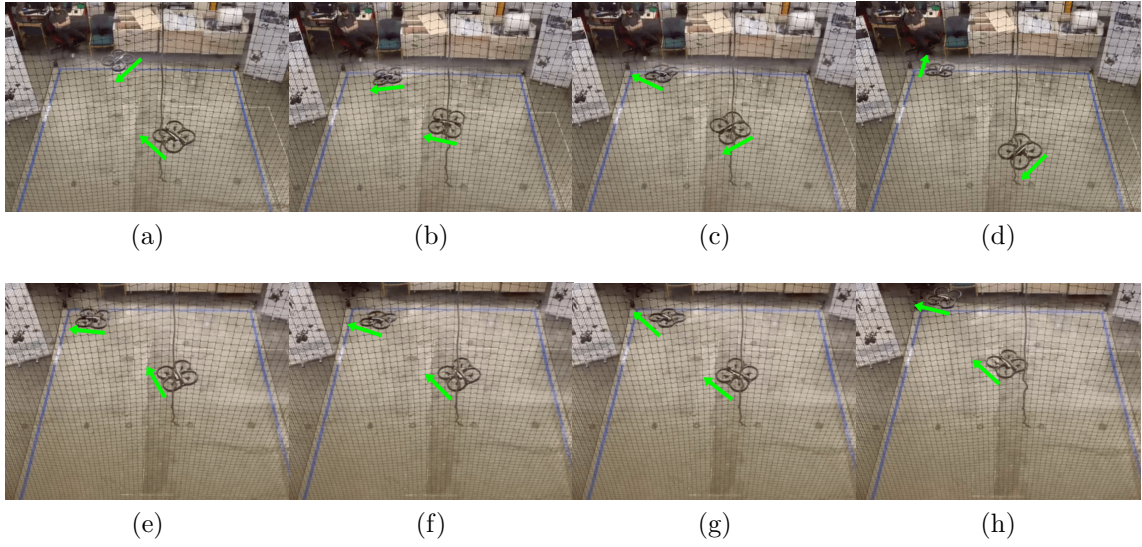
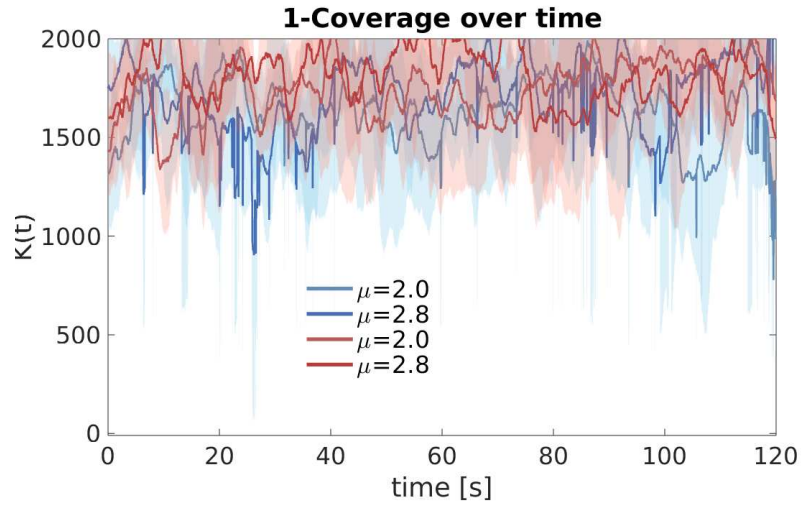
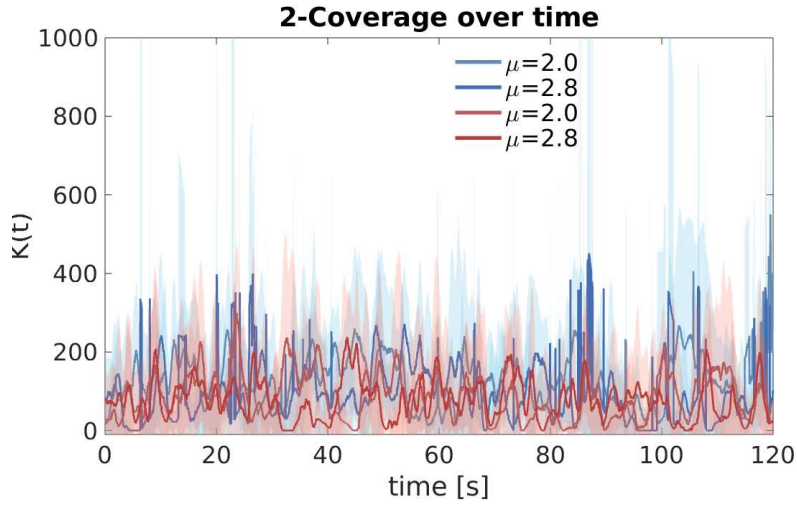


Figure 3.6: Trajectories of 2 ar-drone using only avoidance (a)(b)(c)(d) and our proposed model (e)(f)(g)(h) ³

Similarly to the simulated experiments, we first plot the total number of cells sensed by k UAVs over time t . Figures 3.8a and 3.8b show these results.



(a) 1-coverage with our model (blue) and the baseline (red).



(b) 2-coverage with our model (blue) and the baseline (red).

Figure 3.8: Experimental number of cells under k -coverage for $k = [1, 2]$ with our model (blue) and the baseline (red). Even though the difference between temporal evolutions across methods is not as noticeable as in simulation experiments on still observes a similar relationship. For $k=1$, the collision avoidance approach leads to higher number of cells being sensed (3.8a) while for $k=2$, our model provides with a slightly improved solution (3.8b) considering how the domain dimensions are considerably smaller.

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.

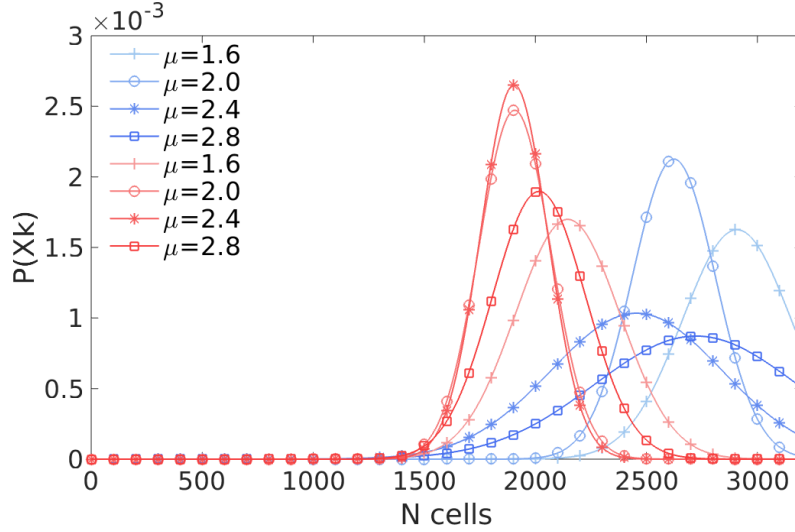


Figure 3.9: Experimental $P(\mathcal{X}_k)$ for $k=2$, for our model (blue) and the baseline (red).

The same is true for the probability distributions of \mathcal{X} , depicted in Fig. 3.9, where our model continues to show a higher average number of cells being sensed by k UAVs simultaneously.

3.4 Summary

In this Chapter we proposed a Lévy Swarm Algorithm (LSA) that combines coordination and exploration strategies using UAVs for collaborative surveillance. Our model is fully decentralized, with minimal direct communication between robots (Das et al., 2016) 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 to tackle the task of k -coverage.

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, $P(\mathcal{X}_k)$, 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 $k = 2$. 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. Such 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, $P(\mathcal{X}_k)$. 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 $P(\mathcal{X}_k)$ between our model and the baseline, the mean value of $P(\mathcal{X}_k)$ 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 real than in simulated experiments, due to the relative size ratio between the Parrot AR drones and the domain.

This Chapter has addressed the first research question presented in Chapter 1, Section 1.3. By presenting a hybridization which leverages the synergies of two biologically inspired models, one may conclude that LW-based strategies can indeed be used in cooperative tasks such as cooperative surveillance, specially when integrated with a suitable coordination strategy, providing a stepping stone towards the main contributions of this Thesis. The following Chapters 4 and 5 will focus on the mechanisms of behavioural adaptation responsible for triggering the transition between local searches and ballistic relocation, as response to environmental conditions.

Chapter 4

Endocrine Lévy Walk Model for Adaptive Foraging

In the previous Chapter it was discussed how Lévy Walks (LW) can be employed in an explicit manner to potentiate the applicability of traditional coordination strategies, by imbuing an exploratory component in each agent's movement.

However, as it has been noted by previous works, the emergent search pattern associated with LWs, has long been postulated to be the consequence of an underlying adaptive response to external environmental conditions such as water or food sources (Reynolds and Rhodes, 2009). Following that premise this Chapter explores the application of an Artificial Endocrine System to model the aforementioned adaptive response to external stimuli and in doing so, addresses Research Questions 2 and 3, recalled below:

- **RQ 2** - Can an Artificial Endocrine System, be used to model adaptive Lévy Walks while maintaining inherent properties of exploitation and exploration, for a single agent performing foraging?
- **RQ 3** - Is such a model able to outperform other strategies aimed at the same foraging task?

The argument for the adoption of LW-based approaches to search and foraging is subsequently being made more compelling, in no small measure, by the evolutionary argument put forward by authors such as Wosniack et al. (2017). Wosniack argues that this emergent behaviour in many natural societies is indeed a product of the evolution of natural perception and regulatory systems.

A particularly strong evidence of regulated behaviour in foraging scenarios, are environments where desirable conditions, or rewards, are clustered together in patches, highlighting the LW transitions between local searches, in reward dense areas and ballistic motion in reward-scarce ones (Fricke et al., 2013; Jandhyala and Fotopoulos, 2018). A good practical example of such conditions happens in the field of precision agriculture more concretely in tasks such as the mapping of weeds in a field, where resources (weeds) tend to be clustered together in *patches* Castaldi et al. (2017).

To explore this subject we recall the definition of patch by Danchin et al. (2008) as “*an homogeneous resource containing area (or part of habitat) separated from others by areas containing little or no resources*”—. Such definition is of crucial importance for the solution we here present. Since resources are not distributed uniformly, but exist in regions of locally high density, there is an imposing drive for an autonomous agent, to be able to adapt its behaviour in order to find such rewards efficiently (Wawerla and Vaughan, 2009).

In fact, LW motion patterns observed in nature can be viewed precisely as a consequence of an underlying adaption mechanism, switching to localized search when inside a patch, and switching back to ballistic motions once no new resources are found. To interpret adaptation in the context of autonomous agents we recall Ashby’s definition by which *a form of behaviour is considered **adaptive** if it maintains the essential variables within physiological limits* Ashby (1960). Such an ability to maintain an internal equilibrium, known as *homeostasis*, is ubiquitous in the animal kingdom (deFur, 2004), and is strongly entwined to the endocrine systems these animals developed over the course of their evolution (Vargas et al., 2009).

Despite the strong argument in favour of adopting explicit Lévy Walks as a motion strategy to tackle adaptive foraging, others have proposed alternatives to this approach (Benhamou, 2007; Bovet and Benhamou, 1988; Nurzaman et al., 2010). Nurzaman’s proposition of the Yuragi model, is particular important in this regard. By emulating, and applying, the concept of biological fluctuation it shows it is indeed possible to achieve adaptation, and indeed a Lévy approximate motion, without an explicit component generating walks based on the Lévy distribution. Therefore, a comparison between the model described in this Chapter and the Yuragi model, is

unavoidable to establish which approach possesses the best features to tackle adaptive foraging. Moreover, Nurzaman and his colleagues describe their experiments in detail, making them straightforward to be replicated, thus providing a sound ground to serve as a benchmark.

To bring together the concepts of behavioural adaptation in patched environments, this Chapter proposes an AES which regulates the motion of a single agent performing LWs. Studying a single agent's behaviour before pursuing an adaptive swarm approach is intended to provide more insight about the adaptation mechanism itself, and zoom in on the model's properties. Similarly to Chapter 3 this Chapter is divided as follows: Section 4.1 describes the proposed model and its benchmark; Section 4.2 details the setup used both in simulation and in physical experiments ; Section 4.3 analyses the results in a comparative manner with a benchmark model and highlights the more significant differences between the two; and finally Section 4.4 summarizes the contributions made in this Chapter and provides a discussion on the most notable issues.

4.1 Model Description

Central to development of every model proposed by this Thesis is the Lévy distribution which, as mentioned in Chapter 2, can be approximated by power-law distribution. One may recall equation (2.1)

$$P(l) \sim l^{-\mu}, \quad 1 < \mu \leq 3$$

where the parameter μ controls the shape of the distribution's tail, making ballistic relocations more (or less) common. As discussed in the previous Chapters it has been shown that for $\mu \geq 3$ the motion becomes Brownian, whereas when $\mu \rightarrow 1$, it becomes a series of straight motions with negligible local searches (Bénichou et al., 2011).

One should highlight that at each reorientation step, a new heading τ is generated such that $\tau \sim \mathcal{U}(-\pi, \pi)$, as also described in Algorithm 1. In this Chapter, recalling this particular aspect is of some import as, some authors have proposed replacing an uniform turning angle, with the use of a correlated reorientation, which has shown to

produce some improvement in search efficiency, particularly in environments where resources are sparsely distributed (Bartumeus et al., 2005; Dimidov et al., 2016).

To assert if this claim holds for patchy environments, the model proposed in this Chapter will be tested both with and without correlation. Correlation is achieved by drawing τ from a wrapped Cauchy distribution, whose probability density function, given by Dimidov et al. (2016), is as follows:

$$\mathcal{C}(\rho, \tau) = \frac{1}{2\pi} \frac{1 - \rho^2}{1 + \rho^2 - 2\rho \cos(\tau)} \quad (4.1)$$

where the parameter ρ represents how correlated the direction of consecutive walks is. On the one hand, when $\rho = 1$, correlation is complete and therefore the entire motion is a continuous straight line, while on the other hand, when $\rho = 0$, reorientations are in fact not correlated and τ assumes a uniform distribution.

As described by Algorithm 2 the underlying Lévy controller of most (if not all) artificial agents, or foragers, can be implemented by, firstly generating a tuple (τ, l) depending on μ and, if correlated, on ρ , and secondly by executing a motion in direction τ while the distance travelled d is lower than l .

The fundamental goal of this Chapter is to test the claim that, in order to achieve behavioural adaptation and therefore switch from ballistic relocation to local search inside patches, both μ and l need to change dynamically according to sensory input. Firstly, as the forager enters a patch it is straightforward to envision that μ should increase, so that the behaviour converges to a local search. However, only changing the value of μ will have little or no effect if the current step is not completed within the patch in time for another tuple (τ, l) to be generated.

In order to harness this intuition we introduce a *desire* to interrupt the current walk, which will translate to a gradual decrease of l for the ongoing step, meaning in fact that the value of the travelled distance d will reach its updated target l sooner, thus triggering the generation of a new tuple (τ, l) .

The specific AES proposed for Lévy walk adaption is built upon the concepts put forward by Wilson et al. (2018) and *et al.* Stradner et al. (2009), where the level of a hormone H at time t can be modelled by the following expression:

$$H(t) = c_0 + c_1 H(t-1) + c_2 S(t) \quad (4.2)$$

where c_0, c_1, c_2 are constant coefficients, $H(t-1)$ represents the previous hormone level and $S(t)$ is the stimulus received from sensory input. The first term, c_0 , represents a base increment simulating a default and constant hormone production, the second term $c_1 H(t-1)$ acts as decay over time, and $c_2 S(t)$ represents the contribution from the sensory stimulus to the overall level of $H(t)$. Wilson et al. (2018) highlight that one could calculate the settling point of $H(t)$, when no stimulus is received, as $H_s = c_0/(1 - c_1)$. Using (4.2) we model the variation of μ as the hormone level itself and define:

$$\mu(t) = a_0 + a_1 \mu(t-1) + a_2 S_\mu(t) \quad (4.3)$$

where $S_\mu(t)$ assumes a binary value depending on the variation of number of resources sensed according to (4.4) where $f(t)$ represents the number of rewards found at time t . Therefore, as the forager enters a patch of resources, μ tends to increase, while if there are no new resources $\mu(t) \rightarrow \mu_s = a_0/(1 - a_1)$.

$$S_\mu(t) = \begin{cases} 1, & \Delta f(t) > 0 \\ 0, & \Delta f(t) \leq 0 \end{cases} \quad (4.4)$$

Modelling the aforementioned *desire* to interrupt the current walk is done in a similar fashion, by considering the hormone level λ defined as:

$$\lambda(t) = b_1 \lambda(t-1) + b_2 S_\lambda(t) \quad (4.5)$$

Note that there is no b_0 term, allowing in fact the value of $\lambda(t)$ to decrease to zero. The stimulus function for λ is given in (4.6), where if $f(t)$ is increasing, there is no stimulus to the *desire* to interrupt the current walk since this means the current walk step is providing a good strategy to find resources. Conversely, if the $f(t)$ is

decreasing this *desire* increases, and does so proportionally to the normalized value of $\mu(t)$ between its settling point (μ_s) and its maximum value ($\bar{\mu} = 3$), creating an interdependence of these two artificial hormone quantities as it is also the case in several natural systems (Vargas et al., 2009).

$$S_\lambda(t) = \begin{cases} 0, & \Delta f(t) \geq 0 \\ \frac{\bar{\mu} - \mu(t)}{\bar{\mu} - \mu_s}, & \Delta f(t) < 0 \end{cases} \quad (4.6)$$

As one can see, when $\mu(t) \rightarrow \mu_s$ then the stimulus $S_\lambda \rightarrow 1$ and when $\mu(t) \rightarrow \bar{\mu}$ $S_\lambda \rightarrow 0$. In practical terms this means that if the forager is finding fewer resources but the its $\mu(t)$ value is large, it is already performing a local search and the *desire* to interrupt that walk is irrelevant since it would already be a local step. On the other hand, if $\mu(t)$ is small in the presence of a varying number of resources then the *desire* is relevant and it is stronger as $\mu(t)$ is further from $\bar{\mu}$. Updating the target step length is, in our model simply done by computing (4.7).

$$l = l(1 - \lambda(t)) \quad (4.7)$$

Our model, the Endocrine Lévy Walk (ELW) is conceptually depicted in Figure 4.1, and has three main components, namely: the Hormone production module (\mathcal{H}) that updates the values of $\mu(t)$ and $\lambda(t)$; the Lévy controller (\mathcal{L}) which controls the pose of the forager, generates l depending on μ (and, if correlated, on ρ), updates it depending on λ ; and finally the sensory input module, \mathcal{S} , which given the new pose $x(t)$ and the previously sensed resources updates the stimulus functions.

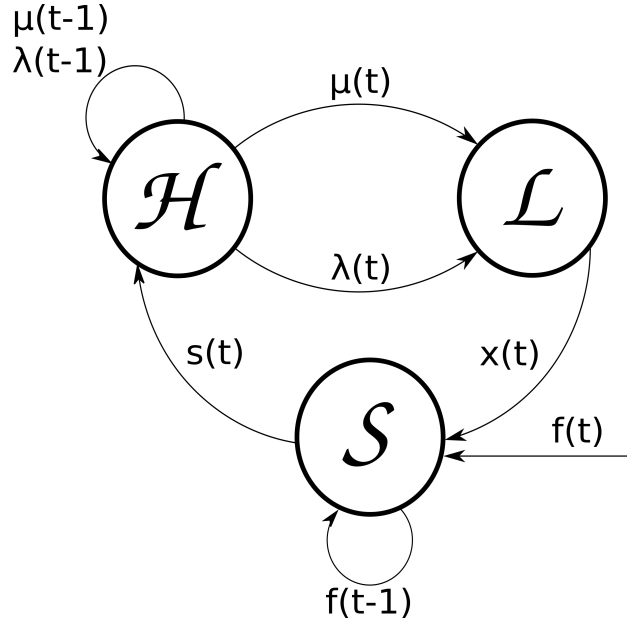


Figure 4.1: Endocrine-based Lévy Walk model.

Indeed one could rewrite Algorithm 2 to include the adaption of LW parameters in computing the control action employed in each individual agent. Such step is highlighted below in Algorithm 7 where the command $\vec{\mathbf{u}}_h$ denotes the velocity generated by the ELW adaptation mechanism.

Algorithm 7: LW Controller with ELW adaption

Initiate $\mu = 2$; Generate tuple (τ, L) ; Set $l = 0$;

if $l \leq L$ **then**

μ, λ and L according to (4.3), (4.5) and (4.7) ;

$\vec{\mathbf{u}}_h = [v_x, 0]^T$;

else

Generate tuple (τ, L) ;

while $|\theta - \tau| \leq \epsilon$ **do**

$\vec{\mathbf{u}}_h = [0, \omega]^T$;

end

Set $l = 0$

end

In the next section we will describe the scenarios where our model was tested as well as how the parameters of the model were chosen. Furthermore, in section 4.3 a comparison between the ELW and the Yuragi model, described in section 2.1.2, is

made both in simulated and physical experiments.

4.2 Experimental Setup

The performance of our proposed model is assessed by a series of experiments in different environments. The first of which is the one chosen by Nurzaman et al, (Environment I) and comprises an arena of 1000x1000m where 10 patches are randomly distributed. These patches are 10x10m and contain 100 rewards each, also uniformly distributed.

