



Automatic design of behavioural models for bio-hybrid systems of animals and robots

Leo Cazenille

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Leo CAZENILLE

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Automatic design of behavioural models for bio-hybrid systems of animals and robots

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mixed-societies, collective behaviour, multi-level modeling, multi-objective optimisation, biohybrid systems, animal-robot interaction, biomimetic robotics, collective decision-making, zebrafish

Abstract

Robots are increasingly used in behavioural research as tools that can induce multimodal stimuli to interact with animals. However, the robots used in most studies are simple entities without the ability to make their own decisions and can only be used in simple short-lived interactions with the animals. This approach can be extended further by using autonomous and biomimetic robots able to socially integrate groups of animals with closed-loop of interactions: the robots influence the animals, which, in turn, influence the behaviour of the robots. However, the design of these robots is challenging, as they have to be accepted by the animals as social companions and respond accordingly to social and environmental stimuli.

This thesis addresses the problem of automatically designing animal behavioural models, that are implemented as controllers to drive biomimetic robots into socially integrating animal groups, and forming mixed-groups of animals and robots. In particular, we investigate the integration of robots driven by biomimetic behavioural models into groups of zebrafish (*Danio rerio*) and into groups of cockroaches (*P. americana* and *B. germanica*). In both cases, we show that these models can be automatically calibrated to drive the robots into integrating groups of animals, mimicking their behaviour and exhibiting similar collective dynamics compared to animal-only groups.

The main contributions of this thesis are:

- a methodology to automatically design microscopic models of agents behaviour to correspond to the dynamics exhibited by a macroscopic model of behaviour. This allows the automatic transition from a macroscopic description to a microscopic one. This methodology was then used to design the controllers of robots driven to socially integrate groups of cockroaches.
- a methodology to use automatically designed behavioural models to drive socially integrated robots into modulating the collective behaviour of mixed-groups of cockroaches and robots.
- a behavioural model that captures zebrafish behaviour individual and collective behaviour in a fragmented environment (*i.e.* environment with topological discontinuities).
- a methodology to calibrate this model to exhibit the same individual and collective behaviour as the animals. We describe a set of metrics used to assess the biomimetism of this calibrated model.
- a methodology to create mixed-groups of fish and robot. We used this calibrated model to drive robots to socially integrate groups of zebrafish.

Résumé

Les robots sont de plus en plus utilisés dans la recherche en ethologie collective comme outils interagissant avec des animaux et pouvant induire des stimuli multimodaux. Cependant, les robots utilisés dans la plupart de ces études sont des entités simples qui ne possèdent pas la capacité de prendre leurs propres décisions et qui ne peuvent être utilisés que dans de simples interactions de courte durée avec les animaux. Cette approche peut être étendue en utilisant des robots autonomes et biomimétiques capables d'intégrer socialement des groupes d'animaux avec des interactions en boucle fermée : les robots influencent les animaux, qui, à leur tour, influencent le comportement des robots. La conception de ces robots est cependant difficile, car ils doivent être acceptés par les animaux comme des compagnons sociaux et répondre en conséquence aux stimuli sociaux et environnementaux.

Cette thèse aborde le problème de la conception automatique de modèles comportementaux d'animaux. Ces modèles sont utilisés comme contrôleurs de robots biomimétiques qui vont intégrer socialement les groupes d'animaux pour former des groupes mixtes d'animaux et de robots. En particulier, nous étudions l'intégration de robots pilotés par des modèles comportementaux biomimétiques avec des groupes de poissons zèbres (*Danio rerio*) et avec des groupes de blattes (*P. americana* et *B. germanica*). Dans les deux cas, nous montrons que ces modèles peuvent être calibrés automatiquement et utilisés comme contrôleurs de robots. Cela permet aux robots d'intégrer des groupes d'animaux en imitant leur comportement et en présentant des dynamiques collectives similaires à celles des groupes d'animaux.

Les principales contributions de cette thèse sont :

- une méthodologie permettant de concevoir automatiquement des modèles microscopiques de comportement pour correspondre aux dynamiques d'un modèle macroscopique de comportement. Cette méthodologie a ensuite été utilisée pour concevoir des contrôleurs de robots destinés à intégrer socialement ces groupes de cafards.
- une méthodologie permettant d'utiliser des modèles comportementaux conçus automatiquement pour amener des robots socialement intégrés à moduler le comportement collectif de groupes mixtes de cafards et de robots.
- un modèle comportemental qui capture les comportements individuels et collectifs des poissons zèbres dans un environnement fragmenté (*i.e.* environnement avec discontinuités topologiques).
- une méthodologie pour calibrer ce modèle afin qu'il présente les mêmes comportements individuels et collectifs que les animaux. Nous décrivons un ensemble de mesures utilisées pour évaluer le biomimétisme de ce modèle calibré.
- une méthodologie pour créer des groupes mixtes de poissons et de robots. Nous avons utilisé ce modèle calibré pour amener les robots à intégrer socialement des groupes de poissons zèbres.

Lecture Guide

For really fast readers Read only **framed texts** in chapter 1, the 2 first pages (summaries) of chapters 3,4,5,6, and the first and last sections of the conclusion (chapter 7).

For fast readers Read chapter 1, the 2 first pages (summaries) and figures of chapters 3,4,5,6, and the conclusion (chapter 7).

For people already knowledgeable with mixed-societies You can skip chapter 2.

For others Please read everything !



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Chapter 1

Introduction

The best way to observe a fish is to become a fish.

Jacques Yves Cousteau

1.1 Concept and Objectives

The study of animal interactions and collective dynamics is a long-standing interest of ethology. Animal communication rests on multimodal signals [2, 3, 4]. A typical methodology to study animal behaviour consists of using artificial artifacts to interact with animals by generating and exploiting the signals relevant for social behaviour [5, 6]. This method was, at first, only used with simple and passive mock-ups (*i.e.* lures) to study specific behaviours (*i.e.* the lure sends a particular signal to the animal to trigger a response, then the interaction stops). An increasingly popular way of handling more complex interactions is to use robotic devices instead of passive lures, and to teleoperate them. Robots can produce calibrated social stimuli to test the animal responses [7, 8, 9, 10, 11, 12, 13]. Recently, efforts have been made to make these robots fully autonomous, capable of interacting with groups of animals in a repetitive and sustained way, and to adapt their behaviour to the animals [14, 15, 16, 17, 18].

This allows the creation of mixed-groups of animals and robots. These **mixed-groups** are **bio-hybrid systems** (*i.e.* incorporating both living and artificial entities) where one or several robots cooperate with the animal group with closed-loop interactions: the robots influence the animals, which, in turn, influence the behaviour of the robots. The robots have the capabilities to respond to animal behaviour. Mixed-groups could be further developed toward the creation of mixed-societies of animals and robots. **Animal societies** are interdependent systems where animals interact with one another to develop organised patterns of relationship (*e.g.* hierarchical relationship, division of labor) and form enduring and cooperating social groups. **Robot societies** can be defined with the same manner. **Mixed-societies** would be an extension of mixed-groups, where robots societies

would cooperate with animal societies [19, 20, 21]. All individuals of a mixed-society, natural or artificial, would be perceived as equivalent, and their collective dynamics would result from the interactions between natural and artificial agents [1, 22, 23].

These mixed-groups and mixed-societies can serve several functions [14, 15, 16, 17, 24]:

- as a benchmarking tool for biomimetic robotic design.
- as an advanced tool for animal behavioural studies.
- to control the animals (*e.g.* for shepherding, wild-life species control, control of welfare of domestic animals, etc.).
- to create societies with more capabilities as either animals-only or robots-only groups (*e.g.* combine the extensive sensing capabilities of the animals with the programmability and responsiveness of the robots).

However, the design of such social robots is challenging, not only because it requires a luring capability (including appropriate robot behaviours), but also because the robots have to be accepted by the animals as social companions. Their design can aim to mimic features of the studied animal and using similar signals and behaviours: we call this design aspect "**biomimetism**". Several strategies exist to build robot and animal interactions:

- the artificial systems do not copy any feature of the animal but send signals that the animals responds to. For example, it can make use of supernormal stimuli (exaggerated versions of stimuli *e.g.* larger shapes [5]), repellent stimuli (*e.g.* threats, pain, like electric shocks), or be attractant (*e.g.* food). This approach is not biomimetic as the aim of the design of these robots is not to mimic a feature of the studied animal. Indeed, being biomimetic is not a necessity to interact with animals.
- the artificial agent acts as a *heterospecific* entity (inter-species interactions). The robot can be biomimetic (and pertains to the next strategy below) but to another species (*e.g.* a dog for the sheep), if it copies the features and behaviour of this other species [25]. Otherwise, this approach is not biomimetic (*cf.* first strategy), the robot being just an alien agent interacting with the animals [15].
- the artificial agent is mimicking the animal, luring it as if it were of the same animal species (*conspecific*) and using similar signals and behaviours [1]. This approach is biomimetic and we define **social integration** as being part of a group displaying repetitive interactions with biomimetic features similar to the animals.

Robots must be socially integrated to make possible sustained closed-loop interactions with the animals, which are necessary to study more complex collective behaviours through the creation of mixed-groups of animals and robots. In this thesis, **we adopt the third strategy and we investigate how biomimetic robotic system can socially integrate groups of animals**. We focus on describing methodologies to automatically derive models of animal behaviour from experimental data, and use them as robotic controllers. This allows the robots to mimic animal individual and collective behaviours, making possible their social integration in animal groups.

We aim to investigate the following scientific questions:

Main scientific questions addressed in this thesis
<ul style="list-style-type: none"> • Can we control biomimetic robots to socially integrate groups of animals (with closed-loop interactions) and mimick their individual and collective behaviour, thus creating mixed-groups of animals and robots ? • Can robots in mixed-groups be accepted by the natural groups as if they were animals ? Do mixed-groups display similar collective behaviours as animal-only groups ? • Can we automatically design robotic controllers directly from behavioural experimental data extracted by observing the target species ? • Can we use these robots, integrated in mixed-groups, to modulate the collective behaviour of the target animals ?

Our overall approach can be summarised by the workflow diagram in Fig. 1.1. Behavioural models pertain mainly to two different levels of description: **macroscopic** (analytical description of the behaviour of the population [26]) or **microscopic** (explicit description of the behaviour and states of individuals and their interactions with the environment [27, 1, 28]). We consider both types of models, and show methods to design them automatically from observed behaviour in experiments involving animal groups. Only microscopic models can be implemented in robots. Our approach is to first design models of animal behaviour, and then use these models as robotic controllers to drive the behaviour of biomimetic robots into the groups of animals, forming mixed-groups of animals and robots.

We consider two kind of social animal species (Fig. 1.2) commonly used in ethological studies: **zebrafish** (*Danio rerio*) and **cockroaches** (*P. americana* and *B. germanica*). They each exhibit different type of collective behaviours and decision-making strategies. Zebrafish in shoal form short-lived and dynamic sub-groups, and tend to move continually from one point of interest to another, with only very few periods of stationary behaviour. The cockroaches tend to explore their environment until they find a point of interest, where they aggregate. As a result, mixed-groups of fish and mixed-groups of insects involve different approaches and technical difficulties. In both cases, we show that we can automatically design models of their behaviour to drive robots into integrating groups of animals, mimicking their behaviour and exhibiting similar collective dynamics compared to animal-only groups. Our methodology is validated in "real-world" experiments for our studies involving fish, and in simulations for our studies involving insects.

1.2 Scientific collaborators and acknowledgments

This thesis was part of (and funded by) the European project (FP7) ASSISIBf (Animal and robot Societies Self-organise and Integrate by Social Interaction with bees and fish) [24].

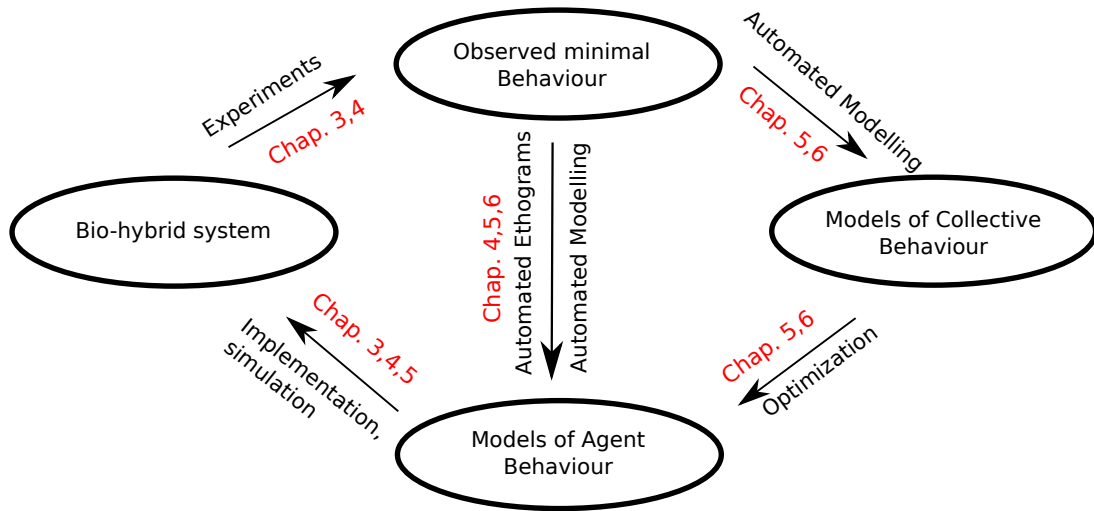


Figure 1.1 – Workflow of the methodology used in this manuscript to automatically model observed behaviours of animal groups. The chapters addressing each part of the workflow are reported in red. From experimentally observation of behaviours (e.g. animal trajectories) we derive models of individual or collective behaviour. These models are then used to drive biomimetic robots into groups of animals to socially integrate them with closed-loop of interactions, and creating mixed-groups of animals and robots. Individual behaviour models are microscopic and collective behaviour models are macroscopic.

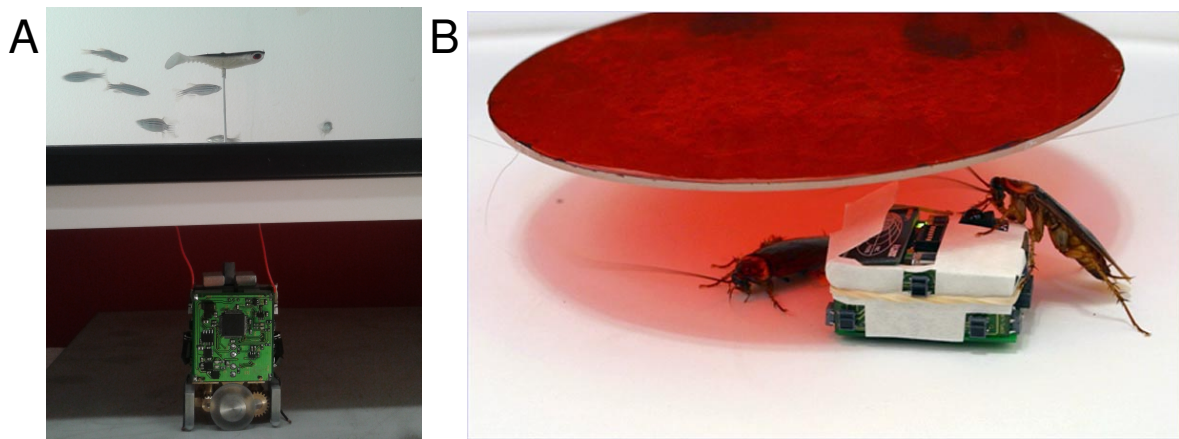


Figure 1.2 – Mixed-groups of animals and robots studied in this thesis. Panel A: Zebrafish (*Danio rerio*) group interacting with one Fishbot robot [29, 30]. Panel B: Cockroaches (*P. americana*) group interacting with one robot (this figure was taken from [1]).

The goal of ASSISibf is to conceive autonomous and self-organised mixed-societies of animals (in this case, with fish and bees) and robots, with robots capable of learning how to interact with the animals, of adapting their behaviour to the animals response, and of modulating their collective behaviour, by using the methodology described in [1], and adopted in this manuscript.

Six partners are part of the ASSISibf project. Our team at the Université Paris Diderot (LIED lab) developed fish behavioural models and performed experiments involving fish and robots. The roboticists at the EPFL (LSRO lab) designed and built the robots used during our experiments with fish and robots. Meanwhile, the four other partners were involved with mixed-groups of bees and robots. The roboticists from the university of Zagreb (LARICS lab) designed and built robots and software tools used to conducts experiments involving mixed-groups of bees and robots, with some parts developed by another partner, the company Cybertronica. The ethologists from the University of Graz (Artificial Life lab) performed these experiments. The group from the University of Lisbon (FCiências.ID lab) developed multi-agents simulation tools and optimisation frameworks.

As such, most of the work involving mixed-groups of fish and robots presented in this thesis was made in collaboration with several partners of the project. This allowed me to collaborate with people with various scientific interests, including: ethologists (Bertrand Collignon, Axel Seguret, Yohann Chemtob), roboticists (Frank Bonnet, Francesco Mondada, Alexey Gribovskiy), as well as my two supervisors: Nicolas Bredeche (evolutionary roboticist) and José Halloy (physicist).

Note that the works presented in this thesis involving mixed-groups of cockroaches and robots were not made in collaboration with the teams of the ASSISibf project. Their realisation involved only myself and my two supervisors. They, however, used experimental data from the LEURRE European project [1].

1.3 Contributions

This thesis has a multi-disciplinary nature, with contributions in the fields of artificial intelligence, robotics, ethology and collective adaptive systems.

Prior to this thesis, few works established the social integration of a robot into a group of animals (despite a very large number of ethological works using robots to study animal behaviour). Even fewer works demonstrated this social integration by a rigorous quantification of the biomimetism of the robot (either in term of physical or behavioural features) [1]. Specifically, the integration of robots into a group of cockroaches was already demonstrated in [1].

We extend further this approach, by automating the design of robotic controllers to drive robots in a mixed-group settings, either with groups of cockroaches and with groups of fish. We present the first system making possible a closed-loop social integration of a robot in a mixed-group of fish and robots, and demonstrate this social integration by quantifying the biomimetism of the robot behaviour. Previous works on fish-robot interactions did not create mixed-groups of fish and robots: they did not create closed-loop animal-robot interactions, or did not demonstrate robot social integration [31, 32, 33, 34].

Here is a list of the main contributions of this thesis:

Main contributions

- a methodology to automatically design microscopic models of agents behaviour to correspond to the dynamics exhibited by a macroscopic model of behaviour. This allows the automatic transition from a macroscopic description to a microscopic one. This methodology was then used to design the controllers of robots driven to socially integrate groups of cockroaches.
- a methodology to use automatically designed behavioural models to drive socially integrated robots into modulating the collective behaviour of mixed-groups of cockroaches and robots.
- a behavioural model that captures zebrafish behaviour individual and collective behaviour in a fragmented environment (*i.e.* environment with topological discontinuities).
- a methodology to calibrate this model to exhibit the same individual and collective behaviour as the animals. We describe a set of metrics used to assess the biomimetism of this calibrated model.
- a methodology to create mixed-groups of fish and robot. We used this calibrated model to drive robots to socially integrate groups of zebrafish.

Additionally, we collected ethological knowledge, through our study of fish in mixed-group settings, that portrays how fish interact with each other (and with artificial agents), and how these interactions affect their collective behaviour.

We constructed a set-up and frameworks to conduct long-lasting experiments involving mixed-groups of fish and robots. This experimental framework was designed during this thesis in collaboration with roboticists from the EPFL and with ethologists from Université Paris Diderot. In particular, the EPFL designed and built the robots used for our experiments involving fish (mainly Frank Bonnet, supervised by Francesco Mondada). My most significant personal contribution to this framework was the development of a control and tracking software (named *CATS*) to drive these robots in a biohybrid setting, in collaboration with roboticists from the EPFL (Alexey Gribovskiy, Frank Bonnet and Marcello Elias de Oliveira). The fish behavioural models used in this thesis were designed in collaboration with ethologists from the Université Paris Diderot (Bertrand Collignon, Axel Séguret, and Yohann Chemtob), and coded and implemented in robots by myself.

1.4 Outline

This manuscript is divided in two parts: the first part investigates mixed-groups of fish and robots (Chapter 3, 4 and Annex A); the second part investigates mixed-groups of insects and robots (Chapter 5, 6).

Chapter 2 presents a general introduction to biohybrid systems, and describes how robots can be controlled in such settings.

Chapters 3, 4, 5 and 6 are based on several scientific articles written during this thesis. Each of these chapters tackles different aspects of the problematic posed in this thesis. These aspects, and the links between these chapters, are found in Fig. 1.1 which describes the general workflow of our approach.

Chapter 3 tackles the problem of integrating a biomimetic robot driven by a biomimetic behavioural model into a zebrafish group. We investigate how to quantify and to discriminate between sets of biomimetic features needed for a robotic fish to become socially integrated into a group of fish as an autonomous member of the group. We detail the design (realised empirically) of this microscopic, agent-based, biomimetic, and multi-level model of fish behaviour. We present an experimental framework enabling long-lasting experiments involving groups of fish and a biomimetic lure, magnetically coupled with a wheeled robot positioned under the experimental fish tank. We use this biomimetic model to drive the robot into the fish group. We define metrics assessing the degree of biomimetism of the model compared to the experimental behavioural data, and the degree of social acceptance of the robot. We show that both visual appearance of the lure and the biomimetism of the robot behaviour are important for the robot to be socially integrated.

Chapter 4 builds on the results of chapter 3, and describes a methodology to automatically calibrate a microscopic biomimetic model of fish-behaviour to match fish behaviour observed in experiments. This calibrated model is used to drive the behaviour of a robot into a group of fish.

Chapter 5 tackles the problem of automatically deriving a microscopic model of insect behaviour (that can be implemented as the controller of a robot in a mixed-group setting) from a macroscopic description of the collective dynamics of an animal group (calibrated to match the observed collective dynamics from experiments). Then, these microscopic models are tested in simulation to build a biohybrid collective adaptive system of cockroaches and robots.

Chapter 6 builds on the results of chapter 5. While the microscopic models presented in chapter 5 were automatically calibrated to exhibit the same dynamics as those of a given macroscopic description, chapter 6 describes a method to automatically calibrate microscopic models to drive the behaviour of robots in a mixed-group setting to modulate the collective dynamics of this group, compared to the dynamics found in animal-only experimental data.

Chapter 7 summarises the contributions of this thesis, and provides perspectives.

Chapter 8 lists the publications written during this thesis (including several works outside the scope of this manuscript).

Annex A details the set-up used to conduct experiments with mixed-groups of fish and robots.

Annex B includes additional supplementary information materials for the papers presented in chapters 3 and 5.

Chapter 2

Control of biohybrid systems

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Society exists only as a mental concept; in the real world there are only individuals.

Oscar Wilde

Society does not consist of individuals but expresses the sum of interrelations, the relations within which these individuals stand.

Karl Marx

2.1 From passive lures to mixed-societies

2.1.1 The use of passive lures in ethology

Research in ethology and behavioural biology has shown that interaction with animals can be achieved using simple signals that are socially relevant for the animal [35]. This method was first applied by early ethologists in the twentieth century [5, 6, 36, 37], who designed simple artificial artifacts (*e.g.* lures, decoys) to interact with an animal (as illustrated in Fig. 2.1). These artifacts were designed to test only one specific behaviour (*e.g.* attraction or repulsion towards stimuli, motor response to stimuli, etc.), then the interaction stopped. They were only simple passive devices that lacked the capability to respond to the animal and the ability to entertain sustained interactions.

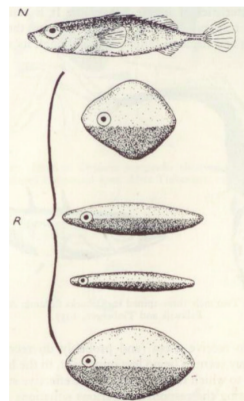


Figure 2.1 – *Example of passive lures used by Nikolaas Tinbergen to study fish behaviour: five stickleback lures, one mimicking accurately the stickleback (N), the four others only displaying particular aspects of the fish characteristics (R). [5]*

2.1.2 Using robots to study animal behaviour

Since then, this method has been developed to handle more and more complex kind of interactions (Table 2.1, *e.g.* repetitive movements, emission of sounds).

In particular, the availability of low-cost robots allowed researchers to use actuated robotic artificial devices (*e.g.* robotised lures) to interact with animals, and test more complex hypotheses [8, 38, 11, 18]. There is a growing number of scientific projects using robotic systems to study animal behaviour [7, 9, 10, 12, 13] (examples are found in Fig. 2.2). However, the robotised artifacts used in most studies are still rather simple from a robotic point of view, as they are not autonomous entities capable of making their own decisions and repeat or modulate stimuli. Often they are teleoperated by a human, and can only work for short amount of time (limited battery), which limits their use in sustained interactions with the animals. It also renders the interaction with groups of animals challenging, and most studies only use a single robot to interact with a single animal (very few research projects deal with such issues).

2.1.3 Autonomous robots interacting with animal groups

More recently, several studies (examples in Fig. 2.3) have used artificial systems able to respond to the animals and adapt their behaviour. This allows these robotic devices to handle more complex interactions, not just with one animal, but with groups of animals.

The first example of using an autonomous robot to interact with a group of animals is the Robot Sheepdog project, where an autonomous mobile robot was designed to gather a flock of ducks and lead them to a specified location [15] (Fig. 2.3a) by using behaviours inspired from sheepdogs. This research made use of a model of duck flocking to design and predict the global behaviour. This showed that a robotic system can use animal collective behaviour to solve a possibly useful task.

Several kind of autonomous mobile robots have also been designed to interact with rats [44, 45, 46, 47] (Fig. 2.3f, *e.g.* the WR-4 robot) and study their behaviour. These robots were made to only interact in a one-robot-to-one-animal manner, and with limited adaptability. The associated studies aimed either to autonomously teach a rat tasks by exploiting principles of operant conditioning [44, 45], or to model the development of behavioural disorders. In [47], a system is presented where an autonomous rat-like robot interacts with a rat and modulates its behaviour, by exhibiting several pre-programmed behavioural patterns.

There is a growing interest in using autonomous robots to study honeybees behaviour. In particular, Landgraf et al. [48] (Fig. 2.3d) investigates the honeybees dance communication system: a challenging open subject with many unproven hypothesis on which stimuli are involved in the communication process. The use of robots helps to study the impact of different signal combinations.

Several studies designed autonomous mobile robots to play the role of the leader in a group of domestic chicks [49, 50, 51]¹ or quail chicks [52, 53]. They relied on the filial imprinting mechanism: the robot was presented to the animals shortly after hatching, which brought about a following behaviour in the chicks, as if they followed their mother hen. In these study, the interaction between autonomous robots and animals were sustained for long period of time (40 min or more for [49, 50], 11 days for [53]), however, the robots

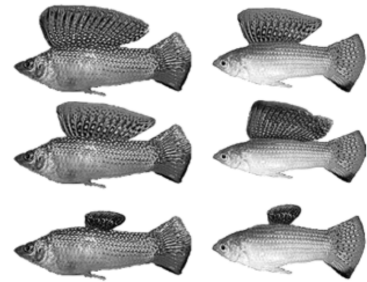
¹Note that I am co-author of [51]



(a) Patricelli et al. 2002 [7]



(b) Goth et al. 2004 [9]



(c) MacLaren et al. 2004 [39]



(d) Brian Smith et al. 2006 [40]



(e) Rundus et al. 2007 [41]



(f) Taylor et al. 2008 [12]



(g) Leaver et al. 2008 [42]

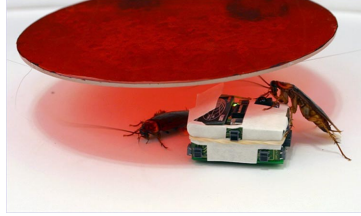


(h) Le Maho et al. 2014 [43]

Figure 2.2 – Several examples of robotised lures in behavioural studies. (a) robotic female satin bowerbird to study sexual selection. (b) robotic brushturkey chick to test nest mate recognition. (c) dummy fish with different details to test mating preference of female sailfin mollies. (d) robotic Sagebrush lizard to test nonverbal communication. (e) robotic squirrel to study predator avoidance. (f) robotic tungara frog to study mate selection. (g) life-size dog replica with an actuated tail. (h) penguin chick replica mounted on a teleoperated rover.



(a) Vaughan et al. 2000 [15]



(b) Halloy et al. 2007 [1]



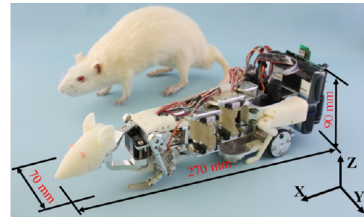
(c) Correll et al. 2008 [17]



(d) Landgraf et al. 2010 [48]



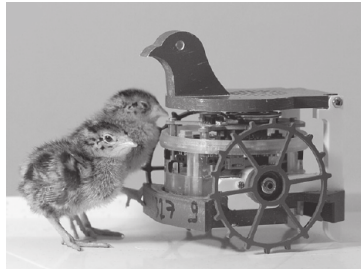
(e) Gribovskiy et al. 2010/2015 [49, 51]



(f) Shi et al. 2013 [47]



(g) Griparic et al. 2015 [54]



(h) Jolly et al. 2016 [53]



(i) Donati et al. 2016 [34]

Figure 2.3 – A selection of previous works where autonomous robots interacted socially with animals. (a) The robotic sheepdog with a flock of ducks. (b) The InsBot mobile robot with cockroaches. (c) Social control of cows herd by a mounted sensing and actuation device. (d) Robotic lure dancing with honeybees. (e) The PoulBot mobile robot with chicks. (f) WR-4 robot built to interact with rats. (g) A stationary robotic unit with actuators and sensors designed to interact with honeybees. (h) Modified e-puck mobile robot used to interact with quail chicks. (i) Biomimetic robot lure interacting with *M. rume* electric fish.

	Passive lures (Fig. 2.1)	One non-autonomous robot (Fig. 2.2)	One or several autonomous robot(s) (Fig. 2.3)	Mixed-group of animals and robots (Fig. 2.3b)	Mixed-society of animals and robots
Biohybrid	yes	yes	yes	yes	yes
Number of animals	single animal	single animal	groups	groups	groups
Number of devices	one	one	one or small-group	one or small-group	group
Autonomous artificial devices	no	no	yes	yes	yes
Sustained interactions	no	no	yes	yes	yes
Social integration	no	no	possible (<i>e.g.</i> [54, 55, 53])	yes	yes
Able to modulate while integrated	-	-	possible	yes	yes
Closed-loop	no	no	no	yes	yes
Organised patterns of interactions	no	no	no	no	yes
Description	Immobile or manipulated by humans [5, 6].	Few or no sensors and actuators, little autonomy, remotely teleoperated by human. Only test one animal behaviour, then the interaction stops [7, 9, 39, 40, 41, 12, 42, 43].	Respond and adapt to animal behaviour. Autonomous, sustained interactions, open-loop interactions [15, 17, 48, 49, 51, 53, 34].	Closed-loop interactions. Social interaction possible by using biomimetic robot(s) that socially integrate the group of animals. Collective dynamics depends on animals-robot(s) interactions [1].	Societies are enduring and cooperating social groups whose members have developed organised (<i>e.g.</i> hierarchical interactions) patterns of relationships through interaction with one another. No scientific work exist yet (by 2018) that demonstrate animals-robots interaction in a society context.

Table 2.1 – *Types of animal(s)-robot(s) interactions. We define **Social integration** as being part of a group displaying repetitive interactions with biomimetic features similar to the animals. The term **Closed-loop** refers to closed-loop interactions between animal(s) and robot(s): the robot(s) influence the animal(s), which, in turn, influence the behaviour of the robot(s).*

did not adapt their behaviour to the animals (*i.e.* with open-loop interactions).

Finally, several research projects used autonomous robots to interact with fish (Fig. 2.3i). This subject is developed in detail in Sec. 3.1 and Table 3.1.

2.1.4 Types of autonomous artificial devices

The autonomous artificial agents interacting with animals can be of three different types (Fig. 2.4):

Mobile devices are autonomous robotic devices able to move with the animals (Fig. 2.3a,b,d,e,f,h). As such, they can have very close interaction with the animals and make use of spatial interactions. This involves two main technical difficulties: it is necessary to make the autonomous devices accepted by the animals and to understand which parameters affect animal-robot interactions.

Static devices can be networks of immobile sensors-actuators devices that can monitor the behaviour of the animals and environmental changes (Fig. 2.3g,i).

Depending on the observed behavioural features, they can be programmed to emit adequate signals (*e.g.* sounds, pheromones) or modify the physical environment (*e.g.* temperature, light, humidity, distribution of food). The main technical difficulty is to find the appropriate algorithms to link observed features to actuated response [54, 55].

Mounted devices are autonomous sensors-actuators devices, mounted on the animals to confer them new capabilities (Fig. 2.3c). They can be used to monitor the animal activities (*e.g.* GPS or RFID tags). The most challenging technical aspect is to develop a system capable of managing individuals interacting with each other and to determine the response of the artificial systems to environmental changes [17]. For example, studies employed smart collars to study and potentially control the herding behaviour of cattle [16, 17] (Fig. 2.3c) in large, open fields. These smart collars contained an embedded computer with a wireless network connection, sensors (including a GPS), and devices to send stimuli to the cows. This project also exploits some social behaviour of the cows, by using a dynamical model describing social dynamics of animals during grazing periods. Note that mounted devices do not create a single cyborg (cybernetic organism) entity, as the natural and artificial parts are still two different entities that are just attached to one another; the mounted device interact with the animal, but does not control it directly, as in animals cybernetics studies (*e.g.* [56, 57]).

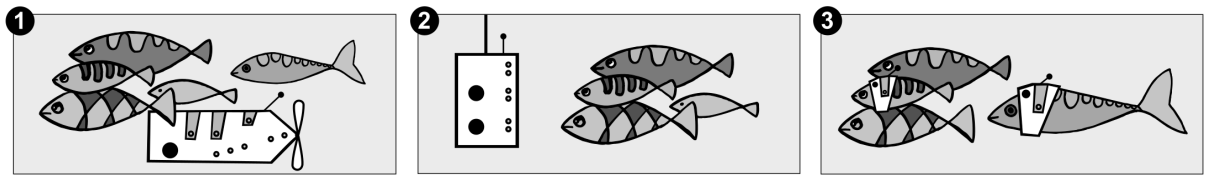


Figure 2.4 – *Abstract illustration of artificial devices used to interact with animal societies: (1) mobile devices, (2) static devices, and (3) mounted devices. This figure was taken from [19].*

Research projects involving animal-robot interactions and using either mobiles devices or static devices can also be further separated into those based either on a conspecific or a heterospecific relationship between animals and artificial devices:

Artificial devices seen as conspecifics The artificial device design incorporate physiological and behavioural aspects of the animals it interact with, in the hope that it will be seen as a congener (Fig. 2.3b,d,f,i). The difficulty is to identify the set of attributes needed to be seen as a conspecific by the animal, and to implement it in the artificial device design.

Artificial devices seen as heterospecifics The artificial device is not designed to be seen as a congener by the animals (Fig. 2.3a,e,g,h). It can be designed to mimics physiological and behavioural attributes of the member of another species, or be seen as an alien entity by the animals.

Additionally, a close field of study is the use of autonomous robots to treat plant organisms (*e.g.* used for automating gardening tasks) [58, 59, 60].

2.2 Mixed-groups of animals and robots

2.2.1 Definitions

While the studies presented in Sec. 2.1.3 enabled more complex animal-robot interactions by using autonomous robots, they did not make the robots capable of replying in an autonomous and biomimetic way to the animals. As such, there was no closed-loop of interaction between animals and robots. Two main strategies exist to create a system with a closed-loop of interaction between animals and robots, depending of how the robot(s) are seen by the animals:

Robots seen as conspecifics The robots socially integrate into the animal groups by mimicking the physiology and behaviour of the animals (*cf.* definition of **biomimetism** and **social integration** in Sec. 1.1).

Robots seen as heterospecifics The robots must find other form of interactions to socially integrate the animal groups, for example by using coercion (*e.g.* a sheepdog to the sheep).

Using one of these strategies, it is possible to create mixed-groups of animals and robots.

What is a mixed-group ?

Mixed-groups are **bio-hybrid systems** where one or several artificial agents socially integrate the animal group and interact with the animals in a sustained and closed-loop way: the artificial agents influence the animals, which, in turn, influence the behaviour of the artificial agents.

Mixed-group have the following defining properties:

Bio-hybrid Mixed-group incorporate groups of animals and groups of artificial agents.

Autonomous artificial agents Artificial agents in a mixed-group must be autonomous and adapt their behaviour to both environmental cues and social (animal response) signals. They are capable of handling sustained interactions with the animal society.

Closed-loop social interactions between animals and robots In mixed-group, artificial agents can interact and communicate with the animals. They are coherently integrated with the animal society (closed-loop interactions): they influence the animals, and, in turn, the animals influence the behaviour of the artificial agents (*cf.* Sec. 1.1 for a description of social integration and biomimetism). The technical difficulties are to identify the sets of physical inputs and outputs the artificial agents should provide to establish interactions with the animals, and implement them in the artificial agents design. The artificial and natural agents reach together collective decision from their interactions, without being individually aware of any collective patterns.

The next step toward even more complex animal-robots interactions would be to create mixed-societies of animals and robots, which would extend the notion of mixed-group to include organised patterns of interactions between individuals (in all three kind of interactions: animal-animal, animal-robot and robot-robot interactions) [19, 20, 21]. Using the definition of Mondada et al. [19]:

What is a mixed-society ?

Mixed-societies are dynamical systems, where animals and artificial agents interact and cooperate to produce shared collective intelligence. In such societies, the artificial agents do not replace the animals but both collaborate and bring new capabilities to the mixed society that are inaccessible to the pure groups of animals or artificial agents.

Mixed-societies would have several defining properties (in addition to the previously listed properties of mixed-groups):

Heterogeneous capabilities of the agents The individual capabilities of the artificial agents and their interactions with the animals are diverse: each category of agents, animal or artificial, may react to signals or exhibit specific behaviours that the

other category does not detect or exhibit. The animals can induce new interactions between the artificial agents, or the artificial agents can increase the range of interactions between natural agents. In turn, the union of agents of different categories can bring additional capability to the mixed-society, that are not present in either category of agent.

Society They are dynamical systems where both animals and robots cooperate to form enduring social groups. The interactions between agents induce organised patterns of relationships (*e.g.* hierarchical relationship, division of labor), that are not present in classical mixed-groups.

No scientific work exist yet (by 2018) that demonstrate animals-robots interaction in a society context, and no work exists that present an effective mixed-society. However, it is generally held as an important goal to reach by the animals-robots interactions community. Establishing an actual mixed-society would first involve an animal species living in society, with complex (*e.g.* hierarchy) and heterogeneous interactions between individuals (*e.g.* ants, bees). Robots would have to form a society of their own, with sustained, heterogeneous behaviours (and possibly several morphologies). They also would have to learn in real-time how to socially integrate the animal society in very long-lasting experiments (*i.e.* several days, or weeks) and cope with hardware failure, changes in animal social dynamics and adversarial environmental factors. We are still very far from this goal.

Mixed-groups, and mixed-societies can be realised using artificial devices pertaining to any of the three types presented in Sec. 2.1.4.

2.2.2 State of the art

Halloy *et al.* (2007, Fig. 2.3b) presented the main scientific work establishing experimentally a mixed-group of animals and robots [1]. In this study, the authors socially integrate a group of mobile robots (InsBot robots) into a group of cockroaches and modulate their collective behaviour in simple site-selection collective decision-making experiments. The robots are capable of reacting to the animal response by making use of a model of cockroach decision-making dynamics, and are interacting in closed-loop with animals. The resulting mixed-group is effectively a self-organised entity where collective decision emerges from feedbacks based on local interactions. It is shown that even when in a minority (*i.e.* smaller number of robots than animals), robots can modulate the collective decision-making dynamics of the entire mixed-group and produce a global pattern not observed in their absence. However, the work of [1] is still not a mixed-society, as it does not incorporate organised relationship between agents and lasting interactions (*e.g.* hierarchy, division of labor).

Other studies provide preliminary work towards the development of effective mixed-groups (in particular [34, 33, 47, 61, 51, 53]), but do not create actual mixed-groups because they either do not demonstrate formally the social integration of the robot, or do not use a robotic system capable of sustained closed-loop interactions with the animal group. The work of Shi *et al.* (2013 [47]) does indeed demonstrate both closed-loop control

and social integration, and can be considered as a mixed-group, but with only one robot and only one animal. The research of Halloy *et al.* (2007) remained the only work prior to this thesis (by 2018) that mixes experimentally a group of robots with a group of animals to form a mixed-group. Moreover, no scientific work exist yet (by 2018) that demonstrate animals-robots interaction in a society context.

The ASSISIBf project [24] are also currently working on the development of mixed-groups and mixed-societies of bees and static artificial devices (which integrate an extensive range of sensors and actuators) [62, 54, 55] (Fig. 2.3g). While most of their achieved work is unpublished (including works presenting experimentally a working mixed-group of bees and robots), they showed a working mixed-group of bees and robots in simulation [63]. Additionally, the Flora Robotica project [60] aim to build mixed-societies of plants and robots.