As in Nurzaman’s work, we consider an agent whose field of view is 2x2m travelling at a speed of 1m/s over 10000s. Furthermore we expand testing to environments where patches are 50x50 (Environment II) and 100x100 (Environment III) maintaining reward density (as depicted in Figure 4.2), and use these three environments to test the influence of correlation ρ in our model. In such environments, and similarly to the implementation tested by Nurzaman et al. (2010), a series of particle-based experiments are conducted. Conducting such simulations before embodied experiments with real robots is intended to facilitate testing on larger scale, before deploying the model in embodied agents.

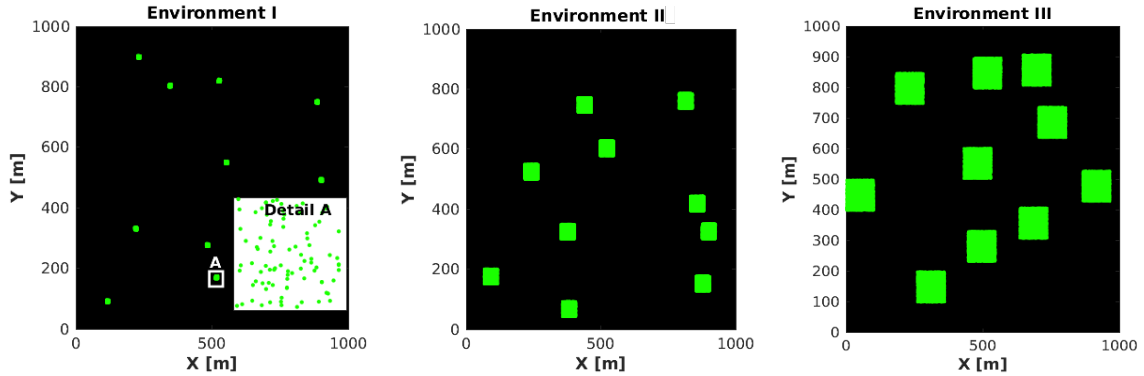


Figure 4.2: Environments with uniformly distributed rewards.

To further test the flexibility of both approaches, in scenarios where rewards within patches are distributed differently we further extend our analysis to Environments IV and V (Figure 4.3) where rewards within patches have Gaussian distributions.

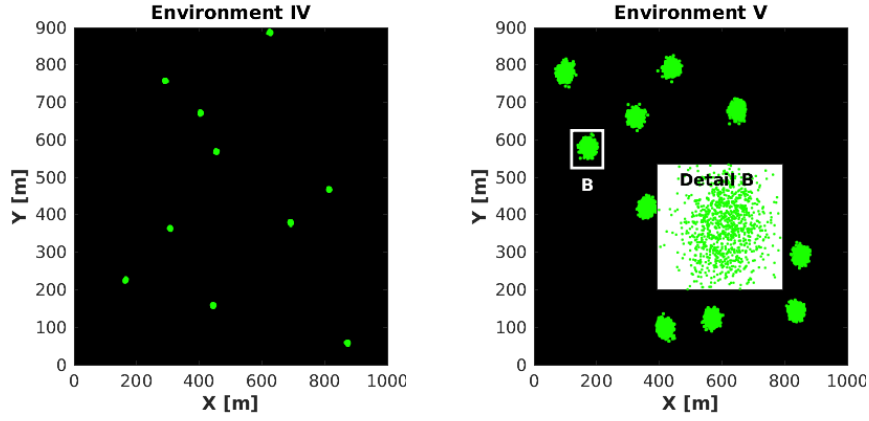


Figure 4.3: Environments with Gaussian distributed rewards.

To choose the parameters for our model, namely the coefficients in (4.3) and (4.5), we implemented a Real-Coded Genetic Algorithm (RCGA) where each solution is represented by a generic chromosome of the type:

$$\mu_s \quad a_1 \quad a_2 \quad b_1 \quad b_2 \quad \rho$$

Choosing μ_s as a decision variable makes for a more straightforward analysis of the solution, since μ_s represents the settling point for μ , and a_0 can be obtained from $\mu_s = a_0/(1 - a_1)$. To optimize the model without correlation, ρ is set to 0 and dropped from the chromosome. Parameters are evolved to maximize search efficiency defined in (4.8), where P is the total number of rewards found and D the total distance travelled. Individuals for crossover are selected by tournament and an arithmetic crossover operator is used.

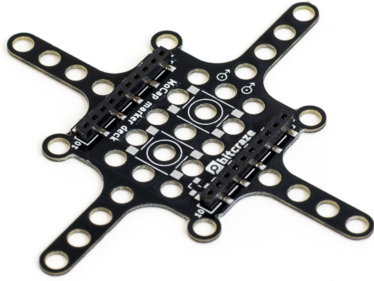
$$\eta = P/D \tag{4.8}$$

Mutation is done by selecting a random allele and changing its value randomly between its predefined limits, i.e., $\mu_s \in (1, 3]$ and $a_1, a_2, b_1, b_2, \rho \in [0, 1]$. The RCGA runs over 250 generations with a randomly initialized population of 100 and a 5% elitism. Even though search efficiency is the function used to optimize the RCGA, results will also compare the number of clusters found as well as the total number of rewards found, in the same manner as proposed by Nurzaman et al.

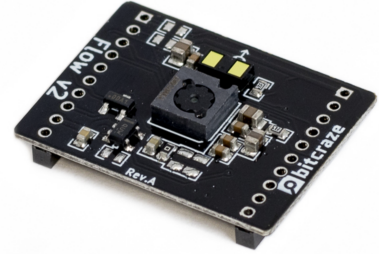
(2010).

After conducting particle based simulations on Environments I - IV, this Chapter also provides results on embodied agents. In this Chapter, as well as in Chapter 5 the platform of choice is the Crazyflie mini-drone, for its aforementioned target design at robotics development and experiments (Hönig and Ayanian, 2017a).

Making use of the modular approach of the Crazyflie, two add-ons are included, namely: the flow-deck board, that allows for ground referencing and reception of velocity commands; and the motion capture deck, where reflective markers are mounted to be tracked by the Vicon Motion Capture system. Contrarily to the Parrot AR drone, commands are exchanged via radio signal, also using a Crazyflie purpose build component, the Crazyradio. All these components are depicted in Figure 4.4.



(a) Motion-capture deck to mount reflective markers.



(b) Flow deck which includes an optical flow and distance sensor.



(c) Crazyradio connects to a PC, providing communication with the Crazyflie



(d) Assembled Crazyflie used in the embodied experiments, featuring 4 reflective markers.

Figure 4.4: Assembled Crazyflie and peripheral equipment used in embodied experiments. Figures 4.4a to 4.4c taken from bitcraze commercial catalog (<https://store.bitcraze.io/>). Figure 4.4d captured by the author at the time of experiments.

Similarly to the setup in the previous Chapter the position and orientation of the Crazyflie is tracked by the Vicon Motion Capture system and an updated version of that system is shown 4.5.

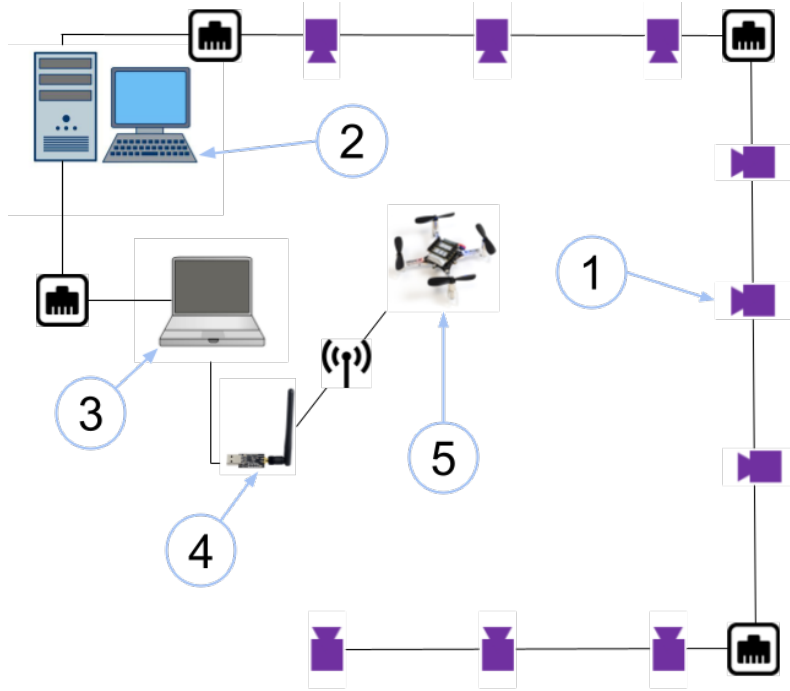


Figure 4.5: Setup for the ELW experiments, which components are: 1-Vicon Motion Capture System; 2-Vicon workstation where measurements the pose of objects is estimated; 3-Laptop running the different foraging models; 4-Crazyradio connected to 3 which enables communication to and from the Crazyflie; 5-Crazyflie mini drone.

Similarly to the experiments in Chapter 3, embodied experiments were performed under ROS Kinetic, using the latest compatible Crazyflie firmware. Each crazyflie is mounted with four reflective markers, as depicted if Figure 4.4d and a list of available resources is given by Table 4.1. Vicon cameras are connected to the workstation via a dedicated Ethernet network as per the default setup. Even though only four cameras are needed to track an object, in experimental work nine Vicon cameras are used to ensure there is redundancy in motion capture according to the official documentations¹. Due to the smaller size of the experimental arena in comparison to the environments used in particle-base simulations, the distribution and number of clusters was modified.

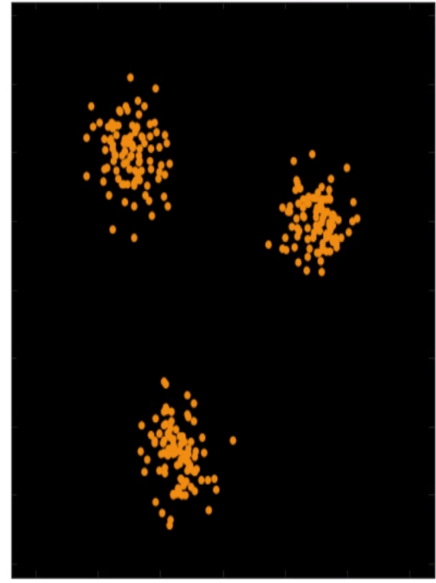
Installing ROS	http://wiki.ros.org/kinetic
Gazebo Crazyflie model	https://github.com/wuwushrek/sim_cf
Configure Crazyflie Firmware	https://www.bitcraze.io/documentation/start/
Acquiring Vicon data in ROS node	http://wiki.ros.org/vicon_bridge
Install ROS drivers for the Crazyflie	https://crazyswarm.readthedocs.io/en/latest/index.html

Table 4.1: Resources for Crazyflie embodied experiments.

In order to still observe a difference in the models tested, three clusters were placed sufficiently apart, with Gaussian distributed rewards, as depicted in Figure 4.6.



(a)



(b)

Figure 4.6: Environments with Gaussian distributed rewards.

In these embodied experiments, to further take into consideration the difference in scale, the sensing radius was set to 10cm. Indeed, these necessary changes, made due to the size of the available experimental arena, could lead to argument that results would lack statistical significance. However as it will be observed in the next section, the behaviour of the different models produces sufficiently different outputs for a meaningful comparison to still be possible, and valid conclusions drawn in tandem with the particle-based simulations counterpart.

¹Vicon documentation: <https://docs.vicon.com/display/Tracker39>

4.3 Comparing the ELW and Yuragi models

This section analyses the results obtained after deploying the ELW to tackle adaptive foraging in clustered environments. In a first instance particle-based simulations are performed. These simulations include a replication of the results obtained employing Yuragi model (Nurzaman et al., 2010), and the subsequent comparison with the ELW proposed in Section 4.1. By doing so, these results aim to show, not only that the ELW is able to achieve adaptation, but also that it presents a more performant alternative model. To ensure there is no bias in favor of the ELW, the same metrics proposed by Nurzaman are used, and both models are tested in an environment with the same characteristics as the one used in the original Yuragi study. Furthermore, results are extended to scenarios with different characteristics regarding patch size and distribution. Both models are also tested in embodied physical experiments to test their ability to be deployed in real platforms, and how their performance compares in such a setting.

4.3.1 Particle-Based simulations

Before delving into comparing the two models, this section also analysis the results of the optimization for the ELW parameters shown in Table 4.2, with and without correlation. The first observation we can make is that, as the size of patches increases from environment I to III, the value of μ_s decreases. In fact, this was an expected result, since in an environment where patches are of considerable size, a strategy that favours more frequent ballistic motions, will tend find new rewards more efficiently. On the other hand, in an environment where patches are very small, more frequent changes of direction are necessary to find these rewards, and therefore the μ_s is higher. We also observe that parameter a_1 increases with the increasing size of patches. Recalling (4.3), the higher a_1 becomes the slower is the decay of $\mu(t)$.

Environment	μ_s	a_1	a_2	b_1	b_2	ρ
I	2.344	0.196	0.179	0.995	0.235	—
	2.422	0.216	0.599	0.962	0.424	0.073
II	1.625	0.503	0.254	0.976	0.185	—
	1.809	0.507	0.354	0.917	0.563	0.029
III	1.129	0.841	0.619	0.918	0.191	—
	1.428	0.758	0.681	0.904	0.153	0.077

Table 4.2: Parameters optimized for environments I,II and III.

An increasing value a_1 with patch size shows that it is beneficial to not let the value of $\mu(t)$ decay too abruptly, sustaining more localized search for a longer period. Concurrently a_2 , the weight of the stimulus to the value of $\mu(t)$, also increases. Since μ_s is smaller for such environments, the change of $\mu(t)$ to a point that translates into local search needs to occur at a higher rate, and thus the stimulus has a bigger weight. As for the coefficients that modulate λ , we see that b_1 always maintains a high value, but decreases only slightly with increasing patch size, showing that a slow decay of the *desire* to interrupt the current walk is always desirable regardless of the size of patches. As for the stimulus to this *desire*, i.e., the b_2 parameter, has a higher value when patches are smaller. Naturally, given the smaller size of patches, the weight of the stimulus must be stronger so that the current walk is interrupted sooner.

Perhaps the more interesting result is the one concerning the correlation ρ . These results show that ρ always converges to very small values, hinting that, in patchy environments, directional correlation between steps might not play a significant role. To confirm this hypothesis we show in Table 4.3 the average values for *Efficiency*, number of *Rewards Found* and number of *Patches Found*, for both the Endocrine-based Lévy Walk (ELW) and its correlated version (CELW). These results show that, in fact, even a negligible correlation can have an apparent negative impact on the overall performance of the system, since the ELW tends to outperform its correlated counterpart for most metrics in all environments.

To further investigate the statistical difference between models, we calculate the

Search Behaviour	Efficiency(10^{-2})	Rewards Found(10^2)	Patches Found
ELW-I	0.42 ± 0.12	4.18 ± 1.13	7.48 ± 1.56
CELW-I	0.41 ± 0.15	3.98 ± 1.22	7.04 ± 1.73
ELW-II	15.02 ± 2.14	126.50 ± 11.32	9.58 ± 0.58
CELW-II	11.70 ± 1.70	104.24 ± 13.39	9.66 ± 0.55
ELW-III	39.93 ± 4.78	372.39 ± 42.00	9.95 ± 0.21
CELW-III	36.71 ± 3.48	351.60 ± 31.93	9.98 ± 0.14

Table 4.3: Comparison between ELW and CELW over 100 runs.

Search Behaviours	Efficiency	Rewards Found	Patches Found
ELW-I / CELW-I	0.443	0.432	0.893
ELW-II / CELW-II	$\ll 0.01$	$\ll 0.01$	0.987
ELW-III / CELW-III	$\ll 0.01$	$\ll 0.01$	0.998

Table 4.4: p-value for the 2-sample Kolmogorov-Smirnov test, for all metrics between ELW and CELW behaviours.

p-value for the 2-sample Kolmogorov-Smirnov (KS) goodness-of-fit hypothesis test. For the 2-sample KS test, the null hypothesis is that “*two data vectors belong to the same continuous distribution*” and therefore, the hypothesis is rejected, at the 99% confidence level, if the p -value < 0.01 . Table 4.4 summarizes the p -values between each uncorrelated and respective correlated model, for each different metric. These results show that for the models optimized for Environment I, there is no statistical difference in results for any of the metrics, confirming that including correlation, for small patch environments, does not have any impact on the system’s performance. However, for Environments II and III the respective optimized models are in fact statistically different for both the *Efficiency* and *Rewards Found*. In these particular cases it shows that including correlation actually has a detrimental effect to the system’s performance, since metrics’ values shown in Table 4.3 are higher for the ELW.

Having established that correlation either does not affect or worsens the performance of the system, the next set of results will only compare the ELW and the Yuragi approaches.

The parameters of our model for these environments were also obtained via the aforementioned RCGA, and are shown in Table 4.5. For a fair comparison with the Yuragi model, we conduct the same sensitivity analysis as Nurzaman *et al.* to select

the value of R in (2.4), which maximizes *efficiency*. These results are summarized in Table 4.6, where we include the values reported by Nurzaman, in brackets, to validate our own implementation. In the following analysis, we refer to Yuragi A/B or C depending on which R is best suited for a particular environment.

Environment	μ_s	a_1	a_2	b_1	b_2
IV	1.659	0.152	0.511	0.940	0.499
V	1.445	0.489	0.495	0.980	0.194

Table 4.5: Parameters optimized for Environments IV and V

Table 4.6 shows that Yuragi-A is best suited for Environments II, IV and IV, and Yuragi-B for Environments I and III. We also note that the values obtained with our Yuragi implementation yield very close results to those reported by Nurzaman, validating our implementation for the subsequent analysis. Finally, the comparison between the ELW and Yuragi approaches is presented in Table 4.7. This table compares the results obtained with the optimized ELW model for each particular environment (ELW-I, ELW-II, etc.) with the corresponding Yuragi model chosen from the sensitivity analysis in Table 4.6. Highlighted values for each metric show that the ELW always yields best performance both across the different metrics and different environments. However, one could still argue that our model requires prior knowledge in order to select optimal parameters for the task. To address this question, we perform a cross-testing analysis and run each ELW model (ELW-I, ELW-II, etc.) in every environment, and compare those results, both with the optimal results for such environment, and with those achieved with the Yuragi approach. This comparison is made in Table 4.8, where the optimal efficiency values for each environment are highlighted in green and the best Yuragi approach for each environment is highlighted in red. Furthermore, we also highlight the performance obtained with ELW-II and ELW-IV, since these are able to consistently outperform the best Yuragi solution, even in those environments for which the ELW was not specifically optimized. The existence of sets of ELW parameters that lead to a higher performance, in comparison to the Yuragi approach, and regardless of the environment is an important evidence of the superiority of the ELW model, and its inherent increased

Model	R	Env I	Env II	Env III	Env IV	Env V
A	0.99	0.26±0.11 (0.23±0.11)	8.98±2.38	19.74±3.51	0.35±0.13	3.93±0.99
B	0.90	0.29±0.10 (0.28±0.11)	7.41±1.98	24.07±4.48	0.29±0.11	3.19±0.89
C	0.50	0.21±0.09 (0.17±0.06)	6.72±1.61	20.70±4.69	0.24±0.10	2.49±0.79

Table 4.6: Sensitivity Analysis on Efficiency with varying R

adaptation ability. It is also interesting to point out that the performance, with respect to every metric, of ELW-II and ELW-IV in environments I,III and V is considerably closer to the optimal value, than to the Yuragi approach, often lying within the standard deviation of the former. This is yet another evidence that improvement in performance can be achieved mostly due to the model itself and that RCGA optimization is mostly useful in fine-tuning.

Behaviour	Efficiency (10^{-2})	Rewards Found (10^2)	Patches Found
ELW-I	0.42±0.12	4.18±1.13	7.48±1.56
Yuragi-B	0.29±0.10	2.61±1.01	5.20±1.53
ELW-II	15.02±2.14	126.50±11.32	9.58±0.58
Yuragi-A	8.98±2.38	64.40±14.50	6.03±1.30
ELW-III	39.93±4.78	372.39±42.00	9.95±0.21
Yuragi-B	24.07±4.48	180.59±29.03	6.07±1.48
ELW IV	0.39±0.01	3.83±0.97	6.89±0.97
Yuragi-A	0.35±0.13	3.03±1.12	4.45±1.37
ELW V	6.22±0.85	56.71±7.13	9.73±0.48
Yuragi-A	3.93±0.99	29.91±6.67	6.19±1.41

Table 4.7: Metric comparison between Yuragi and ELW

Behaviour	Metric	Env I	Env II	Env III	Env IV	Env V
ELW-I	Efficiency (10^{-2})	0.42±0.12	10.09±1.74	20.64±2.63	0.37±0.15	4.40±0.81
	Rewards Found (10^2)	4.18±1.13	72.70±9.97	124.68±12.17	3.59±1.30	34.00±5.42
	Patches Found	7.48±1.56	6.01±1.04	3.91±1.73	5.18±1.62	6.83±1.17
ELW-II	Efficiency (10^{-2})	0.40±0.10	15.02±2.14	38.81±3.74	0.38±0.11	6.17±0.92
	Rewards Found (10^2)	3.92±0.99	126.50±11.32	266.51±18.25	3.73±1.05	55.92±7.74
	Patches Found	7.27±1.43	9.58±0.21	8.59±1.08	7.08±1.38	9.80±0.47
ELW-III	Efficiency (10^{-2})	0.24±0.07	9.98±1.73	39.93±4.78	0.21±0.07	3.82±0.64
	Rewards Found (10^2)	2.36±0.69	98.12±16.84	372.39±42.00	2.18±0.78	37.82±6.35
	Patches Found	7.56±1.32	9.85±1.03	9.95±0.21	7.10±1.57	9.93±0.32
ELW-IV	Efficiency (10^{-2})	0.41±0.10	12.92±2.02	38.22±3.46	0.39±0.01	5.20±0.79
	Rewards Found (10^2)	4.16±0.95	113.35±15.87	276.95±18.67	3.83±0.97	48.12±6.85
	Patches Found	7.32±1.29	9.87±0.37	9.49±0.67	6.89±1.29	9.85±0.36
ELW-V	Efficiency (10^{-2})	0.36±0.11	15.01±1.87	39.01±3.61	0.35±0.11	6.21±0.85
	Rewards Found (10^2)	3.60±1.12	127.10±13.51	274.55±17.48	3.56±1.11	56.71±7.13
	Patches Found	6.98±1.50	9.66±0.55	8.87±0.87	7.12±1.45	9.73±0.46
Yuragi-A	Efficiency (10^{-2})	0.26±0.11	8.98±2.38	19.74±3.51	0.35±0.13	3.93±0.99
	Rewards Found (10^2)	2.01±1.01	64.40±14.51	121.61±16.64	3.03±1.12	29.91±6.67
	Patches Found	4.81±1.16	6.03±1.31	3.86±1.4	4.45±1.37	6.19±1.41
Yuragi-B	Efficiency (10^{-2})	0.29±0.10	7.41±1.98	24.07±4.48	0.29±0.11	3.19±0.89
	Rewards Found (10^2)	2.61±1.01	61.80±15.68	180.59±29.03	2.58±0.95	27.17±7.29
	Patches Found	5.20±1.53	7.19±1.41	6.07±1.48	4.85±1.45	7.43±1.65

Table 4.8: Cross-testing of ELW parameters across environments.

4.3.2 Embodied Experiments

To validate the results found in particle-based simulation, further experiments were conducted with embodied agents, both in simulated and physical setups. For a more thorough evaluation of such experiments we will present the temporal evolution of the the metrics considered in the previous subsection, as well as their deviation from the mean value.

The first metric analysed is the number of rewards found, depicted in Figure 4.7 showing the both the simulated (4.7a) and physical (4.7b) embodied experiments, highlighting the consistency between the two. The clear difference between the the ELW and the Yuragi models corroborates the initial particle-based results, showing the advantage of employing the ELW to the problem of adaptive foraging.

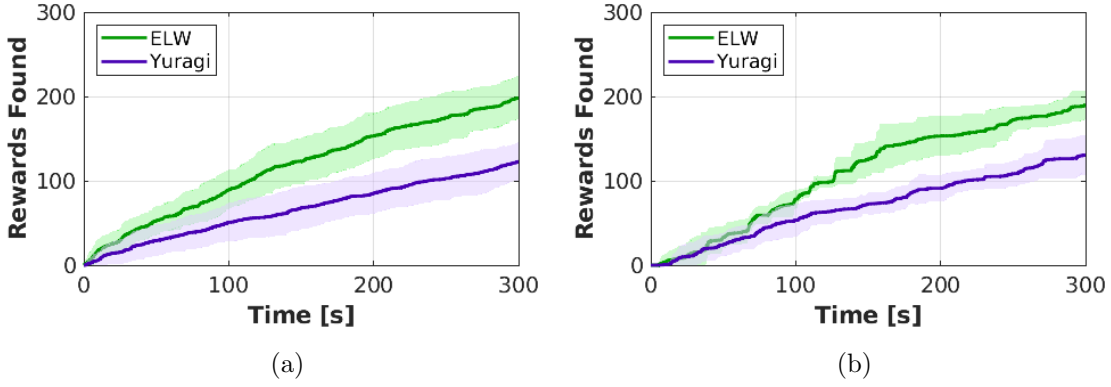


Figure 4.7: Temporal evolution of the number of rewards found in physical experiments.

These results are also a first step to show, through the similarity of the curves, that besides the performance differences between models, the ELW displays evidence that it may overcome the reality gap.

Secondly, Figure 4.8 displays the temporal evolution of the number of clusters found. These results show that, the difference in this metric is less significant than in particle-based simulations. The difference in size of the environments and the consequential increased proximity of clusters as well as their smaller number, leads to this result. However, one still observes that, on average, the ELW still discovers all clusters faster than the Yuragi model. Together with the results obtaining rewards found, this evidence lends strength to the claim that ELW model provides a control approach more capable of adaptive foraging.

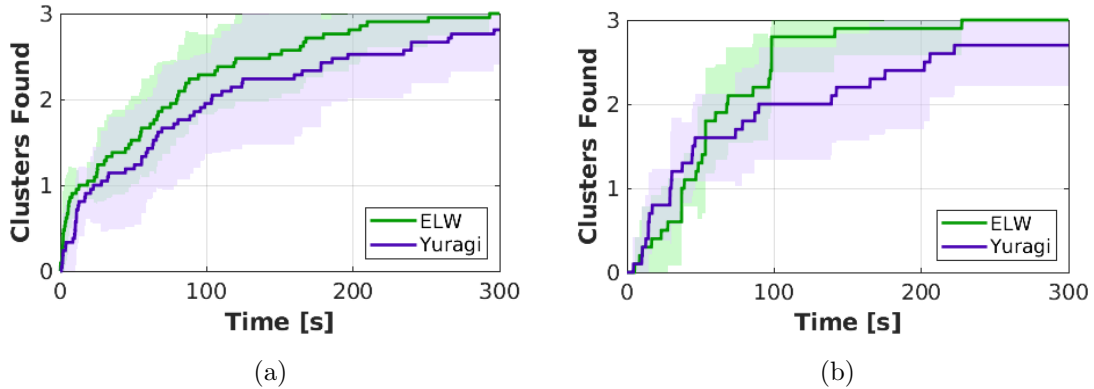


Figure 4.8: Temporal evolution of the number of clusters found in physical experiments.

Lastly, to complete the metric comparison as proposed by Nurzaman et al.

(2010), the temporal evolution of search efficiency is depicted in Figure 4.9. Contrarily to the previous two metrics the temporal evolution of search efficiency does not seem to show any significant difference between models. However, since the number of rewards found by the ELW is significantly higher, and the search efficiency is defined by the ratio of such rewards over distance travelled (eq.(4.8)) this then implies that when the Yuragi is employed the agent does not travel as large distances as when the ELW is chosen. This particular realization means that search efficiency, as defined, may lead to erroneous conclusions when comparing methods in particular for smaller environments.

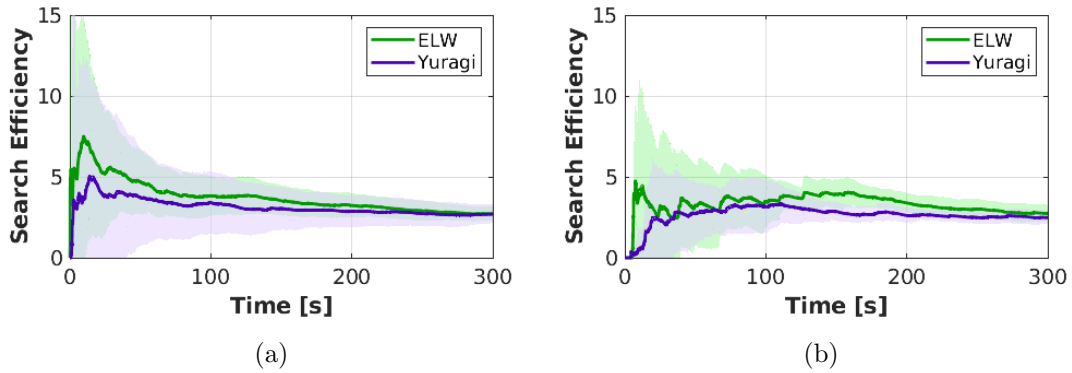


Figure 4.9: Temporal evolution of search efficiency in physical experiments.

In fact the similarity between behaviours is such that the p-value, as shown in Table 4.9, is so high that from a perspective of statistical significance perspective there is no difference between models in what concerns search efficiency as well as the number of clusters found. However, one notices how this is the opposite conclusion regarding the number of rewards where the p-value is indeed within the range that let us reject the null hypothesis with 99% certainty.

Search Behaviour	Efficiency	Rewards Found(10^2)	Patches Found
ELW	2.73 ± 0.44	1.98 ± 0.26	3.00 ± 0.00
Yuragi	2.73 ± 0.36	1.23 ± 0.23	2.80 ± 0.40
p-value	0.9728	$\ll 0.01$	0.7974

Table 4.9: Comparison between ELW and Yuragi in Gazebo simulation over 20 runs.

The conclusion that the Yuragi model may not allow the agent to travel as much

across the domain, rests on the specific probabilistic component of the biological-fluctuation model that allows for a reorientation event to happen more frequently and therefore, since rotations are not instantaneous, more time will be spent at this stage therefore hindering exploration. To assert this affirmation, the number and length of walks generated by both models were fitted to a power-law, as depicted in Figure 4.10, and the goodness-of-fit metrics computed and shown in Table 4.10.

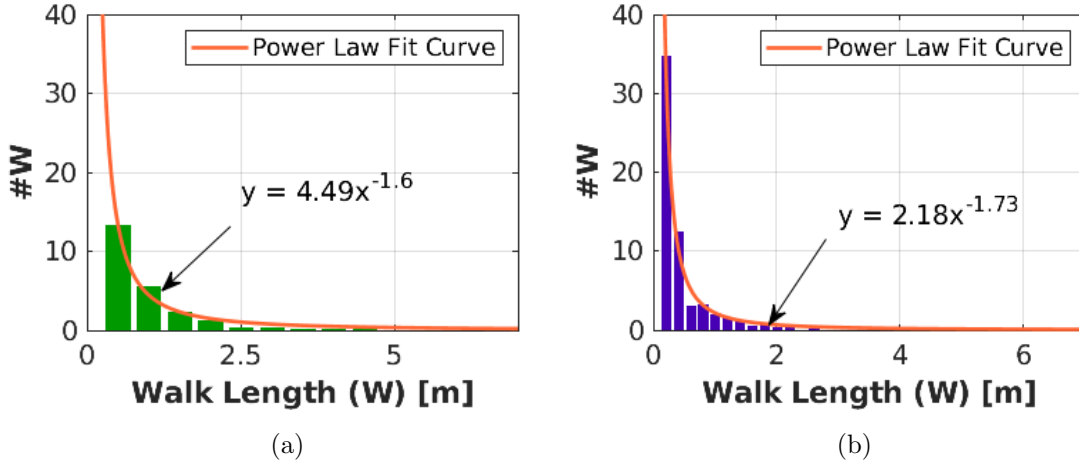


Figure 4.10: Power-law curve fitted to walk lengths of the Yuragi and ELW models for Gazebo simulations.

Analysing Figure 4.10 shows that Yuragi model leads to much more common short walks than the ELW. Since every walk is interspersed with a reorientation event, we may also conclude that these are more frequent and therefore infer that the similar values of search efficiency in the presence of contrasting values of rewards found are due to the underlying modelling differences between models. However, from the the power-law approximation one notices that the μ power is similar in both cases, while in fact a pattern where there are smaller walks and more frequent reorientations should indeed lead to a value μ close to 3, which seems to contradict the previous statements. Nevertheless, by analysing the goodness-of-fit metrics in table 4.10, it is evident how the distribution of walk lengths achieved by the Yuragi model produces a pattern with considerable higher error.

Search Behaviour	SSE	RMSE	R ²	Adjusted R ²
ELW	11.61	0.61	0.98	0.98
Yuragi	333.23	2.82	0.86	0.86

Table 4.10: Goodness-of-fit metrics to a Power Law curve, for the Yuragi and ELW models in Gazebo simulations.

Such evidence, may lead to further questioning the claim that the Yuragi model produces indeed a LW behaviour, since it does not seem to fit the power-law curve that several authors have corroborated as a reasonable approximation for a LW pattern. Indeed, in such a circumstance the value of μ computed, for the Yuragi model, is of little significance.

Since reorientation events seem to differ in frequency in both models, and therefore so does the length of walks travelled, it is plausible to assume that energy spent will also be quite different. Even though energy modelling is outside of the scope of this Thesis, embodied experiments in physical agents have the advantage of providing real battery data which makes it possible to propose an alternative metric for efficiency in eq(4.9), where P is the number of rewards found, V_0 is the initial battery level in [volts] and V_t the battery level at time t .

$$\eta_e = \frac{P}{(V_0 - V_t)} \quad (4.9)$$

The temporal evolution of the energy efficiency metric, depicted in Figure 4.11, shows the definite superiority of the ELW in this respect, which is corroborated by the p-value shown in Table 4.11, which lets one reject the null hypothesis that both sets of experimental samples belong the same distribution, with 99% confidence.

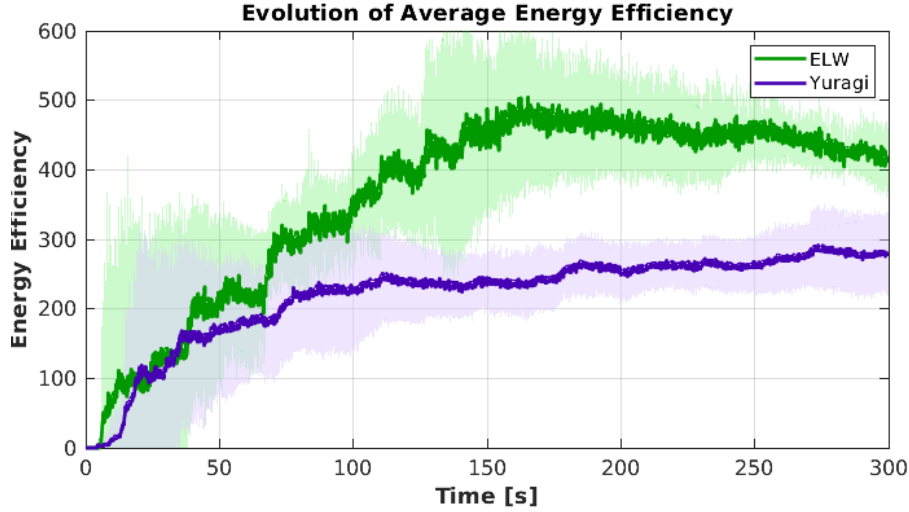


Figure 4.11: Temporal evolution of energy search efficiency for both the ELW and Yuragi methods.

Search Behaviour	Efficiency	Rewards Found(10^2)	Patches Found	Energy Eff.
ELW	2.78 ± 0.34	1.88 ± 0.30	3.00 ± 0.00	4.17 ± 0.45
Yuragi	2.65 ± 0.28	1.34 ± 0.17	2.90 ± 0.32	2.82 ± 0.61
p-value	0.3129	$\ll 0.01$	0.6751	$\ll 0.01$

Table 4.11: Comparison between ELW and Yuragi after physical experiments over 10 runs.

In fact, the intuition that reorientation maneuvers would be more energy expensive, is also corroborated by the power-law curve approximation, depicted in Figure 4.12, as well as by the goodness-of-fit metrics, shown in Table 4.12. The histograms depicted below, show exactly that the Yuragi model produces a considerably higher number of shorter walks (and therefore more reorientation events), leading to more localized search. Consequently, and as in the embodied simulated results, the goodness-of-fit metrics show that such tendency to generate shorter walks leads to higher divergence from the common power-law approximation for LWs for the Yuragi model.

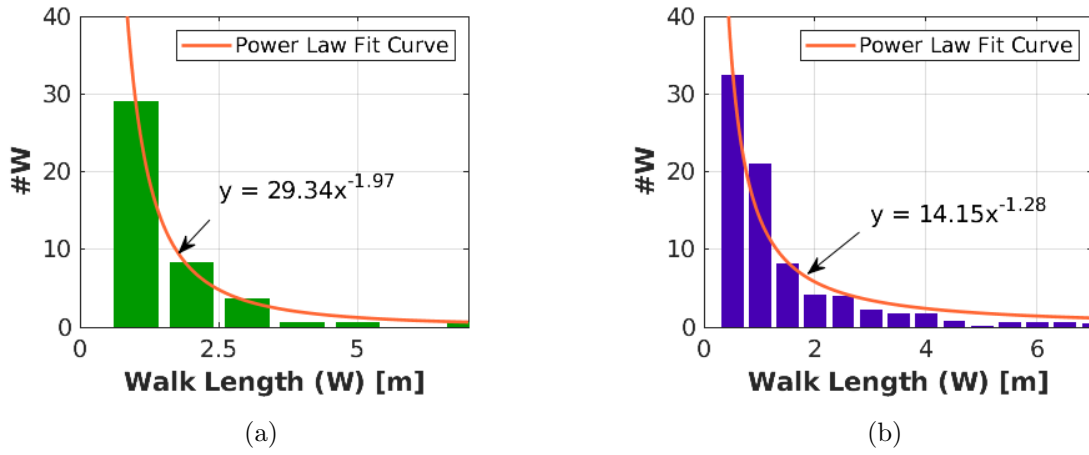
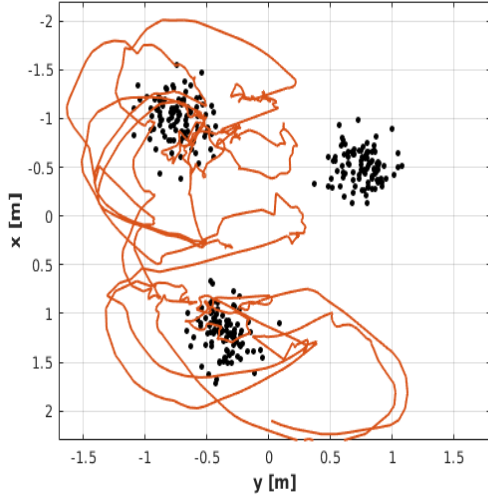


Figure 4.12: Power-law curve fitted to walk lengths of the Yuragi and ELW models in physical experiments.

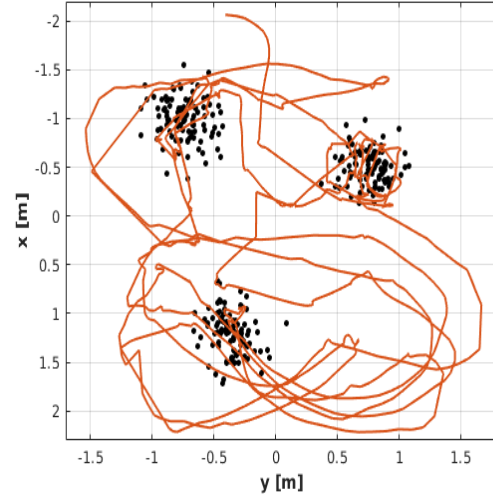
Search Behaviour	SSE	RMSE	R ²	Adjusted R ²
ELW	3.42	0.40	0.99	0.99
Yuragi	69.80	1.78	0.95	0.95

Table 4.12: Goodness-of-fit metrics to a Power Law curve, for the Yuragi and ELW models

To finalize the comparative analysis between the ELW and the Yuragi models on a more qualitative manner, Figure 4.13 depicts an example of trajectories achieved with either model.



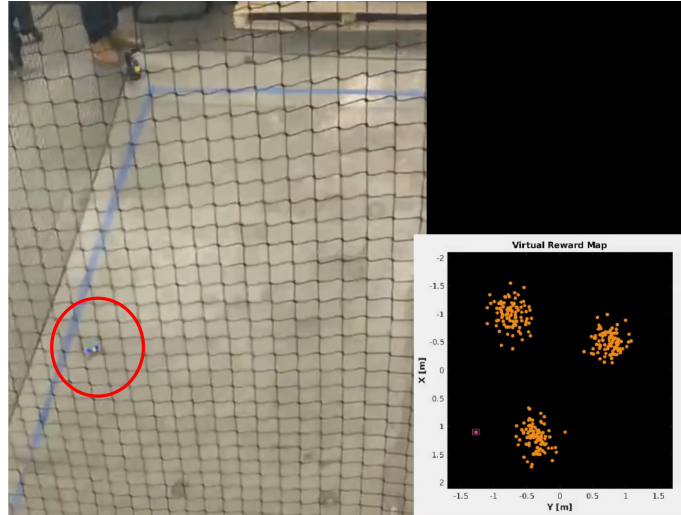
(a) Example of Yuragi trajectory



(b) Example of ELW trajectory

Figure 4.13: Example of trajectories obtained with both the Yuragi and ELW behaviours, as detected by the VICON system in physical embodied experiments.

These trajectories lend further weight to the claim of superiority of the ELW, as one can observe how the ELW is able to explore the environment in a manner which not only finds all clusters but correctly adapts to the discovery of rewards. As an example of the temporal discovery of rewards, Figure 4.14 shows two screenshots of the rewards found using the ELW model in the physical scenario.