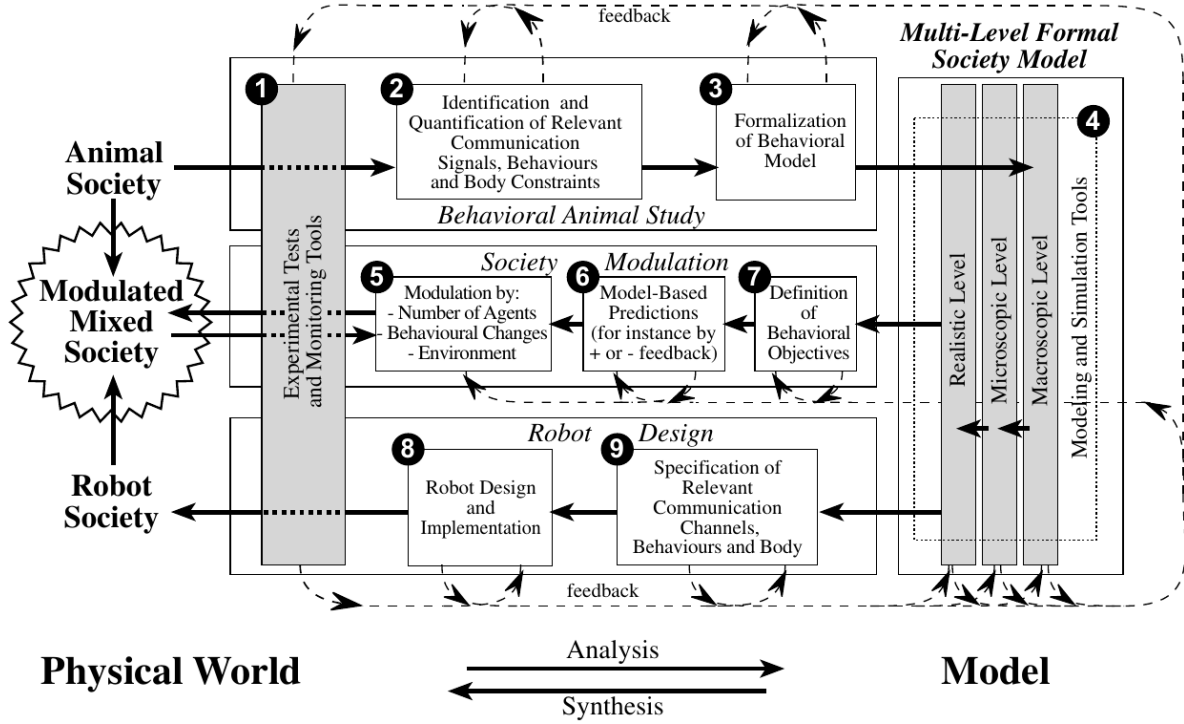


Figure 2.5 – Methodology used to create mixed societies of animals and robots. Figure was taken from [19].

2.2.3 General design of mixed-groups

A general methodology to design mixed-groups and mixed-societies was presented by Mondada *et al.* [19] (Fig. 2.5). The same methodology was used by Halloy *et al.* [1] to establish the first example of an actual mixed-group of animals and robots. Since then, several research teams have followed this methodology to make the preliminary work towards the construction of mixed-groups and mixed-societies involving other species

(*cf.* previous section). The main difficulty solved by this methodology is how to define and model physiological and behavioural features of the animal group in order to drive the design of the artificial devices. This methodology poses the following hypothesis (from [19]):

<p>Main hypothesis for mixed-groups design</p>
--

<p>Our hypothesis is that in the design of mixed-groups, despite the diversity of the problems to solve and the size of societies, the dynamics of these systems can be reduced to the interplay of a limited number of generic rules and thus, in turn, a unique methodology could be developed, depending on formal models.</p>

Animal groups, and mixed-groups, are difficult to model and predict because they are complex systems with dynamic interactions. While simple observations can be sufficient to gather an intuitive understanding on how a group works, it is not sufficient for the creation of a society model to drive the behaviour of the artificial devices made to be socially integrated with the animals. This advocates for a more thorough analysis to formulate rigorous models embodying hypotheses of how the group works. This can be done through the following methodology:

- The modelling process must be based on a formal description (*e.g.* mathematical equations of behaviour) of the individual and collective dynamics of the group. Often (as in [1]), the starting point for the creation of the model is the analysis of the global patterns arising at the macroscopic level (*i.e.* collective dynamics).
- Each conjecture must be evaluated and validated by experiments or by simulations. A procedure must be specified to quantify the realism and biomimetism of these conjectures. The models must be refined incrementally to change their level of abstraction (from mathematical equations to realistic simulations: indeed, only models of agents behaviour can be implemented as controllers of artificial devices), with a real system implementation as final validation.
- The methodology must be iterative, and must be re-applied and validated for each new conjecture, and each new modelling effort.

The main steps of this methodology are graphically presented in Fig. 2.5. It starts from the *animal society*, to results in the formation of a *modulated mixed-society*. It is composed of several keys processes, each of them encompassing local iterative loops, generating feedback loops for the other processes. These processes can be split into three main blocks:

Behavioural animal study First, behavioural analysis must be performed on animal-only societies, using systematic experiments and appropriate monitoring tools (Boxes 1,2,3. See Sec. 2.3). This allows the generation of a multilevel formal (mathematical) model of the society, taking into account individual and collective interactions and dynamics (Box 4. See Sec. 2.4).

Robot design (Boxes 8 and 9) Both animal observations and formal models of their behaviour are important to drive the robot design process. The goal is to design robots that only copy a selection of animal characteristics, to be efficient and functional in a social interaction context. In particular, relevant communication signals and behaviours must be identified (by the help of observations and formal modelling), implemented on the robots and experimentally validated. As such, the specification of the robots is an iterative approach where different sets of biomimetic aspects needed to establish interaction with animals are incrementally tested [19]. This subject is not elaborated further in this manuscript.

Society integration and modulation The formal model can be used to identify key parameters and behaviour needed for the robots to socially integrate the group of animals (Boxes 6, 7). In particular, these formal models can be transformed and implemented as robotic controller. Once they are socially accepted by the animals, the robots controllers can be adapted to also modulate the collective dynamics of the entire society (Box 5). This subject is detailed in Sec. 2.5.

These three blocks share common *experimental tests and monitoring tools* (box 1, see Sec. 2.3) and *modelling and simulation tools* (box 4, see Sec. 2.4), which attest to the fact that models of both animal-only groups and mixed-groups must be tested, modeled, and monitored using the *same* tools.

With the popularisation of optimisation, machine-learning and model-building algorithms, it is now possible to automate certain parts of the modelling process; this subject is covered in Sec. 2.4.5.

This thesis follows the general methodology of [19], and the thesis general workflow (Fig. 1.1) is inspired from it – but with a strong focus on robot control, social integration, and behavioural animal modelling, with only few consideration about robotic design: the robot design for mixed-groups of fish and robots was essentially investigated by our EPFL partners, sometimes with my collaboration [64, 30, 29, 65, 66].

2.3 Study of social animals behaviour

In behavioural studies of social animals (of any species), the objective is to find relevant behavioural signals and patterns exhibited by the animals during interactions, and how they influence the collective behaviour of the group. To this end, a large set of observations must be gathered from experiments to identify the individual capabilities of the agents, the nature of their interactions, and the global pattern of the group collective dynamics. This allows researchers to establish hypothesis on how the animal group works. These hypotheses must then be validated in experimental tests, and will be the first step towards the formulation of a formal model (*i.e.* with a mathematical representation) of individual and collective behaviour.

2.3.1 Experimental tests

The experimental tests on animal collective behaviour can be based on the study on their collective decision-making. Specifically, these tests often focus on the collective choice made by the group in patchy environments found in natural conditions. In ethology, animal *choice* is defined by the selection by the animal of two (binary choice) or more (multi-choice) alternatives which will impact their survival or well-being. It can be generalised to a collective context: being part of a group, the individual decisions can be partially or totally surpassed and subsumed to the decisions of the group, and individual decisions are influenced by the decisions of other members of the group. This gives rise to emerging collective dynamics, like self-organisation, characterising collective behavioural patterns emerging of individual decisions and interactions. Typically, two kind of choices can be investigated experimentally:

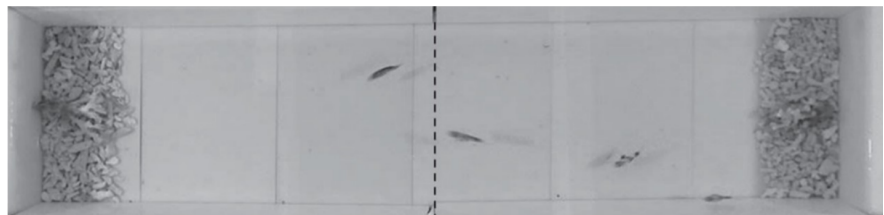
Choices between identical options Animal groups must choose between several identical artifacts (*e.g.* food, shelters, natural resources).

Choices between different options Animal groups must choose between quantitatively different artifacts (*e.g.* shelters with different sizes, patches with different food quality).

The aim is to find positive retroactive feedback loops (retroactive signals induce an amplification, a perturbation of this signal in the group): *e.g.* aggregation, establishment of consensus of site occupation (examples in Fig. 2.6 [27, 67]). These choices are measured experimentally (using metrics assessing for example, shelter occupation, individual response to an environment stimuli,). The experiments must be replicated several times to gain statistical significance.



(a) Ame et al. 2006 [27]



(b) Mann et al. 2014 [67]

Figure 2.6 – Examples of binary choice experiments for (a) cockroaches and (b) humbug damselfish.

2.3.2 Monitoring tools

Experimental tests must be monitored to gather sufficient data on individual and collective dynamics. The challenge is finding which features at the individual and collective levels are significant for the subsequent modelling process. Specifically, the number of relevant

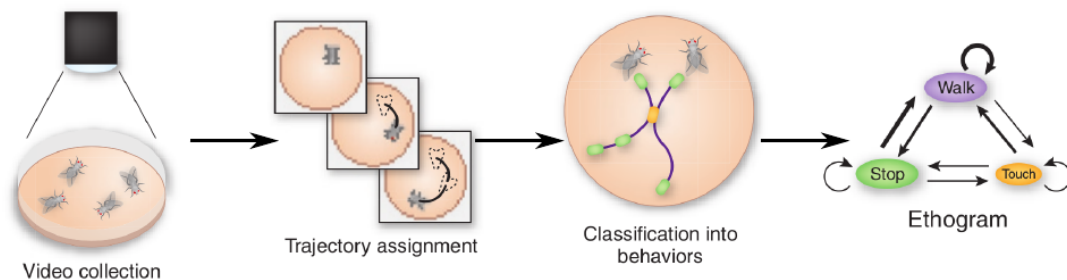


Figure 2.7 – Typical workflow of the high throughput ethology approach. This figure was taken from [68].

behavioural features needed to untangle collective dynamics are often extensive [68, 69, 19], and advocates for the use of efficient and possibly automated ways of gathering behavioural data. These considerations have recently given birth to the novel field of *high-throughput ethology*, where methodologies are being developed to cope with a large amount of behavioural data and to compile them into ethograms of animal individual and collective behaviour [69, 70, 71, 72, 68] (Fig. 2.7).

2.4 Collective behaviour modelling

2.4.1 From qualitative to quantitative modelling of behaviour

Models of the individual agent dynamics and of the collective behaviour of the entire group can be generated from the analysis of experimental behavioural data. This serves two purposes:

- It allows to describe and validate the hypotheses on how collective behaviour emerge from individual interactions.
- It provides a predictive and generative capacity, that can be used to drive the design of artificial devices and capture both physical (robotic hardware) and behavioural (robotic controller) aspects.

Two types of models can be defined:

Qualitative models They provide an intuitive and empirical analysis of behavioural dynamics, without explicitly defined variables and parameters.

Quantitative models They use a mathematical description where solutions can be compared with variables measures experimentally, and experimentally-calibrated parameters.

The modelling process is iterative and incremental (Fig. 2.8). It aims to refine a *qualitative* description of the biological system into a *quantitative* formal model.

2.4.2 Formal modelling of behaviour

Formal models are mathematical representation of the behaviour of a system, with precisely defined variables and parameters. They can be formulated by explicit equations, which can be solved analytically or numerically (*analytical models*). Alternatively, these solutions can be obtained by *simulations* (numerical experiments) on the model. Formal models are interesting for the modelling of collective behaviour:

- They ease the identification of interactions, which are then viewed as regulating feedback loops.
- They can describe the domain of validity of the modeled dynamics.
- They can be used to make predictions, or used as generative models (*i.e.* to generate possible instances of the modeled dynamics).
- This generative aspect allows to explore the dynamics of the modeled system in cases that would be difficult to assess experimentally. As such, they can also be used as surrogate models [73] (*i.e.* models of the expected dynamics, instead of the observed dynamics).
- The use of formally defined metrics (*e.g.* by comparing bifurcation diagrams, or relevant collective dynamics) helps the validation of formal models against dynamics observed experimentally.

Formal models are often used to describe the behaviour of complex systems. However, the rigorous approach presented in the previous section is seldom done in ethology as it is difficult and time-consuming; it may also involve extensive data acquisition, data analysis, and environmental control, which were only becoming available recently. For example, they have been used to model the behaviour of cockroaches in an arena [74, 75, 27].

2.4.3 Multi-level modelling

Models can capture phenomenological information and represent them at several levels of abstractions. Distributed systems have a very large parameter space, ranging from individual physiology, individual and collective behaviour, and features of the environment [19, 76, 77]. One difficulty of the modelling process is to find the appropriate parameters to describe the studied phenomenon with sufficient accuracy. The principle of parsimony (Occam's razor) asserts that models should be as simple as possible to serve their expected purpose (describe a phenomenon accurately, or generate instances of a phenomenon). Furthermore, a large number of these parameters must be measured experimentally, to correspond as much as possible to the observed system.

Models can represent information at different levels of abstraction, and with varying amount of details. They can focus more on representing information at the level of the overall system, or more at the level of its constituents. Similarly, groups of agents (natural or artificial) can be modeled as dynamical systems, with dynamics at different levels of

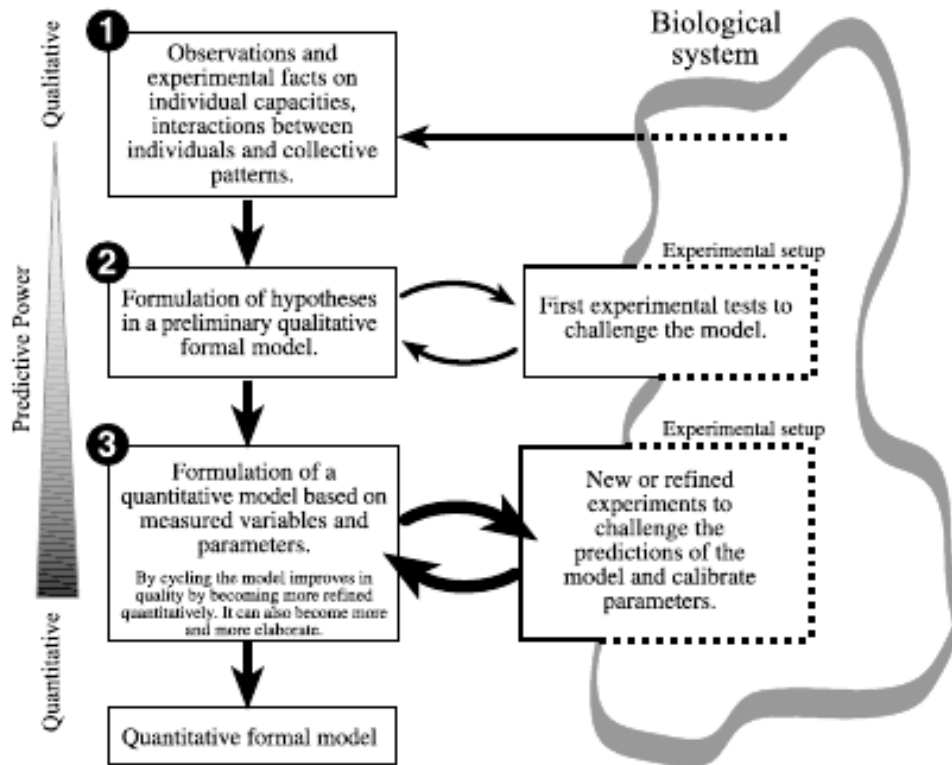


Figure 2.8 – Three main stages of building a quantitative behavioral model. Stage 1 implies gathering information of what is known about the considered biological system. Stage 2 could be skipped; it is used to build the first experimental studies and qualitative formal model. Stage 3 is the main and longest step in producing a quantitative model based on experimental determination of the main control parameters. It is also a test of the predictive value of the model. Often the journey of building a model is as important if not more important than that the final destination that is the model itself, as it ensures a deep understanding of the biological system considered. This figure was taken from [19].

abstraction. At the level of the group, collective dynamics can emerge from individual behaviours and interactions, with feedbacks links between group and individual behaviour. Another difficulty of the modelling process is to find which level of abstraction is better suited to represent the studied phenomenon [19, 78, 77].

Dynamical systems can typically be modeled at two levels of abstraction (Fig. 2.9):

Macroscopic level Macroscopic models describe the system at the population level, and typically do not describe the state of individual agents. They can describe the collective dynamics exhibited by the group. Using a formal macroscopic formulation, these models can be solved analytically or numerically [26]. However, they cannot be used to drive the behaviour of agents in simulation, or to drive the behaviour of robots in experiments.

Microscopic level Microscopic models (typically multi-agents models in behavioural studies) capture the state of each individual, their behaviours and their relations with the environment (*e.g.* agent-based models of flocking, like the Vicsek model [79]). However, they do not explicitly describe information at the population level, which will emerge from individual behaviour. They can be used to simulate agent spatial behaviour [80, 27, 1, 28], and as such are easier to implement into robotic controllers.

There is a vast literature, in physics and multi-agents systems, exploring methods and applications for both categories of models and the relations between them. These two kind of models offer complementary descriptions of the system, and both are useful to model agent behaviour. It is also possible to design "hybrid" multi-level models that integrate both macroscopic and microscopic components. This allows them to capture both the state of the population and of individual agents, and can possibly describe explicitly the feedback links between individual behaviours and group dynamics. In such multi-level models, several parameters can be shared between both macroscopic and microscopic representations.

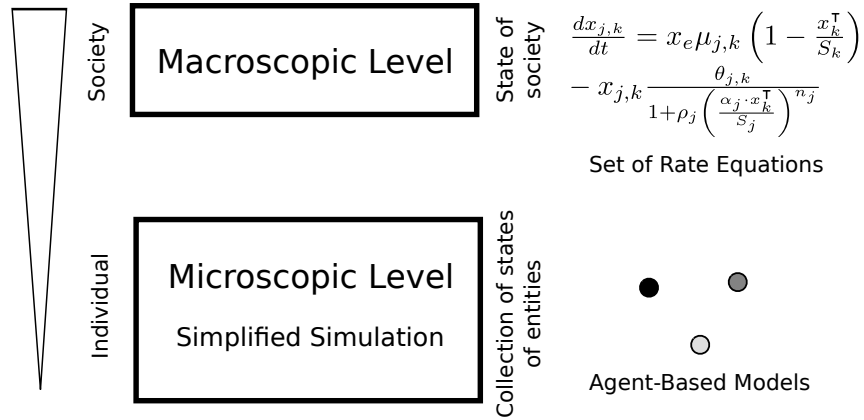


Figure 2.9 – Differences between macroscopic and microscopic models Models of dynamical systems can be separated into two categories: macroscopic and microscopic. Macroscopic models describe the global state of the system (*i.e.* the state of a population). They usually take the form of sets of equations (*e.g.* ODE) encapsulating a mean-field hypothesis. Microscopic models (usually agent-based) describe the state of each individual agent. The agent motion strategy is often represented as a Markov chain. Macroscopic and microscopic models complement each other, describing dynamics at different levels. Microscopic models can include spatial information about the agents, which enables them to be used to simulate the modelled behaviour, or to be implemented as a robotic controller.

2.4.4 Model validation

Models can be used to generate possible instances of the system. For macroscopic models, these data can be extracted either analytically (resolution of the equations), or using simulations. If the model is stochastic, it may be necessary to use a method that takes

into account fluctuations when generating instantiations (*e.g.* Gillespie algorithm [81]). For microscopic models, instances can be obtained in simulations.

Then, these behavioural data can be analysed, with the same data-analysis methods used with animal-only experimental behavioural data, and described in Sec. 2.3. The analysis part must capture the expected individual and collective behavioural patterns.

Finally, the realism (compared to animal-only experimental results) of the model can be assessed by computing a behavioural biomimetism score. Behavioural biomimetism (using similar signals and behaviours as the animals) can be quantified by using carefully handcrafted metrics capturing the expected behavioural dynamics. This can be used to compare different models. The associated metrics can pertain to individual behaviours (*e.g.* description of movements like speed distributions, mean distance to an object, etc.) or to collective dynamics (*e.g.* number of aggregated individuals in a site of interest, alignment, inter-individual distances, attraction, etc.).

2.4.5 Automated model design, calibration and optimization

Modelling dynamical systems can be challenging and time-consuming. It is especially the case with the design of multi-level behavioural models capable of driving robots socially accepted in a mixed-group. However, the overall modelling process can be facilitated and automated through the use of advanced statistical methods and machine learning algorithms. In particular, these methods can be used to ease the following stages of the modelling process.

To determine which parameters are important (feature selection)

In machine learning and statistics, feature selection is the process of finding a subset of relevant features (variables, parameters) to design parsimonious models. This allows models to integrate to be simplified (reducing parameters number) allowing them to be easier to interpret, design and calibrate [82]. Some parameters can provide redundant (correlated parameters) or irrelevant information and can be removed without much loss of information [83].

To find appropriate parameters values (calibration)

Some model parameters can be directly measurable from experiments (*e.g.* distribution of speed of individuals, individual sizes, distance to an artefact of the environment, etc.) to ease the search for appropriate parameter values to fit the experimental data. However, most models need to also consider parameters that cannot be directly measured (*e.g.* impact of social signals vs. environmental cues). It is possible to use optimisation algorithms to fit these parameters to match experimental data [77], in a process that we call *calibration*.

In the most simple cases (low-dimensional problems), popular regression analysis methods ("curve fitting") can be used (*e.g.* linear regression, least squares, etc.). However, these

methods will often provide sub-optimal solutions, as they stay in the same local optimum of the parameter space.

Evolutionary algorithms [84, 85, 86] can provide a more complex and powerful alternative, as they can be used to optimise efficiently the parameters of high-dimensional problems. They gather a widespread use in robotics control problems [87, 88]. Amongst evolutionary algorithms, multi-objective evolutionary algorithms [89, 90, 91] can cater to modelling problems involving compromises between several conflicting behaviours (*e.g.* aggregation towards other agents vs. wall-following vs. attraction to an artefact); in this case, it is difficult to find a global optimum that generalise well across different initial conditions.

To identify interactions between parameters

Finding the interactions between model parameters is the more extensive part of the modelling process. There exist methods to automate this part, depending on which kind of models one wants to design:

White-box models The model is meant as a tool to explain the observed phenomenon, with explicit description of the interactions between parameters. Examples include mathematical equations (for macroscopic models) and finite-state machines (for microscopic models). Methods that automate the design of white-box models must present an understanding of the underlying biological concepts by describing and explicitly explaining how the interactions between parameters bring about the modeled dynamics. This can be achieved by developing automated ethograms of individual and collective behaviour. Examples include finite-state machines, hidden markov models, decision trees and other explicit graphical models at the microscopic level; and mathematical equations for macroscopic models. Methods to automatically generate finite-state machines from behavioural data have been explored in the literature, especially in the high-throughput ethology community [68, 69, 72, 71] by using machine-learning classification algorithms [92] (*e.g.* decision trees, SVM, etc.) to identify behaviours in behavioural traces and then use statistics to make graphical models. The automatic generation of formal models and differential equations directly from experimental data have been investigated in the genetic programming community, using symbolic regression methodologies [93, 94].

Black-box models The model is a generative construct to reproduce instances of the observed phenomenon. The interactions between parameters is implicit rather than explicit, and is not represented to be easily understood by a human. Examples includes artificial neural networks. There exist numerous methods (supported by a large scientific literature) to automatically generate artificial neural networks, including recent popular deep-learning methods [95] (*e.g.* gradient-descent), deep reinforcement-learning algorithms [96, 97], generative adversarial nets [98], neuro-evolution [99, 100, 101]. Furthermore, more biologically plausible neural models could be used to make the link between animal perception and biomimetic motor response, by using for example spiking neural networks models [102, 103, 104].

Hybrid of the two: grey-box models The model mixes white-box and black-box components to only describe explicitly certain interactions between parameters, while keeping generative capabilities [105, 106]. It allows, for example, to only explicit relations that pertain to group dynamics of interest, without describing explicitly individual spatial movements. The resulting model is still capable of generating instances of trajectories. To automate the design of grey-box models, it is necessary to use conjointly the methods previously presented to automate white-box and black-box models design.

Additionally, the interactions between model parameters for all three types of models could be found from experimental data in real-time: several recent works focused on on-line evolution techniques to design and calibrate robotic controllers (*e.g.* [107, 108, 109]). This allows models to adapt to change in dynamics during experiments.

2.5 Control of mixed-groups

2.5.1 From animal behavioural models to robotic controllers

The robots must respond to the animals and be socially integrated into the animal groups to form a mixed-group. This social integration is made possible by using biomimetic robot design, both physiologically (hardware design) and behaviourally (control).

The previously refined formal models of animal behaviour can be adapted and implemented as robotic controllers. Robotic controllers make the link between robot inputs (*e.g.* position in the arena, visual perception, etc.) and outputs (motors activation, movements, tail beats, emission of lights, odor and noise, etc.). As such, only behavioural models entirely or partly at the microscopic level of abstraction can be implemented as robotic controllers. Moreover, these controllers must also take into account low-level control aspects, like collision avoidance (that might not be taken into account in the formal models), inter-robot communication, or how to link the adapted microscopic model with on-board sensors (*e.g.* camera, IR sensors, etc.) and actuators (*e.g.* motorised wheels control).

2.5.2 Validation: social integration

Social integration can be viewed as a validation task for biomimetic models: if the behavioural model driving the robots results in their social integration, it means that it exhibits sufficient biomimetic properties to trick animals into seeing the robot as a conspecific.

Furthermore, it is possible to quantify social integration using empirically defined metrics that evaluate expected individual behaviours or collective dynamics. Such quantified social integration can be used to measure the biomimetism of several models, by implementing them as robot controllers, and then testing their social integration scores experimentally. In this setting, social integration metrics can be the same as biomimetism metrics defined in Sec. 2.4.4.

Social integration has often been used to assess the realism of a behavioural model in previous animal-robots studies. For example, Halloy *et al.* [1] used site selection dynamics and robot attraction to validate the social integration of robots in a group of cockroaches (*P. americana*). With fish, Faria *et al.* [110] assessed the social integration of a robot with biomimetic colour and shape into a group of three-spined sticklebacks (*Gasterosteus aculeatus*). Butail *et al.* [111] used algorithms to determine animal response to the robot. With rats, Shi *et al.* [47] validated the social integration of a complex mobile robot capable of biomimetic movements with a living rat using rat-robot distance and statistics on physical contacts. With chicks (*Gallus gallus domesticus* and *Coturnix coturnix japonica*), Gribovskiy *et al.* [49, 50, 51] and Jolly *et al.* [53] made use of the *filial imprinting*—*mechanism* to integrate socially robots as mother hen surrogates and quantified this integration.

2.5.3 Group modulation

Even simple non-actuated devices can modulate the behaviour of a studied animal. This modulation can make the animal behave according to a specific goal. However, fine control of the animals becomes more difficult in the case of a group or a society (*i.e.* systematic change in characteristics of the collective dynamics, or collective decision choices). A modulated mixed-group allows the mixed-group to exhibit dynamics and patterns not present in an animal-only groups (*e.g.* site occupation, or reduction of panic frequency, task specialisation instead of unspecialisation, periodic collective behaviour instead of stationary behaviour)

In the case where robots are designed to be seen as heterospecifics, they can control the animal group through coercion [15], or cooperative strategies [54, 55, 62, 63].

On the other hand, if robots are designed to be seen as conspecifics, they can control the animal group while being socially integrated. Indeed, groups of animals are self-organising dynamical systems, where interactions instigate positive and negative feedbacks. The network of individual responses and interactions governs the collective response of the group. Socially integrated robots can introduce new feedbacks in the group and induce large change in the collective response of the group with only small alteration of their behaviour.

The following methodology can be applied to effectively modulate the collective behaviour of the group [19]:

- First, it is necessary to identify which characteristics of agent interactions (and corresponding control parameters in the robot controller) produce these feedbacks. It can be done by using a multi-level modelling approach, capturing both of individual interactions (at the microscopic level) and the collective dynamics (at the macroscopic level). It allows to identify which generic behavioural rules and feedbacks induce relevant collective patterns (*e.g.* work allocation, social differentiation, synchronisation, aggregation, etc.). The implementation of these rules on the robots can be challenging, and the selected rules to be implemented on them is not necessarily the most optimal ones.

- The next step of the analysis is to find how parameter values corresponding to the identified behavioural rules affect collective responses. Two key parameters are the number of agents (natural and artificial), and the intensity of the interactions. In mixed-groups we can only modulate the animal-robot and robot-robot interactions, not animal-animal interactions. If the intensity of animal-robot interactions is high enough, it is possible to modulate the collective dynamics of the group with only a small number of robots. Mixed-groups are stochastic systems, so individual behaviours may only lead to an expected collective response with a set probability. The intensity of the interaction is a way to circumvent the impact of randomness: strong animal-robot interactions are more deterministic than weak interactions. However, this randomness aspect must not be eliminated, as the stochasticity of collective dynamics allows to characterise the exploration of different concurrent alternatives and to find effective solutions.
- Finally, the microscopic models driving robot behaviour have to be calibrated to make use of these generic behavioural rules to modulate the dynamics of the group. The difficulty is thus to find relevant parameters values of these models, all of which could be found using an automated calibration methodology as described in Sec. 2.4.5.

2.6 Conclusions

In this chapter, we presented a state-of-the-art of biohybrid systems and animal-robot interactions (Sec. 2.1). We described what are mixed-groups (and mixed-societies) of animals and robots (Sec. 2.2, and how to design them (Sec. 2.2.3). In particular, we outlined how to design formal multi-level models (Sec. 2.4) of animal individual and collective behaviours from experimental observation (Sec. 2.3), and how to construct the controllers of autonomous robots capable of socially integrating into animal group with closed-loop of interactions with the animals (Sec. 2.5). We succinctly presented how the design of these models could potentially be automated (Sec. 2.4.5)

In the following chapters, we will extend further these aspects by effectively automating the general methodology presented in Sec. 2.2.3 to generate the controllers of robots in mixed-groups of zebrafish (Chapter 3, 4 and Annex A) and cockroaches (Chapter 5, 6). We present a multi-level behavioural model of zebrafish behaviour (Chapter 3) and use it to drive a biomimetic robot into a group of zebrafish with closed-loop interactions, and quantify (and demonstrate) its social acceptance by the fish by measuring the biomimetism of robot behaviour (Chapter 3). This model is then automatically calibrated (Chapter 4) by methods listed in Sec. 2.4.5. We show that it is possible to automatically translate a macroscopic model of group dynamics into microscopic models of agent behaviour in a mixed-group setting (Chapter 5), and how to use this approach to modulate the collective behaviour of the entire mixed-group (Chapter 6) by methods listed in Sec. 2.5.3 and Sec. 2.4.5.

Part I

Mixed-groups of fish and robots

Chapter 3

Social integration of a biomimetic robotic fish into zebrafish groups

Everyone is a genius. But if you judge a fish by its ability to climb a tree, it will live its whole life believing that it is stupid.

Albert Einstein

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This chapter tackles the problem of integrating a biomimetic robot driven by a biomimetic behavioural model into a zebrafish group. This work is based on the publication [112]:

Cazenille L, Collignon B, Chemtob Y, Bonnet F, Gribovskiy A, Mondada F, Bredeche N, Halloy J. How mimetic should a robotic fish be to socially integrate into zebrafish groups ? Bioinspiration & Biomimetics 2017

A number of recent works used robots to study fish individual and collective behaviour. They demonstrated that artificial agents can be used to influence or control the behaviour of a single fish, or of a shoal of fish. One of the main objective of this process is to make the robotic lures accepted by the animals as social companions. These studies show that a robotic fish needs to be biomimetic in order to be socially integrated into a fish group. However, most studies focused only on inducing attractive visual or mechanical stimuli. Often, this translated to the search of attractive biomimetic lure morphologies.

In this article, we investigate the impact of robotic behaviour on social integration into a group of zebrafish. Our hypothesis is that the robotic lure not only needs to have a biomimetic visual appearance, but also needs to be driven by a biomimetic behavioural model, in order to be socially accepted. We describe a robotic behavioural model inspired from a model of fish behaviour of the literature. [113] We validate this model experimentally, and compare it to experiments where the robot is not driven by a biomimetic model. We complement this study by investigating the effect of lure visual appearance on social integration. We show that both robot behaviour and lure appearance are relevant for a robotic lure to be socially integrated into a group of fish. Our results confirm that both aspects need to be designed to be biomimetic. This study is novel, as we present the first integration of a biomimetic robot driven by a biomimetic model of behaviour, in a population of zebrafish.

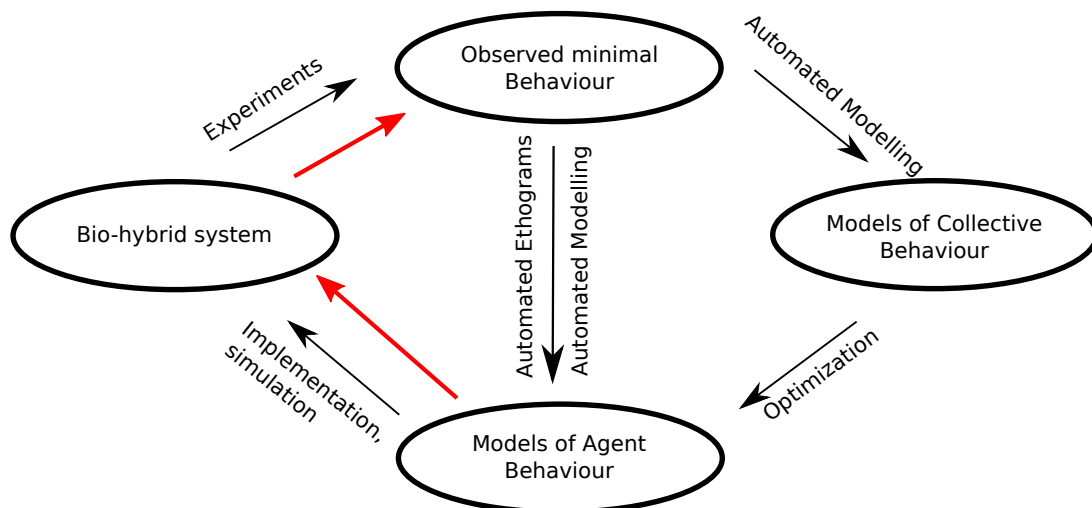


Figure 3.1 – Workflow of the methodology used in this chapter, with red arrows showing the addressed topics.

Figure 3.1 shows how this chapter is linked to the workflow of this manuscript: here, we use a microscopic and biomimetic model of fish behaviour and implement it as a robot controller to drive a robot to socially integrate into a group of zebrafish. Related supplementary information of this article can be found in annex B.1.

Contributions to this chapter

The experimental set-up was designed and built by Bertrand Collignon, Axel Seguret, Yohann Chemtob, José Halloy and myself. The FishBot robot was developed at the EPFL, by Frank Bonnet and Francesco Mondada. The experimental arena was built by Axel Seguret and Yohann Chemtob, based on a early implementation by Frank Bonnet. The control and tracking system was jointly developed by Frank Bonnet, Alexey Gribovskiy and myself. I implemented the data analysis scripts and miscellaneous code. This paper was mainly written by me, with the help of José Halloy and Nicolas Bredeche.

3.1 Introduction

Robots are used in ethology and behavioural studies to isolate the behavioural features and modes of interactions that mediate communication between animals. They can be biomimetic mechanical artefacts that are teleoperated in order to trigger a response from the studied animals. This allows testing various hypothesis on the type of signal used by animals for social interactions [7, 11]. In those studies the human is still in the loop of interactions between the artefact and the animal. This simplifies the design, the implementation and the control of the robotic lures. Alternatively, since the pioneer work of the robot sheepdog and ducks [15], an increasing number of studies [14] have used fully autonomous robots to interact with animals. These robots are programmed to induce reproducible stimuli (possibly embedded in the social context), in order to observe the response of the studied animals during repetitive, sustained and long-lasting social interactions. In this case, the human is not in the experimental loop, and doesn't even need to be present during the experiments. Examples of autonomous robots used in ethology include cows [17], drosophila flies [114] or fish [110].

Different strategies exist to build robot and animal interactions:

(i) First, the artificial systems do not copy any feature of the animal but send signals that the animal responds to. It can for example make use of supernormal stimuli [5]. The signals can also be abiotic repellent stimuli such as threats or pain (like electric shocks), or can be attractant such as food or any other attracting chemicals or features. The devices can be carried by animals that are somehow tele-operated by these devices [17]. We call this approach *non-biomimetic* as the aim of the design of the robots or devices is not to mimic a feature of the studied animal. Indeed, being biomimetic is not a necessity to interact with animals.

(ii) Second, the artificial agent acts as a different animal species such as a sheepdog. The robot can be biomimetic but to another species like a dog for the sheep. This can be a special biomimetic case of inter-species interactions [25] if the robot copies the sheepdog-like animal in its features and behaviours and pertains also to the next category below. But this approach can also be non biomimetic and fall back to the the first approach, the robot being just an alien agent interacting with the animals [15].

(iii) Third, the artificial agent is mimicking the animal, luring it as if being the same animal species and using similar signals and behaviours [1]. We call this approach *biomimetic* and it is the approach developed in this study. However, the biomimetic parameter and feature space are very large. The challenge is to choose the most relevant features like some specific visual resemblance, olfactory signature, behavioural similarity. This approach needs metrics to compare each selected features or set of features to select the most relevant ones to avoid the elusive task of building an artificial animal in all its features. We define *social integration* as being part of a group displaying biomimetic features compared with the animals. The *social integration* (and its quantification using these metrics) of a robot in a group of fish is the main contribution developed in this study.

Several studies (see Tab. 3.1) have used robots to influence or to control the behaviour of fish, either alone or in a shoal. Most studies involve a robot driven by simple and non-

adaptive behaviours (termed *fixed pattern* in Tab. 3.1), and open-loop social interactions. Closed-loop interactions occur when the robot influences the behaviour of the fish, and the fish influence the behaviour of the robot. The study on the electric fish (*Mormyrus rume*) opens interesting perspectives where a physical communication signal is used by both the animals and the robots in a closed loop [34]. The electric fish study is closer to the work done on cockroaches where a chemical signal was used [1]. However in [34], the fish robot system represents a breakthrough where a modulated signal is used to achieve a close-loop communication, in this case electric. In the case of the cockroaches the chemical signal was not dynamically modulated. It remains to be shown that this interesting closed-loop communication channel can be used to modulate collective choices like in the case of the cockroaches.

The studies [31, 32, 33] describe experiments where there is a closed-loop of social interactions and adaptive robotic behaviour. Additionally, [33] presents experiments where the robot was driven by a biomimetic behaviour; but it was not adaptive (with respect to the fish behaviour) and only followed fixed-patterns of behaviour. However, in these studies, the integration of the robot in fish groups is not quantified and not established. Indeed, this kind of controller implies that the robot is more a *follower* than a real group-member (*i.e.* integrated into the group) making its own decisions. Simply following the centroid of the group is not biomimetic as fish do not exhibit this kind of behaviour, and such controller does not allow the robot to initiate action but forces it to simply follow fish. In this regard, the embodiment of biomimetic behavioural models could lead to a better integration of artificial agents in animal groups and could allow the robots to influence the collective decision of the mixed group by giving specific preferences to the robot by tuning parameter values of the model [1]. While such controllers have been said to be developed in [32], no experiments have been analysed and reported in the literature yet. Moreover, social integration can only be measured on long-lasting experiments, as it allows to test robot social integration across a large set of social and environmental contexts. While such long-lasting experiments were described in [32] (30 minutes experiments), the non-adaptive biomimetic experiments in [33] were relatively shorter (5 minutes experiments).

In this study, we ask the following question: **can we quantify and discriminate between sets of biomimetic features needed for a robotic fish to be socially integrated into a group of fish as an autonomous member of the group? We make the hypothesis that this robot must be designed not only to be biomimetic at the level of the lure morphology and other physical aspects but also at the level of its social behaviours.**

Here, we propose to implement, in a closed-loop of social interaction, a multi-level and context-dependent biomimetic behavioural model as a controller of a small mobile robot moving a biomimetic fish-lure in a closed tank with a shoal of zebrafish.