(a) $t = 0$ secs

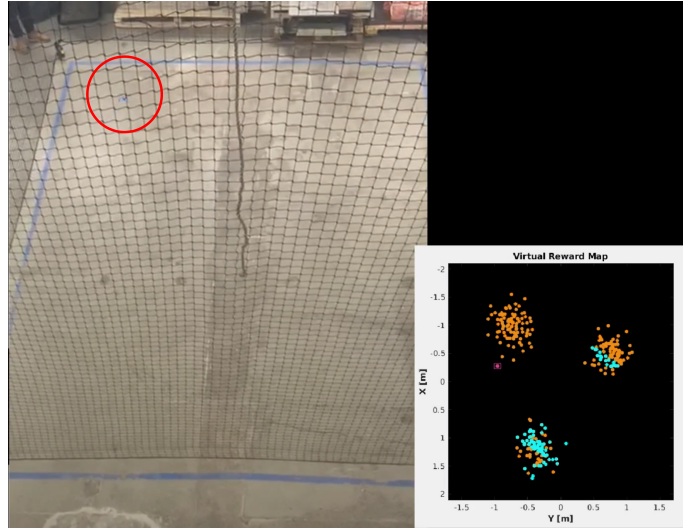
(b) $t = 60$ secs

Figure 4.14: Screenshots of the ELW behaviour at different time steps, showing the flying arena the crazyflie robot and the virtual reward distribution. Undiscovered rewards are plotted in orange and discovered ones plotted in blue².

Indeed, across the metrics analysed, both in simulated and physical settings, as well as the fitting of power-law to walk lengths and respective levels of the goodness-of-fitness metrics and lastly the trajectories of both models, one can argue favourably for the employment of the ELW model to the task of adaptive foraging due its more biologically plausible components. To conclude this Chapter, a summary of these insights and conclusions is presented in the next Section.

4.4 Summary

In this Chapter the ELW was proposed, deployed and evaluated in autonomous agents. With the intent of answering Research Questions 2 and 3, the ELW makes use of an AES which in turn modulates the parameters of a Lévy controller for foraging in patchy environments. Firstly, the hypothesis that angular correlation between steps can benefit the search efficiency was analysed. This analysis has shown that in fact, correlation either does not have any statistical impact on results, or slightly decreases the efficiency of the model in environments with larger patches. Secondly, the ELW was compared to a benchmark model based on biological fluctuation, across environments where rewards were either uniformly or

²A video of these experiments is available at <https://youtu.be/gH6jITF4C0o>.

normally distributed within patches. Both models were compared using three different metrics: *Efficiency*, *Rewards Found* and *Patches Found*, and the obtained results have shown that ELW outperforms the benchmark model in all scenarios.

Furthermore, experiments with embodied agents were also conducted. Anticipating the goal of deploying the ELW as the basis for an adaptive swarm approach, the Crazyflie drone was the chosen platform for such embodied experiments due to its small dimensions and development philosophy which by design targets the execution of research projects. In experiments with the Crazyflie drone, due to the restricted characteristics of the domain, results have shown only marginal difference in the efficiency as defined by Nurzaman et al. (2010). Even though efficiency was similar, experimental results show that the ELW model endowed the agent to find more rewards than the Yuragi model. Since efficiency was defined by Nurzaman et al. (2010) in eq.(4.8) as a ratio between rewards found and distanced travelled, indeed similar ratios can be achieved by different models. This implies that, even if the number of rewards found is substantially lower when employing one of the models, the proposed definition of efficiency can lead to the erroneous interpretation of results, namely by concluding that both models are equivalent in their performance when in fact, if a lower amount of rewards found is accompanied by a smaller distance travelled (for the same period), the model from which such a result is obtained does not exhibit a desirable behaviour.

Even though the proposal of novel metrics is outside the scope of the current work, this Chapter ventured to suggest a possible alternative, namely by considering *energy efficiency* instead, and define it as the ratio between the rewards found and the variation of battery level since the beginning of the experiment. In doing so, making use of real data provided by embodied experiments, results were more conclusive, and have shown a clear superiority of the ELW with respect to Yuragi when employing a metric that is far less ambiguous. Furthermore, this Chapter also analysed the trajectories of the agent when the different models are employed. This analysis corroborated the conclusions drawn from inspecting the standard metrics proposed by Nurzaman et al. (2010) in what concerns the exploration of the domain and the ability to exhibit adaptive behaviour. By proposing that trajectories be analysed on their goodness of fit to power-law distribution, one observes that

indeed the better fit to such a distribution (to which the Lévy distribution can be approximated) coincides with a better performance of the ELW model.

Next Chapter aims to answer the final Research Question (Section 1.3) by extending the ELW model to be used as a component of an adaptive swarm strategy.

Chapter 5

Endocrine Lévy Firefly Model for Collective Foraging

In the previous Chapter, this Thesis focused on deriving an individual adaptation mechanism based on Artificial Endocrine Systems. In doing so it was observed how such a mechanism, applied to explicit formulation of the Lévy Walk, was able to outperform the concept of biologically fluctuation in a series of metrics, both in simulated and real experiments.

However the envisioned foraging task in real-world scenarios is well documented to be too vast of an undertaking for a single agent to tackle (Trianni, 2008). In this regard the present Chapter proposes an augmentation of the Endocrine Lévy Walk (ELW) by overlaying it with a social interaction component derived from the interactions of fireflies. Mimicking fireflies has firstly been adopted as an optimization method by Yang (2009), and has in following years gained a foothold in robotics applications (Palmieri and Marano, 2016; Zedadra et al., 2019, 2018), making it a prime approach for modelling interactions in swarm robotics.

Indeed, as it was described in Section 2.5.2, an important contribution to the branch of swarm robotics that tackles collective foraging has been made by Sutanryo et al. (2013) where the concept of firefly interaction was firstly employed to the task of collective and the Lévy+ model was proposed to the collective adaptive foraging problem such as the one this Chapter tackles. Moreover, and also as highlighted in Section 2.5.2 Table 2.5, another important contribution to tackling this problem was made by Nauta et al. (2020) by proposing the Adaptive Collective Lévy Walk

(ACLW) model which, albeit the absence of a firefly component, also addresses the problem of collective adaptive foraging employing a swarm robotics approach. Indeed these two models are of fundamental importance to the experiments, results and conclusions drawn within this Chapter.

In proposing the Endocrine Lévy Firefly model (ELF), a swarm robotics model that simultaneously brings together the concept of Artificial Endocrine Systems applied to LWs while mimicking firefly behaviour, this Chapter addresses the last Research Question asked in Section 1.3 namely:

- Can the ELW be extended to a robotic swarm, and still be able to deliver an increased performance in comparison to other swarm strategies which tackle adaptive foraging?

Thus this Chapter represents the culmination of this Thesis' efforts to propose alternative models to the study of foraging, performed by swarms of robots, as well as to clear new avenues of potential future research in the field.

5.1 Model Description

The model proposed in this chapter builds on two of the main concepts presented thus far, namely: the ELW model for individual adaptation, and the firefly algorithm for social behaviour. By recalling Figure 4.1, equations (4.3) to (4.7), and Algorithm 7 one is able to compute the velocity vector, $\vec{\mathbf{u}}_h$ that would serve as the command action of a single agent. In the ELF model, detailed below, this vector is weighted by the contribution of the firefly algorithm, i.e., the attraction exerted by neighbouring agents, and collision avoidance mechanism discussed in Chapter 2.

Recalling the computation of collision avoidance one defines a set \mathcal{A}_i of all those agents which are below a certain threshold δ_c with respect to the i^{th} agent.

$$\mathcal{A}_i = \{j : \|\mathbf{p}_j - \mathbf{p}_i\| < \delta_c, \forall j \neq i\} \quad (5.1)$$

Set \mathcal{A} allows the computation of geometric centre formed by the positions of its members using , where n_j is the number of j agents in set \mathcal{A}_i as:

$$\bar{\mathbf{p}}_j = \frac{1}{n_j} \sum_{\forall j \in \mathcal{A}_i} \mathbf{p}_j \quad (5.2)$$

Knowing $\bar{\mathbf{p}}_j$, computed in the fixed global frame O , one derives its value with respect to the local frame of agent i by using (5.3), where $\mathbf{R}^{O \rightarrow i}$ represents the rotation matrix from the fixed frame O to the i^{th} local frame.

$$\bar{\mathbf{p}}_j^{(i)} = \mathbf{R}^{O \rightarrow i}(\mathbf{p}_j - \mathbf{p}_i) \quad (5.3)$$

Consequently the relative orientation of $\bar{\mathbf{p}}_j^{(i)}$ can be extracted with respect to the i^{th} frame, $\theta^{(i)}$, through (5.4), where atan2 is the numeric arc-tangent function, $\bar{\mathbf{p}}_{jy}^{(i)}$ and $\bar{\mathbf{p}}_{jx}^{(i)}$ are respectively the x and y components of $\bar{\mathbf{p}}_j^{(i)}$.

$$\theta^{(i)} = \text{atan2}(\bar{\mathbf{p}}_{jy}^{(i)}, \bar{\mathbf{p}}_{jx}^{(i)}) \quad (5.4)$$

Since this angle represents the direction *towards* $\bar{\mathbf{p}}_j^{(i)}$ the subsequent angular velocity command, needs to be such that the agent i moves *away* from this position. We compute it using (5.5), where ω_a^i represents the contribution of the collision avoidance mechanism to the angular velocity of agent i , and K is a simple proportional gain. We can then define the velocity command component from the collision avoidance mechanism for agent i , in (5.6).

$$\omega_a^i = K \times (\theta' - \pi) \quad (5.5)$$

$$\vec{\mathbf{u}}_c^i = [v, \omega_a^i]^T \quad (5.6)$$

In summary the output velocity command, $\vec{\mathbf{u}}^i$, for every agent i becomes a conditional value, subject to the conditions of the ELW controller, and collision avoidance. Therefore the velocity command in the scenario where individual agents perform ELW and collision avoidance is defined by (5.7).

$$\vec{\mathbf{u}}^i = \begin{cases} \vec{\mathbf{u}}_c^i, & \mathcal{A}_i \neq \emptyset \\ \vec{\mathbf{u}}_h^i, & \text{otherwise} \end{cases} \quad (5.7)$$

Secondly one should also recall how the contribution of the firefly attraction rules impacts the velocity command. To compute such contribution one defines a

second the set \mathcal{B} containing the agents within the communication range δ_r that have a brightness β larger than the i^{th} the agent's own brightness β_0 .

$$\mathcal{B}_i = \{j : \|\mathbf{p}_j - \mathbf{p}_i\| < \delta_r \wedge \beta_j > \beta_0, \forall j \neq i\} \quad (5.8)$$

where brightness is computed using the method proposed by Sutanty et al. (2013), which considers that brightness is a function of the frequency with which rewards are found, in other words, the more frequently new rewards are found the higher will the brightness be. This value subsequently decreases if no new rewards are found, as shown by eq(5.9) where f is the number of rewards found and m is a positive unitary scalar reflecting a linear decrease of brightness over time.

$$\beta_0(t) = \begin{cases} \delta t^{-1} & , f > 0 \\ \min(0, \beta_0(t-1) - m) & , f = 0 \end{cases} \quad (5.9)$$

From set \mathcal{B} one selects the member j with the highest brightness and use its position, $\hat{\mathbf{p}}$, compute a angular velocity using a similar approach to collision avoidance, only this time the agent i will be rotating *towards* agent j , such as depicted if Figure 2.16. Knowing $\hat{\mathbf{p}}$, and employing (5.3)-(5.4), we compute its relative position to agent i , extract the relative direction $\hat{\theta}$, and compute the angular velocity component as:

$$\omega = K \cdot \hat{\theta} \quad (5.10)$$

as well as the subsequent velocity command, $\vec{\mathbf{u}}_\beta$, which provides a contribution to steer the agent towards its brighter neighbour:

$$\vec{\mathbf{u}}_\beta^i = [v, \omega_a^i]^T \quad (5.11)$$

By taking these two aspects of angular velocity into consideration, a conceptual diagram representing the ELF model can be drawn, by extending that presented in Figure 4.1 by introducing two extra nodes \mathcal{F} and \mathcal{A} that represent respectively the firefly computation of ω (5.10) and the collision avoidance computation of ω_a (5.5), based on an information stream $c(t)$ which encompasses both position and

brightness of neighbouring agents. The ELF model diagram is depicted in Figure 5.1.

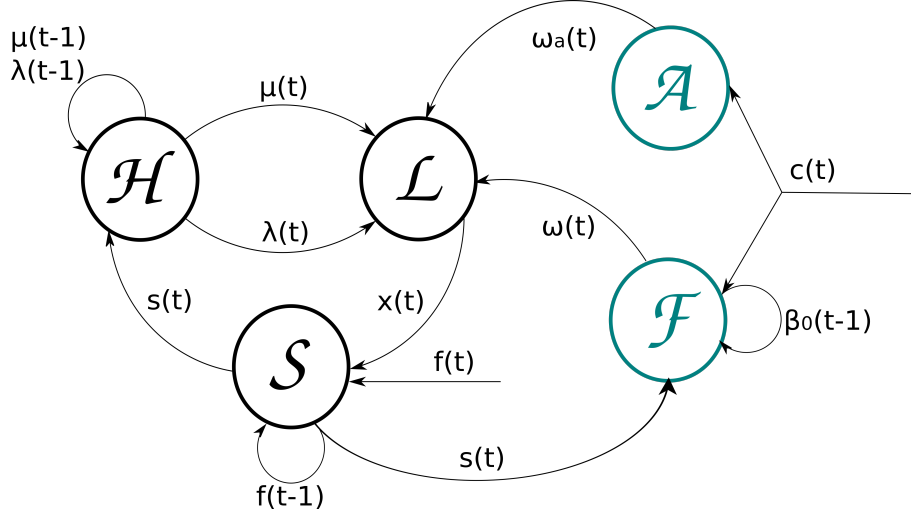


Figure 5.1: Endocrine Lévy Firefly model.

Finally the output of the ELF model written as velocity command is expressed by eq.(5.12), where the agent follows the collision avoidance rule if the set \mathcal{A} is not empty; steers towards its brighter neighbour if there is one or performs the ELW behaviour if none of the above conditions are met.

$$\vec{u}^i = \begin{cases} \vec{u}_c^i, & \mathcal{A}_i \neq \emptyset \\ \vec{u}_\beta^i, & \mathcal{A}_i = \emptyset \vee \mathcal{B}_i \neq \emptyset \\ \vec{u}_h^i, & \text{otherwise} \end{cases} \quad (5.12)$$

Recalling the models for collective foraging presented in Section 2.5.2, namely the Lévy+ and the ACLW, which will serve as benchmark for the ELF, one should highlight the following key aspects in which all these models differ. With regards to the ACLW, ELF considers that interactions between agents are based on the concepts of the firefly algorithm and that adaptation of the μ parameter is based on the ELW (and therefore on AES), whereas the ACLW model simply switches from a $\mu = 2$ to $\mu = 3$ when encountering rewards, and slowly decreases its value again according to eq(2.20).

Moreover the ACLW also considers a long range avoidance for agents performing long walks (walks with a length superior to a threshold \bar{L}) in order to ensure these

long walks are in fact not truncated by collision avoidance and other parts of the domain are explored. The Lévy+ method mainly differs from ELF by considering a fixed μ parameter and using the density of rewards to modulate the robot’s velocity. Since the the μ parameter in the Lévy+ model is used to generate, not a distance, but the time that a robot travels in a certain direction. By decreasing the speed the motion will effectively switch from global relocations at high (or nominal) speeds to local searches at low speeds. A similarity between the Lévy+ and the ELF is that both do employ a firefly based interaction strategy to cooperation thus contributing, in this regard, to a much focused comparison on adaptation strategies of individual agents.

5.2 Experimental Set Up

To compare the different approaches detailed so far, a series of experiments were conducted both in simulation and in real robots. For simplicity, the first set of these experiments were conducted in MATLAB®[®], using a particle based approach to facilitate the testing of large numbers of agents. Following the approach of previous chapters, the second set of simulations was also conducted in GAZEBO, using the Robot Operating system to control the behaviour of a group composed of Crazyflie mini-drones (Hönig and Ayanian, 2017a,b). Finally experiments with the real drones were also conducted to validate those obtained in the GAZEBO simulation.

5.2.1 Particle-based Simulations

Conducting large scale particle-based simulations of the competing models is meant to provide a first insight, in an abstract manner, about how the different models perform with respect to different initial conditions. To do this we test all such models in two different scenarios where rewards have different distributions within each patch, either Uniformly or Gaussian, as depicted in Figures 5.2a and 5.2b respectively.

Each patch center is chosen randomly and uniformly across the domain. Employing different environments where rewards are distributed uniformly follows the most common approach in the literature (Nauta et al., 2020; Nurzaman et al., 2010;

Sutantyo et al., 2013), while a scenario with a normal distribution tends to represent better real-world phenomena such as the growth of weeds in agriculture, or pollution (Trianni, 2008).

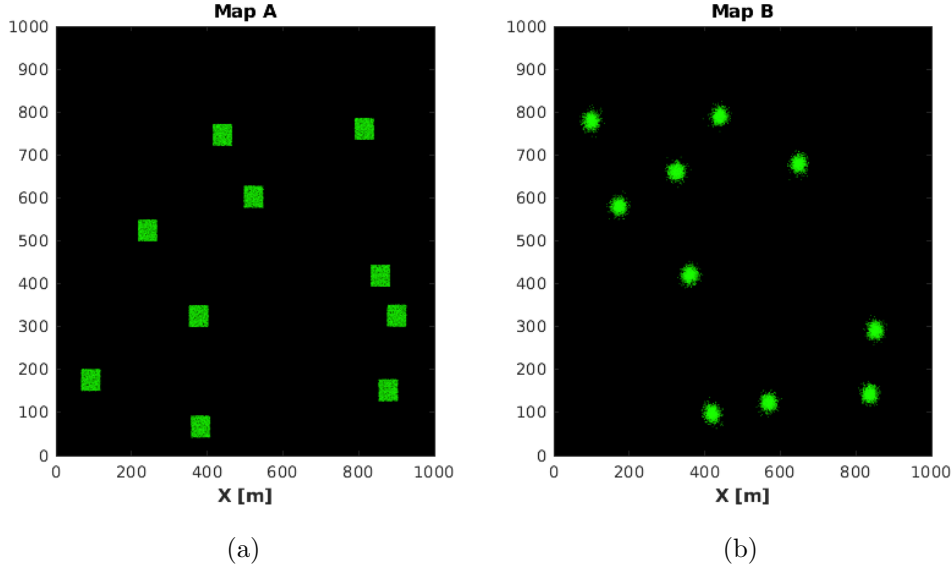


Figure 5.2: Distribution of rewards in particle-based simulations.

The characteristics of these maps are summarized below in Table 5.1, derived from the preceding work on single agent foraging (Sardinha et al., 2020b).

Map	Number of Patches	Reward Distribution	Characteristic Dimensions	Number of Rewards
A	10	Uniform	Lateral side length: 50 [m]	2500
B	10	Gaussian	Standard deviation (σ): 5	1000

Table 5.1: Environmental parameters particle-based simulations.

The parameters used in each method are summarized in Table 5.2. Where possible the same parameters were used as specified in the respective original works that serve as a benchmark without further optimization. Doing so serves to show how these algorithms perform in a *off-the-shelf* manner. Where this information was not available values were set empirically from insight gained from other works such as Nurzaman et al. (2010).

Testing different algorithms in an *off-the-shelf* manner provides qualitative insight on how models perform without any optimization for a particular scenario. However,

it could be argued that a drawback of this approach could lead to an assessment that is biased, namely by not considering potential solutions where the relative performances of competing approaches would differ. In order to mitigate this drawback all models are tested in different scenarios and with different swarm sizes.

Parameter	Units	Value	Description	Method
N	–	{5, 10, 20, 40}	Swarm size	All
δ_r	[m]	5	Communication range	
δ_c	[m]	30	Collision avoidance threshold	
s_r	[m]	2	Sensing radius	
v_x	[m/s]	1	Fixed Forward velocity	ELF & ACLW ¹
γ	–	{0.01, 1, 10}	Light absorption coefficient	ELF & Lévy+
$\overline{v_x}$	[m/s]	1	Maximum forward velocity	Lévy+ ²
$\underline{v_x}$	[m/s]	0.05	Minimum forward velocity	
μ		2	Fixed Lévy parameter	
ζ	–	0.04	Decrease coefficient of eq.(2.20)	ACLW ³
C		50	Cutoff value of eq.(2.20)	
\overline{L}	[m]	80	<i>Long walk</i> threshold	
μ_s		1.659	Settling point of μ	ELF ⁴
a_1		0.152	Hormonal decay for μ	
a_2	–	0.511	Hormonal production for μ	
b_1		0.940	Hormonal decay for λ	
b_2		0.499	Hormonal production for λ	

Table 5.2: Model parameters used in particle-based simulations

From Table 5.2 we highlight that two parameters exist for which a set of values was used, namely: the size of the swarm (N) and the light absorption coefficient (γ). Simulations were conducted using every combination of these parameters where

¹Value of v_x is variable for Lévy+ method

²Value of μ is variable for ELF and ACLW methods

³Values used in the original work from Nauta Nauta et al. (2020)

⁴Values optimized for a single agent in the work from Sardinha et al. (2020b)

they apply. One should note that no attraction mechanism exists in ACLW making it independent of (γ) . Therefore, in all results shown in Section 5.3 and Appendixes A and B, every metric value that assesses the performance of the ACLW does so with respect to the size of the swarm alone.

5.2.2 Embodied Experiments

To validate the particle-based simulations in a realistic environment we have conducted experiments where the three aforementioned strategies were deployed in group of Crazyflie mini drones, first in the GAZEBO simulator, and afterwards using the physical drones. The Crazyflie drone, depicted in Figure 5.3 is quite a versatile platform that through its various extension boards can be configured to suit the needs of the user.