We observe 10 different groups of four zebrafish and one fish-robot moving in a two-patch square tank for 30 minutes. For each trial, we track and identify all agents. Contrary to more cohesive species, the zebrafish often tend to have a very dynamical collective behaviour, with short-lived sub-groups of individuals. Because such splitting influences their behaviour as it changes the social context, we use a simple clustering method to

Number of lures	Study	Robot behaviour	Social Interaction	Number of fish	Type of lure
Fixed to mobile arm	Phamduy <i>et al.</i> 2014 [115]	Fixed pattern	open-loop	Single	Biomimetic
	Polverino <i>et al.</i> 2013 [116]	Fixed pattern	open-loop	Shoal	Biomimetic
	Polverino <i>et al.</i> 2013 [117]	Fixed pattern	open-loop	Shoal	Larger Size
	Abaid <i>et al.</i> 2012 [118]	Fixed pattern	open-loop	Single	Biomimetic
	Butail <i>et al.</i> 2014 [119]	Fixed pattern	open-loop	Single	Biomimetic
	Ladu <i>et al.</i> 2015 [120]	Fixed pattern	open-loop	Single	Biomimetic
	Ladu <i>et al.</i> 2015 [121]	Fixed pattern	open-loop	Single	Biomimetic
	Polverino <i>et al.</i> 2012 [122]	Fixed pattern	open-loop	Shoal	Larger Size
	Spinello <i>et al.</i> 2013 [123]	Fixed pattern	open-loop	Single	Larger Size
	Polverino <i>et al.</i> 2013 [124]	Fixed pattern	open-loop	Single	Biomimetic
	Ruberto <i>et al.</i> 2016 [125]	Fixed pattern	open-loop	Single	Biomimetic
	Bartolini <i>et al.</i> 2016 [126]	Fixed pattern	open-loop	Single	Biomimetic (several lures)
	Kruusmaa <i>et al.</i> 2016 [127]	Fixed pattern	open-loop	Shoal	Biomimetic (shape only)
Self-propelled	Donati <i>et al.</i> 2016 [34]	Fixed pattern, communication by electric signals and tail beats	closed-loop	Shoal	Biomimetic (shape and communication)
	Romano <i>et al.</i> 2017 [128]	Fixed pattern	open-loop	Single	Biomimetic
	Abaid <i>et al.</i> 2013 [129]	Fixed pattern	open-loop	Single	Larger Size
	Butail <i>et al.</i> 2013 [130]	Fixed pattern	open-loop	Shoal	Larger Size
Moved by a mobile robot	Butail <i>et al.</i> 2014 [111]	Fixed pattern	open-loop	Shoal	Larger Size
	Faria <i>et al.</i> 2010 [110]	Fixed pattern	open-loop	Single	Biomimetic
	Swain <i>et al.</i> 2012 [31]	Follow the centroid	closed-loop	Shoal	Biomimetic
	Landgraf <i>et al.</i> 2014 [32]	Follow the centroid or Recruitment	closed-loop	Shoal	Biomimetic
	Landgraf <i>et al.</i> 2016 [33]	Follow the centroid or Recruitment	closed-loop	Shoal	Biomimetic

Table 3.1 – Recent research using robots to study fish behaviour. We classified the studies according to the technique used to move the lure, the behaviours of the lure, the number of fish swimming with the robot and the shape of the lure. The robots used in these studies can be classified into three categories: First, by using a fish-lure fixed to a mobile arm. This allows to test the reaction of one (or a few) fish to lures that differ by one characteristic, e.g. colour, size, tail-beating frequency. Second, by using a self-propelled aquatic robot that swim in the water with the animals. Such robots are fully autonomous and are a first step towards robots that can be used out of the lab in natural conditions. Third, by using a fish-lure linked through magnets to a mobile robot that moves under the tank. This allows the decoupling of the stimuli shown to the fish (the mock-up fish in the water) and the robot responsible for mobility. By doing so, it is possible to develop a biomimetic lure that has the same size and aspect as a real fish but also capable of reproducing their movement patterns. Four types of lures are used in the literature: biomimetic lures are designed to look like (in term of shape and texture) a fish and are of similar size of a fish; biomimetic (several lures) involves several lures actuated by a single robot; biomimetic (shape only) lures have a biomimetic shape, but not a biomimetic texture; large sized lures are not biomimetic, and are (far) larger than a fish. In [34], the lure is equipped with electric sensors and actuators, which enables the lure to communicate with a shoal of electric fish and to create closed-loop interactions between fish and robot.

identify sub-groups of agents. Then, we analyse the collective dynamics of the population, and the propensity of the robot to be integrated into the fish group. These results are then compared with data obtained by observing 5 zebrafish swimming in the same conditions without the fish-robot. In order to compare the experiments with fish and a robot to the control experiments with only fish, we define a similarity measure quantifying the social integration. This measure is based on several metrics characterising the impact of the chosen biomimetic features: the linear speed distribution of the agents, the inter-individual distances distributions of agents in a sub-group, the distribution of sub-group size.

3.2 Materials and Methods

3.2.1 Experimental set-up

We use 10 groups of 5 adults wild-type AB zebrafish (*Danio rerio*) in our experiments.

Our experimental set-up (Fig. 4.2A) is equipped with two environmental patches (rooms) linked by a corridor (see Fig. 3.3A). The geometry of the setup is designed to study collective transitions between patches allowing to quantify the group cohesion and collective decision-making as in [131, 132]. Thus the robot has to be socially integrated to be part of the collective transitions between the rooms. The floor of the aquarium is covered with a sheet of teflon to provide a smooth surface for the motion of the fish-lure. An overhead camera (Fig. 4.2A) captures video frames of experiments. Then, our control and tracking software (called **CATS2** [66]) is able to track the positions of the agents (fish and robots), and to control the robots. A system that controls the robots of a mixed-society containing zebrafish must cope with their fast reaction time and sudden movements. Our system is designed to handle low latencies (less than 70ms, as we work in 15 frames per seconds), both at the tracking and at the control levels.

The control of FishBot motion is done through events that are sent from the control software and that contain the parameters for the locomotion.

3.2.2 FishBot and fish lures

We consider two kinds of fish lures: a biomimetic lure, and a non-biomimetic lure. The biomimetic lure was designed to mimic the visual appearance of a zebrafish as close as possible (Fig. 4.2B) using the methodology presented in [133], based on a 3D scan of a zebrafish. The lure was also covered with a decal to have the similar color patterns as the zebrafish (the methodology is described in Sec. A.4). The non-biomimetic lure is a zebrafish-sized 3D printed black ellipsoid (of $4.5 \times 0.5 \times 0.8\text{cm}$). The lures are linked by magnetic coupling to a mobile robot moving below the experimental tank.

We use the miniature mobile robot "FishBot" described in [29, 30, 65] that can achieve the required speeds and accelerations in order to reproduce the fish displacement under water. The robot is continuously powered as described in Figs. 4.2A and 4.2C and controlled with a wireless bluetooth link, therefore it is possible to achieve long duration

experiments in closed-loop (described in Sec. A.3).

3.2.3 Data analysis

Zebrafish tend to form short-lived sub-groups of individuals (especially in fragmented environments [131]), which often translate to different sub-group behaviour, as sub-group size changes the social context. In particular, fish do not behave the same way when they are alone as when they are in a group (for instance, they have different distributions of linear and angular speeds). As such, we identify sub-groups of agents in each frame of our experimental videos. We use a clustering algorithm that uses only the position of each individual to detect the sub-groups in each frame of our experimental videos. This algorithm is described in Sec. B.1.1.

Then, by using the tracked positions of agents (fish and robot) and the information describing sub-groups membership, we compute several statistics of individual and collective behaviour: the density of presence in the arena, the distributions of linear speeds in each room, the inter-individual distances in sub-groups of size 2 to 5 individuals, and the distribution of the number of agents in sub-groups.

3.2.4 Quantifying social integration

It is not trivial to compare the results of the experiments with a robot with the corresponding results from the biological reference case. Here, we define a similarity measure to compare the results of all experiments, taking into account the distributions of linear speeds in the rooms ($I_{\text{lsr}}(Ci)$) and in the corridor ($I_{\text{lsc}}(Ci)$), the distributions of inter-individual distances for sub-groups of two to five individuals ($I_{\text{iiSG2}}(Ci), \dots, I_{\text{iiSG5}}(Ci)$) and the distribution of sub-groups size ($I_{\text{sgs}}(Ci)$). We postulate that this similarity measure translates directly to the capabilities of the robot to socially integrate into the group of fish. We term this similarity measure the *social integration index* ($I(Ci)$ for the Ci experiment), and define it as:

$$I(Ci) = \frac{I_{\text{lsr}}(Ci) + I_{\text{lsc}}(Ci) + I_{\text{iiSG2}}(Ci) + \dots + I_{\text{iiSG5}}(Ci) + I_{\text{sgs}}(Ci)}{7} \quad (3.1)$$

$$I_a(Ci) = 1 - H(C0_a, Ci_a) \quad (3.2)$$

The *social integration index* $I(Ci)$ of the experiment Ci has a value between 0.0 and 1.0. A value of 0.0 corresponds to the absence of social integration of the robot, and a value of 1.0 corresponds to a social integration of the robot comparable to that of a fish.

The histograms of these parameters are presented in Figs. 3.7, 3.8 3.9, and in Sec. B.1. We hypothesise that these are the most relevant features to identify the social integration of the robot into the group of fish. First, the speed distributions show the ability of the robot to follow the fish at the same speed as the fish. Second, the inter-individual distance distributions show the capability of the robot to be at the same distance to the fish as a fish would be towards its neighbours. Lastly, the distribution of sub-group sizes shows

that sub-group dynamics in experiments with a robot are similar to those in experiments with only fish.

The $H(P, Q)$ function is the Hellinger distance between two histograms. The Hellinger distance [134] is a divergence measure, similar to the Kullback-Leibler (KL) divergence. However, the Hellinger distance is symmetric and bounded, unlike the KL-divergence (and most other statistical distance metrics). It is often used as a metric to compare distributions, and is defined as:

$$H(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^d (\sqrt{p_i} - \sqrt{q_i})^2} \quad (3.3)$$

where p_i and q_i are respectively the i -th bin values of histograms P and Q ; d is the number of bins in both histograms P and Q .

3.3 Multi-level approach for the robot behaviour

We present here a biomimetic model of fish behaviour, that can be implemented as a robotic controller. Our model is multi-contextual, to take into account the different behaviours exhibited by the fish in the different zones of our fragmented experimental set-up (with two rooms and a corridor, *cf.* Fig. 3.3A). We design this model to be multi-level (Fig. 4.3).

The high-level control manages the biomimetic trajectories of the robot. We use different behavioural schemes to generate desired target positions of the robot depending on its position in the arena. These trajectories are calibrated to correspond to the analysed fish trajectories.

The low-level control corresponds to the movement patterns of the robot that are also important to facilitate social integration. It describes how the robot can move from its current position to the target positions provided by the high-level control system.

Control at both levels can be designed to be biomimetic. At the level of trajectories, zebrafish have a complex social behaviour and tend to form dynamic and short-lived groups. At the level of movement patterns, zebrafish move by successive bouts of tail-beats [135]. Each tail-beat can be modelled as a sequence of three steps: first, the tail-beat allows the fish to reorient itself towards its target position; second, the fish accelerates linearly by using the thrusting effect of the tail-beat; third, the tail-beating stops and the fish slides into water with a decreasing linear speed [65]. Here, we present a biomimetic multi-level model of these dynamics, taking into account both high-level (in Sec. 3.3.1) and low-level (in Sec. 3.3.2) controls.

Figure 3.3B and Table 3.2 summarise the different behaviours depending of the position of the robot, and how they are implemented in terms of high-level control (trajectories) and low-level control (movement patterns). A general description of this biomimetic model can be found in Fig. 4.3.

We designed our behavioural model to exhibit different behaviours depending on the spatial position of the robot in the arena. Indeed, we observed that zebrafish exhibit dif-

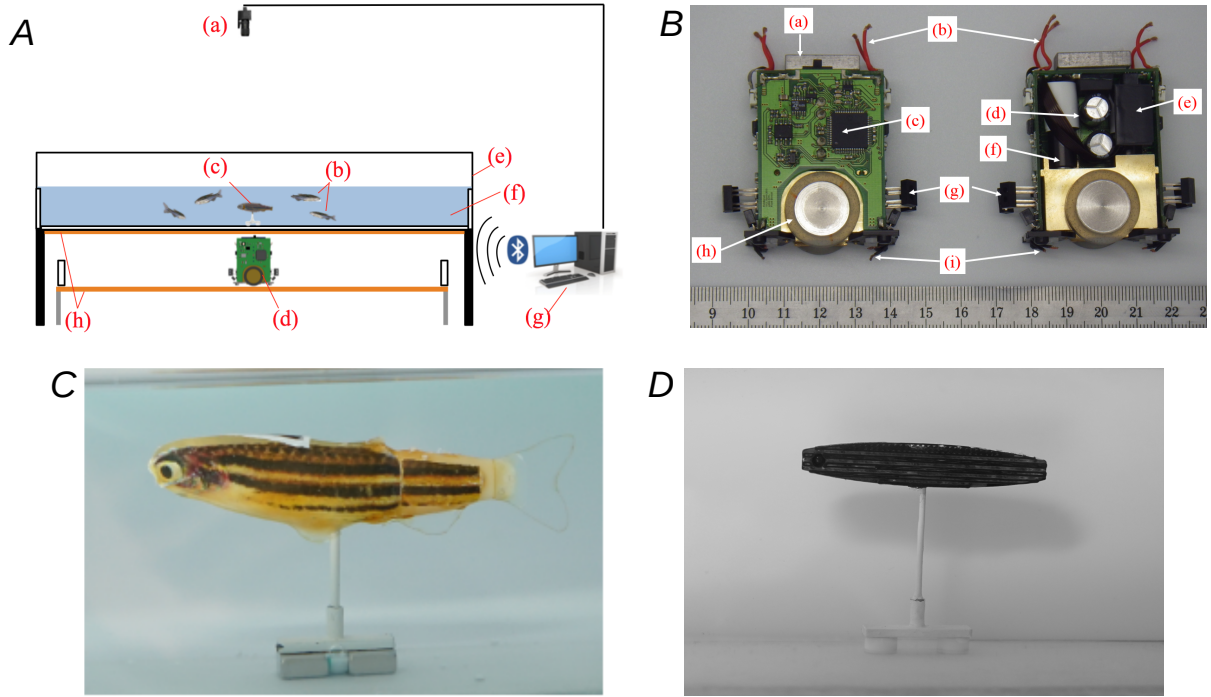


Figure 3.2 – Panel A: Experimental set-up used during the experiments [29, 30, 65]. (a) Camera used to track the lure and the zebrafish. (b) Zebrafish. (c) Fish-lure inside the aquarium linked to the mobile robot through magnetic coupling. (d) FishBot moving under the aquarium. (e) Aquarium of $1000 \times 1000 \times 250$ mm. (f) Water layer of 60 mm depth. (g) The computer that processes the camera frames and remotely controls the robots via Bluetooth. (h) Conductive plates to power the mobile robot. **Panel B:** Description of the FishBot [29, 30, 65], the robot used for mimicking fish motion patterns. a) Magnets to magnetically couple FishBot with the lure module. b) Electric brushes to retrieve the power from the positive conductive plate. c) Microcontroller dspic33f128. d) Supercaps that store power if the contact with the plates is lost. e) Bluetooth antenna. f) Maxon DC motor. g) Infrared Proximity sensors. h) Wheel i) Electric brushes to retrieve the power from the Ground connected conductive plate. **Panel C:** biomimetic lure used during the **C1, C2, C3** experiments (see Table 3.3) [29, 30, 65]. **Panel D:** Non-biomimetic lure used in the **C4** experiment.

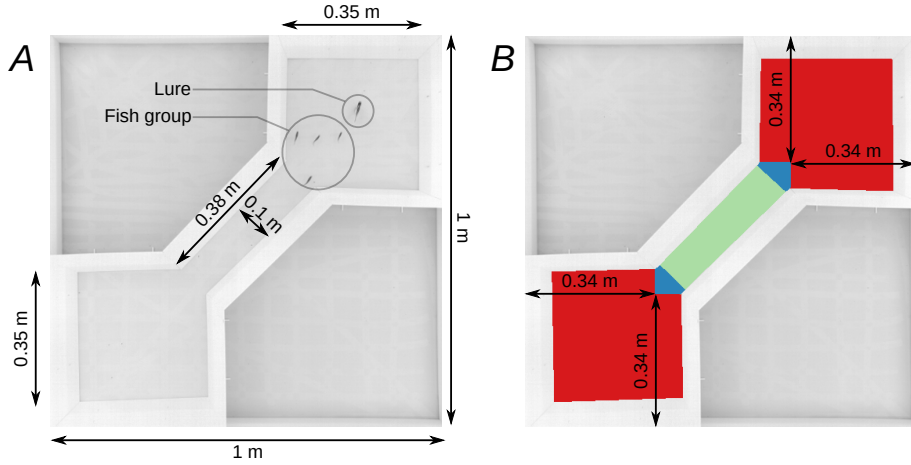


Figure 3.3 – Panel A: Experimental arena composed of two linked square rooms used to study collective transitions and decision-making. Our biomimetic lures, described in Fig. 4.2B, can be integrated within the fish group and mimic their collective behaviours. **Panel B:** Colored zones of the arena corresponding to the three different types of behaviour of the robot. These behaviours are outlined in Table 3.2. When the robot is in the rooms (in red) or near the entrance of the corridor (in blue), it is driven by the biomimetic model presented in Sec. 3.3. This model is used to generate a new target position of the robot every $1/3$ s. If this target position is near the entrance of the corridor (in blue), the target position of the robot is not updated before 5 s are passed, to give the robot enough time to go to the entrance of the corridor. When the robot is in the corridor (green zone), it passes straight through the corridor, with a constant speed.

Color in Fig.3.3B	Robot Zone	Current Zone	Target Zone	Trajectories	Movement patterns	Obstacle avoidance
Red	In Rooms or Near entrance		In Rooms	Probabilistic (cf. Sec. 3.3.1) updated every $1/3$ s	Biomimetic (cf. Sec. 3.3.2)	Turn to avoid (cf. Sec. 3.3.2)
Blue	In Rooms or Near entrance		Near entrance	Probabilistic (cf. Sec. 3.3.1) updated every 5 s	Biomimetic (cf. Sec. 3.3.2)	Turn to avoid (cf. Sec. 3.3.2)
Green	Corridor		any	Pass-through (cf. Sec. 3.3.3)	Constant speed (cf. Sec. 3.3.4)	Braitenberg (cf. Sec. 3.3.4)

Table 3.2 – Robot behaviours depending on the context

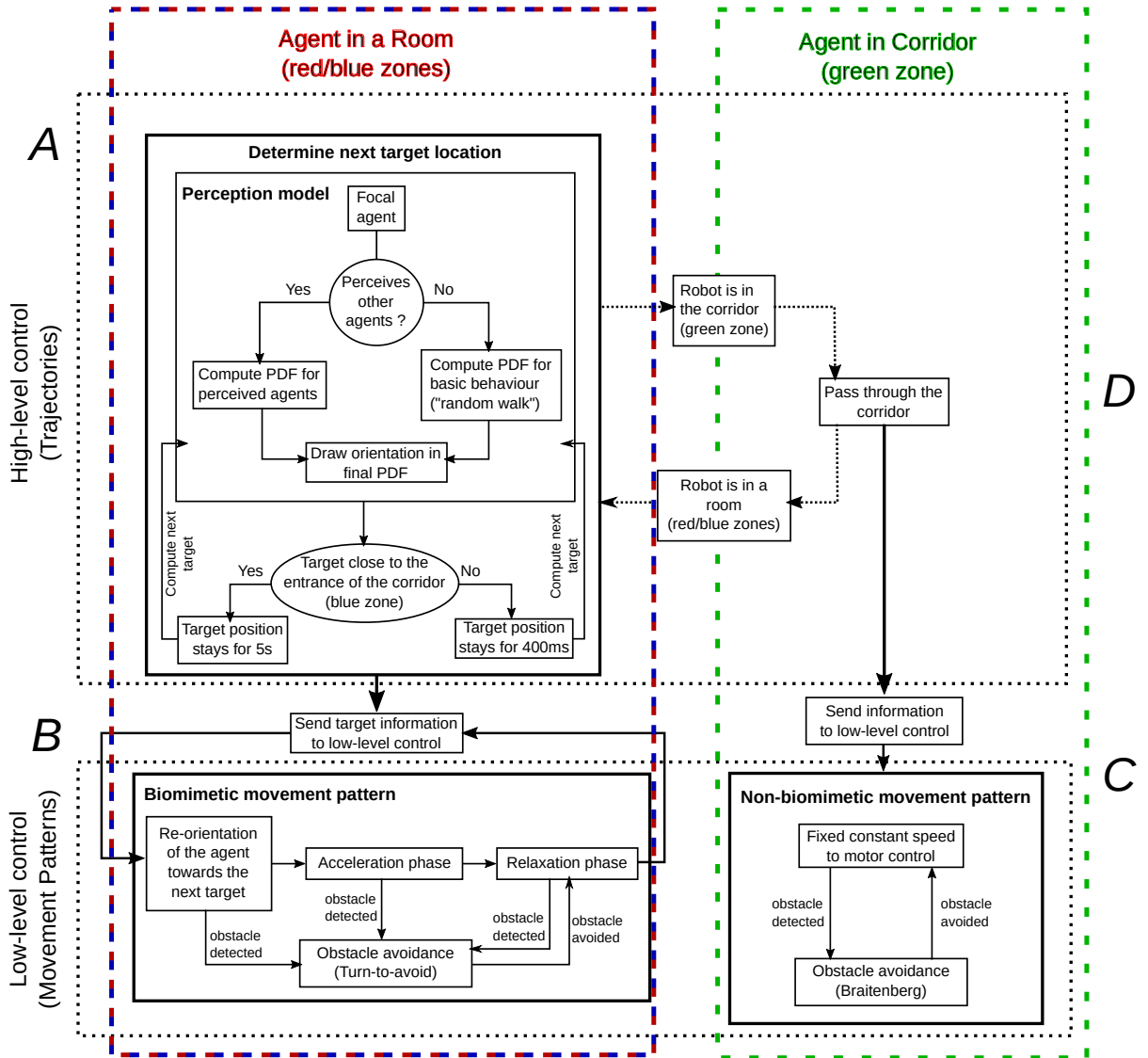


Figure 3.4 – Multilevel behavioural model (here denoted *BM*) used as robot controller. Our robot control system is divided into two layers. The high-level control layer (in A and D) describes the trajectory of the robot in the arena and generates target positions. The low-level control layer (in B and C) handles the movement patterns of the robot to reach the target positions derived from the high-level control layer. The robot has different behaviours depending on whether it is in the rooms (in A and B, represented in red and blue in Fig. 3.3B) or in the corridor (in C and D, in green in Fig. 3.3B). In the rooms, the high-level (in A) and low-level (in B) controls are biomimetic. In the corridor, the high-level (in D) and low-level controls (in C) are not biomimetic, and drive the robot to transit from one room to the other through the corridor. These behaviours are summarised in Table 3.2.

ferent behaviours when they are in the corridor compared to when they are in a room [131] (*cf.* Sec. B.1). When they are in the corridor, they tend to go from one of the entrances of the corridor to the other room, with a different speed distribution. The fish only transit in the corridor in a rather straight manner.

When the robot is in the rooms (in red) or near the entrance of the corridor (in blue), it is driven by a biomimetic probabilistic behavioural model (Fig. 4.3A), and described below (*cf.* Sec. 3.3.1). This model is used to generate new target positions of the robot every $1/3$ s (this time step was chosen to correspond to the tail beat frequency of the zebrafish of ~ 2.5 Hz, as in [113]). The low-level controller of the robot makes it follow and reach these target positions with fish-like biomimetic movement patterns (Fig. 4.3B, *cf.* Sec. 3.3.2). If a target position of the robot is near the entrance of the corridor (in blue), it is not updated before 5 s are passed, to give the robot enough time to reach the entrance of the corridor. When the robot is in the corridor (in green), it passes straight through the corridor with a constant speed.

At present, while the robot can pass through the corridor from one room to the other without wall-collision, it can be difficult for the robot to perform U-turns in the corridor (*i.e.* turn around in the corridor and go back to the room the robot was previously situated) without colliding into the walls due to the narrowness of the corridor. As such, when the robot enters the corridor, it is driven by a *pass-through* behaviour to transit from one room to the other in a straight line, without possibility of U-turn (Fig. 4.3D). We do not use the biomimetic probabilistic behavioural model (Fig. 4.3A) in this case, as it would have a small probability of generating target positions toward the room where the robot was previously situated, thus driving the robot to perform an U-Turn.

Additionally, the teflon sheet that we put on the floor of the aquarium is not perfectly plane (as it is difficult to glue this layer to the aquarium), which can slightly influence the movement of the robot due to the magnetic coupling between the robot and the lure (sliding on the teflon layer). This is especially the case when the robot is moving at high speed, or when it performs strong accelerations, for instance when it is driven by the biomimetic low-level controller (Fig. 4.3B). This is why we use a *constant speed* behaviour (without strong acceleration, Fig. 4.3C) when the robot is passing through the corridor.

3.3.1 High-level biomimetic behavioural model in the rooms

To define the trajectories of the robot in the rooms (red and blue zones in Fig. 3.3B, Fig. 4.3A), we developed a biomimetic behavioural model inspired from the stochastic model of Collignon *et al.* [113], which used a gaussian mixtures agent-based approach to describe zebrafish behaviour in a shoal.

Several kind of models exist to describe fish schooling. The self-propelled particles models [136, 137] describe fish interactions mostly in term of collision avoidance, alignment, and cohesion [138, 139]. Similarly, the social forces models characterise fish as Newtonian particles subjected to social forces (establishing group cohesion) and physical forces (reflecting the interactions with the environment) [140]. The kinematic models represent fish trajectories by stochastic differential equations [141, 142, 135]. They constitute a continuous time formulation of random walks (*cf.* Brownian motion [143, 144]), which describe

stochastic trajectories made of successive random steps. Stochastic formulation of fish behaviours have the distinct advantage of modeling individual choice in decision-making processes. This is especially relevant to the modeling of animal behaviour, where animals often have to make decisions while being exposed to concurrent stimuli (*e.g.* zebrafish larvae that orient towards one of several light sources rather than swimming towards their bisector [145]).

In all types of models of fish behaviour, the agents move according to conspecifics. It can be challenging to model appropriately agent perception, and define which subset of individuals influence the motion of a focal fish. As such, several recent works [146, 147, 148] used agent visual perception information to define movements: in these models, the focal agent interacts with its neighbours not according to their Cartesian coordinates but according to their representation in its visual field. These models are more coherent in term of biological realism: it was shown that fish behaviour is mainly dependent on visual perception [148].

The work of Collignon *et al.* [113] builds on these principles by designing a model of fish trajectories at the crossroads of random walks and self-propelled particules models: agents have a behaviour with a stochastic component (inspired by random-walk models) and react to their perception field (inspired by self-propelled particules models). It involves the computation of a PDF (Probability density function) determined by the presence of stimuli (*e.g.* perception of conspecifics) in their visual perception field. It is computed as a mixture distribution of von Mises distributions centered on each perceived stimulus. At each time-step, the agents randomly choose a direction to move according to their PDF.

The model in [113] was designed to model zebrafish behaviour in an empty square arena. We modified this model to be used as a robotic controller, and to handle our arena with two rooms and a corridor.

In this model, the agents update their position vector X_i with a velocity vector V_i :

$$X_i(t + \delta t) = X_i(t) + V_i(t)\delta t \quad (3.4)$$

$$V_i(t + \delta t) = v_i(t + \delta t)\Theta_i(t + \delta t) \quad (3.5)$$

The speed v_i is drawn from the speed distribution of the fish in the rooms (Fig. B.4, experiment C0). The orientation Θ_i is drawn from the probability density function (PDF) computed as a mixture distribution of *von Mises* distributions centred on the stimuli perceived by the focal agent. In this study, we only take into account the influence of other agents. The attraction towards the walls is not considered yet as it would put the robots too close to the walls, increasing greatly the number of collisions between them. Only agents present in the corridor or in the same room as the focal agent are perceived. The agents present in the opposite room are not perceived.

The PDF $f_0(\theta)$ for an agent to move in each potential direction θ in a bounded environment without perceptible stimulus is given by:

$$f_0(\theta) = \frac{\exp(\kappa_0 \cos(\theta))}{2\pi I_0(\kappa_0)} \quad (3.6)$$

with κ_0 a dispersion parameter associated with movements not influenced by stimulus, and I_0 the modified Bessel function of first kind of order zero, defined as:

$$I_0(\kappa) = \sum_{k=0}^{\infty} \frac{(\kappa/2)^{2k}}{k! \Gamma(k+1)} \quad (3.7)$$

The model computes a PDF for the focal agent to move according to other agents (congeners). The probability of the focal agent to orient towards a perceived agent is given by a von Mises distribution clustered around this agent:

$$f_{f_i} = \frac{\exp(\kappa_f \cos(\theta - \mu_{f_i}))}{2\pi I_0(\kappa_f)} \quad (3.8)$$

with θ the potential direction of movement of the agent, μ_{f_i} the location of the perceived fish i and κ_f a dispersion parameter associated with agent attraction.

The model computes a weighted sum of all distributions f_{f_i} for all agents i , resulting in a PDF $f_F(\theta)$ defined as:

$$f_F(\theta) = \sum_{i=1}^{n_f} \frac{A_{f_i}}{A_{T_f}} \frac{\exp(\kappa_f \cos(\theta - \mu_{f_i}))}{2\pi I_0(\kappa_f)} \quad (3.9)$$

$$A_{T_i} = \sum_{i=1}^{n_f} A_{f_i} \quad (3.10)$$

with A_{T_f} the sum of solid angles A_{f_i} captured by each perceived agent i and n_f the number of perceived agents.

Finally, we calculate a weighted sum of the PDFs to obtain the global probability distribution function $f(\theta)$ of the focal fish to move towards a given direction. This global PDF is different from [113], as we removed the attraction to the walls, and is computed as follow:

$$f(\theta) = \frac{f_0(\theta) + \alpha_0 A_{T_f} f_F(\theta)}{1 + \alpha_0 A_{T_f}} \quad (3.11)$$

with α_0 a parameter weighting the influence of the perceived agents. The parameters $\kappa_0 = 6.3$ and $\kappa_f = 20$ are the same as in [113].

There is a delay (< 500 ms) between the time when a new target position is computed and the time when the robot actually reaches this position. This can have an adverse effect on the desired fish-following behaviour of the model, when the robot is part of a sub-group and is moving alongside its neighbours. Indeed, the target-following system (low-level control) must compromise between efficiency (the capability of reaching the target with a low latency) and biomimetism (fish-like movement, and fish-like speed distribution). To mitigate this effect, we selected a different value of α_0 than in [113]: we consider $\alpha_0 = n_A * 1000 / n_D$ with $n_A = 5$ the total number of agents in the experiment, and n_D the number of detected agents in the current frame. This increases the tendency of the robot to follow fish groups. The number of detected agents is used to normalise the computation

of α_0 as the model only takes into account the agents that are actually detected by the tracking system, which introduces a bias.

Then, we numerically compute the cumulative distribution function (CDF) corresponding to this custom PDF $f(\theta)$ by performing a cumulative trapezoidal numerical integration of the PDF in the interval $[-\pi, \pi]$ (as described in [113]). Finally, the model draws a random direction Θ_i in this distribution by inverse transform sampling. The position of the fish is then updated according to this direction and his velocity with equations 4.1 and 4.2. If the target position of the robot is in an unreachable area (*e.g.* walls), we draw another random direction from the CDF.

3.3.2 Low-level biomimetic movement patterns in the rooms

In the rooms (red and blue zones in Fig. 3.3B), the robot is following trajectories drawn by the high-level biomimetic model described in Sec. 3.3.1. The low-level robot controller (Fig. 4.3B) is programmed to follow the target position computed using the high-level behavioural model. When the target is near the entrance of the corridor (blue zone of Fig. 3.3B), it remains there for 5s to leave enough time for the robot to reach the entrance of the corridor, and then pass through it to the next rooms. We choose the relatively long duration of 5s to prevent the high-level model to generate a new target not situated in the corridor before the robot is able to reach the entrance of the corridor, as it could lead to experiments where the robot never go thru the corridor. Indeed, this target-following control method is simple to implement, but can create a gap between the position of the robot and the desired target position. To compensate for this effect, the low-level robot controller is parametrised with a speed of 12 cm.s^{-1} (higher than the speed of the fish) during the relaxation phase (this parameter value was chosen experimentally). However, the robot will not have this mean speed in practice, but an average speed (7.9 cm.s^{-1}) closer to the fish (8.2 cm.s^{-1}), as can be seen in Sec. B.1.

To accurately mimics the movement patterns of the zebrafish inside the two rooms, we used the low-level robot controller designed in [65]. At each control steps, the desired target position generated by the model described in Sec. 3.3.1 is compared with the current robot position and orientation. The difference in orientation is sent to the robot, that executes a step machine composed of three steps: First, the wheels are controlled in position to reorient the robot towards the desired target. Second, the robot accelerates to 0.7 m.s^{-2} and third, the speed of the robot is set to a constant speed of 8.5 cm.s^{-1} . The robot will keep this speed until the next control step. This mimics the typical locomotion of zebrafish in open areas as demonstrated in in [65].

We use a simple collision avoidance scheme (termed *Turn to avoid*), where the robot stops when it is too close to a wall and then turns at a reduced speed (5 cm.s^{-1}) for 3.5 s before going back to its normal behaviour.

3.3.3 Robot trajectories in the corridor

When the robot is in the corridor (green zone in Fig. 3.3B), it is programmed to transit in a straight line towards the other room (Fig. 4.3D), with a constant speed of 12 cm.s^{-1}

if the robot is not in collision with a wall. This speed is reduced to 5 cm.s^{-1} when the robot is too close to the walls, *e.g.* after a collision. The resulting mean speed of the robot is still lower than the one of the fish (Fig. B.5). We could not increase the speed of the robot to match the mean speed of the fish in the corridor, as it would increase the probability of crashing against a wall.

3.3.4 Biomimetic movement patterns in the corridor

Inside the corridor (green zone in Fig. 3.3B), the zebrafish usually have a constant speed as they are stressed due to the reduced size of the environment. Therefore, we implemented a controller (Fig. 4.3C) for the robot to maintain a constant linear speed of 9.4 cm.s^{-1} inside the corridor while the rotating speed is controlled using a PID (Proportional-Integral-Derivative) controller for the robot to reach the opposite room.

To mitigate the effect of eventual collisions of the robot with the walls, the low-level controller of the robot implements a *Braitenberg*-based obstacle avoidance scheme [149]. While this *Braitenberg* obstacle avoidance scheme is more efficient than the *Turn to avoid* scheme used in the rooms, it only works when the robot is moving with a constant speed. This is why we did not use it in the rooms, where the robot is driven by the biomimetic movement patterns (described in Sec. 3.3.4).

3.4 Results

Our goal is to socially integrate a robot driven by a multi-level biomimetic behaviour into a group of laboratory wild-type zebrafish. The experiments are done in a two connected room aquarium that is designed to study social cohesion, collective departures and decision-making [131, 132]. We consider five different experimental conditions summarised in Table 3.3. Each one of the five conditions is composed of 10 trials during each one 30 minutes. Each experimental condition has thus been tested for 5 hours in total. We tested 10 different fish groups per experimental conditions, *i.e.* 40 different fish with the robot. We compare these five experiments by using the similarity measure described in Sec. 3.2.4.

3.4.1 Individual trajectories

We rebuild the trajectories of each individual (fish and robot) by using the individual tracking of the agents (*cf.* Sec. A.5.3). Figure 3.5 presents examples (of 1 minutes) of such trajectories for experiments C0 and C1 (in Panel B, the robot trajectories are in black). The fish tend to follow walls rather than staying in the center of the rooms.

Even though we did not implement any wall following behaviour into the high-level part of the BM model (Fig. 3.3A, see Sec. 3.3.1), the robot still exhibits a wall following behaviour as it tends to be attracted to fish. The trajectories of the robot appear qualitatively biomimetic. We further quantify the mixed group in the following sections.

Label	Experiment	Number of agents	Robot Trajectories in the rooms	Robot Movement pattern in the rooms	Lure
C0	Wild-type zebrafish only	5 fish + 0 robot	-	-	-
C1	Biomimetic model with Biomimetic lure	4 fish + 1 robot	Biomimetic (cf. Sec. 3.3.1)	Biomimetic (cf. Sec. 3.3.2)	Biomimetic
C2	Random walk with Biomimetic lure	4 fish + 1 robot	Random Walk	Biomimetic (cf. Sec. 3.3.2)	Biomimetic
C3	Biomimetic model with Constant Speed	4 fish + 1 robot	Biomimetic (cf. Sec. 3.3.1)	Constant Speed	Biomimetic
C4	Biomimetic model with non-biomimetic lure	4 fish + 1 robot	Biomimetic (cf. Sec. 3.3.1)	Biomimetic (cf. Sec. 3.3.2)	Non-biomimetic

Table 3.3 – Analysed experiments. The **C0** experiment is the biological reference case, involving a group of 5 wild-type zebrafish and no robot. The **C1** experiment involves 4 wild-type zebrafish and one robot driven by the multi-level biomimetic model presented in Sec. 3.3. These experiments are performed in the set-up described in Fig. 4.2A with the arena in Fig. 3.3B after a 30 minutes period of acclimatization. Each experiment is repeated 10 times and lasts 30 minutes. The **C2**, **C3** and **C4** experiments are control experiments based on the **C1** experiment. The **C2** experiment involves a robot driven by a random walk behaviour, to assess the impact of biomimetic trajectories on social integration. In the **C3** experiment, the robot moves with a constant speed along its trajectory instead of moving using biomimetic movement patterns. The **C4** experiment is performed with a non-biomimetic lure.

3.4.2 Group clustering and social cohesion

We compute the mean inter-individual distances between each pair of agents (fish and robots) of a sub-group for all experiments. Three characteristic cases were considered: all sub-groups (*i.e.* sub-groups of 2 to 5 individuals) in Fig. 3.7, sub-groups of two individuals in Fig. 3.8, and sub-groups of all (five) individuals in Fig. 3.9. For all three cases, the distributions of inter-individual distances of the C1 and C3 experiments are the closest to the ones of the C0 experiment.

We compute the mean fraction of non-isolated individuals in each experiment (Fig. 3.6A). In experiments with a robot, C1 (mean of 78.1%, std of 0.050) is the closest to C0 (mean of 83.3%, std of 0.037), followed by C3 (mean of 75.9%, std of 0.049), C4 (mean of 74.4%, std of 0.622), and C2 (mean of 67.4%, std of 0.062). The robot tends to be isolated slightly more often than the fish. When the robot follows our biomimetic model, it increases its capability to be in a sub-group (experiments C1 and C3). The type of movement pattern and lure also affect the capability of the robot to be in a sub-group (experiments C2 and C4).

Figure 3.6B presents the mean fraction of the population either isolated ("sub-group" of size 1) or in a sub-group with 2 to 5 individuals. Agents in the experiments with the

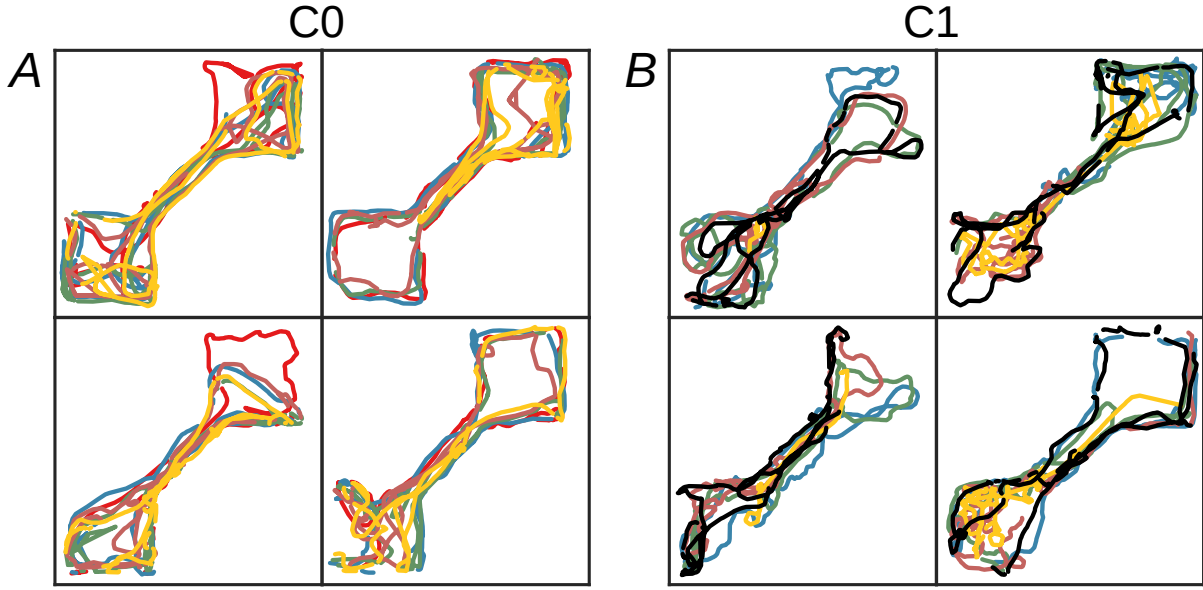


Figure 3.5 – Examples of trajectories of the agents in experiments **C0** (**Panel A**) and in experiment **C1** (**Panel B**). Each subplot corresponds to 1-minute sections of a 30-minutes experiment. In **Panel B**, the robot trajectories are in black.

robot (C1, C2, C3, C4) have a higher probability to be isolated and a lower probability to be in sub-groups of 5 individuals (whole population). Experiments C1 and C3 provide the results that are the most similar to C0. Indeed, while the robot can integrate into the group of fish, especially when driven by a biomimetic model, its behaviour could still be improve to be closer to a fish. In a follow up study we improve the calibration of the model.