Apart from the on-board radio for communication, gyroscope, accelerometer and controller it can be upgraded to carry a distance sensor and optical flow sensor for ground referencing, camera and LED ring. Moreover, its firmware is designed for seamless integration with motion capture systems for tracking of pose, as well as a streamlined integration with the Robot Operating System (ROS) (Hönig and Ayanian, 2017*a,b*), and its small size makes it ideal for multi-robot experiments.



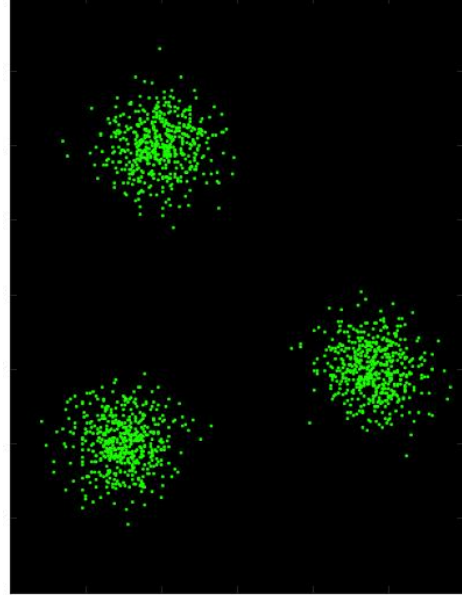
Figure 5.3: Crazyflie mini drones from Bitcraze.

In the particular case of our work we mount two upgrades, namely: the Flow Deck board, which enables ground referencing and velocity commands, which is a

necessary condition for all three models tested; and the motion capture deck, where reflective markers are mounted, which in turn enable the Vicon motion capture system to track each drone individually. The placement of such markers is also visible in Figure 5.3 where the group of four drones used in our experiments is depicted. Our validation scenario for embodied experiments is a 4×3 [m] arena, with nine Vicon infrared cameras placed around flying zone, and three clusters with five hundred rewards each. The arena, the virtual reward scenario and an example of drones in the arena are depicted in Figures 5.4a, 5.4b and 5.5 respectively. Figure 5.6 exemplifies the detection by the VICON system as well as the disposition of its infrared cameras.



(a) Flying Arena



(b) Reward distribution

Figure 5.4: Environment conditions for embodied experiments

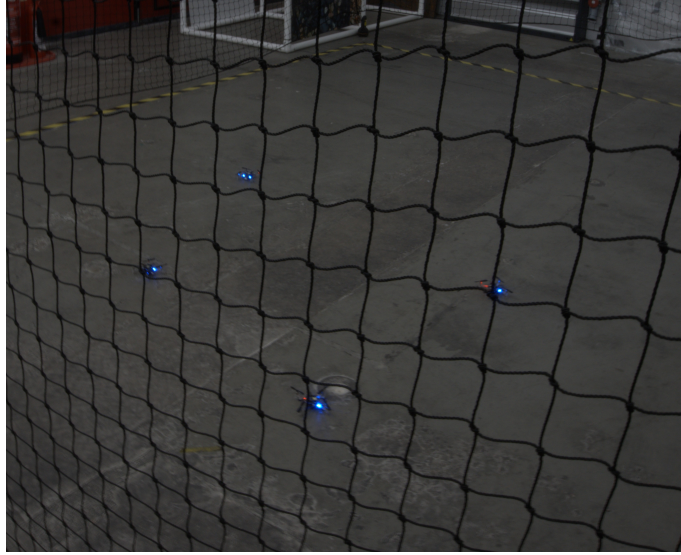
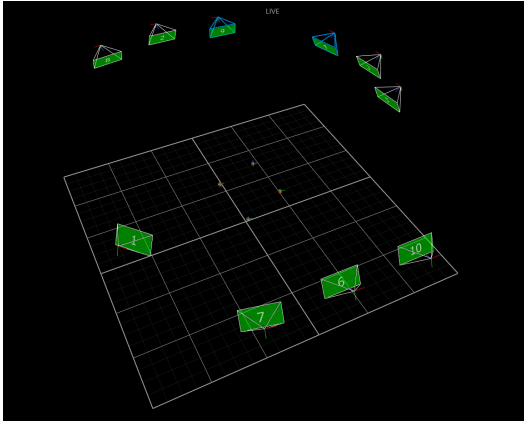
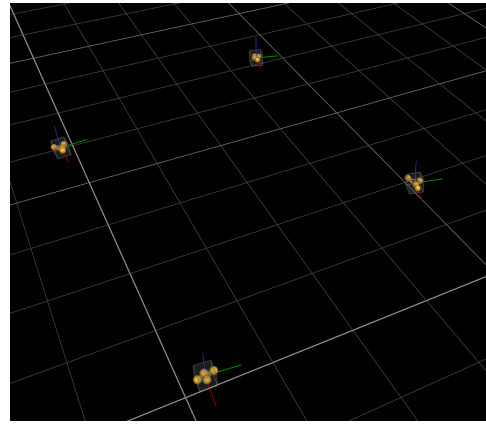


Figure 5.5: Four Crazyflie drones inside the flying arena



(a) Disposition of the VICON cameras.



(b) Detail showing the detection of 4 Crazyflie drones

Figure 5.6: Example of the VICON system base-station's display showing the disposition of cameras in the system 5.6a and the detection of four drones 5.6b

To accommodate, for the difference in scale some of the parameters in Table 5.2 were updated and are present below in Table 5.3. Despite the size of the testing arena constraining the number drones that can be used in our embodied experiments, we will show how these results maintain their validity as a proof-of-concept step towards a large-scale experiment. This is achieved mainly by highlighting how the relative performance of the different models is maintained, between large-scale particle-based simulations and embodied experiments. A similar argument has been echoed by other works such as: Sutantyó et al. (2013) who employs three underwater robots to

the foraging task and McGuire et al. (2019) who tests different drone sizes (between two and six) to test a minimal solution for navigation also employing UAVs.

We should note that only parameters regarding dimensionality were updated, i.e., communication radius, avoidance radius, and velocities. The parameters that regulate the algorithmic performance are kept the same. Doing so, should also provide some insight about the versatility of such methods to maintain their performance when different conditions manifest.

Parameter	Units	Value	Description	Method
N	–	4	Swarm size	All
δ_r	[m]	1.5	Communication range	
δ_c	[m]	0.05	Collision avoidance threshold	
s_r	[m]	0.01	Sensing radius	
v_x	[m/s]	0.25	Fixed Forward velocity	ELF & ACLW
γ	–	0.01	Light absorption coefficient	ELF & Lévy+
$\overline{v_x}$	[m/s]	0.25	Maximum forward velocity	Lévy+

Table 5.3: Updated parameters for embodied experiments

The last consideration regarding the comparison of different models, relates to the different metrics employed to assess the different aspects of the emergent behaviours. The formal description of these metrics is presented in the next subsection.

5.2.3 Metrics

To assess the performance of all the adaptive strategies four different metrics were employed. The first of these metrics is the percentage of rewards found defined below:

$$\eta_r = r/R \quad (5.13)$$

where r represents the number of rewards found, and R the total number of rewards present in the scenario. The second metric is simply the number of clusters discovered, denoted as k_d . Both these metrics are chosen due to their usage as standard metrics in works such as. The third metric, also proposed by Nurzaman, is search

efficiency η_s , which for a single agents represents simply the number of rewards found over the distance travelled. Nauta *et al.* in their work expand the formulation of search efficiency to the swarm case and compute:

$$\eta_s = \frac{1}{N} \sum_{i=1}^N \frac{r_i}{d_i} \quad (5.14)$$

where N is the number of agents in the swarm and r_i and d_i are respectively the number of rewards found and distance travelled by agent i . Finally the last metric employed, and also used by Nauta *et al.*, is cluster search efficiency (ν) which aims to characterize how well each cluster is explored. This metric is defined by Wozniak Wosniack et al. (2015) as:

$$\nu = \frac{1}{D} \frac{k_d}{K} \sum_{k=1}^{k_d} \frac{r_k}{1 + \frac{|\bar{r} - r_k|}{r_k}} \quad (5.15)$$

where D stands for the distance travelled by all agents k_d and K stand for the number of clusters discovered and total number of clusters respectively, r_k stands for the number of rewards found in cluster k and \bar{r} stands for the average number of rewards found per cluster.

5.3 Results

5.3.1 Particle-based simulations

To have statistical significance of our results every method was ran one-hundred times for each combination of parameters. We start by analysing a sub-set of results for Map A depicted in Figure 5.7, where the temporal evolution of all four metrics is plotted for $N = 20$ and $\gamma = 1$. Comprehensive plots of all combinations of parameters can be found in Appendix A. From Figure 5.7 we observe how the ELF model is able to significantly outperform the other two models. The exception is the number of clusters found, which all models are able to maximize, with only a slight advantage of ELF, which is able to do so earlier than the other two models.

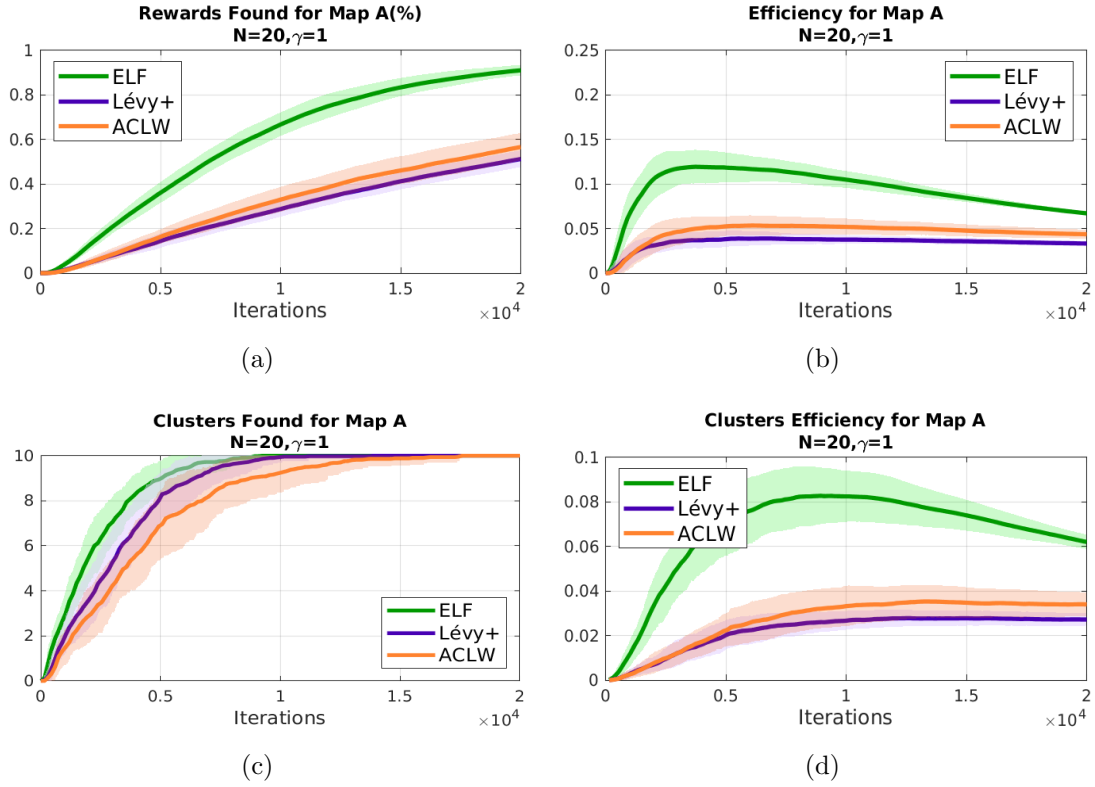


Figure 5.7: Average temporal evolution of metrics for Map A: Rewards Found (5.7a); Search Efficiency (5.7b); Clusters Found (5.7c) and Cluster Search Efficiency (5.7d)

To explain such stark contrast we note that besides the underlying biological inspiration used in the ELF model, the major difference to the other two methods is the explicit modulation of a *desire* to truncate walks (λ), which fluctuates according the principles of an AES. As opposed to this strategy agents using the Lévy+ model slow down to maximize the chance of finishing their current walk within a patch, significantly decreasing the speed of discovery of new points, as it is shown by the the small gradient depicted in Figure 5.7a. The alternative proposed by the ACLW, where agents avoid those performing *long walks*, is only marginally better when it comes to the rewards found. However, we should note that even though the ACLW has no attraction component, and merely exploits the diffusive properties of LWs, it does so successfully since it is able to outperform a method where a such collaboration exists, namely the Lévy+ model.

The other noteworthy comments regarding the values of these metrics, relate to both efficiency metrics depicted in Figures 5.7b and 5.7d. We see that the temporal evolution of efficiency metrics, specially in ELF, tends to increase and reach its

maximum value in the first half of the simulation and then subsequently declines. This happens mainly because rewards can only be discovered once. Since both metrics depend on distance travelled and rewards found, as iterations increase and more points are discovered, each agent will have to travel greater distances to find new rewards.

Similar results were also obtained for Map B and are depicted in Figure 5.8. These curves bellow corroborate the previous findings where one observes the ELF outperforming the other two models. However, we highlight the different scales of values across all efficiency metrics.

Despite the ELF being always the best performing model, we observe the actual value of efficiency is somewhat a different magnitude. This is due to the fact that the definitions of efficiency we have used, as suggested by other works, do not constitute an absolute and normalized metric. In fact it may depend on the disposition of rewards, number of clusters or density of rewards within patches, making comparison between these metrics across maps quite challenging. However, we still observe that in the same conditions, the ELF method has the upper hand across all four metrics.

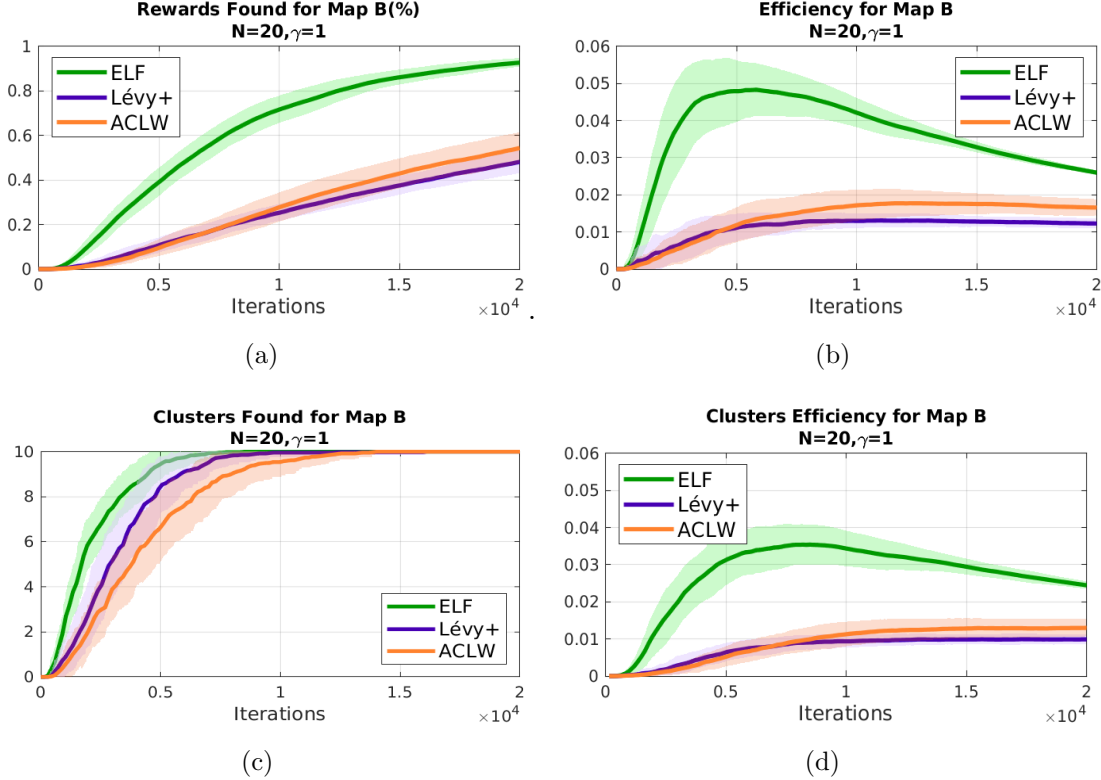


Figure 5.8: Average temporal evolution of metrics for Map B: Rewards Found (5.8a); Search Efficiency (5.8b); Clusters Found (5.8c) and Cluster Search Efficiency (5.8d).

5.3.2 Embodied experiments

Similarly to the particle-based simulations, we analyse the four aforementioned metrics. We performed 20 runs of each method in GAZEBO simulation and a validation run using the Crazyflies in the experimental arena. Each run lasts 180 seconds. For the purpose of comparison between the simulations and real experiments we group each metric obtained in GAZEBO with the results of its real counterpart. Figure 5.9 presents the temporal evolution of rewards found for each method, both in simulation (Figure 5.9a) and using the real-world validation (Figure 5.9b)

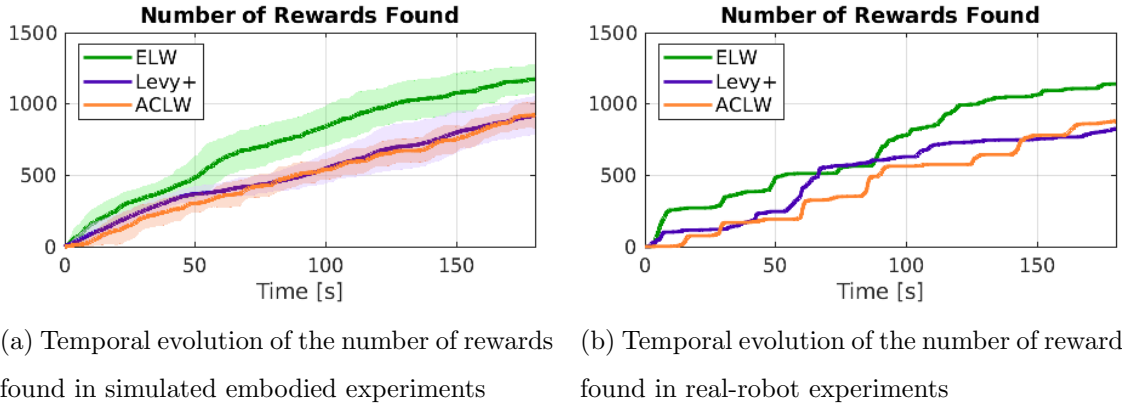
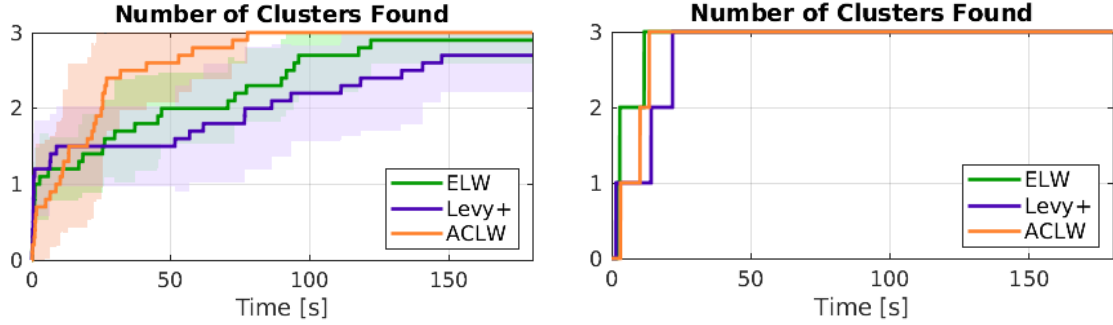


Figure 5.9: Temporal evolution of the number of rewards found in embodied experiments both in simulated (5.9a) and real-robot (5.9b) settings

We see that for this first metric the relative performance of models observed in particle-based simulations holds, mainly since the proposed ELF model is able to discover more rewards than either of the other two models. On the other hand, due the smaller dimensions of the scenario, one observes that both the Lévy+ and ACLW methods have very similar, and quite undifferentiated performances, even more so than previously observed. Despite the greater dimensional constraint of the scenario, we observe that the ELF method is still able to have, not only a differentiated performance, but a better one in discovering rewards.

The number of clusters discovered also evolves in an expected fashion as every method was able to find the totality of clusters. A note must be made however to the fact that these clusters occupy a larger relative area when compared to the dimensions of the domain. Such change was necessary to make clusters that were large enough for the adaptation components of the different models could surface in the

experimental results. Otherwise, keeping the ratio between cluster and environment areas, would lead in our case to extremely small clusters, devolving the subsequent experimental results of significance.



(a) Temporal evolution of the number of clusters found in simulated embodied experiments. (b) Temporal evolution of the number of clusters found in real-robot experiments.

Figure 5.10: Temporal evolution of the number of clusters found in embodied experiments both in simulated (5.10a) and real-robot (5.10b) settings.

The metrics related to efficiency also were affected from the change of scenarios. As we see from Figure 5.11 both the ELF and Lévy+ methods tend to converge to the same efficiency value, a result that is not obtained in particle-based simulations. Looking at (5.14) we see that search efficiency depends on the ratio of rewards found and distance travelled. However, as we have seen in Figure 5.9, ELF was able to find a larger number of rewards, which means that for the same value of efficiency, agents using the Lévy+ method have simply travelled a smaller distance. In fact, this shows how metrics should be considered in their collective rather than individually. Two methods with similar efficiency, may seem to be equivalent but in fact we observe that they are not. Be that as it may, results between simulation in GAZEBO and real-world are still consistent granting further strength to the claim that the ELF method is robust enough to overcome the reality gap.