3.4.3 Quantifying social integration

Table 4.1 presents the resulting *social integration index* and the associated $I_a(Ci)$ values for all experiments with a robot (**C1**, **C2**, **C3**, **C4**). The experiment with the highest number of biomimetic characteristics, **C1**, has the highest integration index: 0.860. Experiment C3 has the second highest integration index: 0.822, followed by C2 (0.810) and C4 (0.734). It shows the veracity of our hypothesis: a robotic fish has higher social integration capability into a group of fish if it is designed to be biomimetic on three key aspects: the morphology of the lure, the type of trajectories, and the type of movement patterns. Here, we show that the morphology of the lure has the highest impact on social integration, followed by the type of trajectory of the robot and by the type of movement patterns of the robot, with differences of social integration indexes (mean score) with C1 of respectively 0.126, 0.050 and 0.038. For several measures (inter-individual distances in sub-groups of 3 or 4 individuals), C3 has a higher score than C1; it shows that our approach in the design of C1 and of the BM model can still be improved.

	C1	C2	C3	C4
Linear speed in the rooms	0.706	0.739	0.708	0.739
Linear speed in the corridor	0.812	0.694	0.608	0.637
Inter-indiv. distances in SG of 2 indiv.	0.894	0.893	0.780	0.524
Inter-indiv. distances in SG of 3 indiv.	0.927	0.897	0.972	0.885
Inter-indiv. distances in SG of 4 indiv.	0.915	0.837	0.953	0.798
Inter-indiv. distances in SG of 5 indiv.	0.866	0.759	0.861	0.706
Distribution of SG size	0.899	0.854	0.875	0.848
Social integration index (Mean score)	0.860	0.810	0.822	0.734

Table 3.4 – *Social integration indexes for all experiments. Higher values correspond to better integration of the robot in the group of fish. Results in bold correspond to the highest values for each feature. The **C1** experiment involves 4 wild-type zebrafish and one robot driven by the multi-level biomimetic model presented in Sec. 3.3. The **C2**, **C3** and **C4** experiments are control experiments based on the **C1** experiment. The **C2** experiment involves a robot driven by a random walk behaviour, to assess the impact of biomimetic trajectories on social integration. In the **C3** experiment, the robot moves in a constant speed along its trajectory, instead of biomimetic movement patterns. The **C4** is performed with a non-biomimetic lure.*

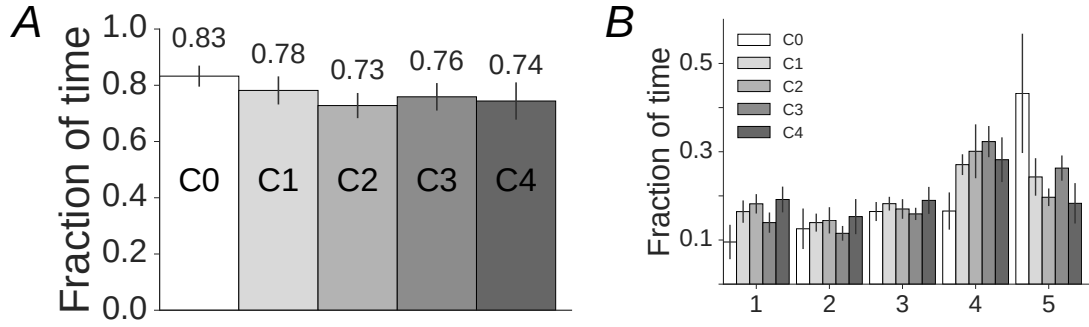


Figure 3.6 – ***Panel A:** Mean fraction of non-isolated individuals in all experiments. The distributions differ significantly (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05 ; cf. Sec. A.5.3). **Panel B:** Mean fraction of the population in a sub-group of 1 (isolated individuals) to 5 (whole population) individuals. The distributions differ significantly (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05 ; cf. Sec. A.5.3). Results are obtained in 10 trials of 30 minutes experiments using groups of wild-type zebrafish moving in the set-up described in Fig. 3.3A.*

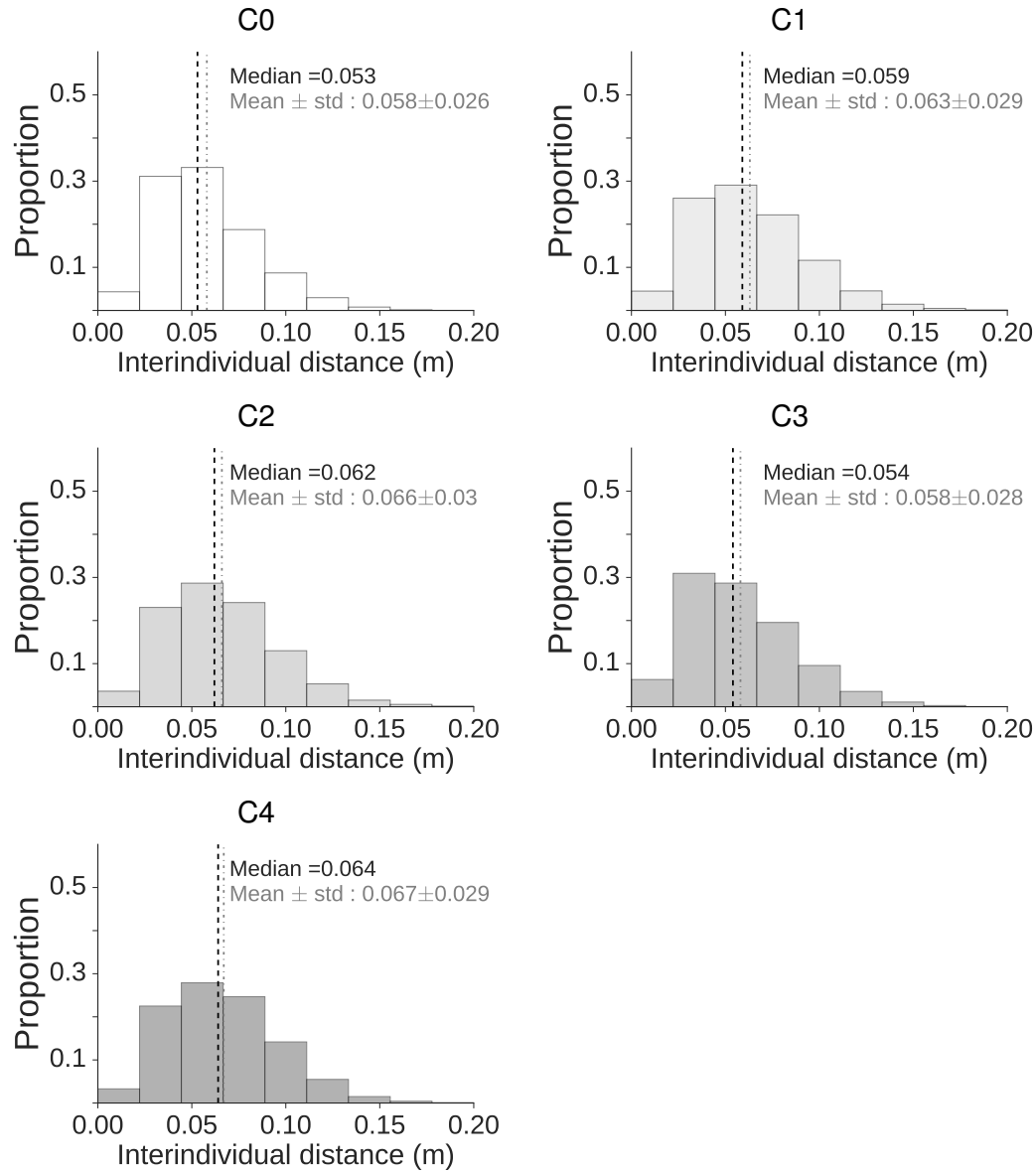


Figure 3.7 – Mean inter-individual distances between each pair of agents (fish and robot) in all sub-groups. Results are obtained in 30 minutes experiments using groups of wild-type zebrafish moving in the set-up described in Fig. 3.3A. Each experiment is reiterated 10 times. All distributions of inter-individual distances differ significantly (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05 ; cf Sec. A.5.3).

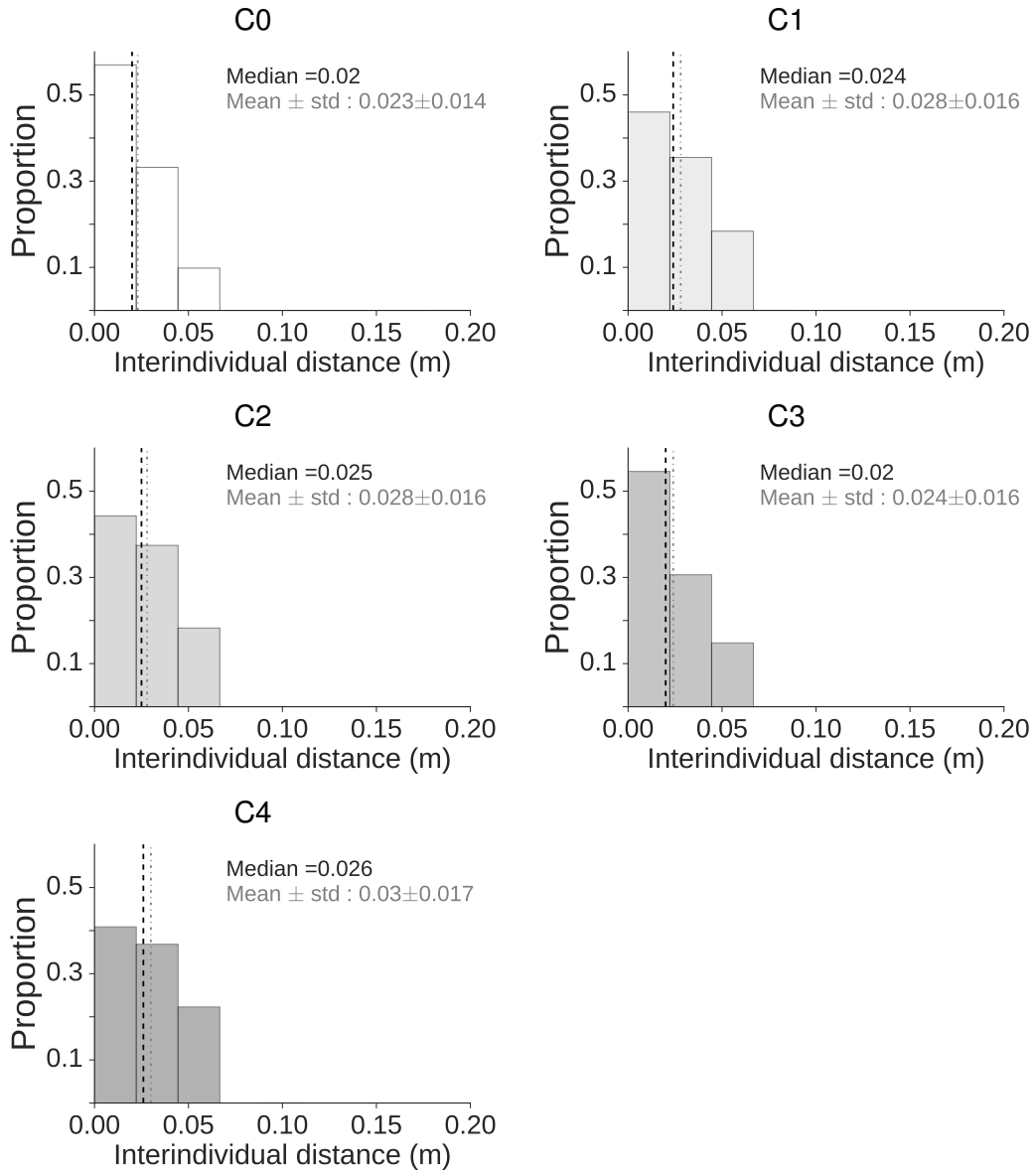


Figure 3.8 – Mean inter-individual distances between each pair of agents (fish and robot) in sub-groups of only two individuals (pairs). Results are obtained in 30 minutes experiments using groups of wild-type zebrafish moving in the set-up described in Fig. 3.3A. Each experiment is reiterated 10 times. All distributions of inter-individual distances differ significantly (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05 ; cf Sec. A.5.3).

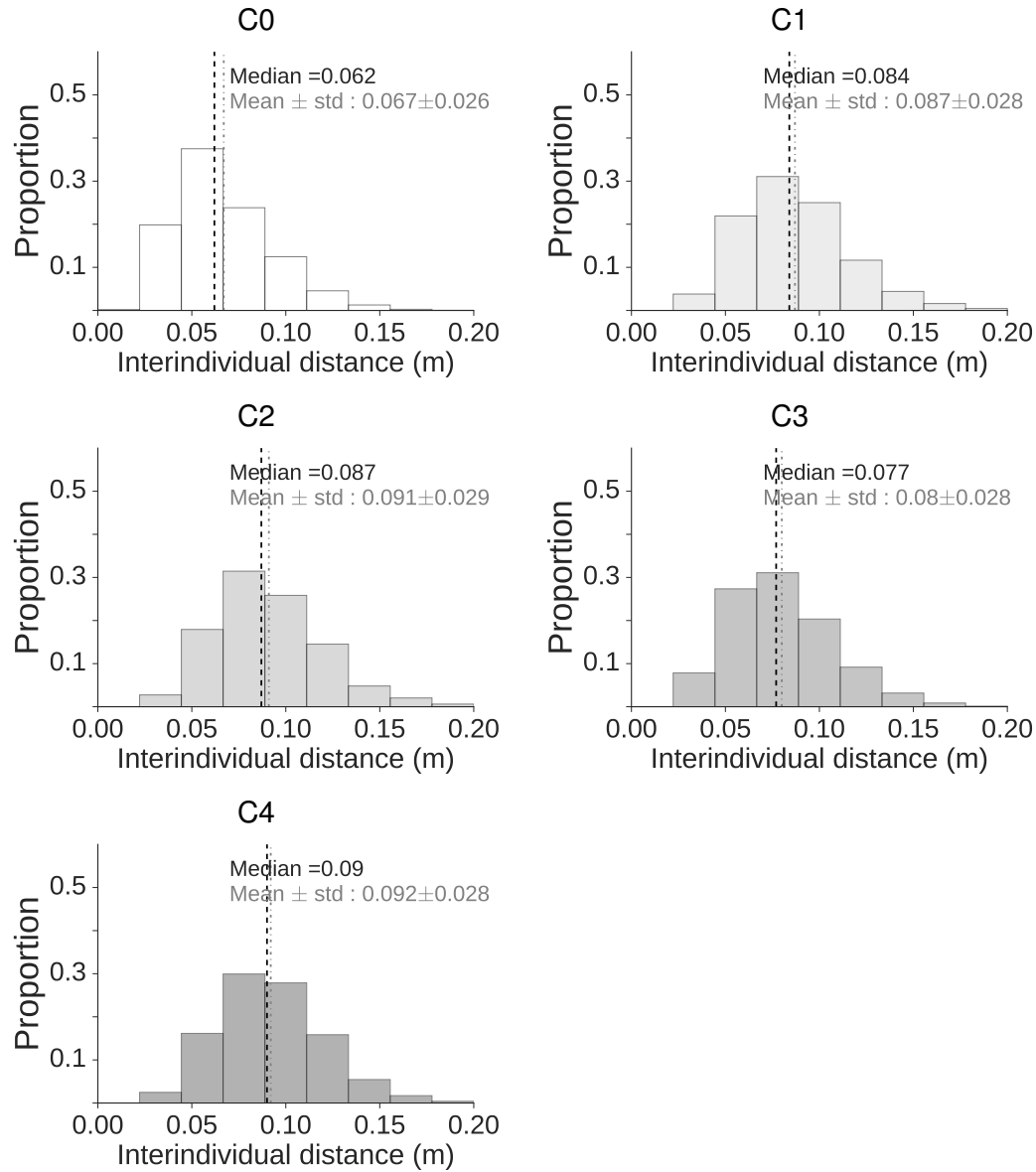


Figure 3.9 – Mean inter-individual distances between each pair of agents (fish and robot) in sub-groups of five individuals (entire population). Results are obtained in 30 minutes experiments using groups of wild-type zebrafish moving in the set-up described in Fig. 3.3A. Each experiment is reiterated 10 times. All distributions of inter-individual distances differ significantly (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05 ; cf Sec. A.5.3).

3.5 Conclusions

In this study, we present a biomimetic model of fish behaviour in a fragmented environment. This model is multi-contextual spatially (square rooms and corridor), multi-level (collective dynamics, collective departures, trajectories, movement patterns) and probabilistic. Then, we describe a methodology to create a closed-loop of social integration between a shoal of zebrafish and a biomimetic fish-lure moved by a robot driven by this biomimetic behavioural model. We use a similarity measure as a metric to quantify the capability of this lure to be socially integrated in the shoal of fish and the biomimetism of the behaviour of the robot.

While previous studies of the literature (Tab. 3.1) showed that a robotic fish needs to be biomimetic in order to be socially integrated in a group of fish, most efforts were made on finding attractive biomimetic lure morphologies, with no or few considerations ([31, 32, 33]) on the effects of robot behaviour (trajectories and movement patterns) on social integration. Both [32] and [33] present experiments involving a closed-loop of interaction between a group of fish and a robot driven by a controller inspired from fish behaviour and magnetically coupled with a biomimetic lure. However, in these studies, the social integration of the robot is not quantified and the robot is more a follower or initiator following fixed patterns of behaviour rather than an entity capable of being integrated with the group of fish and initiating its own decisions during trials lasting 30 minutes.

This issue is addressed in this study, where we show that a robot driven by our biomimetic model of fish behaviour can effectively socially integrate a group of wild-type zebrafish. This problem is challenging because zebrafish present loose social organisation [131]. Indeed this fish species does not form stable schooling patterns (*i.e.* fish aligned and swimming together in the same direction) but forms shoals (tendency to form irregular groups). Moreover, it is difficult to model zebrafish collective behaviour and translate it directly into a robotic controller. Here we consider complex social behaviour in a designed set-up to study social cohesion and collective departures. This fragmented set-up induce more elaborate behaviours than simpler round or square empty tanks. Such environment requires to develop context dependent collective behaviour models taking into account spatial context and social effects.

In this study, we compare mixed groups of 1 robot and 4 fish to groups of 5 fish and no robot. It allows us to quantify the social integration of the robot *i.e.* if the robot belongs to the group, like another fish, for trials lasting for 30 minutes each and during 5 hours in total. Our metrics quantify the distance between a mixed and a pure fish group. According to our metrics, the closer we are to a pure fish group the more the robot is socially integrated.

We analysed the impact of both lure morphology and robot behaviour aspects on social integration and showed that a robotic fish driven by a biomimetic behavioural model is more akin to be socially accepted by the fish compared to a robotic fish driven by a simple non-biomimetic behavioural model. We assessed the importance of biomimetism on different aspects of the robot design: the morphology of the lure, the type of trajectories of the robot, and the type of movement patterns exhibited by the robot, its decision making

capabilities depending on the context. All three aspects were shown to be relevant to facilitate the social integration of the robot. Our results show that both the lure and the behaviour of the robot are important in the design of robots able to socially integrate a group of fish. We showed that the morphology of the lure is the feature with the highest impact, followed by the type of robot trajectories and the type of robot movement patterns.

Additionally, we include a behavioural analysis of the fish group and of the mixed-group of fish and robot. This analysis takes into account the tendency of fish to gather in short-lived and dynamic sub-groups, that can exhibit different behaviour depending on sub-group size and composition. While studies in the literature established the existence of these sub-group dynamics in fish [131], no method was described to identify them. We present an algorithm to identify sub-groups of fish based on their spatial proximity. The results of our sub-groups analysis show that fish exhibit different behaviours depending on the size of the sub-group they are part of, and of their position in the arena. In particular, fish behave differently when alone compared to when in a group. We showed that the inter-individual distances of fish in a sub-groups is dependant of the size of the sub-group. When they are in the corridor, they tend to pass through quickly from one room to the other.

The social integration of the robot into the groups of fish could still be improved by refining the behavioural model. The model could be further calibrated to take into account more aspects of the fish collective behaviour in this complex environment. The robot behaviour could be closer to the fish behaviour that depends on the size of its sub-group and to its spatial position in the set-up. Our model does not yet take into account explicitly the attraction of the agents towards the walls, like the model in [113]. This was mainly motivated by current technical difficulties as this would greatly increase the number of collisions between the robot and the walls. This problem is being addressed in a subsequent study. Robots can still be seen to be following walls in the colored trajectory presented in Fig. 3.5 because they are attracted to fish, which, in turn, tend to follow walls.

Further improvement will be done in follow up studies. We will calibrate the model parameters automatically during an experiment thanks to an optimisation algorithm based on evolutionary computation. Additionally, the social integration can be further quantified by adding other kind of analysis, and by using more behavioural features in the computation of the social integration indexes.

Our study is a first step towards more complex biohybrid societies: instead of just focusing on integration, the robots could be used to control or to modulate the collective behaviour of the mixed group of fish and robots. Indeed taking advantage of specific social behaviours the robots could modulate the whole mixed-groups [1]. The number of robots necessary to have a good control of the mixed societies can also be optimised for example by evolutionary computation [28, 150]. This type of control would be based on natural animal behaviours thus reducing stress and not using coercion to get the target results [14, 1]. Indeed, in zebrafish groups all the fish can be leaders and induce groups transitions from one place to the other. For example, we have shown that the number of initiation is linearly proportional to the number of attempts performed [132]. This allows biomimetic

robots to make use of the fish behavioural features to be capable of inducing collective departures and to modulate the spatial distribution of the groups. Such biohybrid social systems would allow us to modulate and to control group living animals.

Chapter 4

Automated calibration of a biomimetic space-dependent model for zebrafish and robot collective behaviour in a structured environment

Give a man a fish and you feed him for a day; teach a man to fish and you feed him for a lifetime; teach a robot how to behave like a fish, and it will be socially integrated.

An overworked PhD Student

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This chapter extends the methodology presented in the previous chapter and investigate how to automatically calibrate the biomimetic behavioural model from trajectory data of fish-only experiments. This work is based on the publication:

Cazenille L, Chemtob Y, Bonnet F, Gribovskiy A, Mondada F, Bredeche N, Halloy J. Automated calibration of a biomimetic space-dependent model for zebrafish and robot collective behaviour in a structured environment. In Conference on Biomimetic and Biohybrid Systems 2017 Jul 27. Springer, Cham.

Here, we segment our model into several spatial zones corresponding to different fish behavioural patterns. Then we automatically fit the model parameters for each zone to experimental data using a multi-objective evolutionary algorithm. We then evaluate how the resulting calibrated model compares to the experimental data. The model is used to drive the behaviour of a robot that has to integrate socially in a group of zebrafish. We show experimentally that a biomimetic multilevel and context-dependent model allows good social integration of fish and robots in a structured environment.

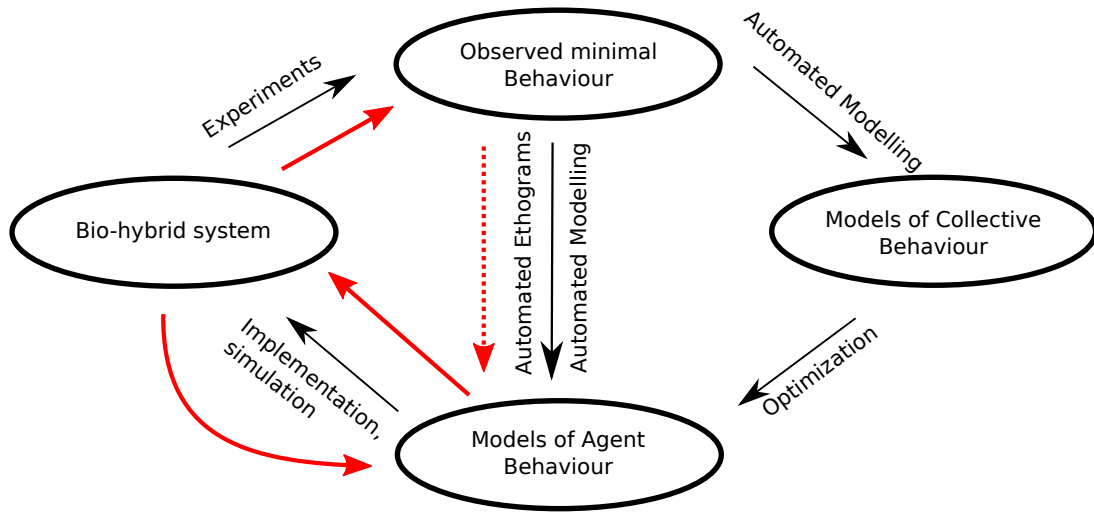


Figure 4.1 – Workflow of the methodology used in this chapter, with red arrows showing the addressed topics.

Figure 4.1 shows how this chapter is linked to the workflow of this manuscript. Here, we extend the approach presented in the previous chapter: we use a microscopic and biomimetic model of fish behaviour and implement it as a robot controller to drive a robot to socially integrate a group of zebrafish. This model is automatically calibrated to fit the behavioural settings observed in experiments involving fish groups. Then, this calibrated model is used to drive the behaviour of a robot in mixed-groups experiments.

Contributions to this chapter

The experimental set-up was designed and built by Bertrand Collignon, Axel Seguret, Yohann Chemtob, José Halloy and myself. The FishBot robot was developed at the EPFL, by Frank Bonnet and Francesco Mondada. The experimental arena was built by Axel Seguret and Yohann Chemtob, based on a early implementation by Frank Bonnet. The control and tracking system was jointly developed by Frank Bonnet, Alexey Gribovskiy and myself. I implemented the data analysis scripts and miscellaneous code. This paper was mainly written by me, with the help of José Halloy and Nicolas Bredeche.

4.1 Introduction

Robotics stands now as a convenient tool to study animal behaviour. In recent ethological and animal behavioural studies, robots are used to induce specific and controlled stimuli and assess the response of the animals under scrutiny. This allows to test various hypotheses on the nature of the signals used by the animals for social interactions [8, 11].

Autonomous robots interacting in real-time with animals [14] make it possible to create social interactions between both of them. This has already been demonstrated by several authors for studying the behaviours of sheepdogs [15], cows [17] or drosophila [114] to cite a few.

In this paper, we focus on zebrafish (*Danio rerio*), and we describe a biomimetic model that can be implemented in a robotic lure and validated its acceptance by four zebrafish in a structured environment.

The main difficulty is to make the robotic lure behave in such a way that it is accepted by the animals as social companion, just as any other interacting fish would be. Beyond the scope of this paper, this is a first step to enable the modulation (through action) of the collective behaviours of the observed zebrafish [1].

Different approaches have been proposed to control the movement of fish-lures [112]. Most of them do not involve a closed loop of social interaction with the fish. This is often the case for lures fixed to a robotic arm that performs repeated movements, but also for studies with autonomous fish-lures. Closing the loop of social interactions requires a real-time tracking, or perception, of the agents (fish and robot), and a decision-making algorithm to control the robot behaviours. In most of the experiments reported in the literature, the robots driven with closed-loop control are programmed to follow the centroid of the fish group, to ensure that the robot will join and follow the group of fish. However, this type of controller implies that the robot is more a passive follower than a real group-member making its own decisions. The embodiment of bio-inspired models can lead to a better social integration of the artificial agents in animal groups and can allow the robots to influence the collective decision of the mixed group by giving specific preferences to the robot by tuning parameter values of the model [1, 112].

We present a method to calibrate automatically a new behavioural zebrafish model by evolutionary parameters optimisation. This multilevel model describes collective behaviour in a structured environment in agreement with experimental observations. This model makes important extensions to our previous model for collective behaviour in a homogeneous environment [113]. The model takes into account a simple structured environment composed of two rooms and the fact that the fish adapt their behaviour to the zones where they are while performing collective behaviour. For such multilevel and spatially dependent social behaviour model it is an issue to calibrate the model because it involves trade-offs between social tendencies (aggregation, group formation), and response to the environment (wall-following, zone occupation). We use an evolutionary algorithm (NSGA-II [91]) to optimise the parameters of this model so that the exhibited collective dynamics correspond to those observed in biological experiments. Then, we validate experimentally this model by implementing it as the controller of robots that are integrated in small fish groups.

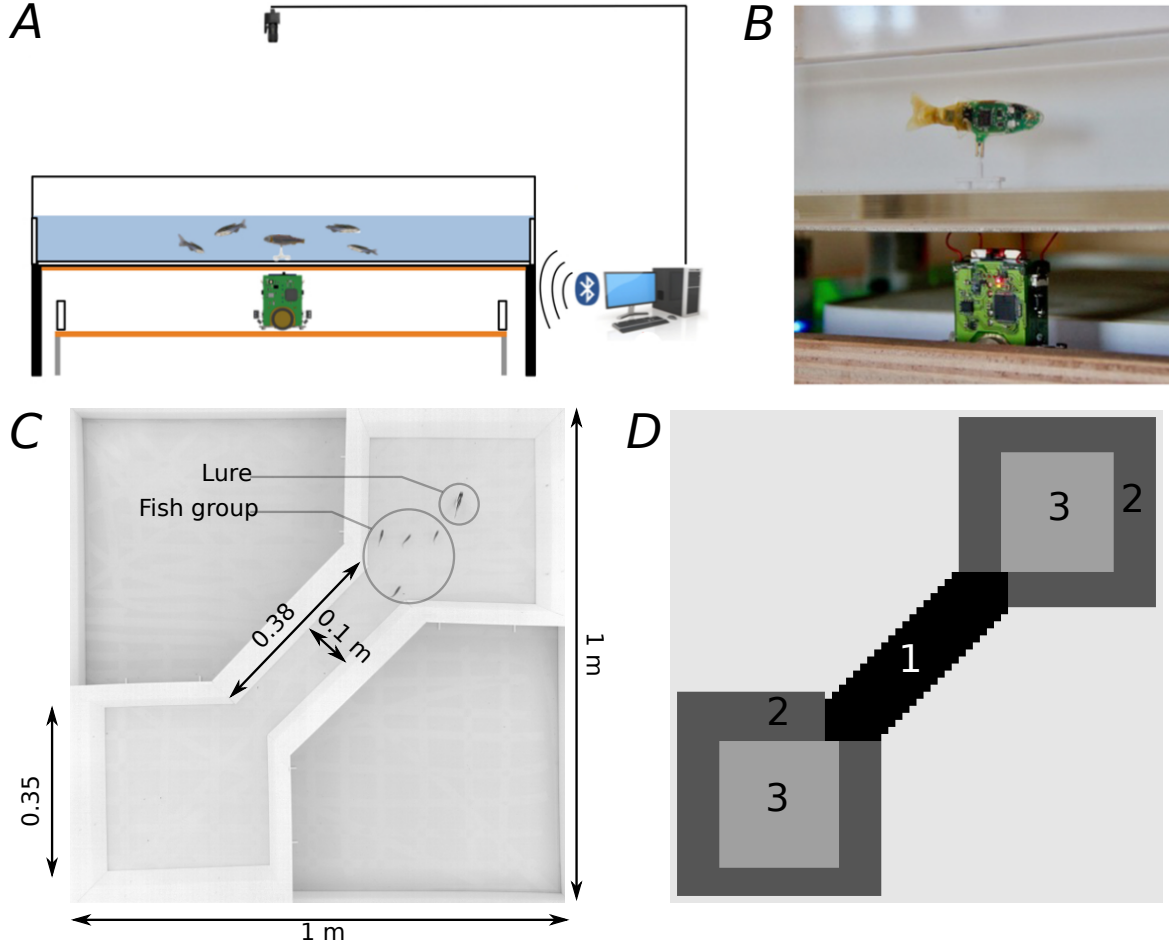


Figure 4.2 – **Panel A**: Experimental set-up used during the experiments [29, 30, 65, 66, 112]. **Panel B**: FishBot [29, 30, 65]: the robot used for mimicking fish motion patterns, with the biomimetic lure used during the reference experiments. This robot was developed by the EPFL for the ASSISI project [24]. **Panel C**: Experimental arena composed of a tank containing two square rooms (350×350 mm at floor level) connected by a corridor (380×100 mm at floor level). The fish tend to swim from one room to the other, either in small groups, or individually. This set-up is used to study the zebrafish collective dynamics. **Panel D**: Positions of the three different zones corresponding to different types of behaviours: in the corridor (zone 1), in the center of each room (zone 2), and near of the walls of each room (zone 3).

4.2 Materials and Methods

4.2.1 Experimental set-up

We use the experimental set-up described in [66, 131, 112, 132], with the arena presented in [112, 131]. This set-up (Fig. 4.2A) consists of a white plexiglass arena (Fig. 4.2C) of $1000 \times 1000 \times 100$ mm, that is composed of two rooms linked by a corridor. To validate experimentally our calibrated model, we use a robot developed by the EPFL [29, 30, 65, 66]

for the ASSISI project [24]. This robot is powered by two conductive plates under the aquarium. An overhead camera captures frames that are then processed for tracking and control purposes (see Fig. 4.2A).

All trials have a duration of 15min. We tracked the positions of the agents by using the idTracker software [151]. Using this software, we obtain the positions $P(x, y, t)$ of all agents at each time step $\Delta t = 1/15$ s for all experiments, and build the trajectories of each agent.

4.2.2 Behavioural model

Most of the fish collective behaviour models do not take into account the environment *i.e.* the walls or the structure of the tanks because they only focus on the social interactions [139, 152].

However, zebrafish show context-dependent behaviours when they are in a structured environment. Depending on their spatial position in the environment they adapt their individual behavioural pattern. Moreover, because they are a gregarious species they also take into account the position and the behaviours of the other fish and can aggregate or start collective behaviours. As many animal species, zebrafish display strong thigmotaxis and follow walls or edges. We show that they adapt their behaviour in three different zones of the structured set-up: first the zone when they are close to the walls, second the zone when they are in the centre of the rooms and third when they use the corridor to change room. We take into account this spatial and context-dependent behaviours.

Each zone corresponds to a behavioural attractor. When the individuals are in one of the three zones they adapt their behaviour and perform specific behavioural patterns. In the zone near the walls they perform mainly thigmotaxis (wall following), in the centre of the room they explore, in the corridor they transit from one room to the other. At the same time they also take into account the behaviour of the other fish as they also do collective behaviour such as collective departures from the rooms. The other fish can be in any of the other zones and thus can also induce behavioural attractor switching of their companions.

We extend the biomimetic hybrid model [113, 112] using microscopic and macroscopic information [28, 150]. This new model (described in Fig. 4.3) takes into account zones that correspond to different behavioural attractors and thus allows context-dependent behaviours. The individual can switch from one behavioural attractor to the other and at the same time perform collective behaviour. Our model describes individual choices close to action selection and collective behaviours at the same time. It is a step towards modelling action selection in the context of collective behaviours.

We present a multi-level and multi-agent biomimetic model, inspired from [113, 112] that describes the individual and collective behaviours of fish. As in [113], this model makes the link between fish visual perception (of congeners and walls) and motor response (*i.e.* trajectories of the agents). However, it is also capable of expressing a variability in agents behaviours when they occupy specific zones of the arena (behavioural attractors). Table 4.4B lists the model parameters.

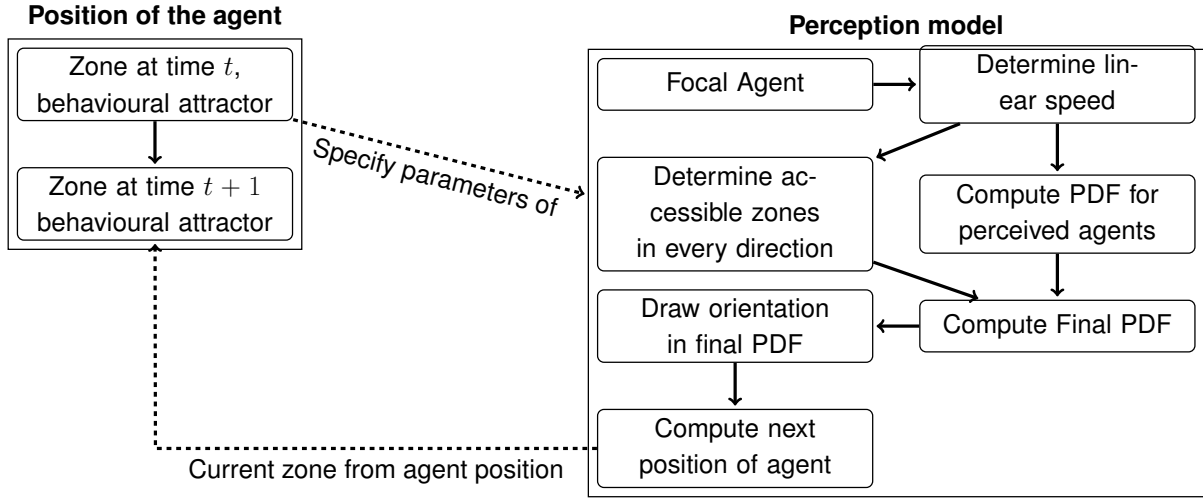


Figure 4.3 – Multilevel model used to describe fish behaviour. The agents display different behavioural attractors depending on the zone where they are situated. Thus, according to the agent spatial position, the physical features of the zone drive them towards a specific behavioural attractor. A behavioural attractor corresponds to a set of behavioural patterns adapted to the zone where they are located. It can correspond to different parameters sets for the same behaviour kind.

In this model, the agents update their position vector X_i with a velocity vector V_i :

$$X_i(t + \delta t) = X_i(t) + V_i(t)\delta t \quad (4.1)$$

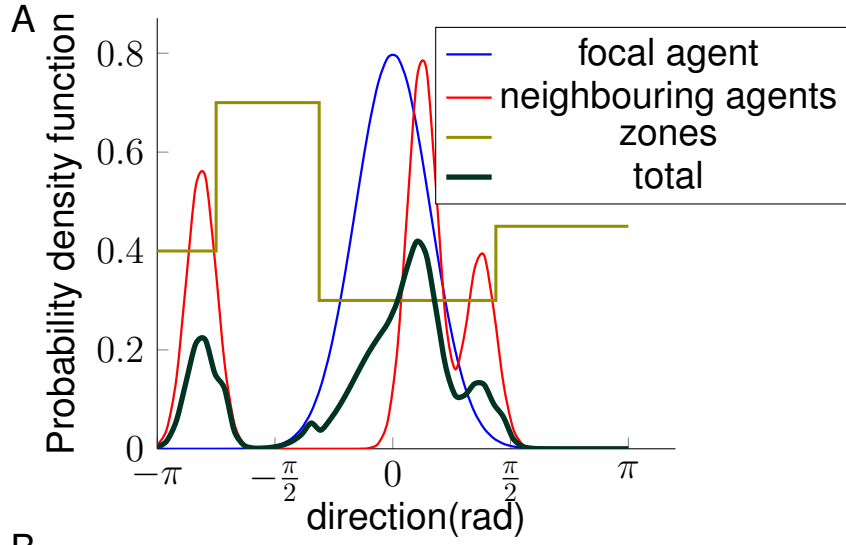
$$V_i(t + \delta t) = v_i(t + \delta t)\Theta_i(t + \delta t) \quad (4.2)$$

The model computes a circular probability distribution function (PDF) [113] corresponding to the probability of the agent to move in a specific direction (Θ_i). This PDF is as a mixture of von Mises distributions, an equivalent to the Gaussian distribution in circular probability. The computation of this PDF involves the calculation of two other PDF functions: the first one describing agent behaviour when no stimuli is present, and the second one characterising agent behaviour when conspecifics are perceived by the agent.

The PDF capturing agent behaviour when no stimuli is present is given by:

$$f_{0,z_j}(\theta) = \frac{\exp(\kappa_{0,z_j}\cos(\theta))}{2\pi I_0(\kappa_{0,z_j})} \quad (4.3)$$

for an agent situated in zone z_j , and with I_0 the modified Bessel function of first kind of order zero. When the agent is situated in a zone close to a wall (zones 1 and 2 of Fig. 4.2D), we implement a wall-following behaviour, by increasing the probabilities of moving towards either side of the closest wall.



B

Parameter	Range	Description
κ_{0,z_i}	[0.0, 30.0]	Dispersion parameter associated with basic-swimming in zone i
κ_{f,z_i}	[0.0, 30.0]	Dispersion parameter associated with a fish in zone i
α_{z_i}	[0.0, 50.0]	Weight of the perceived fish during basic-swimming in zone i
γ_{z_i,z_j}	[0.0, 1.0]	Weight of the attraction of zone j from zone i
v_{z_i}	From Control Distribution	Linear speed of each agent in zone i

Figure 4.4 – Panel A Computation of the PDFs functions used by the model. One function corresponds to the focal fish; another corresponds to the perceived neighbouring agents. The final PDF is a weighted sum of these functions, with a normalisation factor γ_{z_1,z_2} corresponding to the affinity between the zones z_1 (origin) and z_2 (destination). The direction taken by an agent is drawn randomly from the resulting PDF by inverse transform sampling. **Panel B** Table of model parameters for each agent. The zone z_i corresponds to the zone where the agent is situated at time t , and z_j to the zone where the agent would be at time $t+1$. The linear speed distributions of the agents are the same as the ones observed in the Control experiments, and they are not optimised. The other parameters in the table are optimised.