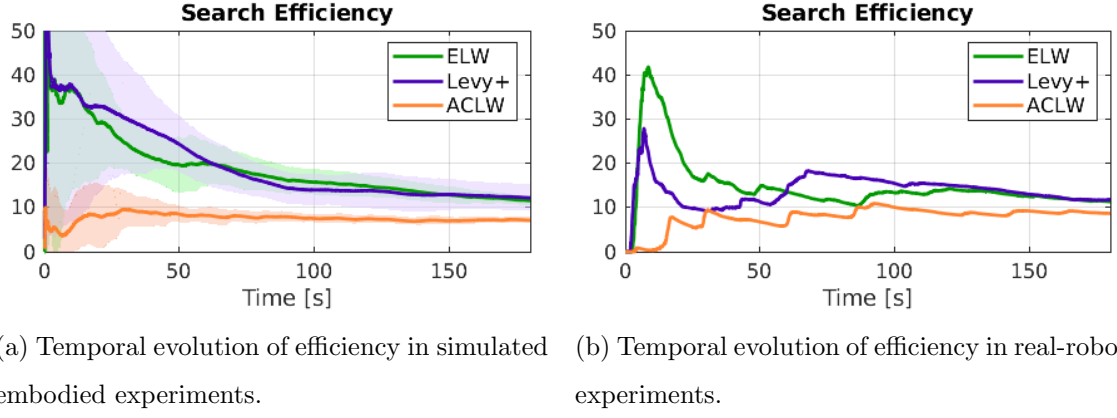


Figure 5.11: Temporal evolution of the search efficiency in embodied experiments both in simulated (5.11a) and real-robot (5.11b) settings.

A similar result is observed for cluster search efficiency, as depicted below in Figure (5.12). In this particular case it is the Lévy+ and ACLW methods that seem to coincide in simulation results, especially towards the time limit, while the average ELF result is still slightly better than the former two. This is also a consequence of the size of the experimental arena relatively to the size of clusters.

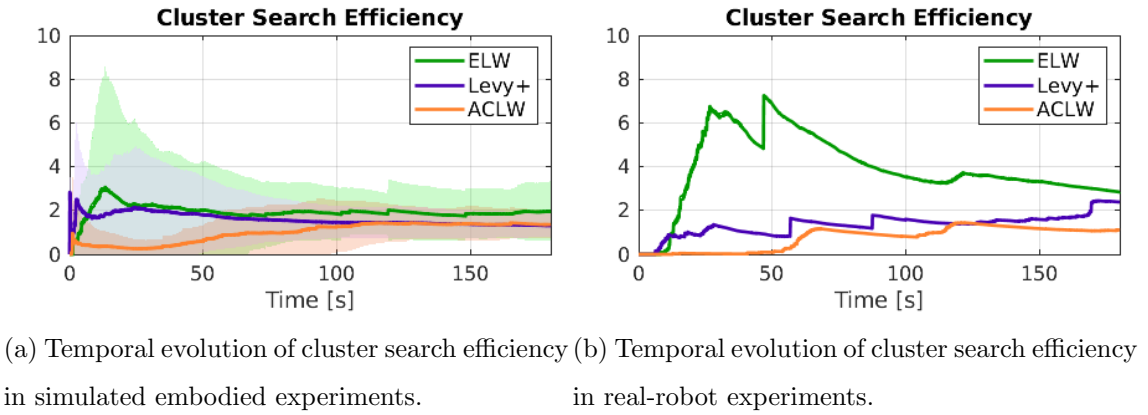


Figure 5.12: Temporal evolution of the cluster search efficiency in embodied experiments both in simulated (5.11a) and real-robot (5.11b) settings.

As clusters occupy a larger amount of the domain, there is an increased chance that all will be explored in more even manner. Recalling (5.15) we note that it depends on the difference between the average number of rewards discovered per cluster (\bar{r}) and the number of rewards discovered in a given cluster (r_k). In the experimental environment, since this difference may be similar regardless of the method, it is therefore expected the value of the cluster search efficiency itself will

also be similar. Once more, we highlight the importance of evaluating metrics collectively, since even if the difference between \bar{r} and r_k is similar for different methods, one can only infer about how evenly each method is able to explore each cluster, rather than *how well* those clusters were actually explored. Despite this, Figure 5.12 still shows the consistency of the previously results, since it not only validates the relation between the performances of the different methods, but also shows how the ELF model is able to maintain its edge against competing strategies. Below, Figure 5.13 shows two screenshots of the ELF behaviour.

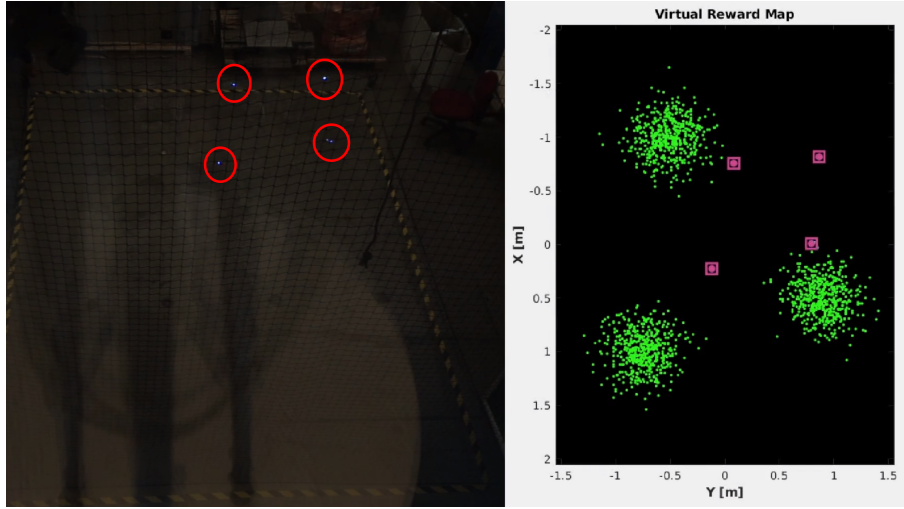
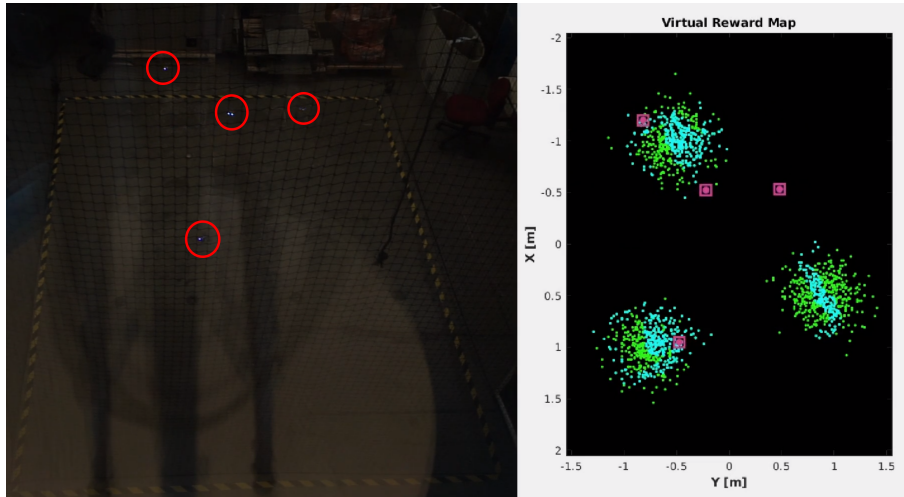
(a) $t = 0$ seconds(b) $t = 60$ seconds

Figure 5.13: Screenshots of the ELF behaviour at different time steps, showing the flying arena the crazyflie robots and the virtual reward distribution. Undiscovered rewards are plotted in green and discovered ones plotted in blue⁵.

⁵A video of the ELF behaviour is available at: <https://tinyurl.com/v33efkvn>

5.4 Summary

The primary goal of this Chapter was to investigate alternative strategies for generating adaptive Lévy Walk behaviours in swarm robotics and tackle the challenge of collective foraging. Since LWs have been extensively referred to in the literature as optimal strategies for foraging, they can be seen as the emerging strategy for foraging in clustered environments. The Endocrine Lévy Firefly algorithm was able to outperform other strategies which aimed to tackle the same problem, and has done so in two separate environments where rewards were distributed uniformly and normally inside such clusters. Even though the scenario where rewards are distributed uniformly tends to be the most commonly used approach, this Chapter also included a normally distributed one. In both scenarios the quantitative assessment of methods showed the benefits of the ELF across four metrics.

Even though these metrics clearly show an advantage of the proposed method, we should note how the efficiency metrics give values that are only interpretable by comparing the different metrics. In other words, since both the search efficiency metric (5.14) and the cluster search efficiency (5.15) can be indirectly affected by the disposition and number of clusters and density of rewards within, the efficiency metrics do not constitute absolute measures of how efficient a method is. In this regards, we believe it would be worth investigating an overarching and comprehensive set of efficiency metrics that could compute values of search efficiency and cluster search efficiency with normalized values where $\eta \in [0, 1]$ like it is the case in a myriad of other disciplines. In this manner, comparing efficiency between methods could potentially be more streamlined by accelerating the benchmark of such techniques, across a set of test scenarios.

The need for comprehensive and meaningful metrics is also highlighted in the Appendixes A.1 and A.2 where we consistently observe a decrease in efficiency with the increasing number of agents in the swarm, even though we also observe that an increased number of rewards is found.

We have also observed that a varying light absorption parameter (γ) only affects the relative performance of the systems when its value is very small since a small value of γ means that agents are *more visible* to each other. An example of this is Figure A.2 for $\gamma = 0.01$, where we see the Lévy+ method outperforming the ACLW

as the number of agents increases. In fact since agents performing ELF and the Lévy+ mimic fireflies in their interaction and increasing values of γ mean that is increasingly harder for agents to attract agents that are further way, the adaption strategy takes a central stage in the performance of the system.

In the future we expect to be able to, besides designing new, more robust metrics, secure a larger experimental facility where a larger swarm of Crazyflie mini-drones can be used. We also intend to conduct an analysis of how each agent behaves where motion patterns are concerned assessing what distribution better fits the obtained trajectories. Furthermore, we envision than an implicit model could derived where, instead of explicit Lévy mechanism this could replaced for a more biologically plausible mechanism such as an artificial neural network (ANN), where the weights between neurons and activation thresholds could be modulated by an AES, thus modulating a more comprehensive artificial homeostatic system (AHS).

Chapter 6

Discussion

Throughout the work developed in the scope of this Thesis, and more precisely the LW-based models that were proposed, several assumptions and choices were made regarding modelling and implementation. Even though such choices were made to focus the research effort on the behavioural aspect of autonomous agents, they invariantly pose other questions worthy of discussion.

This Chapter revisits the main details of modelling, implementation and assessment of models proposed throughout the Thesis and offers insight about their drawbacks and advantages in answering the Research Questions proposed in the first Chapter.

6.1 Modeling

In the course of this Thesis, two distinct approaches to design LW-based models were taken. By recalling eq. (2.1) below, which expresses the approximation of a Lévy distributed variable (l) to a power-law, one highlights the importance of the parameter μ to the shape of the Lévy distribution.

$$P(l) \sim l^{-\mu}, \quad 1 < \mu \leq 3$$

The way that μ is chosen over the course of this Thesis varies considerably. In Chapter 3, μ is a fixed constant throughout the duration of each simulation, and several values are tested in order to test its impact on the performance of the system.

The model proposed, and indeed the task addressed in Chapter 3, function as predecessors of the following Chapters. Results in tackling the cooperative surveillance task, are indeed revealing of the benefit of a LW-based approach to collaborative exploration without prior knowledge of the domain, or pre-assigned regions of interest to monitor, as in fact is the case in several works in the literature.

Conversely, Chapters 4 and 5 propose models that are built on the dynamic fluctuation of the μ parameter, as their contribution focus on a fundamentally different problem. In particular Chapter 4 proposed a model for adaptive foraging where a single agent performs LWs, and the μ parameter is modulated by an underlying AES. This model, the ELW, was compared to the Yuragi approach proposed by Nurzman et al. (2010), based on the concept of biological fluctuation. Besides the models being considerably different in their approach to modulate transitions between local and global searches, a particularly noteworthy feature that distinguishes them is the employment (or the absence) of an explicit LW process to modulate behaviour. This particular topic, has also been subject of discussion in the Computation Ecology field, where the distinction between *process* and *pattern* has been extensively discussed. On one hand Lévy Processes might not produce Lévy patterns, such as in highly constrained environments with high obstacle density, and on the other hand that the conjugation of non-Lévy Processes can originate Lévy Patterns, for instance by drawing walk lengths from two (or more) Gaussian distribution with different means, depending on the desirability of environment conditions.

Arguably, the notion that animals in nature do not preform LWs in a conscious manner, but rather exhibit such a *pattern* in their behaviour through the interactions with their environment, seems to pose a valid and intuitively correct idea. However, the scope of this Thesis was focused, not mainly on explaining animal behaviour, but rather on designing and testing behaviour-based controllers for artificial agents that could perform search and foraging in an adaptive and effective manner. However, despite the biological plausibility of the Yuragi approach, and the fact that the ELW outperformed it, this does not suffice to disregard that strategies focusing on explicit generation of Lévy variables will invariantly outperform others that do not. In fact, one could argue that the simplicity of the Yuragi model, albeit being a notable advantage with respect to implementation, causes the system to not perform as well

as the ELW, a model with higher complexity.

Indeed the argument for increased biological plausibility is made in Chapter 5, where the proposed ELF model is compared against the Lévy+ and ACLW models (Nauta et al., 2020; Sutantyo et al., 2013). Results in Chapter 5 have shown that an adaptation strategy based on an AES, only present in the ELF model, is indeed a considerably important component in the swarm approach, even more so when one considers that other methods such as the Lévy+ also draw inspiration from the firefly algorithm to model interaction between agents.

In this regard, one could envision future iterations of both the ELW and ELF models where the explicit usage of a LW component is replaced with a more biologically plausible description of motion, such as an Artificial Neural Network, and still building on the benefits of an AES, as a primary adaption mechanism. Indeed, such an evolution of the proposed foraging models would greatly benefit from the argument of *pattern* vs *process* through which computation biologists try to explain animal foraging behaviour. Basing models for artificial agents, on a deeper understanding of their natural counterparts, would therefore greatly benefit from the advancement of this field, in search of increasingly effective and adaptive behaviour-based controllers. Nevertheless, it is also worth noting some of the limitations of the proposed models. As the scope of this Thesis was focused primarily on designing novel behavioural models, further considerations must be made if in the future these models are meant to be deployed in a real-world scenario. These models assume, for example, that position and orientation of individual agents are known, as well as available to neighbouring agents. In scenarios outside the controlled environment of a laboratory these assumptions may not always be met and further considerations regarding localisation and communication must be made and taken into account in future iterations of these models. Besides, other considerations such as a low-battery level and a respective fallout behaviour, will need to be taken into account. This can be incorporated in a manner similar to Wilson et al. (2018) where a *homing* behaviour takes precedence directing agents to return to a charging station and recharge. However, despite the challenges ahead in deploying these models outside the laboratory, we should highlight the argument that the main focus of this Thesis was to propose novel behaviour models, and in that regard contribute to the

state-of-the-art.

6.2 Experimental Setup

When performing embodied experiments in the physical domain, and in particular throughout the work of this Thesis, two issues arise of noteworthy importance, namely: communication, sensing and experimental scale.

In what concerns communication, slightly different setups were used as the ground for experimental tests more precisely those depicted in Figures 3.3 and 4.5. In both these setups one observes that agents are connected to a central control point, via wifi in Chapter 3 and over radio in Chapters 4 and 5. However, it is well established that one of the main advantages of swarm techniques is envisioned to be the decentralized aspect of communication and control, in which case it could be argued that our setups infringe a commonly accepted (and indeed required) feature of swarm-robotics approaches. Nevertheless, it should be highlighted that none of the control strategies proposed and tested over the course of this Thesis rely explicitly on a centralized architecture. Instead the setups that in which our proposed models were tested are consequence of the platforms used, which were not designed to establish multiple peer-to-peer connections on the fly. Moreover, even if the flow of information is indeed centralized the control of each agent is not, since only information about each individual agent's surroundings is used to derive the velocity commands that are issued. In fact this raises another question, namely regarding the on-board computing capability of each platform. Naturally, both the Parrot and the Crazyflie possess on board CPUs whose primary task is to manage low-level model-based control techniques such as PID controllers or state estimation.

However the deployment of higher level control strategies such as the models proposed in Chapters 3 to 5 is usually expected to be processed off-board. Indeed, this is a particular sensible approach to minimize unit cost of each drone, as well as battery consumption and therefore size, but with the unavoidable implication that information flow will typically be centralized in such off-the-shelf platforms. In this regard the work of this Thesis, aims to provide a solid proof-of-concept of a novel strategy to generate adaptive LWs in both single and multiple robot scenarios.

Another topic regarding experimental conditions, is the assumption made with respect to sensing, particularly in Chapters 4 and 5. In these chapters both in simulation and in the physical environment, agents are assumed to have a square sensing area which detects the virtual rewards scattered within each cluster. The detection of such rewards is also virtual, in the sense that the agent is informed about the state of the environment rather than actually sensing it. This is an obvious simplification also made in the relevant works to which the presented results were compared (Nauta et al., 2020; Nurzaman et al., 2010; Sutantyo et al., 2013), in order to abstract the complexity of the sensing task itself. Even though sensing models were outside the scope of this work, they are a pervasive topic of research in robotics, and any project that envisions to deploy a robotics application outside the controlled environment of a laboratory must indeed take a comprehensive approach to the problem.

Also in this regard, even though the results that have been achieved seem to indicate the superior performance of the proposed models, in particular the ELW and ELF, a more definite validation of these models will certainly require more realistic communication and sensing models developed around the behaviour-based controllers proposed.

6.3 Methodologies

6.3.1 Assessment Methodologies

At the core of every experimental work or novel methodology to tackle a particular problem there is the issue on how to assess and compare the results. In Chapter 3 the model that was proposed, rather than an alternative to solve a particular problem, focused on providing an initial investigation into the potential of LW-based controllers for exploration in a collaborative manner. In such regard, merging LWs with the flocking rules proposed by Reynolds (1987) meant to endow the swarm to tackle the problem of k -coverage without the major assumptions typically found in such scenarios, such as priory defined regions of interest, or global knowledge of the domain. Therefore the assessment of the proposed model also rested on a particular set of metrics devised specifically to the target application. This is quite a different

case to the task of adaptive and collaborative foraging addressed in the subsequent Chapters 4 and 5.

In these chapters both the ELW and the ELF were assessed against a suitable benchmark and therefore the same metrics that those works proposed were used to drive the comparison between models. In the particular case of the ELW, whose performance was compared the Yuragi approach (Nurzaman et al., 2010), we have observed, especially in particle-based simulations where conditions were able to be replicated, the ability of the ELW to outperform its competitor in virtually every metric. However, in embodied experiments the difference of scale between the particle-base scenario and the experimental one played a significant role in making the same comparison in a more straightforward manner.

Even though the difference of scale between scenarios showed that both methods exhibited similar search efficiency metrics, when the temporal evolution of efficiency was plotted in Figure 4.9, the ELW tended to have higher efficiency in the beginning and subsequently decreased over time. This is indeed an interesting result, explained by the fact that rewards disappear after discovery and so, if a particular strategy is more performant than its competitors, in what concerns exploration and adaptation and therefore finds more rewards earlier, as experimental time goes by, efficiency will decrease as there are fewer rewards to be found. In fact, since rewards disappear after detection, some authors have considered such an environment to be of a dynamic nature (Fricke et al., 2016), regardless the static nature of the rewards.

Claiming that the ELW might be more performant than the Yuragi approach even though efficiencies tend to converge is validated by the temporal evolution of the number of rewards found, depicted in Figure 4.7, showing a constantly higher number of rewards found by the ELW model in comparison to the Yuragi. The fact that, despite similar values of efficiency, different methods differ in the number of rewards found points to the necessity of defining more meaningful metrics to describe search efficiency for adaptive foraging in dynamic environments. Indeed, a similar result was observed in Chapter 5 where the particle-based simulations showed a clear advantage of the ELF model with respect to both the Lévy+ and ACLW models, but, when compared in the physical environment, the same issue was apparent regarding efficiency and rewards found. Even different methods tend

to have similar values of efficiency over time, the number of rewards found is unquestionably different. Arguably considering different metrics should be done in a manner that each metric contributes to a more comprehensive understanding of the model and so, efficiency should not be considered in separation of the other metrics. Conversely, if such a metric is not properly defined it can lead to erroneous conclusions, and in fact, in this particular case, only by considering in tandem with the number of rewards found does the efficiency metric gain meaning. A more desirable metric would add its own value to explain and introspect the characteristics of the emergent behaviour.