This is achieved by using the following PDF:

$$f_{0,z_j,w}(\theta) = \frac{1}{2} \sum_{k=1}^2 \frac{\exp(\kappa_{0,z_j} \cos(\theta - \mu_{w_k}))}{2\pi I_0(\kappa_{0,z_j})} \quad (4.4)$$

with μ_{w_k} the two possible directions along the considered wall.

Examples of agents trajectories are found in Fig. B.3B. The probability of the focal fish to orient towards a perceived fish is given by a von Mises distribution clustered around the fish position:

$$f_{F,z_j}(\theta) = \sum_{i=1}^n \frac{A_{f_i}}{A_{T_f}} \frac{\exp(\kappa_{f,z_j} \cos(\theta - \mu_{f_i}))}{2\pi I_0(\kappa_{f,z_j})} \quad (4.5)$$

with μ_{f_i} the direction towards the perceived agent, $A_{f_T} = \sum_{i=1}^{n_f} A_{f_i}$ the sum of the solid angles A_{f_i} captured by each agent and n_f the number of perceived agents. Only agents present in the corridor or in the same room as the focal agent are perceived. The agents present in the opposite room are not perceived.

The final PDF $f(\theta)$ is computed as follow:

$$f_{z_j, z_k}(\theta) = \gamma_{z_j, z_k} \frac{f_{0, z_j}(\theta) + \alpha_{z_j} A_{T_f} f_{F, z_j}(\theta)}{1 + \alpha_{z_j} A_{T_f}} \quad (4.6)$$

The parameter γ_{z_1, z_2} , used as a multiplicative term of the final PDF, modulates the attraction of agents towards target zones. Figure 4.4A describes how the final PDF is computed and how it is used to determine the agents next positions.

Unreachable areas of the PDF (*e.g.* the walls) are attributed a probability of 0. Then, we numerically compute the cumulative distribution function (CDF) corresponding to this custom PDF $f(\theta)$ by performing a cumulative trapezoidal numerical integration of the PDF in the interval $[-\pi, \pi]$. Finally, the model draws a random direction Θ_i in this distribution by inverse transform sampling. The position of the fish is then updated according to this direction and his velocity with equations 4.1 and 4.2.

4.3 Results

We consider four cases. We define the **Control** results as obtained from biological experiments with five zebrafish in the experimental set-up described in Sec. 4.2.1. The **Sim-MonoObj** and **Sim-MultiObj** results are defined to correspond to the model in simulation with five agents, calibrated respectively using mono-objective or multi-objective optimisation. The **Biohybrid** results are obtained from experiments with four zebrafish and one robot driven by the model using the best optimised parameters.

4.3.1 Optimisation of model parameters

We define a similarity measure (ranging from 0.0 to 1.0) to compare two experiments (e_1 and e_2), and define it as:

$$S(e_1, e_2) = \sqrt[3]{I(O_{e_1}, O_{e_2})I(T_{e_1}, T_{e_2})I(D_{e_1}, D_{e_2})} \quad (4.7)$$

with O_e the distribution of zone occupation, T_e the transition probabilities from zone e to the others, and D_e the distribution of inter-individual distances of all agents in zone e . The similarity measure $S(e_1, e_2)$ corresponds to the geometric mean of these three features. The function $I(P, Q)$ is defined as such:

$$I(P, Q) = 1 - H(P, Q) \quad (4.8)$$

The $H(P, Q)$ function is the Hellinger distance between two histograms [134]. It is defined as:

$$H(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^d (\sqrt{p_i} - \sqrt{q_i})^2} \quad (4.9)$$

We consider two optimization methods. In the **Sim-MonoObj** case, we use the CMA-ES [153] mono-objective optimisation algorithm, with the task of maximising the $S(e_1, e_2)$ function. In the **Sim-MultiObj** case, we use the NSGA-II [91] multi-objective algorithm with three objectives to maximise. The first objective is a performance objective corresponding to the $S(e_1, e_2)$ function. We also consider two other objectives used to guide the evolutionary process: one that promotes genotypic diversity [154] (defined by the mean euclidean distance of the genome of an individual to the genomes of the other individuals of the current population), the other encouraging behavioural diversity (defined by the euclidean distance between the O_e , T_e and D_e scores of an individual). In both methods, we use populations of 60 individuals (approximately twice the number of dimensions of the problem) and 300 generations. The **Sim-MonoObj** stabilises around the 50-th generation. The **Sim-MultiObj** stabilises around the 250-th generation. The linear speed v_i of the agents is not optimized, and is randomly drawn from the instantaneous speed distribution measured in the control experiment. Note that NSGA-II tend to need more evaluations to reach convergence when more than two objectives are considered: it is a known limitation of this algorithm [155], that was rectified in the recent NSGA-III algorithm [156]. We plan to reassess our results using the NSGA-III instead of the NSGA-II algorithm.

4.3.2 Robot implementation

The robot is driven by the model described in Section 4.2.2, after calibration. Robotic trials have a duration of 15 minutes, and are repeated 10 times. They involve one robot and four zebrafish. Every $333ms$, we integrate the tracked positions of the four fish into the model, and compute the target position of a fifth agent. We then control the robot to follow this target position by using the biomimetic movement patterns described in [65, 112].

4.3.3 Model performance analysis and experimental validation

We assess the similarity between the results from the calibrated cases (**Sim-MonoObj**, **Sim-MultiObj** and **Biohybrid**) and those of the **Control** case by using the similarity measure defined in Sec. 4.3.1. The similarity scores are shown in Table 4.1.

Using information about zones occupation and probabilities of transition from one zone to another, we define a finite state machine corresponding to the behavioural attractors dynamics of the entire agent population. The resulting finite state machines obtained from the **Control** and **Biohybrid** cases are shown in Fig. 4.5. The probability of presence of an agent in each part of the arena is presented in Fig. B.3A. Examples of agents trajectories are found in Fig. B.3B.

The best-performing individuals of the **Sim-MonoObj** and **Sim-MultiObj** cases display distributions of inter-individual distances that are relatively close to those of the **Control** case, which suggests that these models can convincingly exhibit fish tendency to aggregate. However, of the two cases performed in simulation, only **Sim-MultiObj**

is capable of displaying zones dynamics (occupation of the zones, and transition probabilities from one zone to the others) similar to the **Control** case. This suggests that multi-objective optimisation is required to handle the conflicting dynamics present in fish collective behaviour.

The robot of the **Biohybrid** case is driven by a controller using our model with the parameters of the best-performing individual obtained in the **Sim-MultiObj**. The ethogram of the **Biohybrid** case (*cf.* Fig. 4.5) shows an increased preference for the centre of the rooms compared to the **Control** case. This could be explained by our current lower level robotic implementation of wall-following behaviour that could still be sub-optimal.

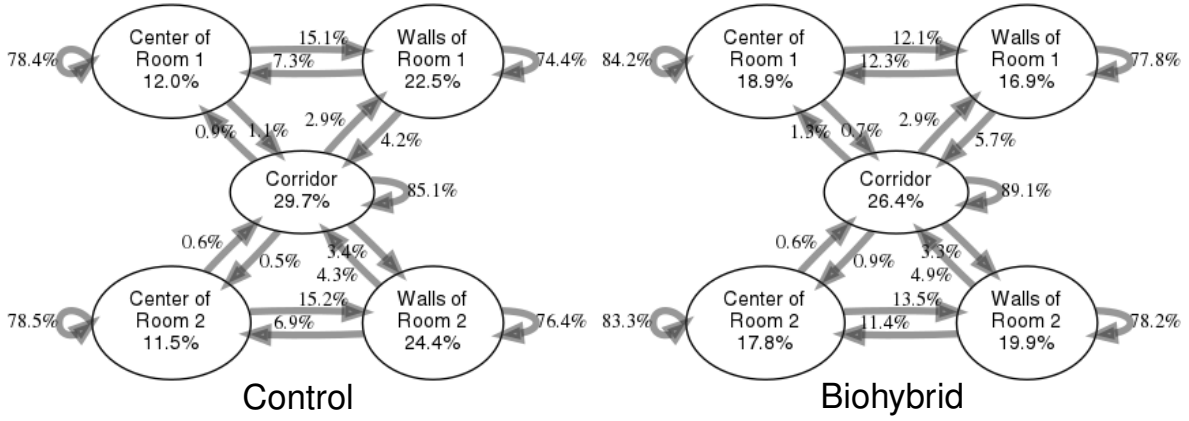


Figure 4.5 – Ethogram as finite state machine corresponding to the behavioural attractors for all agents. Each zones drive the agents into the corresponding behavioural attractor. Thus, agents modulate their behaviour in each zone as if they enter into a specific behavioural state. Here we show the resulting transition probabilities obtained after optimisation and implementation as robotic controllers (biohybrid) based on the experimental observations (control). The number in each state corresponds to the proportion of time agent spend in this state. The numbers on the arrows correspond to the transition probabilities between zones with a time-step of 1/3s.

	Sim-MonoObj	Sim-MultiObj	Biohybrid
Occupation	0.57	0.97	0.89
Transitions	0.76	0.81	0.88
Interindivid. Dists	0.90	0.87	0.89
Fitness	0.73	0.88	0.89

Table 4.1 – Similarity scores between the best-performing individuals of the three calibrated cases and the **Control** case used as reference, as defined in Sec. 4.3.1. We consider three standard features to characterise the collective behaviour exhibited in each case. **Occupation** corresponds to the probability of presence of the agent in each zone. **Transitions** corresponds to the probabilities of an agent to transition from one zone to another. **Inter-individual distances** corresponds to the distribution of inter-individual distances between all agents in a specific zone. The fitness function is computed as the geometric mean of these scores.

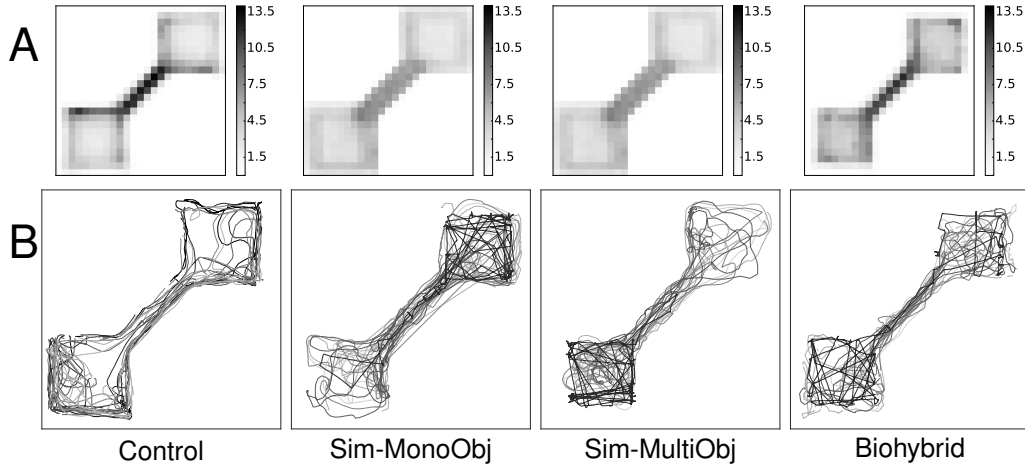


Figure 4.6 – *Panel A* Probabilities of presence in each part of the arena, for all cases. *Panel B* Examples of trajectories over a duration of 2 minutes (1800 frames). In the Biohybrid case, the robot is in black.

4.4 Discussion and Conclusion

Collective behaviour models often focus on collective motion in homogeneous unbounded environment. Here we present a multi-level model that is space-dependent with individuals that behave in a context-dependent way. We make the hypothesis that the type of behaviour displayed by the agents depends on their position in the environment. This allows us to segment our environment into several characteristic zones, each corresponding to a particular behavioural attractor, matching different types of agent behaviour.

We present a methodology to calibrate this model to correspond to the collective dynamics exhibited by fish in the experiments. This calibration process is challenging, as it involves a trade-off between social tendencies (group formation), and response to the environment (wall-following, exploration). Moreover, our model encompasses the notion of behavioural attractors, allowing agents to exhibit several different behaviours depending on the context. Our methodology is able to cope with this trade-off by using multi-objective optimisation.

However, this calibration methodology could still be improved: the similarity measure we use to compare two cases only takes into account three aspects of collective behaviours corresponding to behavioural attractors, and aggregation dynamics. Other behavioural aspects could also be relevant at the level of collective dynamics and can be considered (*e.g.* agent groups aspects, residence time in a zone), or at the level of the individuals (*e.g.* agent trajectory aspects, curvature of trajectories, etc.). Moreover, in relation to the environment (*e.g.* the distance of an agent to the nearest wall) could also be taken into account. Alternatively, it would be possible to perform the calibration without defining a similarity measure explicitly, using a method similar to [101], by co-evolving simultaneously the parameters of the models and classifiers. These classifiers would be trained to identify whether or not the resulting behaviours of the optimised models are distinct from the behaviours from the reference experiments.

Here, we make the assumption that the behavioural attractors are linked to the position of the agent in their environment. This assumption could be relaxed, to handle ethograms with more complex classes of behaviours like behavioural attractors linked to agent group dynamics. Additionally, the idea that actions are selected and segmented by the fish is questionable. While our decomposition of fish behaviour in different behavioural attractors is convenient for modelling purpose and ease the implementation of a biomimetic robot controller by having a collection of discrete acts that it can perform, it is not determined that fish make this kind of decomposition into distinct elements (actions) [157]. Finally, we could apply our model in more complex set-up, involving large societies with a larger number of robots, and with a more complex topology.

Part II

Mixed-groups of insects and robots

Chapter 5

Automated optimization of multi-level models of collective behaviour in a mixed group of animals and robots



I, for one, welcome our new insect overlords

Empire of the Ants

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This chapter describes a methodology to automatically derive a microscopic model of behaviour (able to be implemented as the controller of a robot in a mixed-group setting) from a macroscopic description of group collective dynamics. This work is based on the publication:

Cazenille L, Bredeche N, Halloy J. Automated optimisation of multi-level models of collective behaviour in a mixed society of animals and robots. arXiv preprint arXiv:1602.05830. 2016 Feb 2. (Submitted to PEERJ CS, in review)

Animal collective behaviour can be modelled with dynamical systems and can be described macroscopically (analytical description of the behaviour of the population) or microscopically (explicit description of the behaviour and states of individuals and their interactions with the environment). These two types of models are complementary. Thus, collective choices correspond to the stable steady states of the non-linear system and are governed by control parameters leading to bifurcation diagrams.

In this chapter, we tackle the problem of moving between models of different levels of description. Our methodology enables us to automate the design of a microscopic target model on the basis of a reference macroscopic model, so that the dynamics of the microscopic model can be described with the same bifurcation diagram as the dynamics of the macroscopic model. We apply this methodology to the cockroach shelter-selection experiments described in [1]

We show that we can automatically calibrate both a microscopic model (finite state machine) and hybrid model (non-linear transition probability functions) to exhibit the same dynamics as a macroscopic one (ordinary differential equations), all models describing animal collective behaviour. Our approach can be used to automatically move from models at different levels of description. The relevance of this approach is not limited to the field of animal collective behaviour and bio-hybrid systems, as it tackles the problem of automatically moving between models at different levels of description (from macroscopic to microscopic), a key problem in the modelling of nonlinear dynamical systems. Moreover, in a large portion of the literature, the calibration of model parameters is only done for specific solutions – typically only one state of the system. Here, with our methodology we can automatically calibrate all models for a set of states of the system corresponding to a bifurcation diagram.

This chapter tackles central questions in collective adaptive systems modelling, with a new perspective from computer science and machine learning, addressing both multi-level modelling and automatic calibration of animal or robot collective behavioural models from a macroscopic description. Our theoretical approach makes the link between several scientific communities, ranging from collective behavioural biology to mean-field modelling, and from multi-agent modelling to robotics. The translation from macroscopic to microscopic models is a common, but often challenging, problem both in the non-linear dynamical systems literature and in the robotics literature. We describe a novel methodology to automatize this translation.

Figure 5.1 shows how this chapter is linked to the workflow of this manuscript. Here, we consider macroscopic models of cockroach collective behaviour (calibrated to match the observed collective dynamics from experiments) and automatically translate them into

microscopic models of agent behaviour. This process takes also into account experimental data. Then, these microscopic models are tested in simulation to build a biohybrid collective adaptive system of cockroaches and robots. Related supplementary information of this article can be found in annex B.2.

Contributions to this chapter

I implemented most of the code, including the parameter set optimisation system, and data analysis scripts. This paper was mainly written by me, with the help of José Halloy and Nicolas Bredeche.

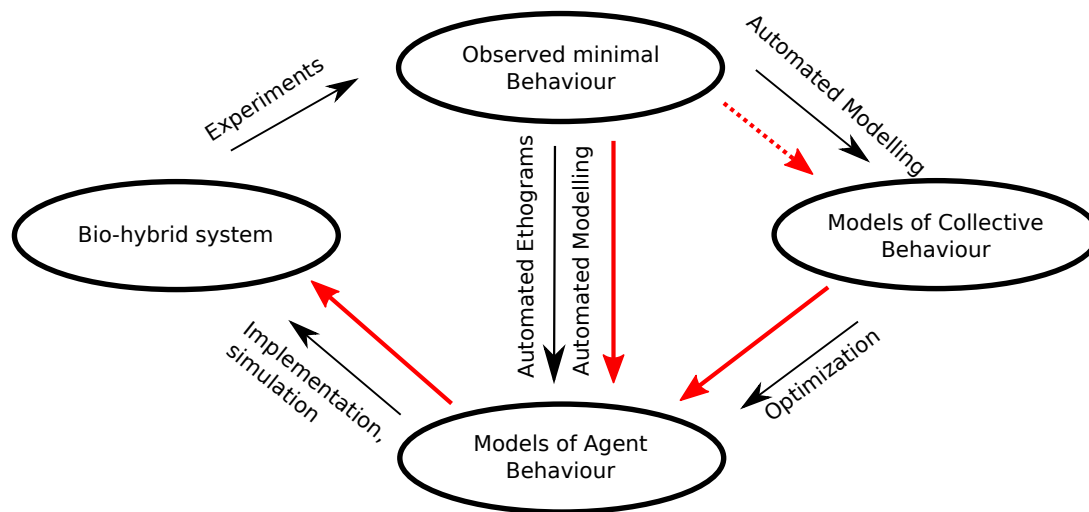


Figure 5.1 – *Workflow of the methodology used in this chapter, with red arrows showing the addressed topics.*

5.1 Introduction

Groups of animals are able to reach collective consensus when presented with mutually exclusive alternatives. Over the years, scientists have compiled a large collection of dynamics observed in collective decision-making systems based on experimental observations. These systems can be complex and it can be challenging to build models that appropriately describe the observed behaviours.

Animal societies are systems with a very large parameter space. They can be modelled in numerous ways, using information about individual physiology, individual behaviour, group behaviour and features of the environment [19, 76, 77]. The collective behaviour of a group of animals can be viewed as a dynamical system, that exhibits dynamics at several levels of organization (hierarchical organization). One of the difficulties in the modelling process is to find the appropriate levels of description.

Models describing dynamical systems can typically be categorized into two groups, describing two different levels of abstraction: macroscopic and microscopic (*cf.* Fig. 2.9). There are many studies, mainly in physics, examining methods and applications for both groups of models and the relations between them. Macroscopic models describe the system at the population level [26]. They formalize the dynamics of the system mathematically, but they generally cannot describe the state of individual agents. They cannot be used directly to drive the behaviour of agents in simulation, or to drive the behaviour of robots in experiments. Microscopic models explicitly describe the state of each individual agent (*e.g.* agent-based models of flocking, like the Vicsek model [79]). They can capture the individual behaviours and their relations with the environment and, moreover are easier to implement into robotic controllers.

These two kind of models offer complementary descriptions of the system. In this context, collective choices can be described by the stable steady states of a nonlinear system and are governed by control parameters leading to bifurcation diagrams. These diagrams give the mean field asymptotic solutions of the system. Microscopic models can be used to simulate the observed spatial behaviour of animals [27, 1, 28].

However, working with several models at different levels of abstraction can be difficult and requires appropriate modelling frameworks and methodologies [19, 76]. In particular, these models must be designed and calibrated to all exhibit the same individual and collective dynamics. This poses the problem of navigating between models of different levels of abstraction [19, 77].

In this article, we present a methodology that automates the calibration of microscopic target models on the basis of a reference macroscopic model, so that the dynamics of the microscopic model can be described with the same bifurcation diagram as the dynamics of the macroscopic model. The scientific question that we address in this paper is thus the following: **how to automatically calibrate models at different level of description to exhibit the same collective dynamics, at all levels of description, for specific sets of parameter values corresponding to a bifurcation diagram leading to multiple steady states.**

We propose to automate the calibration of microscopic models, using information both at the macroscopic level (a pre-existing macroscopic model) and the microscopic level (pre-

established knowledge of the animal individual behaviour). The objective of this approach is to automatically calibrate this new microscopic model (*i.e.* optimize the parameters) to exhibit collective dynamics that fit the predictions of the macroscopic model, with the added ability of accurately simulating the microscopic interaction between individuals.

Methodologies to calibrate microscopic models directly from experimental data, by using optimization algorithms, were already presented in [77, 158]. Our presented methodology improves upon these works by optimizing a microscopic model to correspond to the dynamics exhibited by an entire bifurcation diagram. Our methodology calibrates models with generalization capabilities, enabling them to exhibit different dynamics for different experimental parameters.

In the following, we apply our methodology to the collective decision-making problem described in [27, 1], where a group of cockroaches must reach a consensus on a preferred resting site (a *shelter*). These papers introduced an experimentally validated ordinary differential equations (ODE) model of cockroach shelter-selection dynamics. Here, starting from a mean-field ODE model (macroscopic), we use experimental data on individual cockroach behaviour from [74, 159] as *a-priori* microscopic information. We show how our method can be used to calibrate a target model using these two sources of information. We consider two target models: a Markov-Chain (MC) agent-based microscopic model [28] and an agent-based Hybrid model, combining macroscopic and microscopic information, that was already used with manually defined parameters in [1]. These models drive the behaviour of virtual agents in simulation. We use evolutionary algorithms to automatically calibrate the parameters of the MC and Hybrid models. They are validated by comparing their shelter-selection dynamics to those exhibited by the MF model.

In [1], Halloy *et al.* integrate robots into a group of cockroaches to modulate their collective behaviour. Here, we consider this problem in simulation, with cockroaches agents and a small number of robotic agents. The cockroach agents are driven by the MC and Hybrid models optimized previously in animal-only simulations. The robotic agents are driven by MC and Hybrid models with human-calibrated parameters. We show that it is possible to program the robots to modulate the collective behaviour of the whole society. As such, we show that our methodology could help the design of robotic controllers to modulate the collective behaviour of societies in biohybrid systems (societies of animals and robots).

Macroscopic models can convincingly describe collective dynamics, but cannot be implemented directly in robotic controllers. Robot controllers are intrinsically microscopic, as they describe the behaviour of individual agents. **One major challenge must be overcome to design appropriate robotic behaviour in mixed-societies of animals and robots: how to go from the collective decision dynamics observed in animals to an algorithmic implementation in robots.** In previous studies on mixed societies, this process has been carried out empirically. For example, in [1] collective decision-making in cockroaches is modulated using robots. The authors used observation both to build a macroscopic model and to program the robot behaviour by tinkering. Although the results are promising, designing the robot behaviour proved very challenging, suggesting that automation would be highly beneficial.

The relevance of our approach is not limited to the field of animal collective behaviour

and biohybrid systems, as it tackles the problem of automatically moving between models at different levels of description (from macroscopic to microscopic), a key problem in the modelling of nonlinear dynamical systems. **It is especially relevant to the design of mixed-societies robotic controllers.** Moreover, in a large portion of the literature, the calibration of model parameters is only done for specific solutions – typically only one state of the system. Here, with our methodology we can automatically calibrate all models for a set of states of the system corresponding to a bifurcation diagram.

5.2 Methods

We simulate the experimental set-up from [27, 1] (*cf.* Fig. 5.2): this set-up is composed of a circular arena with two identical shelters (resting sites). Each shelter is sufficiently large to host the entire insect group. Two species of cockroaches are considered: *P. americana* and *B. germanica*, each with a different set of simulation parameters. The cockroaches choose collectively to rest under one of these shelters [160, 27]. Individuals have no *a priori* information about the shelters occupation and spatial position, and decide only between staying under a shelter and leaving it to search for another. The cockroaches tend to aggregate under the shelters.

This set-up is well adapted to the study of collective decision-making because it allows to quantitatively analyse the interplay of social and environmental mechanisms leading to collective choices. Group-living animals have to choose between alternative resource sites. In this context, a central question includes determining which individuals induce the decision, when and how [27, 1].

We consider three models of cockroach collective behaviour in a shelter selection problem (*cf.* Table 5.1): a macroscopic mean-field model (MF model), a microscopic markov chain model (MC model), and a hybrid model combining macroscopic and microscopic levels of abstraction. All three models can handle time-discrete data. The MF model does not include extended spatial information on individuals, while the MC and Hybrid models include explicit spatial information. Because the latter also include a microscopic component, they can be implemented as robotic controllers. A classification of models according to their level of abstraction can be found in [77].

5.2.1 Mean field description: Ordinary differential equation model

Halloy *et al.* [1] describe a mathematical model of the collective dynamics of mixed groups of cockroaches and robots in a shelter-selection problem (from [27]). This model was designed to take in account the following experimental facts: (i) individuals explore their environment by moving randomly, and randomly reach the shelters; (ii) they rest in shelters according to their quality (in this set-up, it is mainly determined by darkness); (iii) the presence of conspecifics influences their behaviour, through social amplification of their resting time; and (iv) no long-range (across shelters) interactions occur among individuals. This model describes mixed groups of animals and robots, in set-ups with two

shelters; animals and robots exercise an equivalent influence on the collective decision-making process, and exhibit similar and homogeneous behaviour. The model is used as a quantitative explanation as well as an overall (macroscopic) guidance for the design of the robot and its controller. The model takes in account the fact that robots and insects do not occupy the same surface.

The following set of ODEs represents the evolution of the number of individuals in each shelter (and outside), in a set-up with two shelters:

$$\frac{dx_i}{dt} = x_e \underbrace{\mu_i \left(1 - \frac{x_i + \omega r_i}{S_i}\right)}_{\text{Probability of animals to join site } i} - x_i \underbrace{\frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n}}_{\text{Probability of animals to leave site } i} \quad (5.1)$$

$$\frac{dr_i}{dt} = r_e \underbrace{\mu_{ri} \left(1 - \frac{x_i + \omega r_i}{S_i}\right)}_{\text{Probability of robots to join site } i} - r_i \underbrace{\frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^{n_r}}}_{\text{Probability of robots to leave site } i} \quad (5.2)$$

$$C = x_e + x_1 + x_2, \quad R = r_e + r_1 + r_2, \quad M = R + C \quad (5.3)$$

We use a mean field description of the system, instead of a exact representation, to take the fluctuations of the system into account. Table 5.2 describes the parameters of this ODE model.

Variables x_i and r_i represent respectively the numbers of cockroaches and robots present in shelter i ; and x_e and r_e the numbers outside the shelters. Parameters C and R are respectively the total numbers of cockroaches and robots. Parameter M is the total number of agents (cockroaches and robots). The parameter ω corresponds to the surface of one robot expressed as a multiple of the surface of one cockroach. Equations 5.1 and 5.2 take into account the probabilities of animals and robots to join or leave (corresponding to $1/\text{mean resting time}$) a site. The parameter μ_i is the maximal kinetic constant of entering the shelters for insects; μ_{ri} is the equivalent parameter for robots. The parameter θ_i is the maximal probability of leaving a shelter for insects (θ_{ri} for robots). The parameters ρ and n characterise the influence of the insect conspecifics (ρ_r and n_r for robots). When both shelters are identical (as it is the case in this study), the parameters describing them are equal: $S_1 = S_2$; $\mu_1 = \mu_2$; $\mu_{r1} = \mu_{r2}$; $\theta_1 = \theta_2$; $\theta_{r1} = \theta_{r2}$. Parameters γ , β and δ are respectively the influence of cockroaches on robots, of robots on cockroaches, and of robots on robots. The greater they are, the greater the mutual influences. The influence of animals on animals (α) is equal to 1.0, and is not considered in [1]: the assumption is made that this parameter is imposed by biology, and cannot be changed in experiments. However, parameters γ , β and δ can be modulated by changing the design of the robots, either in term of hardware or control (behaviour). In [1], the robots are coated with a pheromone, as the interaction dynamics of cockroaches societies is mainly chemotactile. A higher concentration of pheromone corresponds to a higher value of β .

Because of crowding effects, the probability of an individual joining a shelter decreases with its level of occupancy. We define a measure $\sigma = S/C$, corresponding to the sites' carrying capacity as a multiple of the total population.

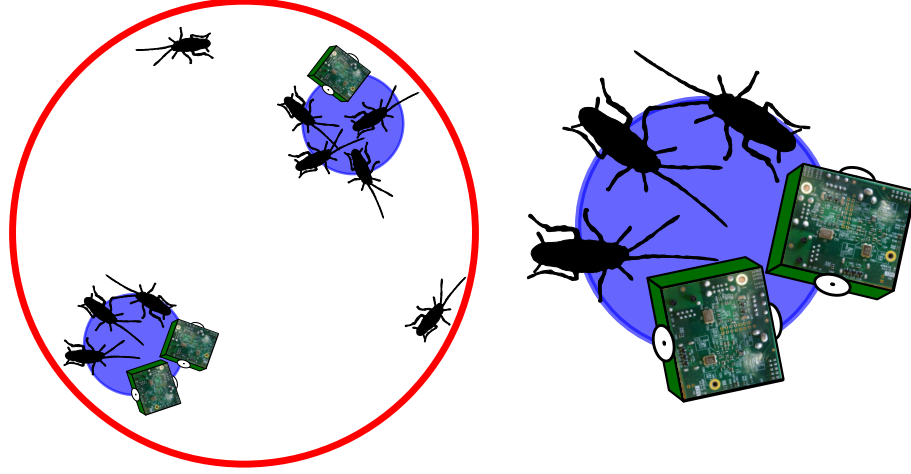


Figure 5.2 – *Experimental set-up used in [1]. It includes two identical shelters and both cockroaches (*P. americana*, approximate size: $\sim 4\text{cm}$, surface: 600mm^2 , or *B. germanica*, size: $\sim 0.25\text{cm}$, surface: 3mm^2) and robots (surface: 1230mm^2 in *P. americana* set-ups, 6.15mm^2 in *B. germanica* set-ups) in a circular arena (diameter: 1m for *P. americana*, 14cm for *B. germanica*).*

Name	Experimentally Validated	Wall-Following Behaviour	Constant Speed
Mean Field (MF)	yes [27, 1]	no	yes
Markov Chain (MC)	yes [74, 159]	yes	no
Hybrid	partially [1]	no	yes

Table 5.1 – *Comparison of the models studied. The MF model is a global description of the problem. The MC model is an agent-based model using a Markov chain representation. The Hybrid model combines macroscopic information (nonlinear propensities drawn from the MF model) and spatial information (with an approach similar to that of the MC model).*

When no robots are present ($R = 0$) and only animals are considered, two different dynamics are observed. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, corresponding of an equipartition of the individuals ($x_1/C = x_2/C = 1/2, x_e = 0$). After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, corresponding to all individuals in one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$) [27]. Only results with a population of 50 cockroaches are represented in Fig. 5.3, but similar dynamics are observed with different population sizes.

	Parameter	Value for <i>P. americana</i>	Value for <i>B. germanica</i>	Optimized	Description
MF	P		2		Number of sites
	S_i				Carrying capacity of shelter i
	C		50		Number of agents
	x_i				Number of agents in shelter i
	x_e				Number of agents outside the shelters
	μ_i	$0.0027s^{-1}$	$0.001s^{-1}$		Maximal kinetic constant of entering a shelter
	θ_i	$0.44s^{-1}$	$0.01s^{-1}$		Maximal rate of leaving a shelter
	ρ, n	4193, 2.0	1667, 2.0		Influence of conspecifics
	l_c	$[1.0, 500.0] cm$		yes	Mean length of path
	a_c	$[-\pi, \pi]$		yes	Geometric mean, angle of departure
MC	$\tau_{c,exit}$	$]0.0, 10.0[s$		yes	Mean time an agent follows a wall
	$v_{c,c}$	$]0.0, 3.0[cm.s^{-1}$		yes	Mean speed in central zone
	$v_{c,p}$	$]0.0, 3.0[cm.s^{-1}$		yes	Mean speed in peripheral zone
	$s_{c,i,n}$	$[0.0, 1.0]$		yes	Probability of stopping in shelter i with n neighbours
	$\tau_{c,i,n}$	$]0.0, 1000.0[s$		yes	Mean stop duration in shelter i with n neighbours
	d	$]0.8, 1.0[m$		yes	Diameter of the central zone
Hybrid	θ_i	$]0.0, 0.50[s^{-1}$		yes	Maximum rate of leaving a shelter
	ρ, n	$[500, 5000], 2.0$		yes	Influence of conspecifics
	l	$[1.0, 500.0] cm$		yes	Mean length of path
	a	$[-\pi, \pi]$		yes	Geometric mean, angle of departure
	v	$]0.0, 3.0[cm.s^{-1}$		yes	Constant speed of agents

Table 5.2 – Parameters in the MF, MC, and Hybrid models. The parameter values for the MF model are from [1] and [27]. We only consider the case where $M = 50$. In set-ups with two shelters, the MF, MC, and Hybrid models have 18, 45 and 20 parameters respectively. The parameter values used for the MC and Hybrid models were obtained through the calibration process described in Sec. 5.3 and Sec. B.2. The animal influence on animals (α) is equal to 1.0, and is kept constant in [1]: we assume that this parameter is imposed by biology and cannot be changed in experiments. All parameters of the MC and Hybrid models are optimized, using the method described in Sec. 5.3, to exhibit the collective dynamics described in the reference MF model.

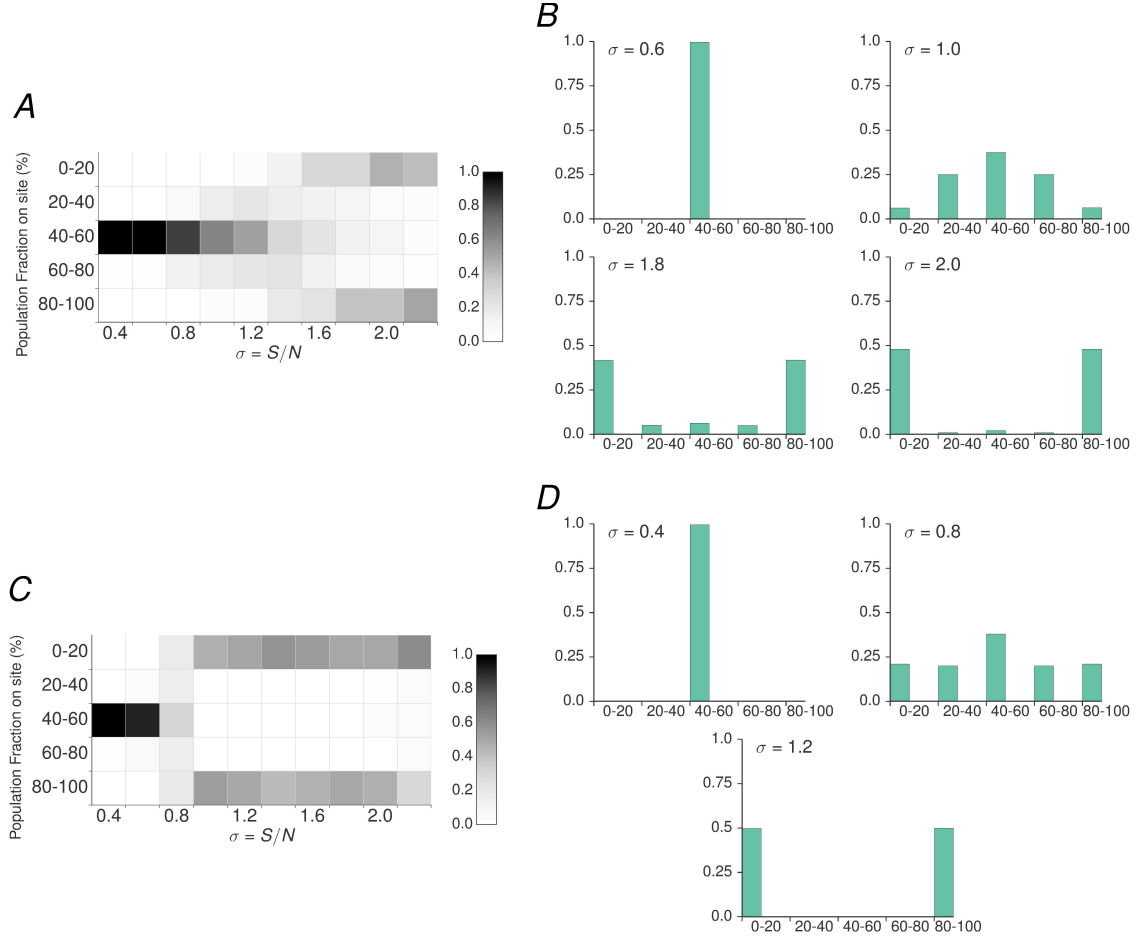


Figure 5.3 – Bifurcation diagrams and distributions of 50 (*C*) *B. germanica* (Panels A and B) or *P. americana* (Panels C and D) cockroaches in the first shelter as a function of σ [27]. The bifurcation diagrams are represented as bi-dimensional histograms of the results of using 1000 resolutions for each parameter set. In the bifurcation diagrams (Panels A and C), the (greyscale) colour intensity of each bin of the histograms corresponds to the frequency of observed experiments. The diagrams are symmetric for all tested values of σ , so only one shelter is represented. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, an equipartition of the individuals between the two shelters ($x_1/C = x_2/C = 1/2, x_e = 0$). After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, with all individuals concentrated in one of the two shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).

5.2.2 Markov chain model

We define a Markov chain model (or Finite State Machine) as agent-based model of cockroaches and robots behavior. This model is very similar to the agent-based aggregation models introduced in [74, 159] to describe the collective behavior of cockroaches in a similar setup. Jeanson *et al.* [74, 160] demonstrated that the aggregation behaviour exhibited by *B. germanica* cockroaches depends on a self-organisation process. The probability that a given moving cockroach stops and join a staying group increases in relation to the size of this group. As such, cockroaches quickly aggregate in dense clusters in a homogeneous environment. However, the natural environment of *B. germanica* is heterogeneous: some sites are more attractive than others, which promotes aggregation in specific sites (*e.g.* in dark places). In an arena with only one attractive site (*e.g.* only one dark site in a bright arena), the cockroaches will aggregate in this site. If the arena contains several sites of equal quality, the group will split and equally occupy these sites. This leads to a collective choice mechanism, which was studied by Ame *et al.* [27], through a mean-field model (cf previous section). This mean-field model assumes that cockroach individual behaviour is linked to the overall density of individuals occupying a site, and suggests that cockroaches have a global perception of the number of conspecifics occupying the shelter. However, Garnier *et al.* [159] built on these results and argued that cockroach individual behaviour was instead only linked to the local perception of the proximate neighbours. This approach would imply the use of a microscopic model of behaviour, instead of a macroscopic description.

Cockroaches tend to follow the walls of the arena when they are already close to them. The model defines two zones in the arena. The ring area that borders the walls of the arena is called the *peripheral zone*, while the rest of the arena is labelled as the *central zone*. In the peripheral zone, agents follow a wall-following behaviour for a random number of time steps (the mean time is denoted $\tau_{c,exit}$). In the central zone, agents follow a random-walk behaviour, with trajectories composed of a recurring alternation of straight lines (of randomly chosen length, with a mean length of l_c) and rotations (of randomly chosen angles, with a geometric mean of a_c). The shelters are all in the central zone. We do not model the actual trajectories of cockroaches.

When agents enter a shelter, they have a probability of stopping (parameter $s_{c,i,n}$) for a random duration (parameter $\tau_{c,i,n}$) before moving away from the shelter. Similarly to [159], this probability depends on the number of agents present under the shelter, as cockroaches are gregarious during their resting period. However, in this model (as opposed to [74, 159]), the probability of stopping when under a shelter differs between shelters: this model is more general, and can be used to describe more complex behaviours with asymmetric decision-making dynamics [28]. When the cockroaches are not under a shelter, their movements are not influenced by the presence or absence of neighbours.

Figure 5.4 represents the Markov chain used in this model. The relevant model parameters are found in Table. 5.2.

We use two different parameter sets of the MC model to describe either cockroaches or robot behaviour. However, all cockroaches are considered to exhibit an homogeneous behaviour (all cockroach agents share the same parameters). Similarly, all robots agents

share the same parameters. We make this choice for simplicity reasons: the message of this paper can be explored without the need to take individual variability into account.