Furthermore, when it comes to assessing the proposed models one should recall the three main characteristics of swarm robotics outlined in Chapter 1, namely: Robustness, Flexibility and Scalability. Indeed even though these three characteristics are often used as a justification to pursue a swarm robotics approach it was not in the scope of this work to provide a quantitative assessment of such, and further validation should be pursued in further work. Nevertheless, from a qualitative point of view, we could argue that the different environments in which the ELW and ELF are tested, particularly in particle-based simulations, show how flexible both models are. This is highlighted, not only by outperforming their competing models, but also to do so (in most cases) with a set parameters not purposely optimized for that scenario as shown in Table 4.8. A similar argument can be made for scalability, specially regarding the ELF, where particle-based simulation show its increased performance when comparing with both the Lévy+ and ACLW models with a varying number of agents. Indeed only robustness cannot be inferred neither on a quantitative nor qualitative manner, and future implementations should take into consideration this gap and perform a robustness study across all methods.

6.3.2 Experimental Methodology

Apart from measuring and comparing the results of experimental work with suitable metrics, it is also important to take into consideration the conditions that enable such experiments.

Across this work, physical experiments were always carried out, employing an external motion-capture system (VICON) to estimate pose of the various agents, as

it has been depicted in Figures 3.3 and 4.5. Furthermore, testing every proposed model relies on sending commands to each agent that are computed off-board. In Chapter 3 these commands are sent via a dedicated wireless network and whereas in Chapters 4 and 5 commands are sent over a purposely-built radio transmitter. These features of the experimental setup, were imposed by the capabilities of the UAVs used in each of the experiments rather than a design choice. Indeed, before being able to claim that these models may be readily used outside a controlled environment, platforms with improved capabilities need to be designed and manufactured, since the commercial available ones (that offer programming capabilities) often lack all the capabilities necessary for completely autonomous flight without external monitoring or localization, which could be achieved, for example, by fusing GPS signals and visual-odometry. Since this avenue of research was outside the scope of our work, it was not pursued, but it should serve as a key requisite for future works which aim to take these experiments further afield.

A similar remark must also be made regarding communication. In this work communication is not peer-to-peer, as it would be expected in a fully decentralised system. Rather, agents receive commands from a laptop, making in fact the flow of information centralized. Even though this is so, control actions do not require global knowledge, in particular regarding the state of each individual agent. Also in this regard, the development of a propose built platform would have to make such considerations before deploying the swarm in a real-world scenario.

6.4 Summary

This Chapter discussed the various options that were taken in the course of the Thesis. In regards to modelling it asserted that increasing the level of biological inspiration could lead to improved results given that the complexity of the desired biological component to be mimicked is captured in sufficient detail. Concerning experimental setup, despite the limitations in sensing and communication of off-the-shelf platforms, these are still able to provide a viable approach to demonstrate the increased performance of the novel models proposed in Chapters 3 to 5. The means by which competitive models are compared, i.e., the metrics used, have also been

subject of discussion as our experimental work has shown the need for a comprehensive and profound analysis and justification of which metrics to serve as assessment in a meaningful manner.

In the next, and final chapter, the conclusions of the work presented are drawn and summarized, and each research question is further discussed in light of the findings presented in this Thesis.

Chapter 7

Conclusions & Future Work

In this Chapter, the main conclusions are drawn with respect to the models proposed in Chapters 3 to 5. These concluding remarks will be made in light of the of the Research Questions and Research Hypothesis posed in Chapter 1. Furthermore, building on the answers to those research questions and the discussion in the Chapter 6, the last section of this Chapter will attempt to provide an outlook into future avenues of scientific research that may lead to increased performance, applicability and more accurate assessment of models that aim to target the same problems.

7.1 Research Questions Revisited

To finalize this Thesis, the Hypothesis that was put forth, as well as the research questions that aimed to validate that same hypothesis are revisited and their respective answers highlighted.

The Hypothesis, targeted in all subsequent work, stated that:

Behaviour Adaptation can modulate Lévy Walks for cooperative and collective tasks in aerial swarm robotics.

Such an hypothesis stemmed from the intuition that LWs could function as the main (but not the single) component of more complex behaviours beyond the interspersed periods of local and global search, to maximize the encounter rate with sparsely distributed rewards (Bartumeus, 2007). In order to test this hypothesis the first question that was asked was:

Q1: *Can Lévy Walk, in conjunction with flocking strategies, be used to tackle cooperative surveillance*

To answer this question Chapter 3 proposed a model where LWs are employed as an augmentation to the Reynolds flocking model (Reynolds, 1987). This model is then employed to the task of cooperative surveillance using k -coverage as metric for the model's performance. Results have shown that not only could this model enable agents to explore the environment thoroughly, leveraging the exploratory elements provided by the LW component, but also explore the majority of the environment while maintaining observed regions under coverage by k agents simultaneously. In doing so the contributions made by Chapter 3 (Sardinha et al., 2020a) function as a stepping stone to the study of role of LWs in more complex tasks, as the emergency of such behaviours as response to changing environmental conditions, addressed by the subsequent research questions.

The second and third research questions aim to inspect precisely this interaction with the environment in particular, regarding a foraging task in environments of clustered rewards, thus imposing the need for behaviour adaptation, upon which a large portion of this Thesis has focused on. Research Questions 2 and 3 are as follows:

Q2: *Can an Artificial Endocrine System, be used to model adaptive Lévy Walks while maintaining inherent properties of exploitation and exploration, for a single agent performing foraging?*

Q3: *Is such a model, able to outperform other strategies aimed at the same foraging task?*

Both these questions are addressed in Chapter 4 where an adaptive LW model is proposed which draws its adaptive capabilities from the modelling of an Artificial Endocrine System to regulate not only the parameter of a Lévy distribution, thus modifying the type of search performed, but also to modulate a desire to stop the current motion, so that the updated parameters can take effect. In Chapter 4, it has demonstrated that the proposed model, i.e., the ELW, was not only able to exhibit the ability to switch between local and global searches but also to outperform a previously proposed model, i.e., the Yuragi, when tackling the same task (Sardinha et al., 2020b). In that sense one could argue that research questions 2 and 3 are

answered favourably since the quantitative metrics proposed by Nurzaman et al. (2010) to assess the Yuragi model, and subsequently used to assess the ELW, show a better performance of the later. However, in the course of analysing the comparison in Chapter 4, a new set of more meaningful metrics, capable of providing better insight into the intrinsic characteristics the behavioural aspects of different models, is necessary to avoid erroneous interpretations particularly when it comes to describing efficiency.

The final contribution of this Thesis, presented in Chapter 5 aims to answer the final research question, which in Chapter 1 was posed as:

Q4: Can this model be extended to a robotic swarm, and still be able to deliver an increased performance in comparison to other swarm strategies which tackle foraging in the similar manner?

Indeed, in answering this question in Chapter 5, the ELF model illustrated its ability to also outperform the proposed benchmarks. It is also quite interesting to highlight that the models to which the proposed ELF model was compared, employed the same strategy on swarm interaction level namely by mimicking the behaviour of fireflies in collective foraging. Having the same swarm level approach to collaboration, indeed stresses the importance of biologically plausible adaptation mechanisms on an individual level and how such may potentiate the performance of the whole swarm. Also in Chapter 5 a similar conclusion can be drawn with respect to the metrics used in assessing of behaviour. Indeed, as it was mentioned in the previous chapter, environments where the rewards are no longer considered after being discovered, can be considered as a dynamic and thus our work reiterates the necessity to bear this into consideration for future works on this subject. Despite this shortcoming of the metrics proposed in other works, and for the sake of comparison, such metrics were also employed in this Thesis. However, in tandem, these metrics were still able demonstrate the increased performance of the ELF model, thus answering the final research question of this work.

In sum, by successively answering research questions, which increase in their complexity, this work has provided solid evidence to the claim that through the employment of plausible biologically inspired strategies, adaptive LWs can be achieved that are highly performant in a complex task such as collective foraging.

Nevertheless, before we can claim that these models are ready to be deployed in a real-world scenario, the following limitations (which were out of scope for the current work) should be addressed, namely:

- The ability of agents to localise themselves depends on the VICON motion-capture system.
- Finding rewards in foraging tasks abstracted issues with perception by considering virtual rewards.
- Communication was made through a ground station thus centralising the flow of information, as this was also the only possible configuration with the available hardware.

Indeed these limitations are the basis for the avenues of research proposed in the following section.

7.2 Future Work

The work carried out in the scope of this Thesis focused mostly on how LW can influence (or be influenced by) other behavioural strategies at play in single and multi agent systems. In Chapter 3 LWs were employed to augment Reynolds flocking rules adding an exploratory component to a behaviour that focuses mostly on coordination. In Chapter 4 the LW component was influenced by the employment of an underlying AES which controlled the distribution's parameters, whereas in Chapter 5 it was further modulated by the social interactions of agents within the swarm. However, in the course of proving the Hypothesis and answering respective Research Questions, other issues arose that are relevant of note, in particular for future iterations of the work presented thus far.

7.2.1 Sensing and Communication

From a generic perspective, modelling sensing in a more realistic manner would be an interesting avenue of research to pursue. Indeed such approach would be particularly problem dependent such as detecting weeds in an agricultural scenarios with specific spectral analysis would be different from, for instance, identifying sources of pollution. By not making any particular assumption on the particular application,

we argue that the models proposed constitute a general approach to identify clustered manifestation of any particular phenomena. Particular applications indeed pose a topic on its own, as communication would be another issue. We have seen that in our communication setup the flow of information is centralised, even if the models do not enforce such a constraint. Developing purpose-built robots would therefore be the alternative to meet the particular demands of a given application, potentially requiring a larger project with multiple collaborative entities. In the scope of swarm robotics, robustness to failures is another topic of particular interest to test the reliability of the system and constitutes another potential venue of research.

7.2.2 Behaviour Design

Regarding Chapters 4 and 5, where interaction with the environment was modelled, there is concrete path of research that could have particular benefits. One could argue that as the agent or agents uncovers more of the domain, and therefore gains information about it, this information could be used to guide the swarm's behaviour. For example by attempting to predict how rewards are distributed within a cluster, by fitting a distribution to the rewards already found, or to predict where other clusters could be located depending on expert knowledge of the phenomena. One could interpret this proposition as color manner of sliding control that would go from a completely random and reactive behaviour in the beginning to an almost plan-based approach at the end when most of the information about the environment has been discovered. Yet another potential venue of research is the substitution of the LW component altogether in the ELW and ELF models with a more biologically plausible mechanism to switch between local and global searches, such as an artificial neural network, which have already demonstrated to successfully generate control motions for autonomous robots (Vargas et al., 2005*b*).

7.2.3 Assessment Metrics

As it was discussed both in this and in the previous Chapter, the definition of reliable metrics is paramount to the unbiased assessment of model's performance in particular in the comparative manner that was made in Chapters 4 and 5.

Albeit outside the scope of this Thesis, Chapter 4 proposed a metric based on the battery level which provided a less ambiguous interpretation of results. In the line with many works in the literature which focusing on modelling the battery consumption of drones and other robots, one is highly inclined to suggest that that such models, even used in simulation, could constitute an important step at clarifying the ambiguity introduced by the efficiency metrics proposed by Nurzaman et al. (2010) and Nauta et al. (2020). Finally, a small consideration is also made about the RCGA that was employed to optimize the parameters of the ELW in Chapter 4. As future iterations of this work towards the field of optimization, several other meta-heuristics exist that could potentially improve the obtained controller.

In summary this Thesis has taken an incremental but decisive, step towards the goal of endowing autonomous agents with adaptive behaviours that replicate patterns found in Nature. In doing so one aims to inspire others into pursuing novel ways to further improve the results presented here and help deliver on the great promise of swarm intelligent robotics.

Appendix A

Extended Results

This Appendix extends the results of particle-based experiments carried out in Chapter 5. The two sections show the temporal evolution of the different metrics proposed in Section 5.2.3 for maps A and B (depicted in Figure 5.2). Sections A.1 and A.2 both show results with varying starting conditions, with the respect to the swarm size and the light absorption coefficient γ . Every combination of these parameters, whose values are shown below in Table A.1 was ran and the subsequent data plotted.

Parameter	Value	Description
N	{5, 10, 20, 40}	Swarm size
γ	{0.01, 1, 10}	Light absorption coefficient

Table A.1: Full-scope of model parameters used in particle-based simulations

These results corroborate the analysis made in Chapter 5 concerning comparative metric values achieved with each of the different models, and supports the discussion and conclusions drawn in Chapters 6 and 7 respectively.

A.1 Map A

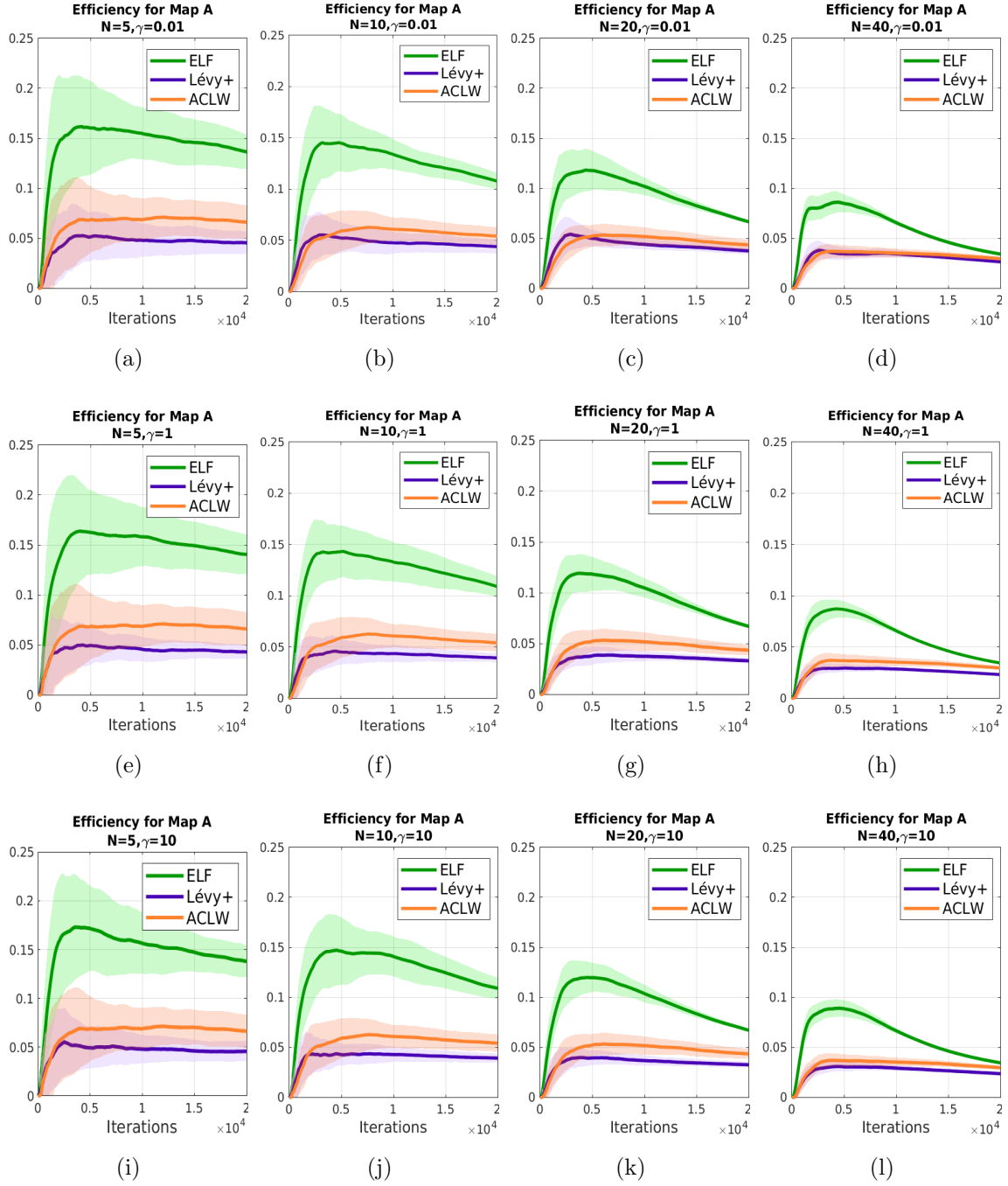


Figure A.1: Efficiency for Map A with varying values of (N, γ)

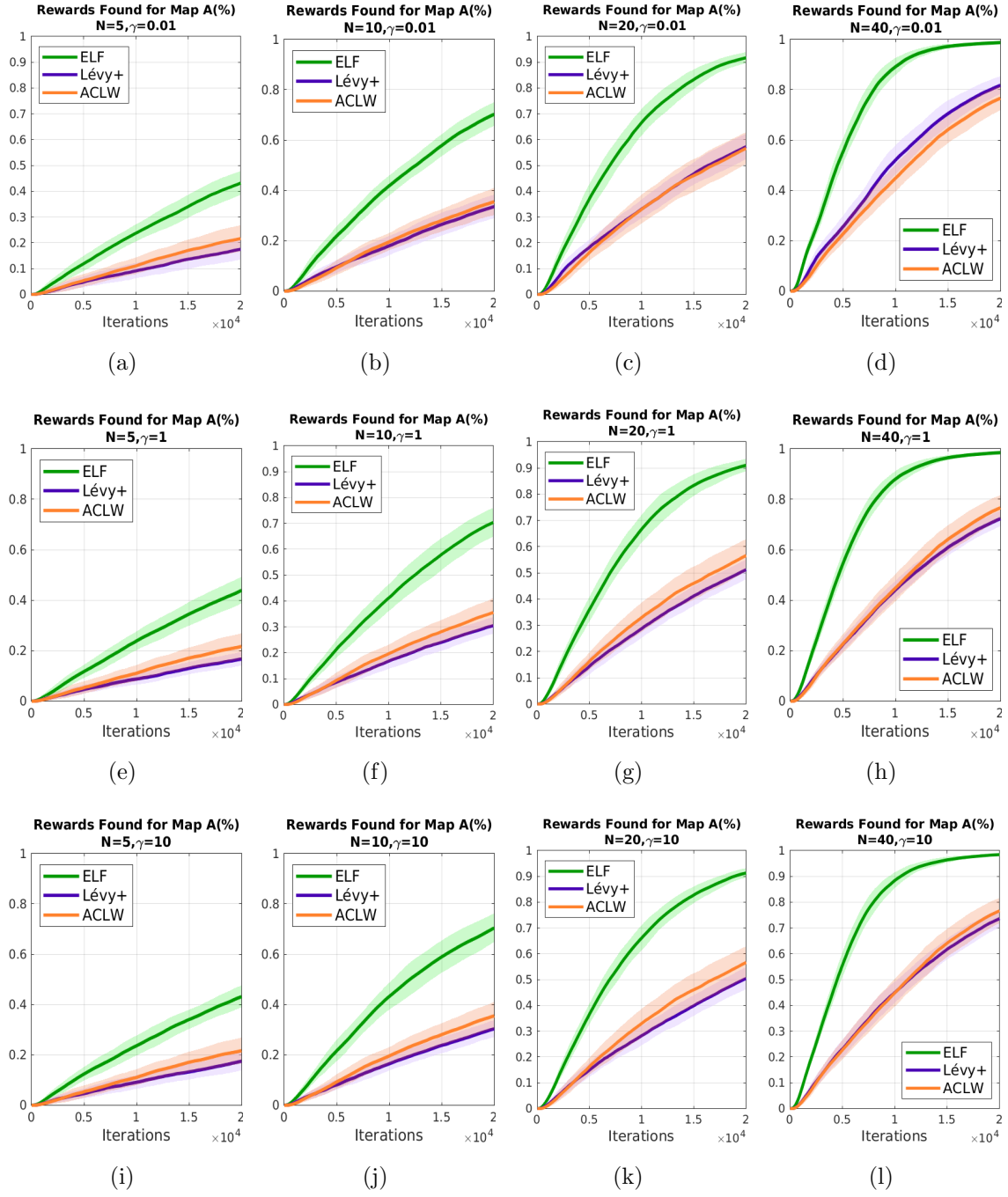


Figure A.2: Rewards found(%) for Map A with varying values of (N, γ)

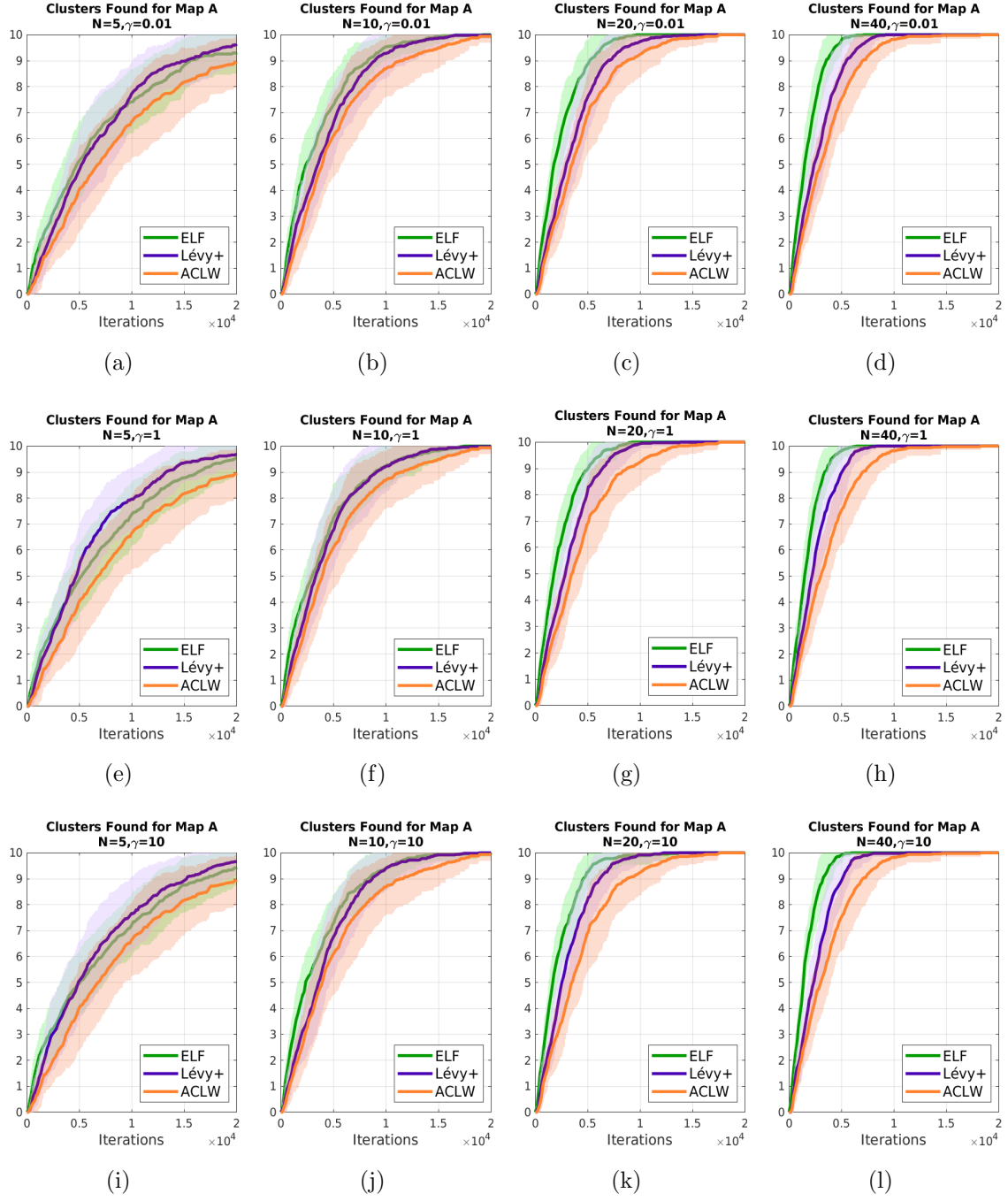


Figure A.3: Clusters Found for Map A with varying values of (N, γ)

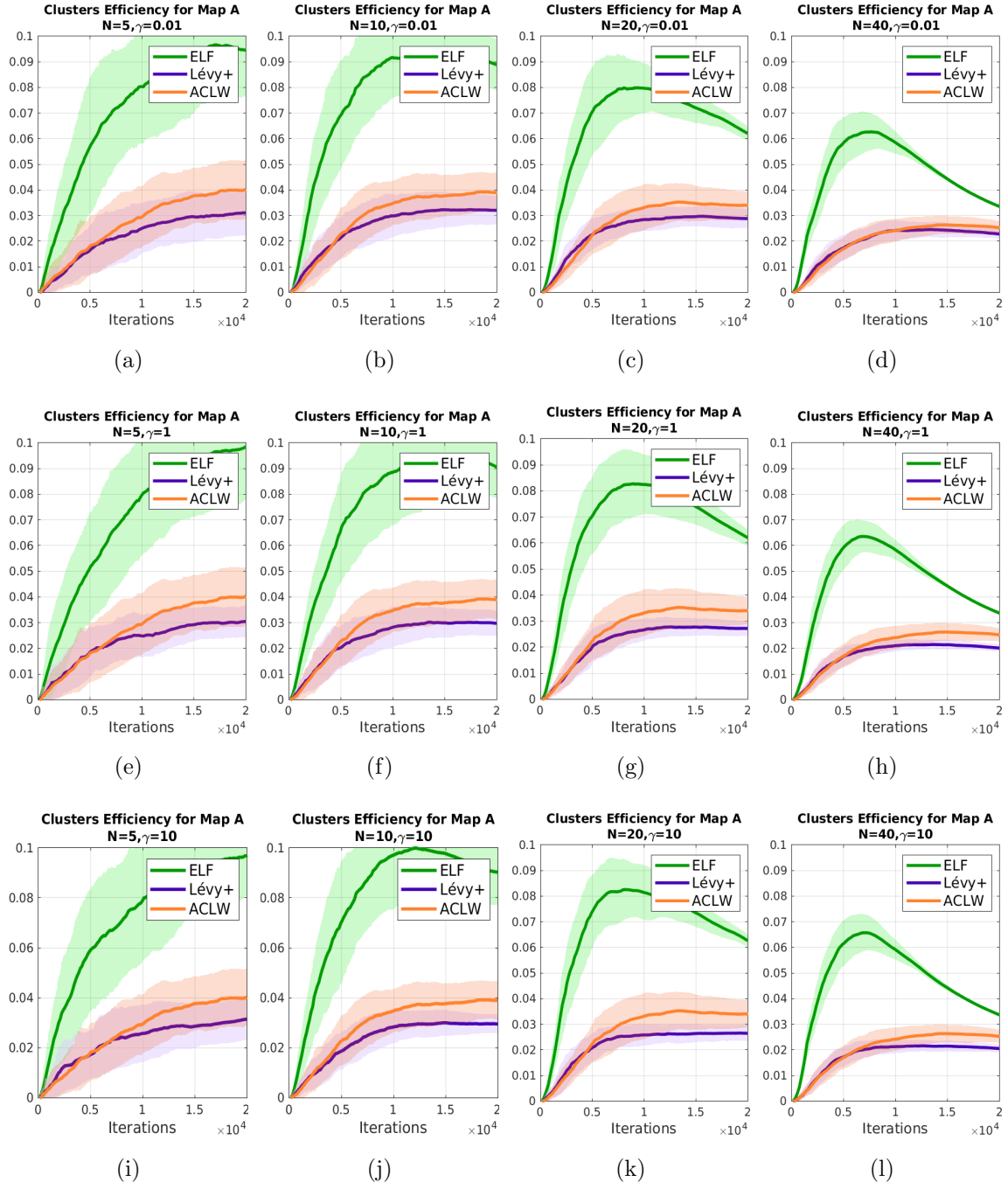


Figure A.4: Cluster Efficiency for Map A with varying values of (N, γ)

A.2 Map B

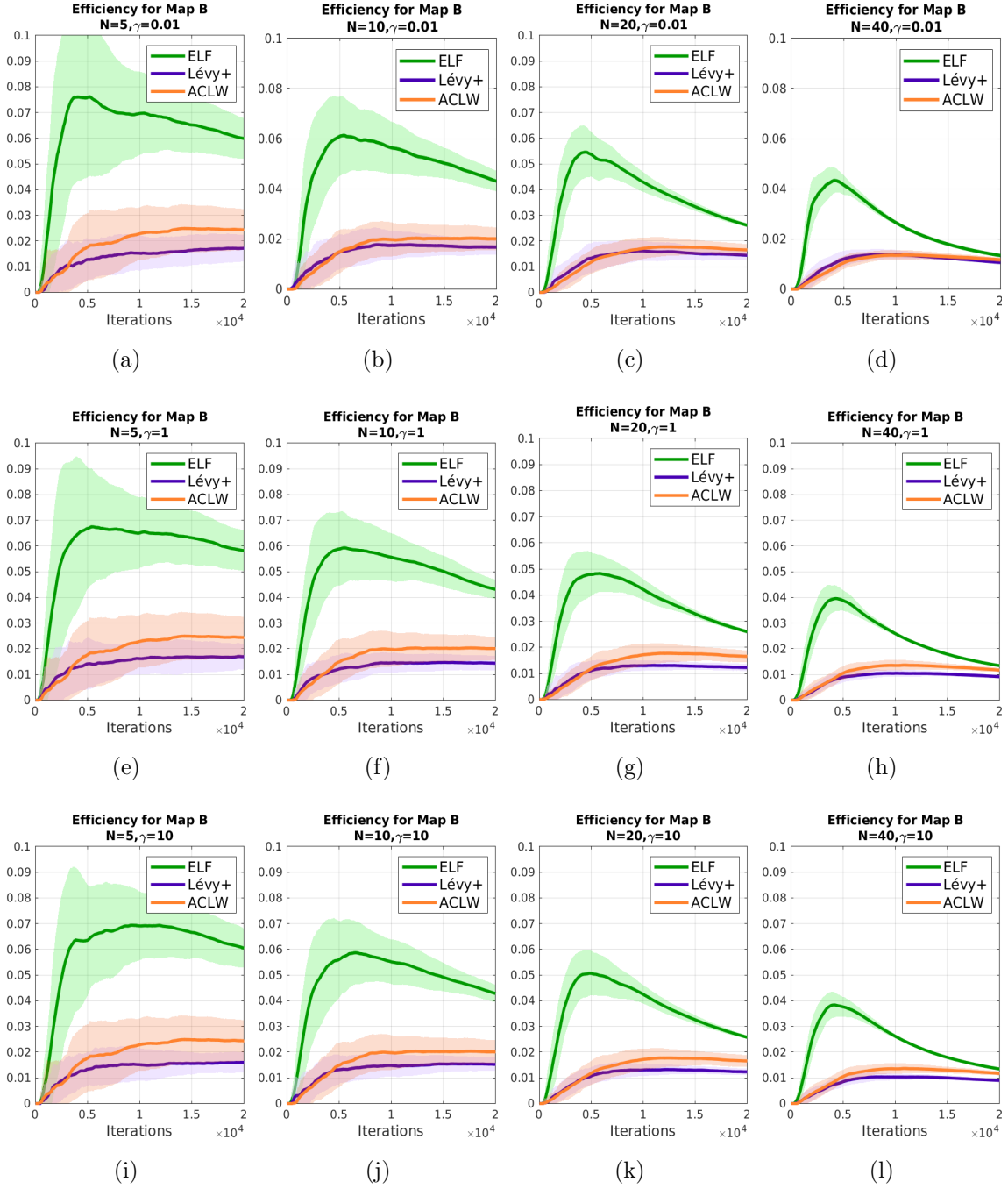


Figure A.5: Efficiency for Map A with varying values of (N, γ)

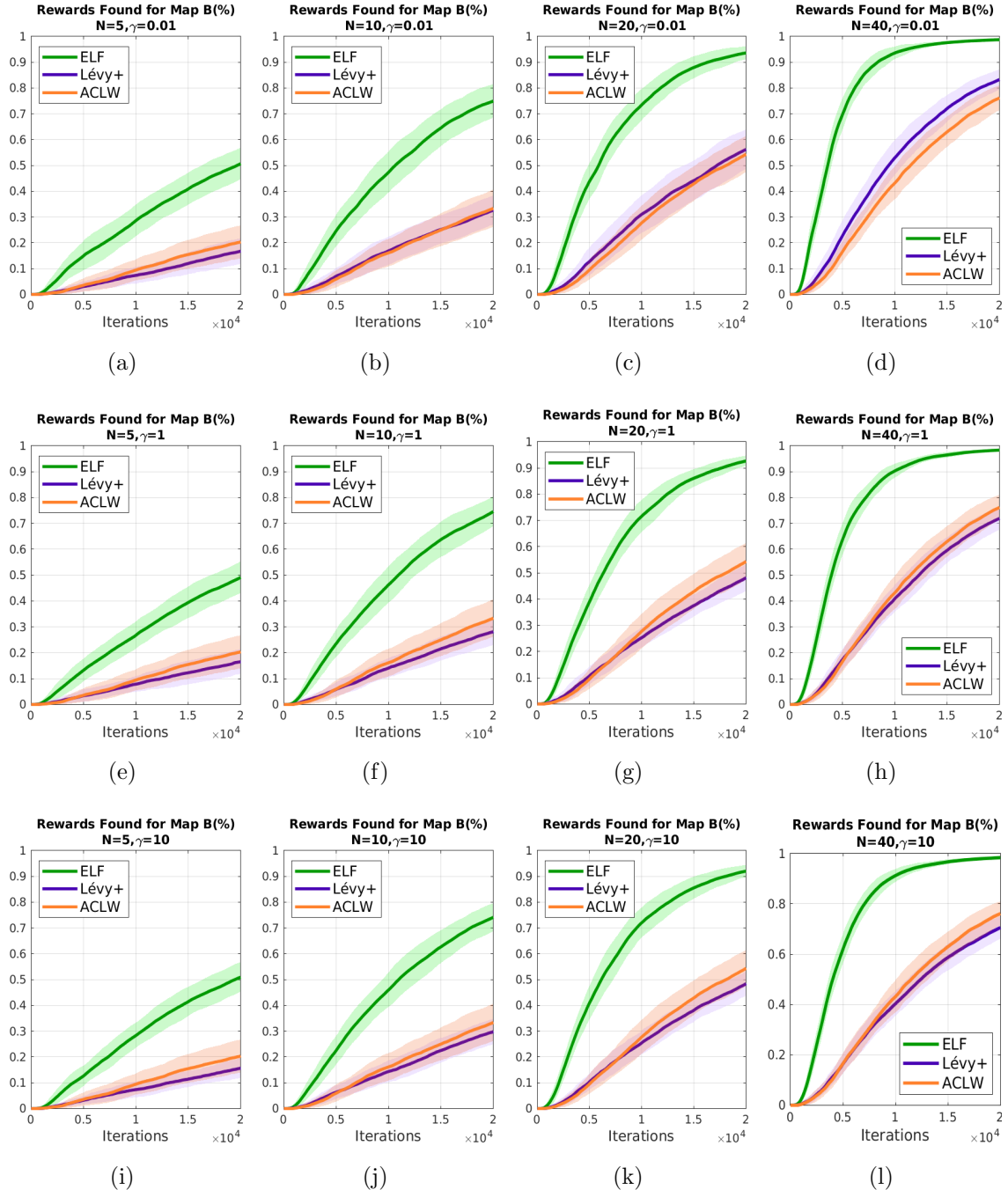


Figure A.6: Rewards found(%) for Map A with varying values of (N, γ)

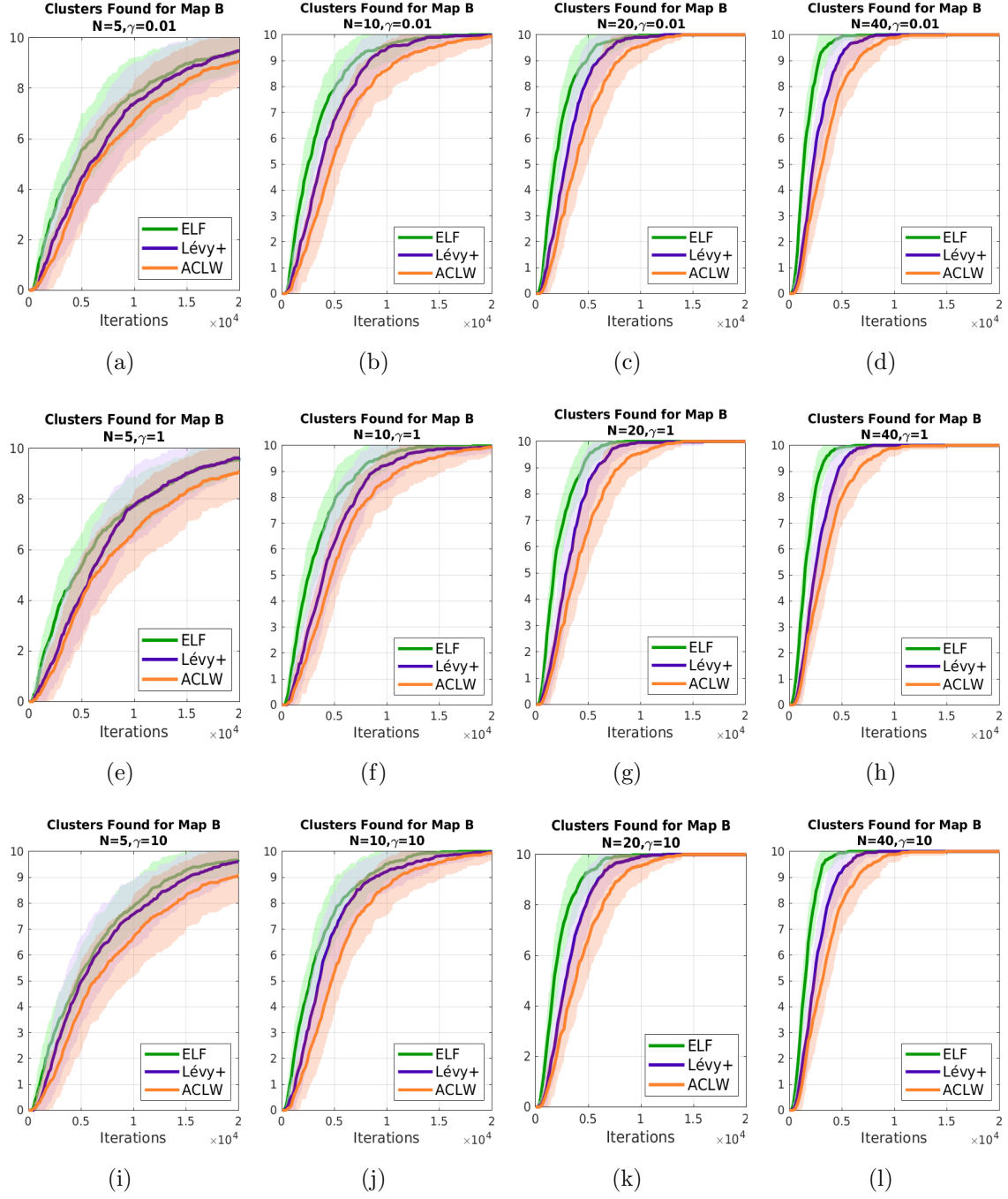


Figure A.7: Clusters Found for Map A with varying values of (N, γ)

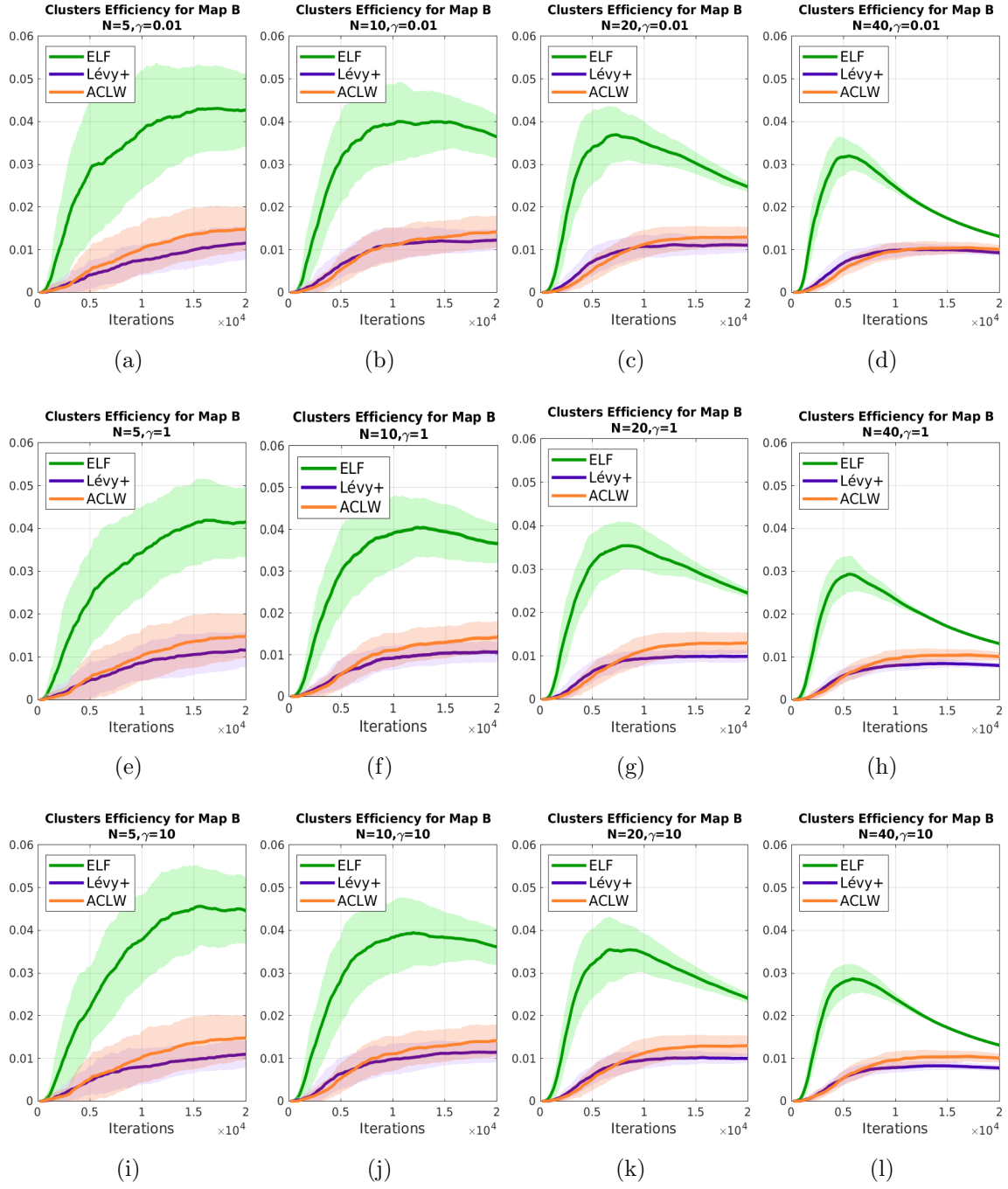


Figure A.8: Cluster Efficiency for Map A with varying values of (N, γ)

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