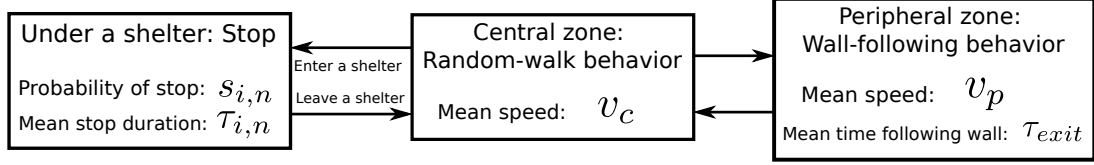


Figure 5.4 – Markov chain model of the cockroach individual behaviours. The arena contains two zones: the peripheral zone (where agents display a wall-following behaviour), and the central zone (where agents display a random-walk behaviour). Shelters are in the central zone. When an agent enters a shelter, it has a probability of stopping for a random duration before exiting the shelter. The probability of stopping under a shelter depends on the number of neighbours present in the shelter, and can differ for each shelter. Only 10 neighbours are considered in our experiments. In set-ups with two shelters, this model has 45 parameters per population.

5.2.3 Hybrid model

Here, we introduce a model of the collective behaviour of cockroaches using information at both macroscopic and microscopic levels of abstraction. We call this multi-level model the 'Hybrid' model. This model was already used with manually defined parameters in [1], but was not formally described previously. This hybrid model was done to facilitate the development of the behavioural architecture of the robots [161, 1]. Compared to the MC model, which presents a biomimetic description of the insects trajectories, the Hybrid model is a compromise between biomimetism and ease of implementation as robotic controller. The robot control architecture is a behaviour-based controller [162] composed of a multi-level collection of behaviours. Each behavioural building block can take inputs from the robot sensors and/or from other behavioural building blocks, and send outputs to the robot actuators and/or to other behaviours. The behaviours are arranged in a hierarchy in which the behaviours on the higher levels integrate or arbitrate the ones on the lower levels. At the higher level the Hybrid model is used as a building block that takes into account the speciality of the agents, and thus allows to build the robot controller. The Hybrid model is a crossover between the macroscopic MF model, which easily describes collective behaviour and site occupation, and the microscopic MC model, which details the spatio-temporal behaviour of single agents. As such, it is a multi-agents model (like the MC model), but it also takes into account macroscopic information (like the MF model). For ease of implementation, the hybrid model does not include a wall-following behaviour, and only considers simple arenas with no distinctions between central zone and peripheral zone. The agents can have two states: moving, or resting under a shelter. In contrast to the MC model, the agents move with a constant speed v .

The Hybrid model builds on the MF model, introducing several parameters from the MF model (Table 5.2). The Hybrid model has a smaller dimensionality than the MC model: in set-ups with two shelters, the MC models has 45 parameters, while the Hybrid

model has 20 parameters. It allows the Hybrid model to be easier to calibrate than the MC model.

Figure 5.6 describes the Hybrid model using a Markov chain representation of the behaviour of a single agent. When the agents are not under a shelter, they follow a random-walk behaviour (microscopic behaviour). As in the MC model, this random-walk behaviour involves trajectories composed of a recurring alternation of straight lines of randomly chosen length, with a mean length of l , and rotations of randomly chosen angles, with a geometric mean of a . When agents enter a shelter, they stop, and have a probability of leaving the shelter at each subsequent time-step. This probability, taken from Eq. 5.1 and 5.2, is computed using macroscopic information. For the cockroaches agents, this probability of leaving the shelter is defined as:

$$\frac{\theta_i}{1 + \rho^{\frac{x_i + \beta r_i}{S_i} n}} \quad (5.4)$$

For the robotic agents, this probability of leaving the shelter is defined as:

$$\frac{\theta_{ri}}{1 + \rho_r^{\frac{\gamma x_i + \delta r_i}{S_i} n_r}} \quad (5.5)$$

This behaviour can be described as macroscopic, as it requires information about the density of agents under the shelter. This combination of microscopic and macroscopic components makes it a multi-level (or hybrid) model.

As in the MC model, we use two different parameter sets of the hybrid model to describe either cockroaches or robot behaviour. However, all cockroaches are considered to exhibit an homogeneous behaviour (all cockroach agents share the same parameters). Similarly, all robots agents share the same parameters.

Figure 5.5 presents examples of the trajectories of single cockroaches in a simulation with a population of 50 cockroaches with the Hybrid model.

5.2.4 Models calibration

To use the MC and Hybrid models describing animal behaviour in simulation, we must calibrate them to exhibit the same decision-making dynamics as the MF model. As the MF model is parametrized using experimental data, it allows the MC and Hybrid models to accurately describe the (macroscopic) site-selection dynamics of the cockroaches. The calibration process is described in Fig. 5.7.

We optimize the parameters for the individual cockroaches in the MC and Hybrid models: Table 5.2 lists the parameters of these two optimized models. Instances of the MC and Hybrid models using these parameters are simulated for different values of σ . This yields bifurcation diagrams for each optimized individual, similar to those in Fig. 5.3.

As there is little *a priori* information about the parameter space, and as it is relatively high-dimensional, we use the state-of-the-art CMA-ES evolutionary optimization method [153] to optimize the parameters of the MC and Hybrid models. To evaluate the

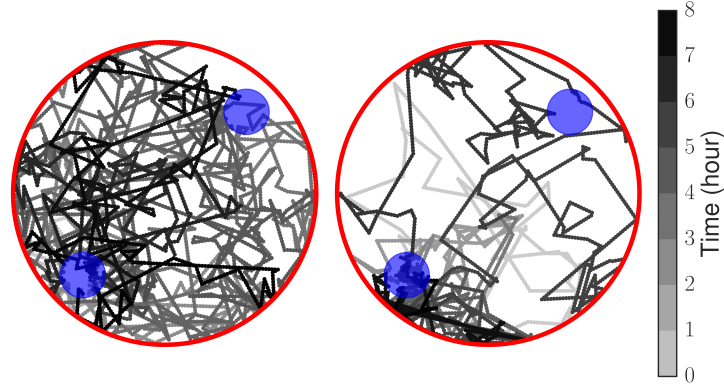


Figure 5.5 – *Two example trajectories of a one simulated cockroach, using the Hybrid model, in a population of 50 cockroaches. The arena contains two shelters. Each grey line represents the (random-walk) trajectory of one agent. These trajectories are not meant to fit the natural trajectories of actual cockroaches: we designed our models to reproduce qualitatively the observed random exploration. The opacity of the line reflects simulation time. The timeframe of all simulations is 8 hours.*

difference between two parameter sets, we use a distance metric between the two resulting bifurcation diagrams.

The fitness, minimized by CMA-ES [153], represents a comparison between an optimized bifurcation diagram and the reference diagram from the MF model. It is computed as follows:

$$\text{Objective}_{\text{calibration}}(x) = D_{\text{Hellinger}}(B_{\text{optimized}}/N_u, B_{\text{reference}}/N_u) \quad (5.6)$$

where x is the tested parameter set (genome), N_u is the number of values of σ in the bifurcation diagrams (10) and $B_{\text{optimized}}$ and $B_{\text{reference}}$ are one-dimensional histogram versions of the bifurcation diagrams. The term N_u is a normalization term. The Hellinger distance [134] is defined as:

$$D_{\text{Hellinger}}(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^d (\sqrt{P_i} - \sqrt{Q_i})^2} \quad (5.7)$$

where P and Q are two histograms, and P_i, Q_i their i -th bins. The Hellinger distance is a divergence measure, similar to the Kullback-Leibler (KL) divergence. However, the Hellinger distance is symmetric and bounded, unlike the KL-divergence (and most other distance metrics). As such, it is adapted to comparing two histograms [134].

All experiments were performed using the Grid'5000 platform (see <https://www.grid5000.fr>). Depending on the model and parameters tested, each experiment were performed in 1 to 15 hours on a 8-cores computer.

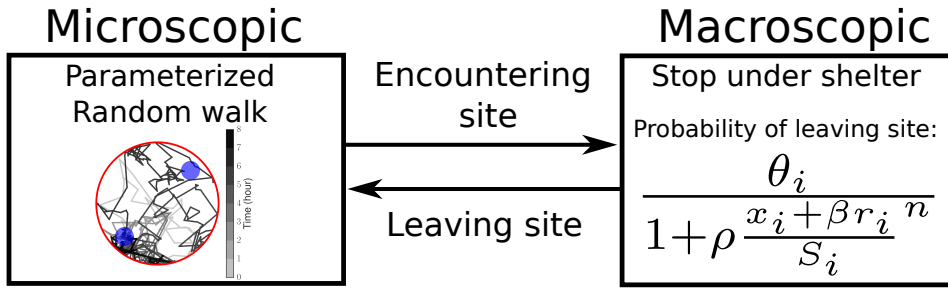


Figure 5.6 – Markov chain representation of the Hybrid behavioural model . Table 5.2 gives the parameters of the model. The model describes two kinds of behaviour: when the agents are not under a shelter, they will exhibit a random-walk behaviour, following a recurring alternation of straight lines and rotations. This behaviour can be described as microscopic because agents use only local information to determine their course of action. When agents encounter a shelter, they stop. At each subsequent time-step, the stopped agent has a probability of $\frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n}$ (for cockroaches) or $\frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^n}$ (for robots) of leaving the shelter and returning to random-walk behaviour. This behaviour can be described as macroscopic, as it requires information about the density of agents under the shelter. This combination of microscopic and macroscopic components makes it a multi-level (or hybrid) model.

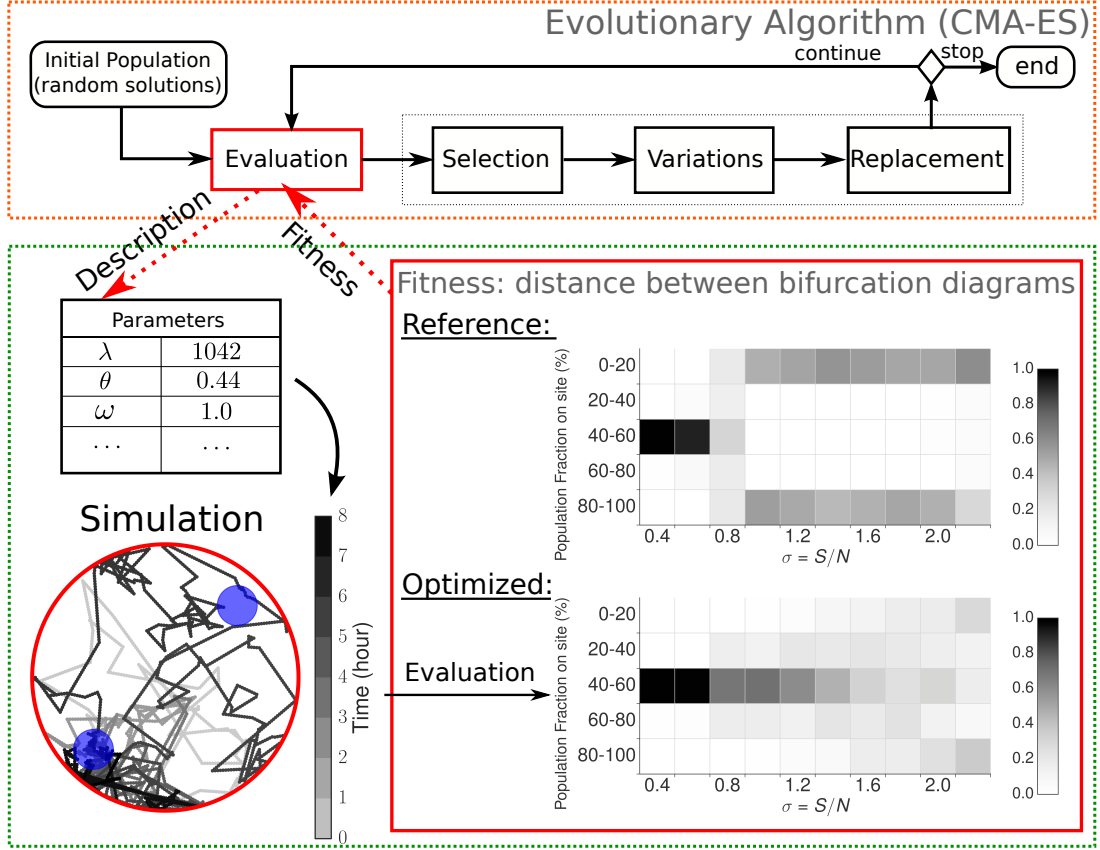


Figure 5.7 – Workflow of the automated calibration of models by optimization. The optimized bifurcation diagram and the reference bifurcation diagram are both converted to one-dimensional histograms, by normalizing the sum of all bin values to 1.0. The optimizer will maximize the objective function, which is computed by the formula: $Obj = 1.0 - D_{hellinger}(B_{optimized}/N_u, B_{reference}/N_u)$ where N_u is the number of columns in the bifurcation diagrams (10) and $B_{optimized}$ and $B_{reference}$ are one-dimensional histogram versions of the respective bifurcation diagrams. The term N_u is a normalization term. $D_{hellinger}(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^d (\sqrt{P_i} - \sqrt{Q_i})^2}$ is the Hellinger distance [134]. This approach is described in detail in Sec. 5.2.4 and Sec. B.2

5.3 Results

5.3.1 Models Calibration

Our goal is to find parameter sets of the MC and Hybrid models describing animal and robot behaviour so that the resulting collective dynamics, observed in simulations, fit the solutions of the MF model describing animal behaviour. We use the methodology presented in Sec. 5.2.4. We consider two types of simulations, for both *P. americana* and *B. germanica* cockroach species. The first type describes a purely biological system, with only 50 cockroaches (either *P. americana* or *B. germanica*) and no robots. It is used as the biological reference case. The second type is devoted to biohybrid groups made up of 45 cockroaches (either *P. americana* or *B. germanica*) and 5 robots. The number of robots is kept small to reflect the settings used in a mixed-society experiment [1], where a minority of robots can control the whole mixed group behaviour. The parameters sets of models describing robot behaviour are chosen empirically.

We consider populations of 50 individuals. **Similar results are observed with populations of 16 and 100** (results not shown).

Figure 5.8 shows the distribution of agents in the two shelters, using parameters from the best-performing optimized individuals after 100 optimization runs. Panels A and C show results from simulations with 50 cockroaches and no robots. Panels B and D show results from simulations with 45 cockroaches and 5 robots. Only results from the bifurcation diagram at selected values of σ are shown. More generally, results before the bifurcation point ($\sigma < 0.8$) are similar to results at $\sigma = 0.4$, and results after the bifurcation point ($\sigma \geq 0.8$) are similar to results at $\sigma = 1.2$.

Both the MC and Hybrid models can be optimized to approximate correctly the decision-making dynamics described by the MF model, as shown in Fig. 5.8. Our methodology can generate many different parameter sets for the MC and Hybrid models. Optimized parameters that produce the collective dynamics described by the MF model can be associated to highly variable agent behaviour. In the MC model, the parameter d , the diameter of the central zone of the arena, is optimized: when this parameter is very close to the diameter of the peripheral zone, the resulting agents do not exhibit any wall-following behaviour. In the MC and Hybrid models, the parameters that influence stopping behaviour ($s_{c,i,n}$, $\tau_{c,i,n}$, θ_i) vary less than the other parameters, with only a few islands of relevant values in the explored ranges.

We show that simulations performed with 45 cockroaches and 5 robots exhibit the same dynamics as the simulations of groups with 50 cockroaches and no robots (Fig. 5.8). In this case the robots are governed by the same behavioural models as the insects, but do not have the same parameter sets as those used to describe the natural behaviour of the cockroaches. The detailed microscopic behaviours of the robots, *e.g.* trajectories and movement patterns, can be very different from the microscopic behaviours of the animals. Nevertheless, we show that our methodology can be used to optimize the parameters of robot behavioural models in biohybrid systems to mimic correctly the decision-making dynamics of the animals.

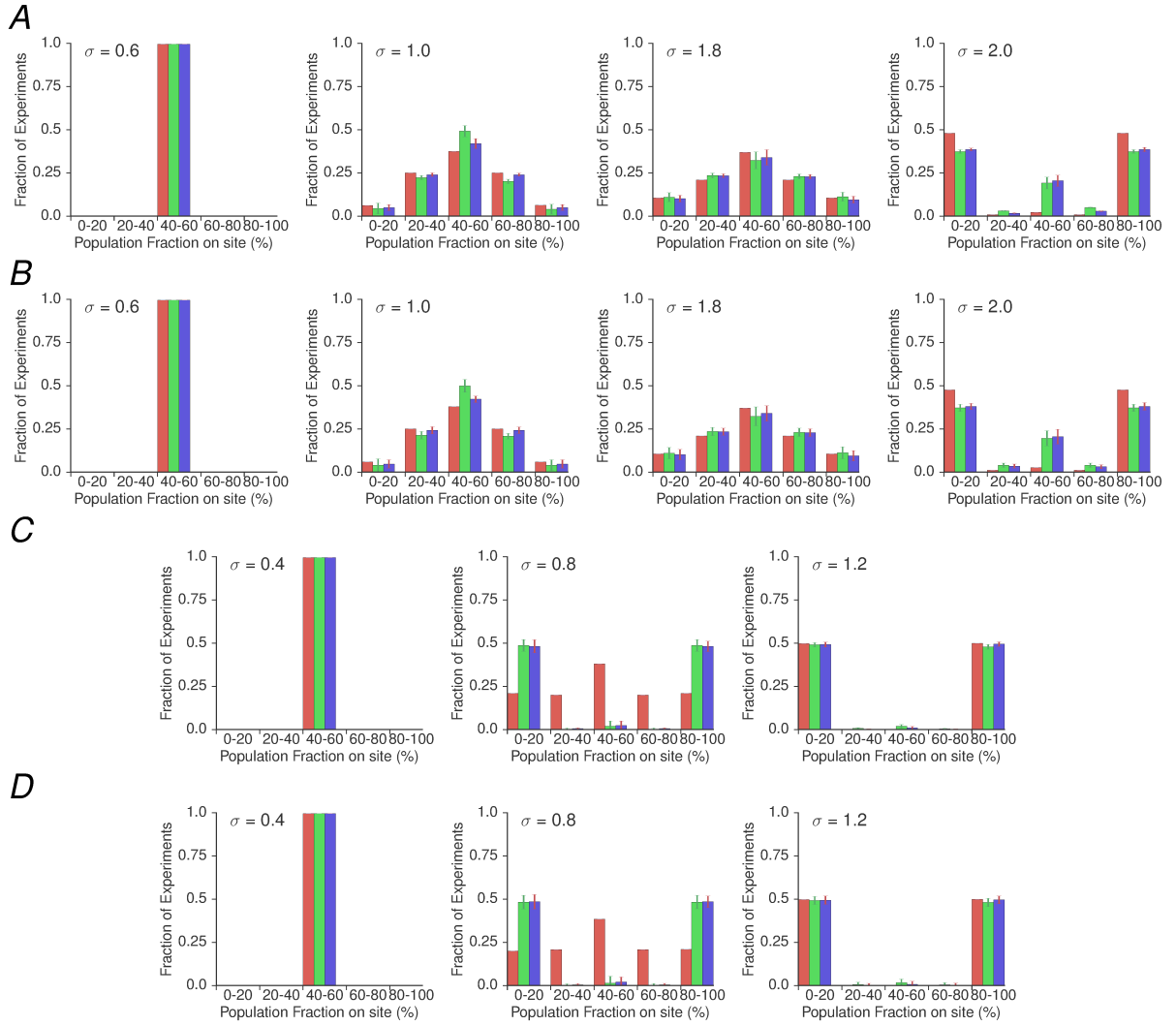
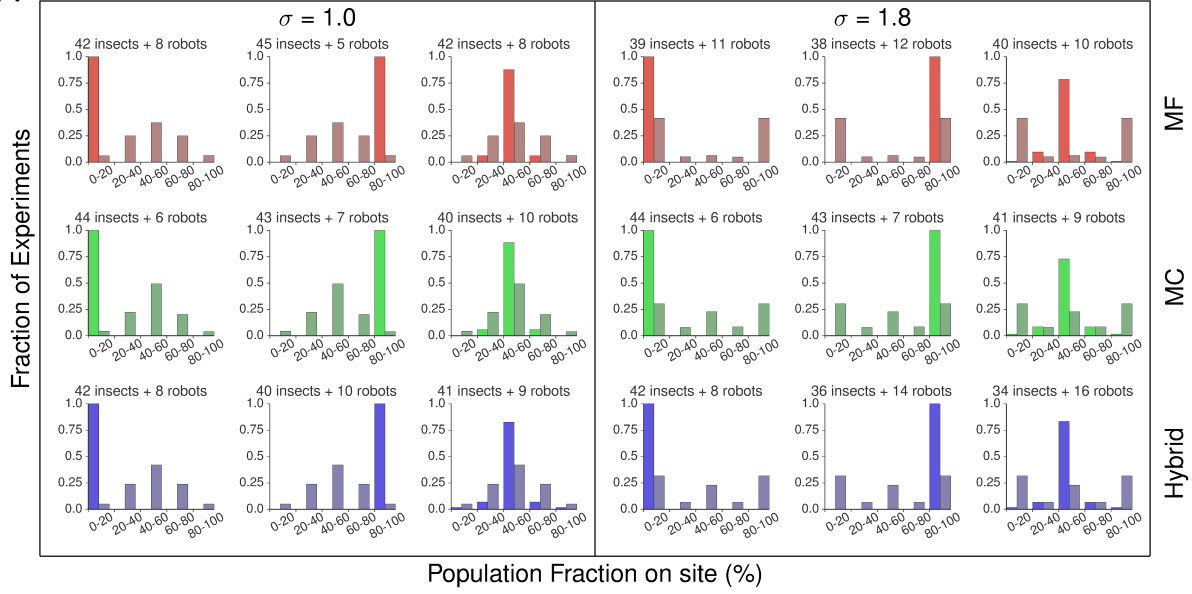


Figure 5.8 – Proportion of 50 agents in the first shelter for chosen values of σ , using three different models: MF, MC and Hybrid. Panels A and C are obtained from simulations using 50 cockroaches (Panel A: *P. americana* ; Panel C: *B. germanica*). Panels B and D are obtained from simulations using 45 cockroaches and 5 robots (Panel B: *P. americana* ; Panel D: *B. germanica*). Results for MF, MC and Hybrid models results are shown respectively in red, green, and blue. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. The other σ parameter values chosen are before the bifurcation point ($\sigma = 0.4$ for *P. americana* , $\sigma = 0.6$ for *B. germanica*), and just after the bifurcation point ($\sigma = 1.2$ for *P. americana* , $\sigma = 1.8$ and $\sigma = 2.0$ for *B. germanica*). The best sets of optimized model parameters are used, after 100 runs of optimization. The diagram is symmetric for all tested values of σ , so only one shelter is represented. Calibrated versions of the MC and Hybrid models behave similarly to the MF model: (1) Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, an equipartition of the individuals between the two shelters ($x_1/N = x_2/N = 1/2, x_e = 0$); (2) After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, with all individuals in only one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).

A



B

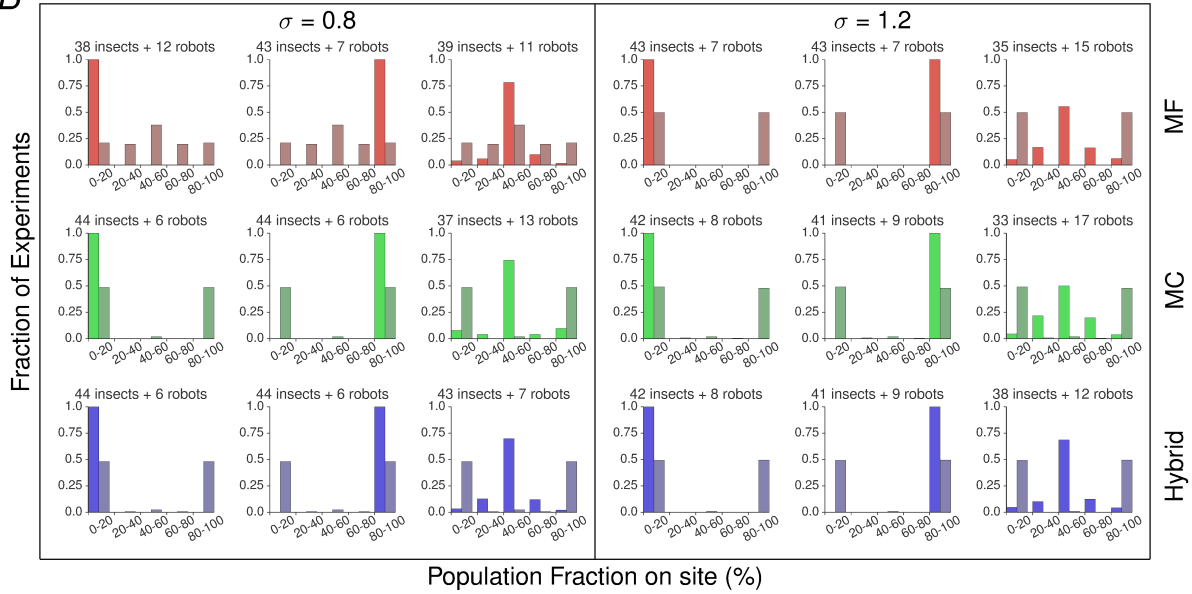


Figure 5.9 – Examples of modulation of the biohybrid group behaviour when robots are optimized to change the behaviour of cockroaches (A: *P. americana*, B: *B. germanica*). (red: MF model, green: MC model, blue: Hybrid model). Results in red, green and blue are the final states corresponding to the change of steady states induced by the robots. Results in dark red, dark green, and dark blue correspond to the reference results, from experiments with only insects and no robots (from Fig. 5.8). Values of σ are chosen around the bifurcation point (*P. americana*: $\sigma = 0.8$, *B. germanica*: $\sigma = 1.0$), and just after the bifurcation point (*P. americana*: $\sigma = 1.2$, *B. germanica*: $\sigma = 1.8$). Results before the bifurcation points are not shown.

5.3.2 Modulation of collective behaviours

We also test if our methodology could be applied to calibrate robot models so that they can modulate the collective dynamics of a group of cockroaches and robots. We consider simulations, for both *P. americana* and *B. germanica* cockroach species. In these simulations, cockroach behaviour is described by the MC or Hybrid models calibrated to have the same collective dynamics as the reference MF model. Robot behaviour is also described by the MC or Hybrid models, but with different parameter sets. We find relevant parameters of models describing robot behaviour empirically, for different proportion of robots, and for different values of σ . These examples of results of the modulation of the mixed-society of cockroaches and robots are found in Fig. 5.9. This shows that our methodology could be also applied to optimize parameter sets of models describing robot behaviour for a modulation task. Additionally, Fig. 5.9 also presents examples of modulation of a mixed-society described by the MF model. In this case, we find empirically interesting robot behaviour related parameters of the MF model. These preliminary results suggest that a larger number of robots than 5 may be needed to modulate a population of 50 agents. We will investigate how robots models can be calibrated automatically to modulate the collective dynamics of a mixed-society in a subsequent study.

5.4 Discussion

We tackle the problem of moving between models of different levels of abstraction in the context of animal collective decision-making. Animal collective behaviour can be described macroscopically (analytical description of the behaviour of the population) or microscopically (explicit description of the behaviour and states of individuals and their interactions with the environment). The two types of models are complementary. Our methodology enables translation from one to the other: we automatically optimize the parameters of microscopic target models on the basis of a reference macroscopic model from the literature. We apply this methodology to the cockroach shelter-selection problem described in [27, 1]. The Mean Field macroscopic model used as a reference is described in [1].

We consider two target models, both agent-based. The MC model [28] is a microscopic model inspired by the literature on individual cockroach behaviour [160, 159]. The Hybrid model uses both macroscopic and microscopic information. Both the MC and Hybrid models can be used both to replay the behaviour of animals in simulation and for implementation as robot controllers. We automatically generate the parameters of the MC and Hybrid models for cockroach agents, calibrating them to display the collective behaviour and site-selection dynamics described in the Mean Field model.

The MC and Hybrid models presented in this study can directly be implemented into a robot. However, here our approach does not explain how to translate them automatically into robotic controllers. This question was tackled in [163] by using formal methods and supervisory control theory to automatically generate robot controller code and to validate it so that it translates into robot behaviours matching a given formal specification.

Here, we use a user-defined metric (the bifurcation diagrams) to compare the results in simulation of two different pairs of models and parameter sets, during the optimisation process. As a result, the obtained models and parameter sets only approximate the collective dynamics of individuals, and not the behaviours (trajectories) of each individual. This could be further improved by considering the calibration of these models as a multi-objective process where the first objective would cater to the collective dynamics, and additional objectives would cater to the individual behaviour of the individuals. Alternatively, one could design a methodology similar as the like in [101], where no metric is specified, by co-evolving simultaneously models of robot behaviours and classifiers of the resulting behaviour in simulation. These classifiers would be trained to identify whether or not the resulting behaviours of the optimised models are distinct from the behaviours from reference experiments.

A "mixed society" is defined as a group of robots and animals that are able to integrate and cooperate: each robot is influenced by the animals, but can, in turn, influence the behaviour of the animals and of the other robots. Individuals, natural or artificial, are perceived as equivalent, and the collective decision process results from the interactions between natural and artificial agents [1, 22, 23]. Robots are useful for a number of reasons [164, 165]: validating models *in silico* [159], inducing stimuli to observe animal feedback [166, 22, 48, 64], modulating animal collective behaviour [1], etc. Recent work has already used robots in mixed society to study individual and collective animal behaviours: robots have been mixed with cockroaches in [166, 1], chicks in [22, 51], honeybees in [48], fruit flies in [114], guppies in [32] and zebrafish in [64, 117, 111, 167]. In such systems, complementary approaches to modelling (macroscopic vs. microscopic; analytical vs. simulation) can be used: different models deliver the data necessary for the robot design process, provide explicit and analytic descriptions of observed collective behaviour, yield predictions that may be used for the modulation of the collective behaviour of the society, and ease the development of robot controllers.

More generally, complex systems exhibit multi-level dynamics (hierarchical organization), with both global and local behavioural patterns. Recent studies have investigated the *micro-macro link*: the relationship between macroscopic and microscopic descriptions of multi-level behavioural dynamics [168, 169, 78, 170]. This problem also applies to the design of swarm group robotic controllers [168, 78, 171, 172, 173]. Our methodology is a first step toward the automatic generation of controllers for robots in a mixed society of animals and robots. Mixing animals and robots can be useful for the study of animal behaviour, and even to modulate their individual or collective behaviour. In this paper, the robotic agents in simulations were driven by models with human-selected parameters. In a subsequent study, we will present how these parameters can be optimized.

Few works in the literature on animals and robotics attempt to tackle the problem of transitioning from models of one level of abstraction (reference model) to another level of abstraction (target model). Moreover, these studies have generally considered the transition from microscopic to macroscopic models [78, 174, 175]. The transition methodology adopted by these studies is incremental, and relies on the creation of intermediate models, dealing with both macroscopic and microscopic information, and that share some parameters with both the reference and the target models. In [78], this methodology is applied

to go from a microscopic model to a macroscopic model of the behaviour of a swarm of autonomous robots in a collaborative task. The resulting model outperforms human-calibrated macroscopic models. In [174], a time-continuous kinetic mean field version of the Couzin-Vicsek model is obtained from its discrete microscopic version. In [175], continuous macroscopic models of pedestrian behaviour are obtained from discrete microscopic agent-based models. Little work in the literature has investigated how to automate and generalize the transition between models at different levels of abstraction. The transition process can also be more challenging if the reference and target models have no (or few) common parameters, or if their formulation is too different.

Another study could include an application of this methodology to more complex set-ups, with more than two shelters and more than two population types. Our methodology could also be extended by generating microscopic Markov Chain models from scratch, without *a priori* structural knowledge (*i.e.* the type and number of states). It may be possible to apply it to model, calibrate, and modulate the collective behaviour of other species (*e.g.* fishes, bees, and others).

Chapter 6

Modulation of animal collective behaviour using biomimetic robots

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This chapter builds on the approach presented in the previous chapter, and present a method to modulate the collective behaviour of a group of insects using biomimetic robots. This work is based on the publication:

Cazenille L, Bredeche N, Halloy J. Multi-objective optimization of multi-level models for controlling animal collective behavior with robots. In Conference on Biomimetic and Biohybrid Systems 2015 Jul 28 (pp. 379-390). Springer.

Group-living animals often exhibit complex collective behaviors that emerge through the non-linear dynamics of social interactions between individuals. Previous studies have shown that it is possible to influence the collective decision-making process of groups of insects by integrating them with autonomous multi-robot systems. However, generating robot controller models for this particular task can be challenging. The main difficulties lie in accommodating group collective dynamics (macroscopic level) and agent-based models implemented in every individual robot (microscopic level). In this study, we show how such systems can be appropriately modeled, and how to use them to modulate the collective decision-making of cockroaches in a shelter-selection problem. We address two questions in this paper: first, how to optimize a microscopic model of cockroach behavior to exhibit

the same collective behavior as a macroscopic model from the literature, and second, how to optimize the model describing robot behavior to modulate the collective behavior of the group of cockroaches.

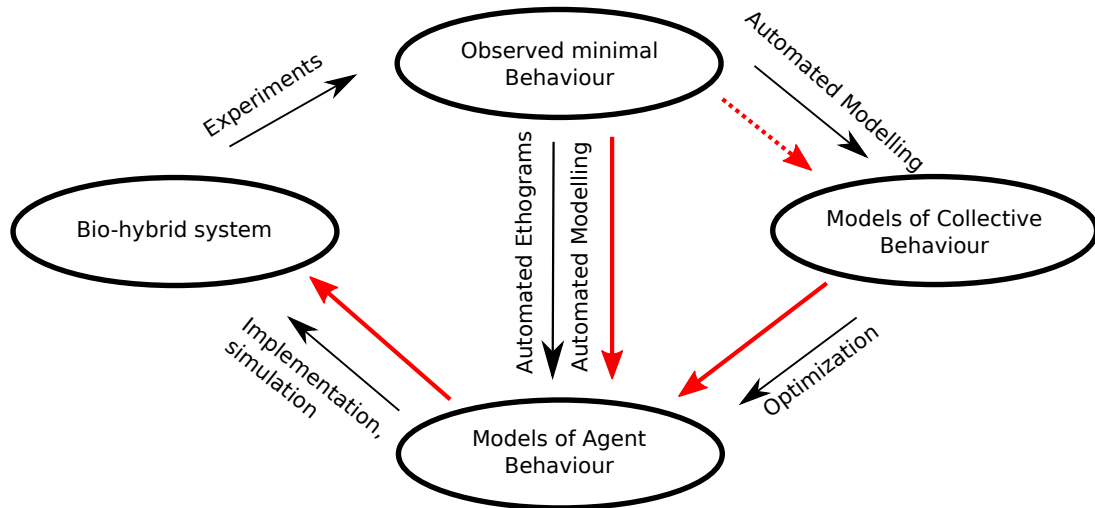


Figure 6.1 – Workflow of the methodology used in this chapter, with red arrows showing the addressed topics.

Figure 6.1 shows how this chapter is linked to the workflow of this manuscript. Here, we consider macroscopic models of cockroach collective behaviour (calibrated to match the observed collective dynamics from experiments) and automatically translate them into microscopic models of agent behaviour. We show that it is possible to modulate the collective behaviour of the animal group by finding appropriate parameters of the behavioural model. We use multi-objective optimization to find these parameter sets.

Contributions to this chapter

I implemented most of the code, including the parameter set optimisation system, and data analysis scripts. This paper was mainly written by me, with the help of José Halloy and Nicolas Bredeche.

6.1 Introduction

Groups of animals are able to reach consensus collectively, when presented with mutually exclusive alternatives. Previous studies have shown that it possible to influence the collective decision-making process of groups of insects by integrating them with autonomous multi-robot systems [1]. A mixed society is defined as a group of robots and animals able to integrate and cooperate: each robot is influenced by the animals, but can, in turn, influence the behavior of the animals and of other robots. Individuals, natural or artificial, are perceived as equivalent, and the collective decision process results from the interactions between natural and artificial agents [1, 22, 23].

A number of recent works in ethology have successfully used robots to investigate individual and collective animal behaviors, in particular by creating mixed robot-animals societies: robots are mixed with chicks in [22], cockroaches in [166, 1], fruit flies in [114], honeybees in [48], guppies in [32] and zebrafish in [64, 117, 111, 167].

In particular, Halloy *et al.* ([1]) demonstrates a system in which groups of robots are used to modulate the collective behavior of groups of animals (cockroaches *P. americana*). The same paper introduces a macroscopic Ordinary Differential Equations (ODE) model of the collective decision-making process of the mixed-society in a shelter-selection problem.

Macroscopic models can convincingly describe collective dynamics, but cannot be implemented directly into robotic controllers. Robot controllers are intrinsically microscopic, as they describe the behavior of individual agents. One of difficulties in experiments involving mixed-societies is to implement the dynamics described in a macroscopic model into robot controllers (microscopic models). In previous studies (including [1]), this process is often done empirically. Ways of handling different levels of descriptions is investigated in [176, 177, 178], but these studies do not address the issue of transitioning between models of different level of description automatically.

This paper introduces a novel methodology to navigate between models of different level of description by optimizing the whole range of parameter sets of models to get the same bifurcation diagram. This methodology is applied to the problem of modulating the collective behavior of a group of cockroaches with robots described in [1]. We take an agent-based modelling approach, and makes a number of assumptions: firstly, a model of the collective behavior of the animals already exists (the ODE model presented in [1]); secondly, robots can be attractive enough to the animals; and lastly, the number of robots is very small compared to the number of animals.

To describe the behavior of individual insects and robots, we use a Finite State Machine (FSM) agent-based microscopic model of cockroaches behavior. To test this FSM model in simulation, two sets of parameters are needed: one describing insect behavior, the other describing robot behavior. We address two questions: first, how to calibrate the FSM model describing insect behavior to exhibit the same collective behavior as the ODE macroscopic model, and second, how to optimize the FSM model describing robot behavior to modulate the collective behavior of the group of insects.

6.2 Multi-level Models

We use the same experimental setup as [1] (cf Fig. 6.2): a number of cockroaches (*P. americana*) are put in a circular arena with two identical shelters (resting sites). Cockroaches aggregate under the shelters. This setup is well adapted to study collective decision-making because it implies a trade-off between competition for resources with limited carrying capacity (the shelters) and cooperation (aggregation of the individuals).

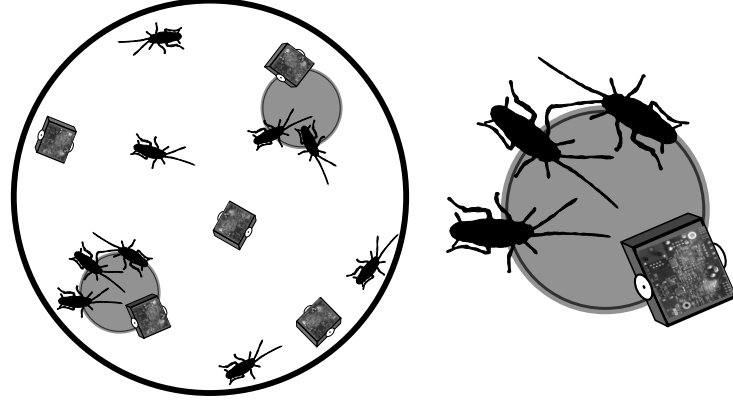


Figure 6.2 – Experimental setup used in [1] includes two identical shelters (150 mm) and both cockroaches (*P. americana*, approximate size: $\sim 4\text{cm}$, surface: 600mm^2) and robots (surface: 1230mm^2) in a circular arena (diameter: 1 m). The setup is symmetric.

6.2.1 Ordinary Differential Equation Model

A mathematical model describing the collective dynamics of mixed groups of robots and cockroaches was developed in [1] (based on [27]). In this model, robots and animals equivalently influence the collective decision-making process, and they exhibit homogeneous behavior. This model handles two populations (robots and animals) in setups with two shelters. The evolution of the number of individuals in each shelter (and outside) is represented by the following set of Ordinary Differential Equations (ODE):

$$\frac{dx_i}{dt} = x_e \mu_i \left(1 - \frac{x_i + \omega r_i}{S_i} \right) - x_i \frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n} \quad (6.1)$$

$$\frac{dr_i}{dt} = r_e \mu_{ri} \left(1 - \frac{x_i + \omega r_i}{S_i} \right) - r_i \frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^{n_r}} \quad (6.2)$$

$$C = x_e + x_1 + x_2, \quad M = r_e + r_1 + r_2, \quad N = M + C \quad (6.3)$$

Table 6.3 lists the parameters of the ODE model.

Because of crowding effects, the probability that an individual joins a shelter decrease with the level of occupation of this shelter.

We only consider the case where the two shelters have the same carrying capacity: $S = S_1 = S_2$. We define the measure $\sigma = S/N$ that corresponds to the carrying capacity as a multiple of the total population.

When only insects are considered, and no robots are present ($M = 0$), two different dynamics can be observed: When $0.4 \leq \sigma < 0.8$, only one configuration exists, corresponding of an equipartition of the individuals ($x_1/N = x_2/N = 1/2, x_e = 0$). In this case, the two shelters are saturated, with the remaining insects remaining outside. When $\sigma > 0.8$, two stable configurations exist, corresponding to all individuals in one of the shelter (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$). These dynamics can be observed in Fig. 6.4, a bifurcation diagram of the occupation of the first shelter, as function of σ . Represented results are obtained by resolution of Eq. 6.1 using the Gillespie method [81]. A resolution using the Gillespie method allows to take into account experimental fluctuations. Figure 6.4 only represents results with population of 50 cockroaches, but similar dynamics are observed with different population sizes.

Parameter for <i>P. americana</i>	Parameter for robots	Value for <i>P. americana</i>	Description
C	M	-	Total number of agents
x_i	r_i	-	Number of agents in shelter i
x_e	r_e	-	Number of agents outside the shelters
μ_i	μ_{ri}	$0.0027s^{-1}$	Maximal kinetic constant of entering a shelter
θ_i	θ_{ri}	$0.44s^{-1}$	Maximal rate of leaving a shelter
ρ, n	ρ_r, n_r	4193, 2.0	Influence of conspecifics

Parameter	Description
S_i	Carrying capacity of shelter i
ω	Surface of one robot as multiple of the surface of one animal
γ	Influence of animals on robots
β	Influence of robots on animals
δ	Influence of robots on robots

Figure 6.3 – Parameters list of the ODE model. Cockroaches (*P. americana*) parameter values are from [1]. We only consider the case where $N = 50$. In setups with two shelters, this model has 18 parameters. The influence of animals on animals is equal to 1, and is not considered in [1]: the assumption is made that this parameter is imposed by biology, and can't be changed in experiments.

Note that while models at the macroscopic level can easily describe the behavior of the dynamical system, in term of shelter selection, and offer a mathematical basis of description, they cannot explicit the behavior of individual agents, and cannot be implemented directly in actual robots.

6.2.2 Finite State Machine Model

We use the Finite State Machine model described in [150] as an agent-based model of cockroach and robot behaviour. This model is inspired by the agent-based aggregation

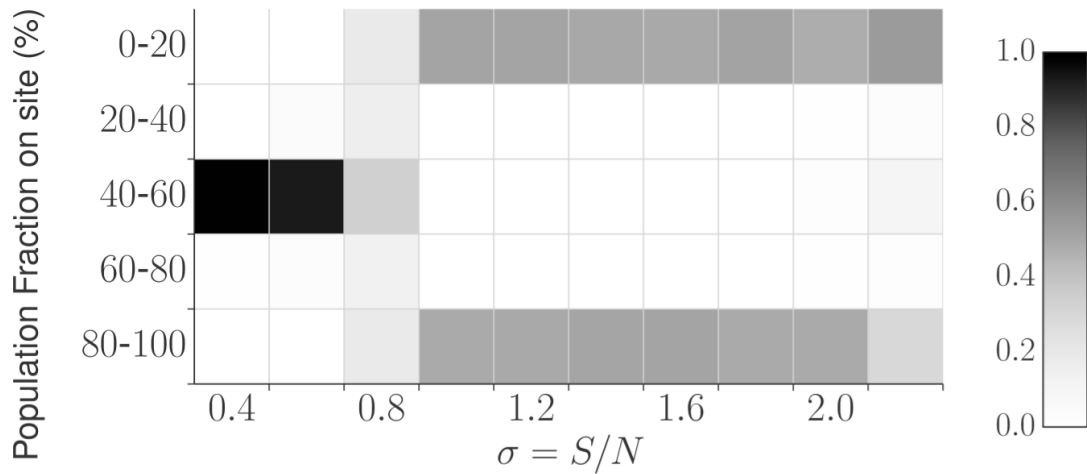


Figure 6.4 – Bifurcation diagram and distribution of $N = 50$ *P. americana* cockroaches in the first shelter, as function of σ . The bifurcation diagram is represented as bi-dimensional histograms of the results using 1000 solutions by parameter sets. The color of each bin of the histogram corresponds to the occurrence of experiments. The diagram is symmetric for all tested values of σ , so only one shelter is represented. When $0.4 \leq \sigma < 0.8$, only one configuration exists, corresponding of an equipartition of the individuals ($x_1/N = x_2/N = 1/2, x_e = 0$). When $\sigma > 0.8$, two stable configurations exist, corresponding to all individuals in one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$). The bifurcation point is close to $\sigma = 0.8$.

models in [74, 159] that describe the collective behaviour of cockroaches in a similar set-up.

Cockroaches tend to follow walls when close to the walls of the arena, and are gregarious during their resting period. We establish two zones in the arena: the peripheral zone, which is the ring that borders the walls of the arena, and the central zone, corresponding to the rest of the arena. In the central zone, agents exhibit a random-walk behavior, by following a recurring alternation of straight lines and rotations. In the peripheral zone, agents exhibit a wall-following behavior. Shelters are in the central zone. When an agent enters a shelter, it has a probability of stopping for a random duration before exiting the shelter. Similarly to [159], this probability depends on the number of present agents. Figure 6.5 provides a description of this model, with the relevant model parameters.

In our model (as opposed to [74, 159]), the probability of stopping when reaching a shelter is not the same for both shelters. While it is not relevant when describing the behavior of cockroaches (the shelters in the setup are identical), it can be useful for describing robots that modulate the collective behavior of cockroaches.

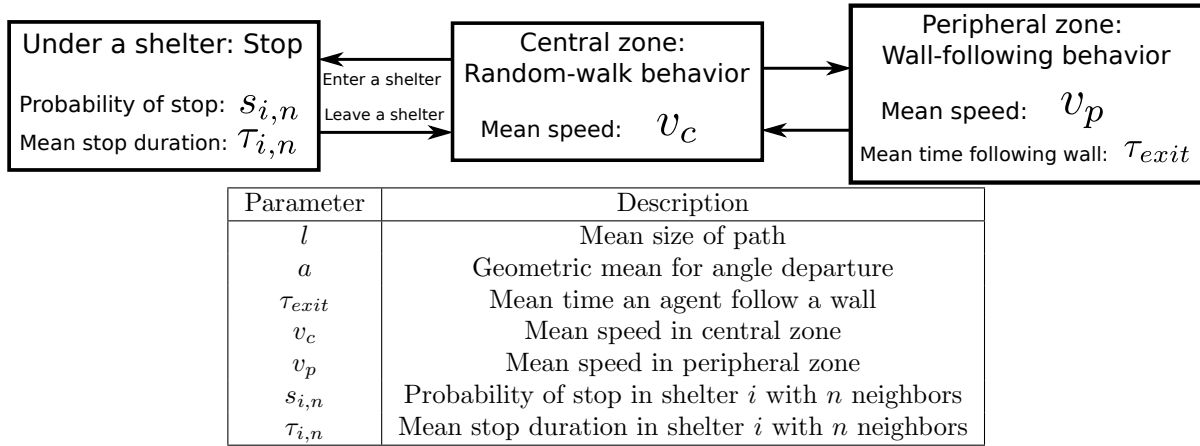


Figure 6.5 – *Finite State Machine Model of cockroach individual behavior. The arena contains two zones: the peripheral zone (agents follow a wall-following behavior), and the central zone (agents follow a random-walk behavior). Shelters are in the central zone. When an agent enters a shelter, it has a probability of stopping for a random duration before exiting the shelter. The probability of stopping under shelter depends on the number of neighbors present in the shelter, and can be different for each shelter. Only 10 neighbors are considered in our experiments. In setups with two shelters, this model has 45 parameters per population.*

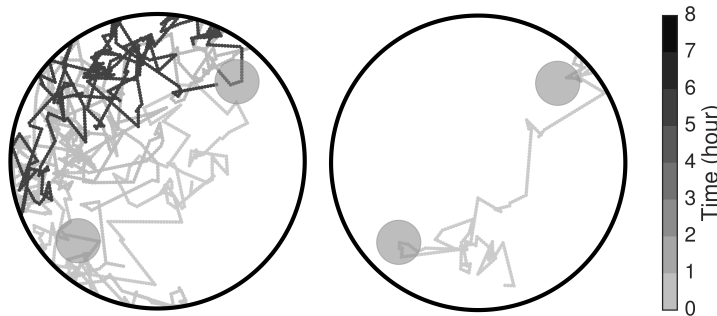


Figure 6.6 – *Examples of the trajectory of an artificial insect, using the FSM model. The arena is circular and contains two shelters. Gray lines represents the trajectory of one agent. The brightness of the line reflects to simulation time. All experiments last 28800 time steps (corresponding to 8 hours). Note that the FSM model do not try to mimic the actual movement patterns of cockroaches. The arena contains two zones: the peripheral zone (agents follow a wall-following behavior), and the central zone (agents follow a random-walk behavior). Shelters are in the central zone. When an agent enters a shelter, it has a probability of stopping for a random duration before exiting the shelter.*

6.3 Results

6.3.1 Numerical Computation

All results from the ODE model were obtained by resolving Eq. 6.1 and 6.2 using the Gillespie method ([81]). Results from the FSM model were obtained from simulations of 28800 time steps, of a setup similar to Fig. 6.2 (used in [1]): a circular arena (diameter 1m) with two identical shelters (diameter 150mm).

For both models, only populations of 50 individuals were considered.

6.3.2 Calibration of Models

In this section, we address the problem of finding parameter sets of cockroaches simulated using the FSM model that exhibit the same collective behavior as in the ODE model. FSM model parameters describing cockroach behavior can be derived (or 'Calibrated') from the ODE model.

As the ODE model is parameterized using experimental data, it allows the FSM model to be as close as possible to the behavior of cockroaches. This process is described in Fig. 6.7.

We optimize the parameter sets of the cockroaches individuals, for the FSM model. Instances of the FSM model using these parameter sets are simulated for different values of σ . The aim is to optimize parameter sets of the FSM model to obtain a similar bifurcation diagram as in Fig. 6.4.

As there is only few a-priori information about the parameter space, and as the parameter space has a relatively large dimensionality, we use the state-of-the-art CMA-ES evolutionary optimization method ([153], population size is 20, maximal number of generations is 500).

The objective function, minimized by CMA-ES, corresponds to a comparison between an optimized bifurcation diagram with the reference diagram from the ODE model. It is computed as follow:

$$\text{Objective}_{\text{calibration}}(x) = D_{\text{Hellinger}}(B_{\text{optimized}}/N_u, B_{\text{reference}}/N_u) \quad (6.4)$$

where x is the tested parameter set (genome), N_u is the number of considered values of σ in the bifurcation diagrams (10) and $B_{\text{optimized}}$ and $B_{\text{reference}}$ are one-dimensional histograms version of the bifurcation diagrams. The term N_u is used for normalization. The Hellinger distance ([134]) is defined by the equation:

$$D_{\text{Hellinger}}(P, Q) = \sqrt{2 \sum_{i=1}^d (\sqrt{P_i} - \sqrt{Q_i})^2} \quad (6.5)$$

where P and Q are two histograms, and P_i, Q_i their i -th bins. The Hellinger distance is a divergence measure, similar to the Kullback-Leibler (KL) divergence. However, the Hellinger distance is symmetric and bounded, unlike the KL-divergence (and most other distance metrics). As such, it is adapted when comparing two histograms ([134]).

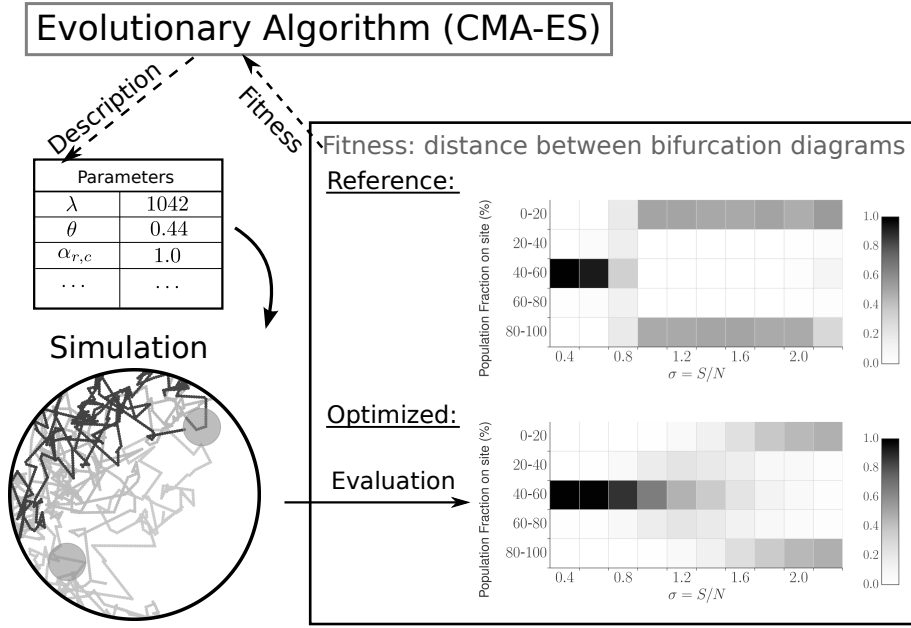


Figure 6.7 – Workflow of the Automated model calibration task by optimization. The optimized bifurcation diagram and the reference bifurcation diagram are both converted to one-dimensional histograms, by normalizing the sum of all bin values to 1.0. We use CMA-ES ([153]) as optimizer. The optimizer minimizes the objective function, which is computed by the formula: $Objective_{calibration}(x) = D_{Hellinger}(B_{optimized}/N_u, B_{reference}/N_u)$ where x is the optimized parameter set, N_u is the number of histograms in the bifurcation diagrams (10) and $B_{optimized}$ and $B_{reference}$ are one-dimensional histograms version of the bifurcation diagrams. The term N_u is used for normalization. $D_{Hellinger}(P, Q) = \sqrt{2 \sum_{i=1}^d (\sqrt{P_i} - \sqrt{Q_i})^2}$ is the Hellinger distance ([134])

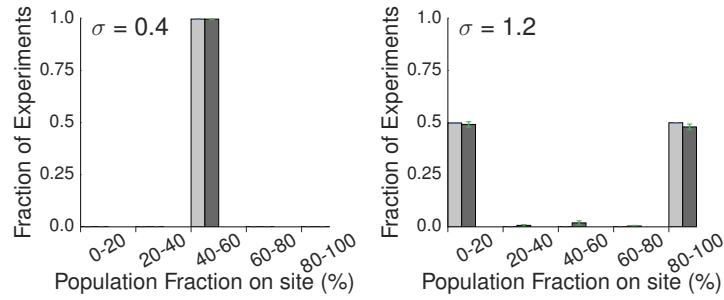


Figure 6.8 – Distribution of 50 cockroaches in the first shelter for chosen values of σ , using two different models: ODE (in dark grey) and FSM (in light grey). The parameter σ values are chosen before the bifurcation point ($\sigma = 0.4$), and just after the bifurcation point ($\sigma = 1.2$). Similar results are obtained for the range of values of σ present in Fig. 6.4. The best sets of optimized model parameters are used, after 100 runs of optimization. The diagram is symmetric for all tested values of σ , so only one shelter is represented. Calibrated versions of the FSM model behave similarly to the ODE model: (1) before the bifurcation point ($\sigma = 0.8$), only one configuration exists, corresponding of an equipartition of the individuals ($x_1/N = x_2/N = 1/2, x_e = 0$); (2) after the bifurcation point, two stable configurations exist, corresponding to all individuals in one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).

Figure 6.8 corresponds to the distribution of cockroaches in the two shelters, using parameters sets from the best-performing optimized individuals in 100 runs. All values of σ present in Fig. 6.4 are tested, and Fig. 6.8 shows typical results before and after the bifurcation point. Results before the bifurcation point ($\sigma < 0.8$) are similar to results at $\sigma = 0.4$, and results after the bifurcation point ($\sigma \geq 0.8$) are similar to results at $\sigma = 1.2$. Results show that it is possible to find parameters sets of the FSM model that exhibit the same collective choice that the ones from ODE. Similar results are obtained using the FSM model from [159] (results not shown).

6.3.3 Modulation of Collective Behavior By Robots

Our goal is to find sets of parameters of robots, capable of modulating the collective behavior of the group of cockroaches.

This process is described in Fig. 6.9. Populations of 50 individuals are considered, with a varying, but small, proportion of robots in the population.

The parameter set used for modeling cockroaches using the FSM model was taken from the best-performing optimized individuals during the calibration process described in 6.3.2.

An optimizer is used to generate the parameter sets of the robots modeled by the ODE and FSM models. Instances of the FSM and ODE models using these parameter sets are either simulated (FSM) or resolved using the Gillespie method (ODE), for specific values of σ .

There are two objectives to minimize:

$$\text{Objective}_1 = D_{\text{Hellinger}}(\text{Hist}_{\text{optimized}}, \text{Hist}_{\text{reference}}) \quad (6.6)$$

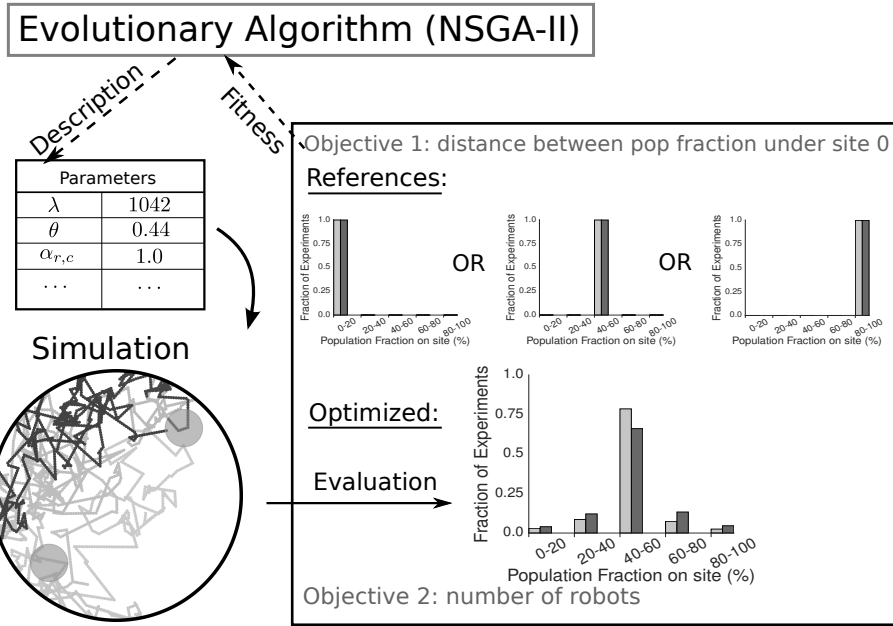


Figure 6.9 – Workflow of the process of modulating of the collective behavior of a group of cockroaches by robots. We use NSGA-II ([91]) as optimizer. The optimizer minimizes two objectives: (1) the difference between the optimized histogram and the reference histogram using the Hellinger distance ($D_{\text{Hellinger}}(P, Q) = \sqrt{2 \sum_{i=1}^d (\sqrt{P_i} - \sqrt{Q_i})^2}$ as described in [134]), (2) the portion of robots in the population. Three reference histograms are considered, resulting of three possible types of modulation.

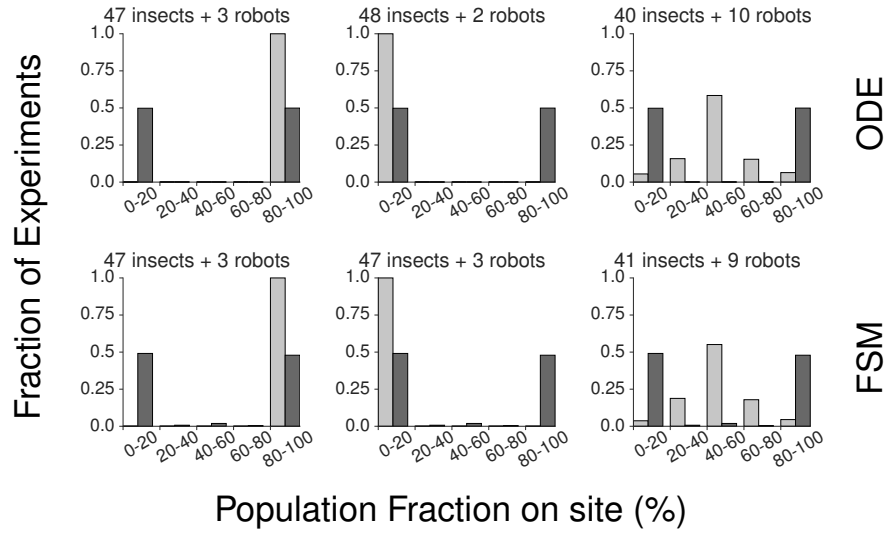


Figure 6.10 – *Instances of results bio-hybrid group behavior when robots are optimized to change the reference behavior of cockroaches alone as much as possible (dark grey: reference animal-only model, light grey: optimized animals-and-robots models). σ values are chosen just after the bifurcation point ($\sigma = 1.2$). Results after the bifurcation point ($0.8 \leq \sigma \leq 2.2$) are similar. The three plots in the first line correspond to results obtained from the ODE model, the three plots in the second line are from the FSM model. These results are taken from the best-performing individuals in 30 runs.*

$$\text{Objective}_2 = M/N \quad (6.7)$$

with $D_{\text{Hellinger}}$ described in Eq. 6.5), and M the number of robots, from Eq. 6.3. We need a multi-objective optimizer to minimize these two objectives: we use the state-of-the-art NSGA-II evolutionary algorithm ([91], population size is 100, maximal number of generations is 1000).

Three reference histograms are considered: (1) where all of the population gather in the first shelter, (2) where all of the population gather in the second shelter, (3) where half of the population gather in the first shelter, and the other half in the second shelter.

Figure 6.10 shows several instances of interesting optimized individuals (on the Pareto Front), for both the ODE and the FSM models, and for the three different reference histograms. Small groups of robots are capable, using the optimized controllers, to modulate the collective behavior of the group of cockroaches to correspond to one of the three considered reference histograms.

When the objective is to force the cockroach population to select one of the two shelters, a very small portion of robots is required (typically 2 or 3). For the ODE model, this can be explained by the proportion of cockroaches to remain under shelter longer when a larger number of neighbors are presents. For the FSM model, the same behavior is evolved. This induces a progressive aggregation of the group of cockroaches toward the shelter occupied by the robots. If the objective is to force the cockroach population to occupy both shelters at the same time, it requires a larger portion of robots (10 robots). In

this case, the robots have to occupy both shelters to lead the cockroaches into aggregating themselves in both shelters. Note that the modulation of the collective behavior of the cockroaches for values of $\sigma < 0.8$ is far more challenging because of the very fast saturation of the shelters, and was not considered in this study. Similar results are obtained using the FSM model from [159] (results not shown).

6.4 Discussion and Conclusion

The problem of modulating the collective behavior of a group of cockroaches with robots is challenging because it involves models of different levels of representation: an ODE-based macroscopic model (describing the collective dynamics), and a FSM-based microscopic model (implementable as robot controller). This paper introduces a novel methodology to navigate between models of different level of description, by optimizing parameter value of models already present in the literature. This approach makes three assumptions: firstly, a model of the collective behavior of the animals already exists ([1, 27]); secondly, robots can be attractive enough to the animals; and lastly, the number of robots is very small compared to the number of animals.

The ODE model can describe the collective behavior of cockroaches, by using a parameter set obtained by experimentation with actual insects in [1]. A FSM model of cockroach behavior is introduced, with inspiration from [160, 159]. This model is calibrated to exhibit the same collective dynamics as in the ODE model, using the CMA-ES evolutionary algorithm. FSM is a microscopic model that can be used as robot controller. The robot controller models are then optimized, using the NSGA-II multi-objective evolutionary algorithm, to modulate the collective behavior of the group of cockroaches, to match a user-defined reference.

Previous mixed-societies studies could only implement empirically the robot controllers used in experiments. The approach presented here is a first step toward generating them automatically, by deriving them from a validated macroscopic model of the animal collective behavior.

A subsequent study would include an application of this methodology to more complex setups, with more than two shelters and more than two population. Additionally, the calibration of models, and the modulation of collective behavior, could be performed in an online fashion, by using online evolutionary algorithms. The models investigated in this paper were only strictly macroscopic (ODE) or microscopic (FSM) – alternatively, a third kind of model could be defined, integrating both macroscopic and microscopic aspects.

Our methodology gives promising results, and could possibly be applied to model, calibrate, and modulate the collective behavior of other species (e.g. fishes, bees, or others).

Part III

Discussions

Chapter 7

Conclusions and perspectives

So long, and thanks for all the fish.

Douglas Adams

7.1 Main contributions

Robots can be used to investigate animal behaviour by sending stimuli and studying the animal response. Past research employed only simple robots to interact with animals in very short experiments. As such, the robot was not able to reply in an autonomous and biomimetic way to the animal, and this limited the scope of animal behaviours that could be tested. In particular, it was difficult to identify the underlying mechanisms of collective dynamics. This thesis tackles this problem by socially integrating biomimetic robots into groups of animals with closed-loop interactions, in order to create mixed-groups of animals and robots. This approach allows us to investigate relevant biological features of animal collective dynamics and render possible the study of more complex animal interactions (either with the robots or with the other animals). Our approach involves the automated generation of models of animal behaviour, which can then be implemented into controllers of robots socially integrated into the same group of animal. This problem is addressed for two groups of animals with different social dynamics: insects (cockroaches) and fish (zebrafish).

In Chapter 5 (based on [150]), we investigate the problem of automatically transitioning from a macroscopic model of insect collective decision-making (which cannot easily be implemented as robot controller) to microscopic (describing only agent states) or hybrid (using both agents states and collective states) models of agent behaviour (which can easily be used as robot controller) that exhibit the same collective dynamics, by using mono-objective evolutionary algorithms. These models are then used to drive the behaviour of robots in a mixed-group setting. The automatic transition of representation methodology is fundamental to the design of robotic controllers in a mixed-group setting, as it allows models of collective behaviour to be easily implemented in robots.

Moreover, the relevance of this approach is not limited to the field of animal collective behaviour and bio-hybrid systems, as it tackles the problem of automatically moving between models at different levels of description (from macroscopic to microscopic), a key problem in the modelling of nonlinear dynamical systems. This transition is usually done by hand and require extensive efforts to link the two types of models (*e.g.* [174, 175]). In a large portion of the literature, the calibration of model parameters is only done for specific solutions – typically only one state of the system (*e.g.* only one distribution of insects under the shelters for experiments of Chapter 5). Here, with our methodology we can automatically calibrate all models for a set of states of the system corresponding to a bifurcation diagram.

The methodology to automatically transition between levels of representations of Chapter 5 was further refined in Chapter 6 (based on [28]) to drive robots socially integrated in a mixed-group of insects and robots to modulate the collective behaviour of the entire group and reach an user-defined state. This methodology makes use of multi-objective evolutionary algorithms to iteratively refine models of agent behaviours, and identify the minimal number of robots to use for the targeted modulation process.

In Chapter 3 (based on [112]), we established a multi-level, stochastic and microscopic model of zebrafish behaviour in a two-patches environment. This model was further refined in Chapter 4 (based on [179]), with a more precise description of behavioural zones. We described a methodology to automatically calibrate these models (in Chapter 4) by using multi-objective evolutionary algorithms. These algorithms are able to cope with the multi-model nature of zebrafish behaviour that involves a trade-off between social tendencies (aggregation, group formation) and environmental response (wall-following, zone occupation). We measured the accuracy of these models compared to experimental data by defining a set of metrics assessing the biomimetism of the exhibited trajectories and behaviours.

We used the biomimetic models designed and calibrated in Chapters 3 and 4 to drive a robot into groups of zebrafish. This creates a mixed-group of zebrafish and robot because we demonstrate quantitatively that: (i) the robot responds to the animals with closed-loop interactions; and (ii) the robot is effectively socially integrated into the group of zebrafish. The social integration is measured using the previously defined metrics of biomimetism.

7.2 Perspectives

The workflow of the methodology adopted in this thesis (Fig. 1.1) specify how observed behaviours of animal groups can be automatically modelled (either with models of individual or collective behaviour) and then used to drive biomimetic robots into groups of animals to socially integrate them with closed-loop of interactions, and creating mixed-groups of animals and robots. In turn, the observed behaviour of these mixed-groups could be used to potentially refine the previously devised behavioural models, which could be then tested again to drive the behaviour of the robots in a mixed-group setting.

This methodology could be performed continuously and iteratively by following "loops" in our methodological workflow – *i.e.* successive bouts alternating ethological models

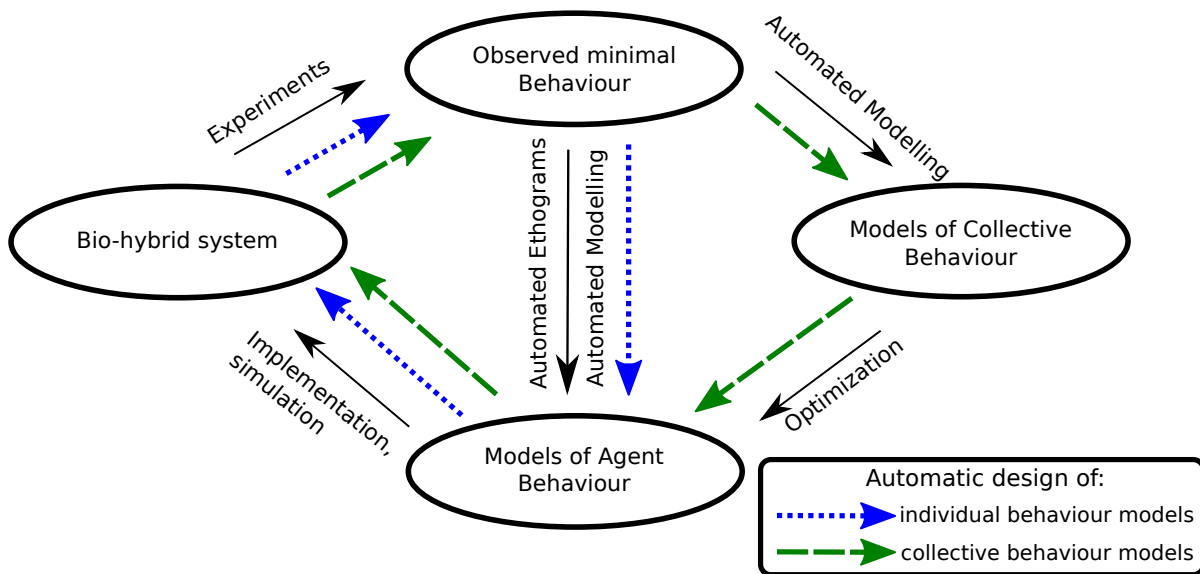


Figure 7.1 – Methodological “loops” in the methodology used in this thesis. The “*small-loop*” (blue dotted arrows) corresponds to the automatic generation of individual behaviour models: it involves the analysis of experimental observations (e.g. trajectories) into microscopic models of agent behaviour (through automated modeling and possibly automated generation of ethograms), that are then implemented as controllers of robots put in a bio-hybrid setting; these robots then interact with the animals in experiments, that could serve as the basis to further experimental observations to improve models of agents behaviour, and so on. The “*big-loop*” (green dashed arrows) corresponds to the automatic generation of collective behaviour models: the experimental observations are used to derive macroscopic models of collective behaviour (often with a formal mathematical formulation), which could then be transformed into microscopic models of agent behaviour exhibit the same collective dynamics, which could then be used as in the “small-loop” case to drive the behaviour of robots.

design and experimental validation tests with robots and animals). Two methodological “loops” can be identified that derive and refine models of either individual or collective behaviours (Fig. 7.1):

Models of individual behaviour (the “Small-loop” methodology) Models of agents behaviour are directly derived from experimental observations. The models are all microscopic, with no explicit description of the state of the group. The approach adopted with zebrafish in Chapter 3 and 4 is a first-step towards the “Small-loop” methodology.

Models of collective behaviour (the “Big-loop” methodology) Macroscopic models of collective behaviour are directly derived from experimental observations: they describe explicitly the state of the group, but not the state of the individuals. Then, these models are automatically translated into microscopic models of agent behaviour that implicitly describe the same collective dynamics (through emerging

complexity engendered by individual interactions). The approach adopted with cockroaches in Chapter 5 and 6 is a first-step towards the "Big-loop" methodology.

In this thesis, we also performed a single iteration of each "loop", but our approach could be improved by making successive iterations of these "loops" to continually refine our generated behavioural models and increase robots social integration into the animal groups. Additionally, our approach could be improved on several aspects, that are presented in the following subsections.

7.2.1 Automatic generation of ethogram of individual and collective behaviour

The recent field of high-throughput ethology [68, 71, 69, 180] (Fig. 2.7) leads toward the automated generation of ethograms: stochastic, time-series models that describes the different behavioural patterns exhibited by individuals and the transition probabilities from behaviour to behaviour. These models can typically be represented by non-deterministic Finite State Machines [181], or Hidden Markov Model [182].

In this thesis, we adopted a methodology where the models of individual behaviour were hand-crafted and then automatically calibrated. This approach could be extended by designing these models directly from experimental data by automatically generating ethograms. This would involve the identification of relevant individual behaviours (classification and clustering algorithms) from a relevant set of experimental parameters (feature identification and selection algorithms), and finding how individual transition from one behaviour to another. These transition probabilities could be computed automatically, either using statistics on experimental data [183], or with other techniques like recurrent artificial neural networks [184] or inverse reinforcement learning [185]. A recent work by Marques *et al.* [186] shows that it is possible to apply this methodology to reveal zebrafish motion patterns by using clustering algorithms.

In the case of fish, using simple probabilities as transition strategies may not be sufficient to model accurately their behaviour, and may need to take into account environmental (*e.g.* presence of walls, geometry of the arena, presence of site of interest) and social (*e.g.* presence of conspecifics, speed and polarity of the group, presence of other groups, preference towards specific individuals) signals: as we have showed in the previous chapters, zebrafish do not behave the same when in group compared to when alone, or when they are close to a wall. These models could also take into account memory and temporal aspects (non-Markovian hypothesis), where behavioural patterns and transitions change according to previously exhibited behaviours or according to hidden states of the system (this could potentially be modeled using Hidden Markov Models).

Animal behaviour is multi-modal, as it can be described as sequences of loosely-defined and loosely-separable actions. The field of "action-selection" [187] describes how these actions (or action sequences) are chosen by the agent given its current state and environmental context.

7.2.2 Improving social integration of the biomimetic robot into groups of fish

The models of zebrafish behaviour used in Chapter 3 and 4 could be improved to become more accurate and take more fish behavioural patterns into account. In particular, the following issues could be addressed:

Modeling of zones Chapter 3 presented a model with a preliminary handling of behavioural zones with separate behaviours in rooms than in the corridor. This was extended in Chapter 4, with a formal definition of behavioural zones, that are modeled as a multiplicative parameter (termed γ_{z_j, z_k}) that modulates the attraction of agents towards target zones. However, this modelling choice does not actually correspond to agent attraction toward a specific zone of the environment, but towards the objects (conspecifics or walls) found in this zone. This could be extended further by considering the behavioural zones like special objects, or site of interests (as was described in [113]). This would allow agents to be attracted directly to behavioural zones, and not just towards the objects placed in them. The difficulty of this approach is that it would bias the resulting PDF by increasing the probability of going towards directions that had previously low probabilities (or null probabilities). As such, the movement of an agent placed in a zone would be closer to a random walk (which was not present in the model presented in Chapter 3 and 4).

Modeling of collective departures The models of Chapter 3 and 4 do not explicitly describe the dynamics of fish collective departures from one room to the other. They exhibit room departures behaviours because of implicit reasons (*e.g.* fish following walls of a room then come and follow into the corridor towards the other room, or they can be attracted to another individual that is transitioning to the other room). These models could be improved by making explicit the collective departures, taking inspiration from recent biological analyses of zebrafish collective departures [132].

Fish tail movement patterns Our modelling approach mainly caters to individual trajectories, with only minimal support of fish tail-beats (low-level fish movement patterns) in Chapter 3. We could complement our models with recent ethological analyses of fish tail-beat patterns [188, 189, 186, 65, 190, 191]. In particular, several works [190, 65, 186] demonstrate that fish movement patterns can be segmented in tail bouts composed of a period of strong acceleration (corresponding to the tail beat) followed by a period of relaxation. These studies also show that the characteristics of fish movement patterns are strongly dependent on the behavioural context, either in term of environmental (*e.g.* proximity to walls) or social (*e.g.* perception of conspecifics, alignment, group size) signals.

Calibration methodology The calibration methodology adopted in Chapter 3 and 4 could be improved. Namely, more work could be done on the handling of the compromise between aggregative and wall-following behaviours, to reach higher performance. Additionally, more metrics could be taken into account, pertaining either

to individual behaviour (*e.g.* tail beats patterns, shape of the body), individual trajectories (*e.g.* sinuosity, curvature, statistics on segmented parts of the trajectories), social behaviour (preference over certain individuals, sub-groups duration and dynamics, polarity and alignment) or response to environmental cues (size of the current room, distance to nearest wall). Alternatively, it could be possible to use a different calibration methodology that would not rely on similarity metrics, like Turing learning [101]. Finally, it could be possible to take into account the behavioural features discovered by the automated ethograms methodology presented in the previous section.

7.2.3 Deep artificial neural networks models of fish collective behaviour based on visual perception

Building models that correctly reproduce fish trajectories is still an open question [192]. These models would be able not just to provide approximately accurate prediction of the next pose of a fish given its current pose in short-lived experiments (as was proposed in [190]), but also be capable of generating entire sets of realistic trajectories across varying initial conditions (*i.e.* initial pose of the fish), possibly taking into account trajectory drifts engendered by the propagation of successive errors in model prediction. A possible methodology to automatically design generative models of fish behaviour would be to train artificial neural network (ANN) on experimental data to make the link between agent visual perception and motor response, by using biologically plausible reconstructions of the perception fields of the fish (generated from the experimentally gathered trajectories). The use of black-box models (like ANN) minimises the need for *a-priori* knowledge and assumptions about fish behaviour, and allows the capture of behavioural features not initially considered by an expert observer. Moreover, these neural networks models, while artificial constructs, could still be used to draw parallels on how perceptual information in zebrafish is linked to their individual and collective behaviour in a neuro-ethological context. This topic will be covered in a work-in-progress study.

Alternatively, one could also use other artificial neural networks models or algorithms for this problem (*e.g.* Generative Adversarial Networks [98], Deep Reinforcement Learning [97], Neuroevolution by Turing Learning [101], or biomimetic neural models like spiking neural networks [102], etc.). However, this problem is particularly challenging, as these neural models must be designed to cope with the ill-defined, non-linear, stochastic, temporal, multi-modal and multi-level nature of fish behaviour, across varying initial conditions.

7.2.4 Automatic generation of macroscopic models from behavioural data

In Chapter 5 and 6, we presented a methodology to automatically calibrate the parameters of ordinary differential equations (corresponding to models of cockroach shelter occupation). This approach could be generalised to automatically generate the entire set of

equations directly from experimental data, find relevant parameters and constants and calibrate them with appropriate values. Some recent studies in the Genetic Programming community [93, 94] have investigated how to derive formal descriptions (equations) of non-linear dynamical systems directly from experimental data and with few *a-priori* knowledge, through the use of symbolic regression algorithms.

This methodology could also be used to automatically translate a microscopic model of individual behaviour into a macroscopic model of collective behaviour (the opposite of the approach from Chapter 5).

7.2.5 Real-time modelling of animal behaviour coupled with real-time generation of robot controller in a biohybrid system

The automated modelling methodologies used in this manuscript were all performed in an off-line fashion. Our approach could be extended further to automatically design and calibrate our behavioural models in real-time during experiments. This would allow the robots to react to environmental and social signals directly observed in experiments (*e.g.* modifying the number of fish or robots during an experiment, changing the geometry in real-time, or taking into account behavioural attractors not expected before the planning of the experiments), or to possibly cope with unpredicted adversarial conditions (*e.g.* unexpected hardware failure of the robots). This real-time approach would be a way of forming the "small-loop" methodology presented in Fig. 7.1, by continuously progressing from experimental observation to automatic model design to test in experiments.

We already investigated this question and adapted our methodology to calibrate our behavioural models in real-time. The tracking and control system presented in Annex A was already designed to track individuals and control robots in real-time. We improved the evolutionary algorithm of Chapter 6 to calibrate in real-time the behavioural model implemented as robot controller. To cope with the increased number of computation performed in real-time, expansive software engineering efforts were needed to split our control and calibration workflow into three interrelated parts that are executed concurrently on three different networked computers able to communicate continuously: (i) the robot control and tracking system, (ii) the data-analysis system, (iii) the calibration system using evolutionary computation. As in Chapter 6, we use a global multi-objective optimiser for the calibration process. Alternatively, we could improve the calibration methodology by adopting a global optimiser built to reduce as much as possible the number of evaluated parameter sets to reduce the computational costs needed (*e.g.* Bayesian Optimisation algorithms [193, 107]), and thus possibly obtain more accurate solutions in real-time.

We successfully demonstrated that our system is capable of calibrating our behavioural model in real-time during one of the final demonstrators of the ASSISibf project [24]. A screenshot of the results of the real-time calibration process can be found in Fig. 7.2. This topic will be covered in a work-in-progress study.

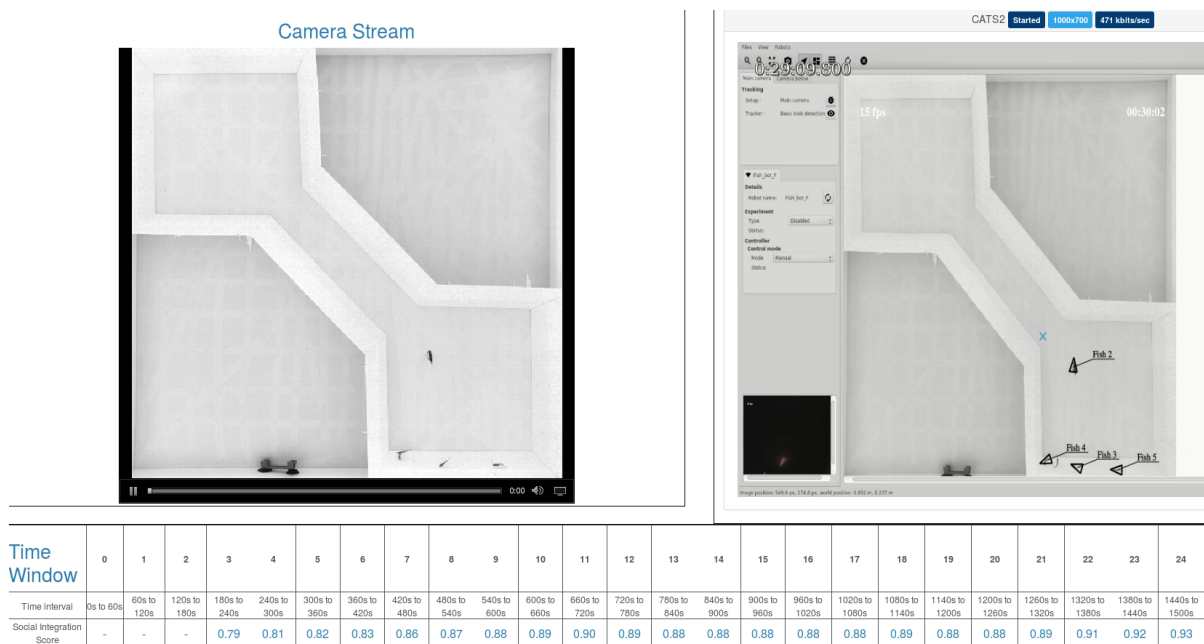


Figure 7.2 – Screenshot of the results of the real-time calibration process. Social integration scores (including inter-individual distances scores, distances to nearest wall scores, speeds scores, and density of presences scores) can be found at the bottom of the picture. Scores are re-computed each passing minute of the experiment, and take only into account the data gathered during the last 3 minutes.

7.3 Concluding remarks

We established methodologies to automatically model animal behaviour and transform it into the controller of robots that socially integrate the animal groups to form mixed-groups. We believe that our approach will be useful in other scientific projects, in particular in robot-ethology and in swarm robotics. Indeed, it could one day be used to understand in real-time animal behaviour and build new recipes to engineer artificial collective adaptive systems (two of the goals of the ASSISIbf project).

The methodologies we describe in this thesis could be used in a broader context, and inspire the establishment of a framework to automate experimental and data-analysis aspects of ethological research. This would make possible the automated design of animal behavioural models directly from experimental observation of animals group by using a high-throughput ethology approach to identify the relevant biological features, classify them through machine learning algorithms, quantify the transition between behavioural states and assemble all of these results into an ethograms (*e.g.* Finite state machines, Markov chains).

While this automated modelling approach can be executed without robots, they Robots are not necessary to this automated modelling methodology. However, they can be used conjointly with this methodology to gather additional animal behavioural data and val-

idate the derived behavioural models. In this scenario, the robots would continuously interact with the studied animals while the automated modelling methodology would derive and refine behavioural models. In turn, these models would serve as the controller of the robots, driving them into the group of animals and be increasingly more socially integrated. They could be automatically programmed to spur the observed animals to study different initial conditions and states (or phases) of the system. Then, another framework could automatically extract scientific conclusions from the generated models and data-analysis results, and possibly compile them into a human readable representation. This approach would prove valuable to scientists as it would help experimental research by automating time-extensive tasks. Additionally, these efforts could also stimulate the creation of increasingly biomimetic robots, either in term of morphology or behaviour, in a mixed-group context.

The next-step would be to design an effective mixed-society, with long-lasting interactions between natural and artificial agents, and complex, hierarchical organisational behavioural patterns. Mixed-societies serve two purposes: they offer a framework to study complex animal behaviours (namely long-lasting organised collective dynamics) and they can bring animals and robots together to create long-lasting added capabilities not present in animal-only and robot-only societies (*e.g.* use the animal capabilities to sense their environment and the robots to react to these environmental factors). This endeavor would prove to be challenging, as it would involve robots with heterogeneous behaviours socially integrated into a complex animal society with hierarchical organisation in very long-lasting experiments (*e.g.* several days, or even weeks). The robots would have to be designed not only to handle long experiments (possibly coping with failures as in [107]) but also to react in real-time to animal behaviour and automatically learn how to be socially integrated. To realise an effective mixed-society of zebrafish and robots, these robots would have to interact with them in long experimental sessions and be driven by heterogeneous and automatically designed or calibrated behavioural models, that would take into account zebrafish leadership behaviour (as described in the previous section) and individual preferences. We are still very far from this goal.

Chapter 8

Publications

Related to the thesis

- **Cazenille L**, Bredeche N, Halloy J. Multi-objective optimization of multi-level models for controlling animal collective behavior with robots. In Conference on Biomimetic and Biohybrid Systems 2015 Jul 28 (pp. 379-390). Springer. [28]
- **Cazenille L**, Bredeche N, Halloy J. Automated optimisation of multi-level models of collective behaviour in a mixed society of animals and robots. arXiv preprint arXiv:1602.05830. 2016 Feb 2. (Submitted to PEERJ CS, in review) [150]
- **Cazenille L**, Collignon B, Chemtob Y, Bonnet F, Gribovskiy A, Mondada F, Bredeche N, Halloy J. How mimetic should a robotic fish be to socially integrate into zebrafish groups ? 2017 (Bioinspiration & Biomimetics 2017) [112]
- **Cazenille L**, Chemtob Y, Bonnet F, Gribovskiy A, Mondada F, Bredeche N, Halloy J. Automated calibration of a biomimetic space-dependent model for zebrafish and robot collective behaviour in a structured environment. In Conference on Biomimetic and Biohybrid Systems 2017. Springer. [179]
- **Cazenille L**, Chemtob Y, Bonnet F, Gribovskiy A, Mondada F, Bredeche N, Halloy J. How to Blend a Robot within a Group of Zebrafish: Achieving Social Acceptance through Real-time Calibration of a Multi-level Behavioural Model. In Conference on Biomimetic and Biohybrid Systems 2018. Springer. [194]
- **Cazenille L**, Bredeche N, Halloy J. Evolutionary optimisation of neural network models for fish collective behaviours in mixed groups of robots and zebrafish. In Conference on Biomimetic and Biohybrid Systems 2018. Springer. [195]
- **Cazenille L**, Bredeche N, Halloy J. Modelling zebrafish collective behaviours with multilayer perceptrons optimised by evolutionary algorithms. (Submitted to Scientific Reports, in review) [196]

- Bonnet F, **Cazenille L**, Séguret A, Gribovskiy A, Collignon B, Halloy J, Mondada F. Design of a modular robotic system that mimics small fish locomotion and body movements for ethological studies. *International Journal of Advanced Robotic Systems*. 2017 May 26;14(3):1729881417706628. [65]
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- Séguret A, Collignon B, **Cazenille L**, Chemtob Y, Halloy J. Loose social organisation of AB strain zebrafish groups in a two-patch environment. *PloS one* 14.2 (2019). [131]
- Collignon B, Séguret A, Chemtob Y, **Cazenille L**, Halloy J. Collective departures in zebrafish: profiling the initiators. *PloS one* 14.5 (2019). [132]
- **Cazenille L**, Bredeche N, Halloy J. Automatic Calibration of Artificial Neural Networks for Zebrafish Collective Behaviours Using a Quality Diversity Algorithm. In *Conference on Biomimetic and Biohybrid Systems 2019*. Springer. [197]

Others

- **Cazenille L**, Bredeche N, Hamann H, Stradner J. Impact of neuron models and network structure on evolving modular robot neural network controllers. In *Proceedings of the 14th annual conference on Genetic and evolutionary computation* 2012 Jul 7 (pp. 89-96). ACM. [198]
- Gribovskiy A, Mondada F, Deneubourg JL, **Cazenille L**, Bredeche N, Halloy J. Automated Analysis of Behavioural Variability and Filial Imprinting of Chicks (*G. gallus*), using Autonomous Robots. *arXiv preprint arXiv:1509.01957*. 2015 Sep 7. [51]
- Aubert-Kato N, Fosseprez C, Gines G, Kawamata I, Dinh H, **Cazenille L**, Estevez-Tores A, Hagiya M, Rondelez Y, Bredeche N. Evolutionary optimization of self-assembly in a swarm of bio-micro-robots. In *Proceedings of the Genetic and Evolutionary Computation Conference 2017* Jul 1 (pp. 59-66). ACM.
- **Cazenille L.**, Comparing reliability of grid-based quality-diversity algorithms using artificial landscapes. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion 2019*. ACM.

Appendix A

Set-up for long-lasting mixed-groups experiments involving fish and robots

STRANGE MAN: I wonder where that fish has gone.
STRANGE WOMAN: You did love it so. You looked after it like a son.
STRANGE MAN: And it went wherever I did go.
STRANGE WOMAN: Wouldn't you like to know? It was a lovely little fish.
STRANGE MAN: And it went wherever I did go.
STRANGE WOMAN: Where can that fish be? It is a most elusive fish!

Monty Python: The Meaning of life.

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The experimental set-up used in the fish part of this manuscript was designed during this thesis, as a joint effort between our research team at the Université Paris Diderot (Bertrand Collignon, Axel Ségurel, Yohann Chemtob, José Halloy, and myself) and our collaborators at the EPFL (Frank Bonnet, Alexey Gribovskiy, Marcello Elias de Oliveira, Francesco Mondada). This set-up can be used to conduct experiments involving mixed-societies of fish and robots.

A.1 Zebrafish as a study species

The zebrafish (*Danio rerio*, Fig. A.1) is a tropical freshwater species, of the Cyprinidae family. It is widely used in biological studies as a model vertebrate organism, focusing either on its physiological or behavioural aspects [199]. Its robustness, rapid breeding, cheap price and broad availability explain its popularity in scientific studies. There exists numerous strains of zebrafish with various genetic and phenotypical properties. Here, we only use AB-strain zebrafish, a recent (circa 1991) strain that is popular in collective behaviour studies. These fish are bred locally, in our laboratory at the Université Paris Diderot (Fig. A.2B).

A.1.1 Ethics statement

The experiments performed in this study were conducted under the authorization of the Buffon Ethical Committee (registered to the French National Ethical Committee for Animal Experiments #40) after submission to the French state ethical board for animal experiments.

A.1.2 Animals and housing

We used 10 groups of 5 adults wild-type AB zebrafish (*Danio rerio*) in our experiments. The fish were 6-12 months old at the time of the experiments. We kept the fish under laboratory conditions, 27°C, 500µS salinity with a 10:14 day:night cycle. The fish were reared in housing facilities ZebTEC and fed two times a day (Special Diets Services SDS-400 Scientific Fish Food). The water pH level was maintained at 7, and Nitrites (NO^{-2}) were below 0.3 mg/l.

A.2 Experimental set-up

The experimental set-up (Fig. A.2A) includes a 1.2x1.2x0.2m fish-tank and is confined in an experimental zone of 2x2x2.35m wrapped by a white fabric (to isolate the experiments and homogenise the luminosity). The structure is supported by a rigid structural aluminum framing system, which is exposed to diffused light in order to reproduce daylight. The tank is filled with water up to a level of 60 mm.



Figure A.1 – *Group of AB-strain zebrafish. Copyright LSRO EPFL.*



Figure A.2 – *Experimental set-up (A) and automated fish facilities in our laboratory at the Université Paris Diderot (B). These figures were taken from [200].*

The set-up includes an arena (Fig. 3.3) of $1000 \times 1000 \times 100$ mm made of white Plexiglass. This arena is composed of two rooms (350×350 mm at floor level) linked by a corridor (380×100 mm at floor level).

The robots are composed of two units: a wheeled mobile robots (FishBot: Fig. A.3 and Fig. A.2B) that move underneath the tank, and a passive lure (Fig. A.2C,D) that is magnetically coupled with the FishBot by magnets placed on top of the FishBot and at the base of the lure. The FishBots are powered using two conductive plates, one glued onto the bottom of the aquarium and one below the FishBot. The tank is covered with white teflon sheets, to avoid reflections on the glass and to provide a smooth surface to ease to motion of the lure module inside the aquarium. We use an overhead high-resolution monochrome camera (2048×2048 px, Basler Scout acA2040-25gm) to record the experiments (Fig. A.2A) at a rate of 15 frames per second and with latencies below 60 ms. This camera is equipped with low distortion lenses CF12.5HA-1 (Fujinon, Tokyo, Japan). In the fish-tank, the fish and lures move in an experimental arena with two rooms linked by a corridor. This particular arena topology was chosen to investigate the collective dynamics of the fish (*cf.* Chapter 3 for more details).

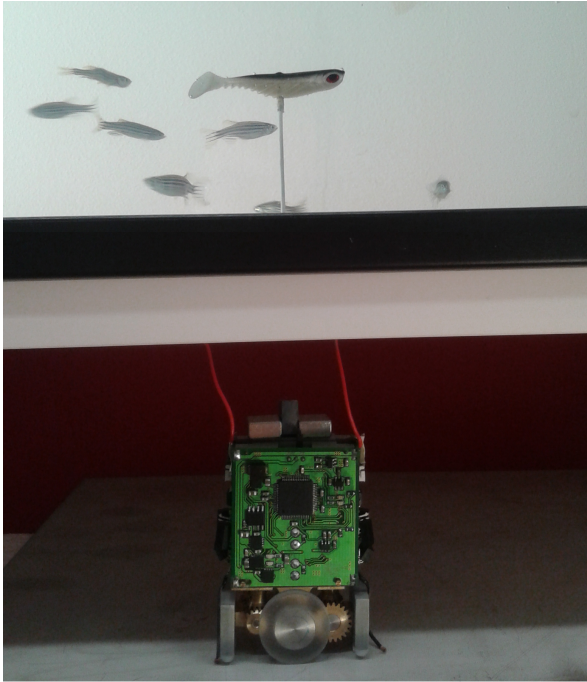
A.3 Robot hardware design

We use the miniature mobile robot "FishBot" (Fig. A.3), designed by our collaborators at the EPFL, for our experiments involving mixed-societies of fish and robots [29, 30, 65]. It can achieve the required speeds and accelerations in order to reproduce the fish displacement under water. The robot is continuously powered and controlled with a wireless bluetooth link, therefore it is possible to achieve long duration experiments in closed-loop.

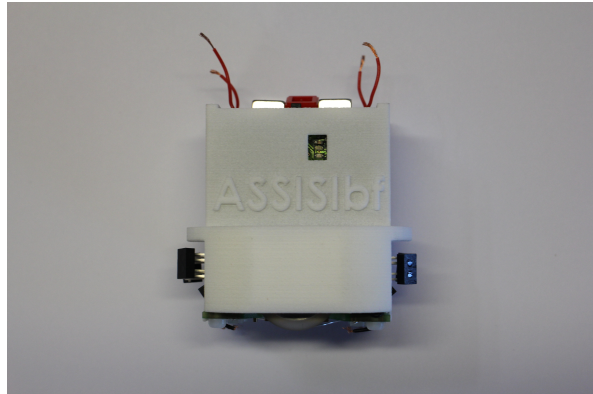
A.4 Biomimetic fish lures

The lures used in our experiments can be found in Fig. 4.2 (in Section 3.2.2). The external shape of the lure was defined from a 3D scan (using a Stereoscan 3D Breuckmann StereoSCAN3D with two cameras of 1.4 megapixels) of a dead zebrafish. The surfaces retrieved by the scanner were processed and scaled in order to design a mold made of ABS using a 3D printer. The fins of the fish were made using Mylar R as it offers good softness and is available in very thin films. The fins have a thickness of $50\mu\text{m}$ and are also designed using the 3D scan of the fish.

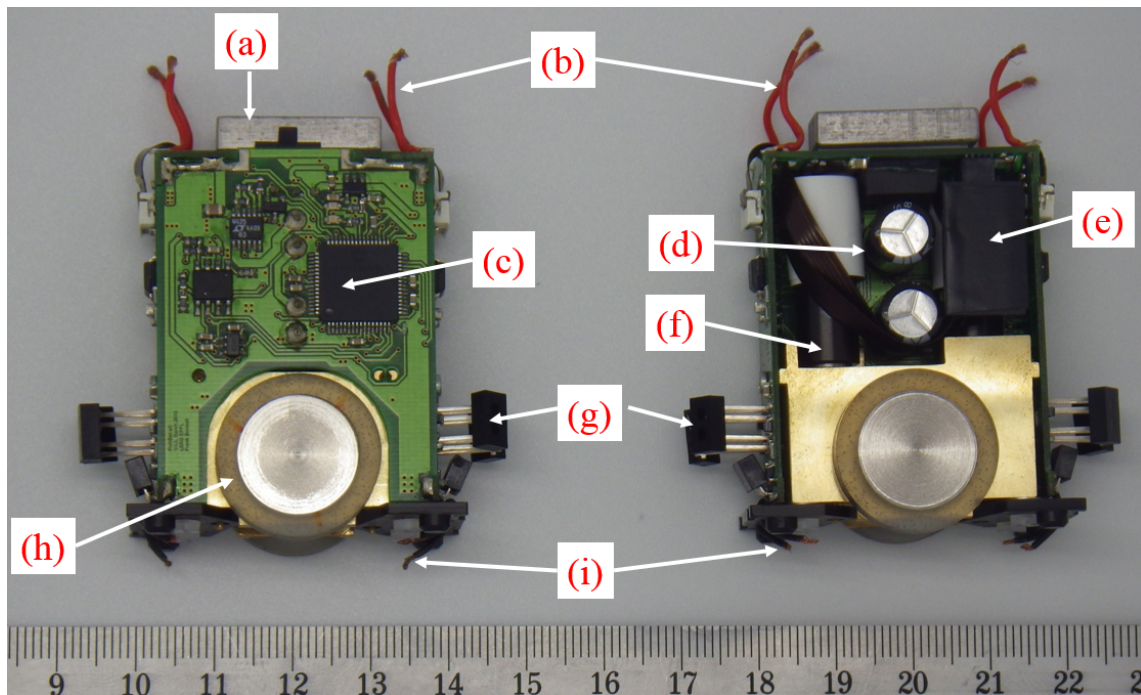
A biomimetic pattern was then fixed on the fish lure. We cropped a picture of a real zebrafish and printed it on inkjet decal paper (provider : <http://www.decalpaper.com/>) with a standard printer. The printed pattern was cut off and placed in temperate water for approximately 50 seconds. Then, the decal was slipped off the paper and was applied on the fish lure. After a few hours, the lure was plunged into liquid latex for a few seconds to form a protective layer once dry.



(a) Zebrafish (*Danio rerio*) group interacting with one Fishbot robot.



(b) The FishBot robot with its protection cover.



(c) The FishBot robot. This figure was taken from [65]. a) Magnets to couple the FishBot with the lure module. b) Electric brushes to retrieve the power from the positive conductive plate. c) Microcontroller dsPIC33f128. d) Supercapacitors that store power if the contact with the plates is lost. e) Bluetooth antenna. f) Maxon DC motor. g) Infrared Proximity sensors. h) Wheel i) Electric brushes to retrieve the power from the ground connected conductive plate.

Figure A.3 – FishBot design [29, 30, 65]. Copyright LSRO EPFL.

A.5 Control and Tracking System (CATS)

The Control and Tracking Software (CATS) is able to track the positions of the agents (fish and robots), and to control the fishBots robots. CATS is able to concurrently handle small groups of robots (10). Each robot can be controlled to display a collection of implemented behaviours. A system that controls the robots of a mixed-society containing zebrafish must cope with their fast reaction time and sudden movements: our system is designed to handle very low latencies both at the tracking and at the control levels.

CATS's architecture is modular. It is composed of four parts, described in Fig. A.4. The first part manages the video stream from the camera of the experimental setup. The second part tracks the positions of fish and fish-CASUs. A Graphical User Interface (GUI) is provided to allow the experimenters to see the video stream, and to change the behaviour of the robots. It allows the experimenter to assess the progress of an experiment, visualise the tracked positions of the agents and control the robots. The Control part contains implementations of the various behaviours and movement patterns of the robots, and low-level methods to communicate with them. A screenshot of a typical use of CATS is found in Fig.A.5.

Note that a new version of the CATS system, named CATS2, was developed (mostly by Alexey Gribovskiy). However, it was not used in the experiments presented in this manuscript. It is described in detail in the publication [66]:

Bonnet F, **Cazenille L**, Gribovskiy A, Halloy J, Mondada F. Multi-robots control and tracking framework for bio-hybrid systems with closed-loop interaction. ICRA 2017 Conference.

A.5.1 Video capture and streaming

We use the library *aravis* (<https://github.com/GNOME/aravis>) to access the camera. All video stream operations are handled using the *GStreamer* library (<http://gstreamer.freedesktop.org/>). We capture greyscale video frames from the camera at a resolution of 2040×2040 pixels, at a frequency of 15 frames per seconds. The video stream from the camera is split in two different streams: one in high-resolution (2040×2040 pixels, grayscale), the other in a lower-resolution (500×500 pixels, grayscale). The video is saved on disk in high-resolution (2040×2040), after been compressed by the Huffman encoding, a simple and fast algorithm for lossless compression. The tracking part uses only the low-resolution video stream to track the positions of the agents. The use of low-resolution frames instead of high-resolution ones allow the tracking process to be less computationally expensive. We tuned the parameters of the *GStreamer* media components to have a very low latency. On our setup, frames from the camera can be converted and sent to the tracking system in approximately $40ms$.

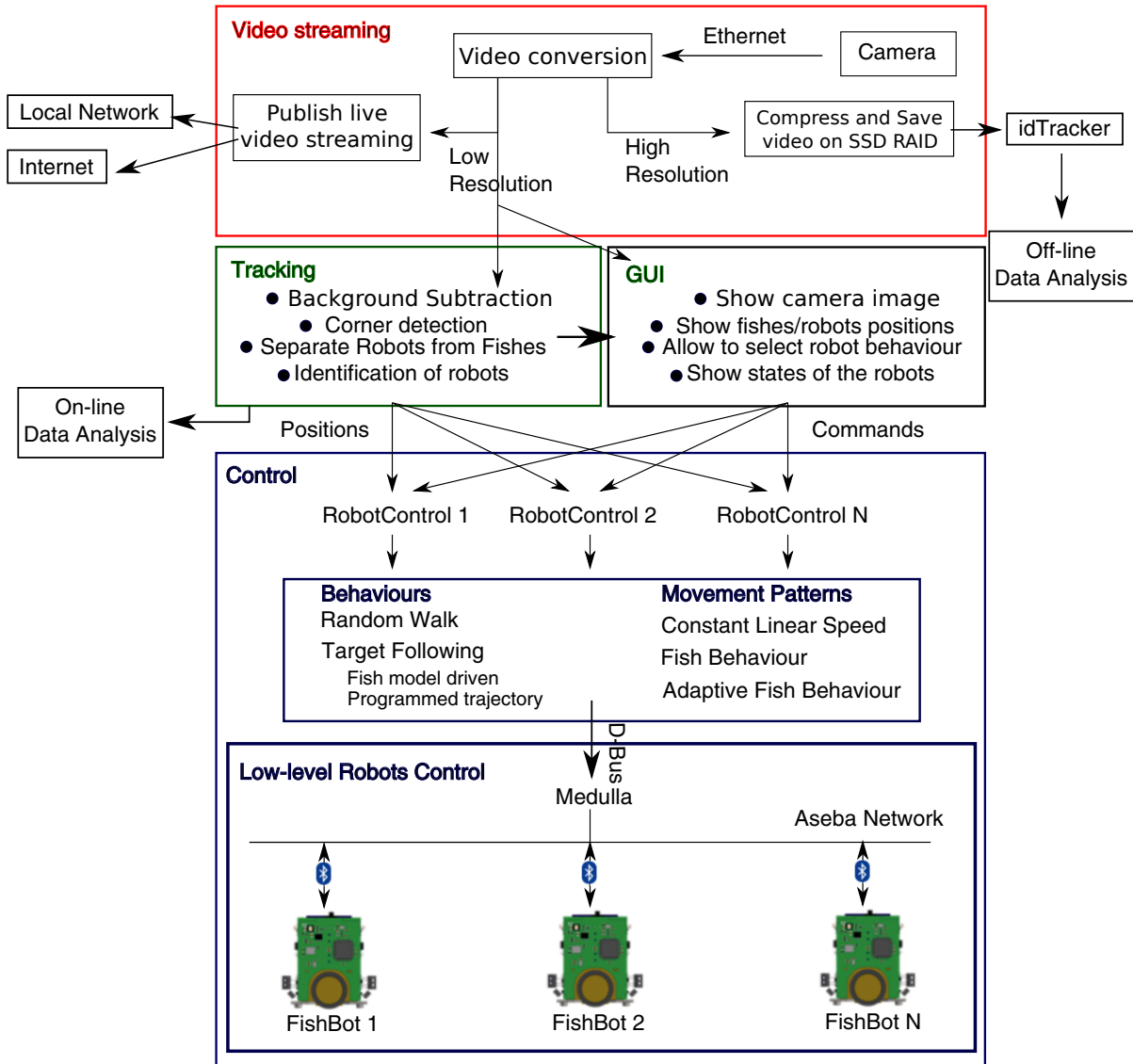


Figure A.4 – Workflow of CATS, the Control And Tracking System. Description of the Control And Tracking Software (CATS), used to save videos of the experiments, track in real-time the positions of the fishes and of the robots, and control robot behaviour. The video stream from the camera is compressed and saved on disk in high resolution (2040×2040 pixels). It is also converted to a lower resolution (500×500 pixels) and published on the internet (<http://streamyfish.com>). The tracking of the fishes and robots is performed in real-time on the low-resolution video stream, using a simple corner detection method. The software provides a GUI that displays the video stream with tracking information. Robot control makes use of the tracked positions of the robots. Several kind of robots behaviours and movement patterns are available, and can be selected by the user in the GUI. Low-level control of the robots is achieved by using the ASEBA system [66].

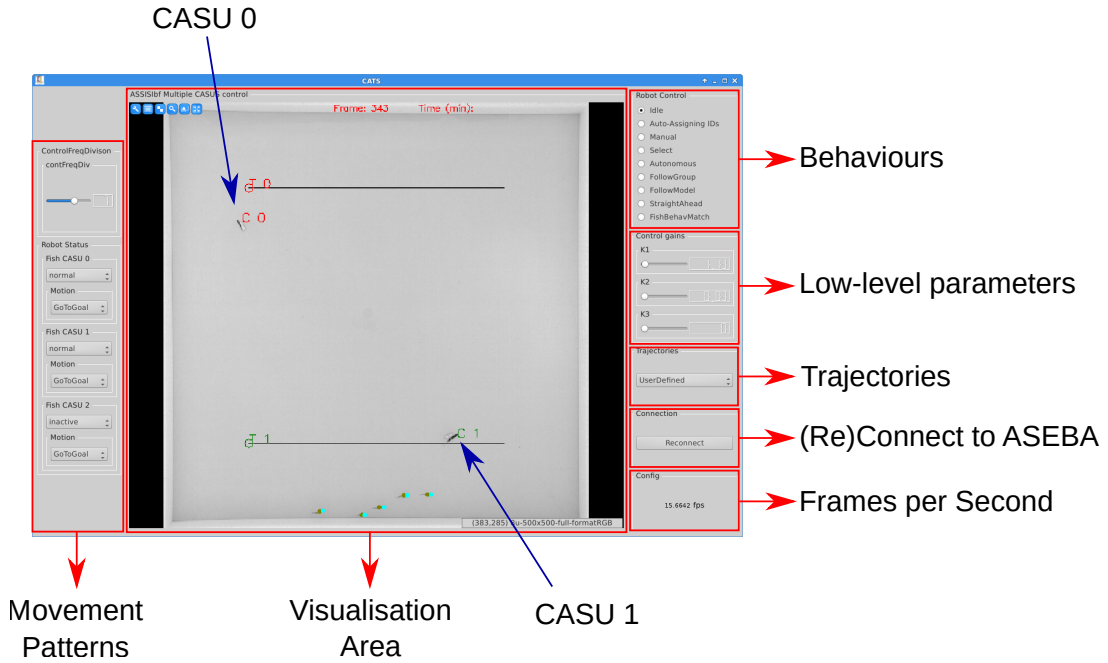


Figure A.5 – Screenshot of the graphical Interface of CATS during a typical experiment. The video stream from the camera is displayed on the visualisation area, at the center panel. Colored disks are placed on the detected positions of the fish and robots: the tracking system detects the centroids of each agent, and the position of the head of the fish or lures. Big colour circles are used to represent the positions of the robots. The user can choose the current behaviour and movement pattern of each robot using the controls on the left and right of the visualisation area.

A.5.2 Tracking

The tracking of the agents is performed on the low-resolution (500×500) video stream. All operations are processed using the OpenCV library (<http://opencv.org/>). First, we apply a background subtraction preprocessing step, on each frame, by using the Gaussian Mixture-based Background/Foreground Segmentation method described by [201]. The position of the agents is detected by using a corner detection method on the resulting foreground frame: the head of the fish and lures has a very sharp corner. We use the Shi-Tomasi method [202]. The "Auto-Assign" control mode of the GUI can be selected to identify manually the positions of the robots. Afterwards, the tracking system updates the supposed positions of the robots by selecting the blob closest to the previous positions of the robots.

Our tracking system can currently only identify (*i.e.* attribute the correct ID to the detected agent) robots in real time (fish are detected, but not individually identified). The high-resolution videos are analysed off-line by the idTracker software [151] to identify the fish. This process is time-consuming and computationally intensive (using a 32-cores computer, idTracker takes 2 days to track and identify 10 fish in 1 hour high definition videos) but relatively reliable: no false positive, no propagation of identification errors, and fishes are identified correctly in 90% of time-steps on average.

A.5.3 Data analysis

For our off-line analysis (after the experiment), we tracked the positions of the agents by using the idTracker software [151] on our high-resolution videos (2040×2040 pixels in 15 FPS). This multi-tracking software is capable of identifying each agent, without the need of markings, throughout the videos, by extracting image features of each agent. This method avoids error propagation, typically seen in other kind of trackers, and successfully solves crossing, superposition and occlusion problems. However, idTracker is designed to work only in an off-line fashion, as its identification methodology involves the creation of a database of agents images. Using this software, we obtain the positions $P(x, y, t)$ of all agents at each time step $\Delta t = 1/15$ s for all experiments, and build the trajectories of each agent. For each video, we manually select which trajectory corresponds to the robot (used to compare the traces of the robot and those of the fish). The idTracker software detected and identified agents (represented by 250-400 pixels) on our videos with an accuracy of 99% on average. We also verified empirically the validity of idTracker identification, and never saw any mismatch on our data.

For each frame of each video, we identified the sub-groups of agents by using the clustering algorithm described in Sec. B.1.1. We also identified which agents occupied each room at all time-steps. Then, we computed several metrics characterising the collective dynamics of the agents, including: the probability of presence in the arena, the mean occupation of each room, the inter-individual distance between individuals of a sub-group, the fraction of time a random fish (or the robot) is in a group with another agent, the distribution of sub-groups sizes, and the distribution of instantaneous linear speed.

The instantaneous linear speed was computed as the distance between $P(x, y, t - 2)$ and $P(x, y, t + 2)$ divided by 4 time steps. The distributions of speed were computed only for parts of the trajectory during which the fish were not in freezing behaviour (*i.e.* immobile). This corresponds to a spontaneous speed higher than 1 mms^{-1} .

We measure the statistical difference between the distributions of results from the different experiments by using the Two-sample Kolmogorov-Smirnov test on 10 random samplings of 1000 points of the distributions; if the resulting p -values are all below 5%, the distributions are considered as statistically different. As we have a large number of points in our experimental distributions, we performed the statistical difference tests on random samplings of these distributions to prevent the resulting p -values to always have a value of 0.

A.6 Acknowledgments

The FishBot robots were designed and built by our collaborators of the EPFL (mostly Frank Bonnet, supervised by Francesco Mondada). The experimental set-up was designed and built by a joint effort of our team at the Université Paris Diderot (Bertrand Collignon, Axel Séguret, Yohann Chemtob, José Halloy, and myself) and of our collaborators at the EPFL (Frank Bonnet, Francesco Mondada). The CATS software was made by a collaboration between myself and the EPFL team (Alexey Gribovskiy, Frank Bonnet, Marcello Elias de Oliveira, Francesco Mondada). The experimental arena was designed and 3D-printed by the efforts of Bertrand Collignon, Axel Séguret, Frank Bonnet and Yohann Chemtob.

Appendix B

Supplementary Information

B.1 Social integration of a biomimetic robotic fish into zebrafish groups

B.1.1 Group clustering

As the number of clusters (sub-groups) is not known in advance, and varies from frame to frame, we do not use classical clustering algorithms (like K-Means) [203], where the number of clusters is a required parameter. Instead, we use a locality-based clustering algorithm: an individual is part of a sub-group if and only if it is within a maximal distance of $d_c = 0.30$ m of another individual of this sub-group (the parameter d_c is the cutoff distance). As we only have few points (our experiments are limited to five agents), our algorithm performs a linear search of all neighbours and iteratively groups points with their neighbours within a maximal distance of d_c . To select the parameter value $d_c = 0.30$ m, we tested several values of d_c (from $d_c = 0.10$ m to $d_c = 0.50$ m) and selected the value that maximized the scores of social integration (*cf.* Table IV).

Our clustering algorithm only uses spatial information, as it is sufficient to provide relevant results. We also tried more complex algorithms, taking into account more features, like the alignment of the agents and their linear speed and acceleration, but they provided similar results.

Figure B.1 presents examples of sub-groups configurations detected by our clustering algorithm in several representative frames. Clustering is more informative than room occupation (see Fig. B.1).

B.1.2 Population fraction in the three set-up zones

We compute the mean population fraction (termed the *mean occupation*) in the three set-up zones (Fig. B.2) over all trial runs. In all experiments, the agents are more frequently present in the two square rooms than in the corridor. The two square rooms have similar occupation, in all experiments (small biases are present in the C3 and C4


```

distMat = generateInterindividualDistanceMatrix();
sortedMatIndexes = indexes of sorted distMat matrix values;
nbClusters = 1;
cluster = matrix containing unset values;
while True do
    quit = True;
    for all indexes (origin, dest) in sortedMatIndexes do
        if cluster[origin] is set and cluster[dest] is not set and distMat[origin, dest]
            < distanceThreshold then
            | cluster[dest] = cluster[origin];
            | quit = False;
        else if cluster[dest] is set and cluster[origin] is not set and distMat[origin,
            dest] < distanceThreshold then
            | cluster[origin] = cluster[dest];
            | quit = False;
        end
    if quit == True and cluster still has unset values then
        | set first unset value of cluster to nbClusters;
        | nbClusters += 1;
        | quit = False;
    if quit == True then
        | break;
    end
end

```

Algorithm 1: Spatial Locality Clustering algorithm

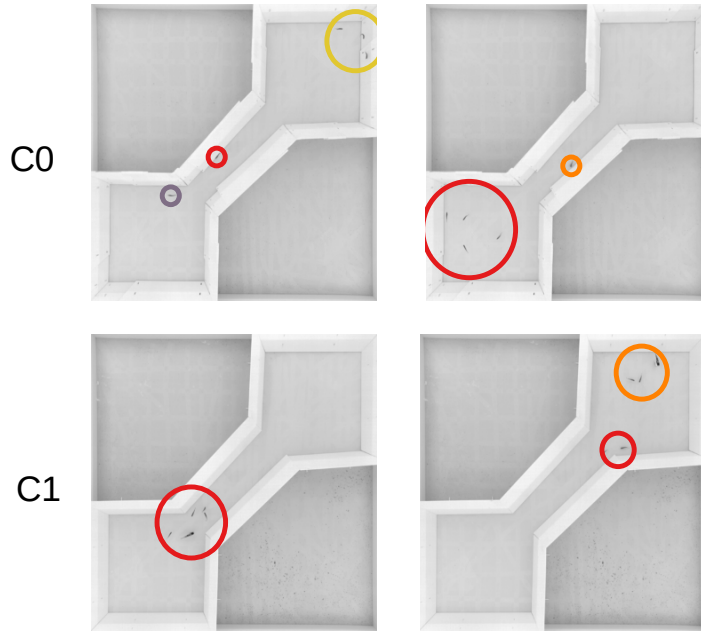


Figure B.1 – Examples of sub-groups configurations detected by our clustering algorithm. The first row corresponds to experiments with five fish and no robot (C0), and the second row corresponds to experiments with four fish and a robot driven by our biomimetic model (C1). Our clustering algorithm is locality-based: to be part of a sub-group, an individual must be at maximal distance d_c of at least one another member of this sub-group. The cutoff distance has a value of $d_c = 0.30$ m.

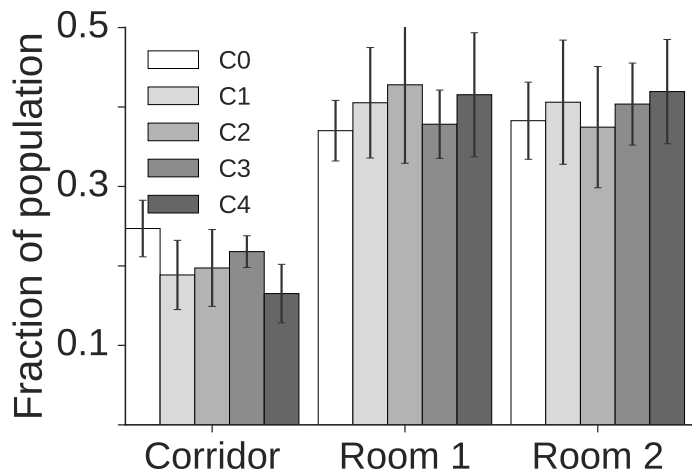


Figure B.2 – Mean occupation of the rooms for all experiments. Each experiment is reiterated 10 times. All distributions differ significantly from each other (Two-sample Kolmogorov-Smirnov test, with p -values < 0.05).

experiments, but may be attributed to experimental fluctuations). In experiments with a robot (C1,C2,C3,C4), the agents tend to occupy the square rooms more frequently than in experiment C0. This is less the case with experiment C2 (with a robot driven by a random walk trajectory model). Indeed, the BM model simplifies the behaviour of the fish in the corridor by only passing through from one room to the other, while fish can sometimes rest in the corridor, or even perform *U-Turns* and return back to the room they occupied before.

B.1.3 Presence density in the set-up

We present the mean probability of presence of agents in Fig. B.3. We separate the cases where individuals are alone (sub-groups of one individual) and where they are in a group because both the fish and the robot behave differently when they are in a group compared to when they are alone. When alone, without any social stimuli or attraction, the fish tend to exhibit a more exploratory behaviour, and pass more frequently through the corridor. This is reproduced adequately by the robot. The fish tend to follow the wall, either alone or in a group. However, it is still difficult for our robot to be too close to the walls (because it would greatly increase the probability of a collision with the walls). Still, we can observe that the agents (presumably not just the fish) follow also the walls in the C1 experiment, but at a larger distance than in the C0 experiment. This can be explained by the attraction of the robot to the fish, which influence the robot to follow a fish, that, in turn, can follow walls. The same dynamics can be observed in experiment C4; it is not a surprising result, as the robot in C4 moves as in C1. On the other hand, C2 and C3 experiments show that individuals (and thus the robot) have a higher propensity to follow the walls.

B.1.4 Distributions of linear speed

We computed the distribution of instantaneous linear speeds of the agents in the rooms (Fig. B.4) and in the corridor (Fig. B.5). In the C0 reference experiment, the fish have a median speed around 8.2cm.s^{-1} in the rooms and 10.7cm.s^{-1} in the corridor. This is coherent with the literature on the subject. Indeed, fish tend to pass through the corridor in fast motion, with a reduced interest in exploring their immediate environment. Fish stop only for a short duration, both in the rooms and in the corridor (*cf.* first bins of speed distribution of Fig. B.4 and Fig. B.5). In the C1 experiment, the medians of speed distributions are similar to the C0 experiment in the rooms (around 7.9cm.s^{-1}), but different in the corridor (9.4cm.s^{-1}). This can be explained by the small number of collisions between the robot and the walls: in case of collision, the robot has to slow down momentarily to reposition itself. These collisions are more frequent in the corridor than in the room (*cf.* first bin of the speed distribution of the C1 experiment in the corridor in Fig. B.5). Similar results are seen with C2 (medians of 8.6cm.s^{-1} in rooms and 10.3cm.s^{-1} in the corridor), C3 (medians of 9.4cm.s^{-1} in the rooms and 10.0cm.s^{-1} in the corridor) and C4 (medians of 8.0cm.s^{-1} in the rooms and 9.8cm.s^{-1} in the corridor) experiments.

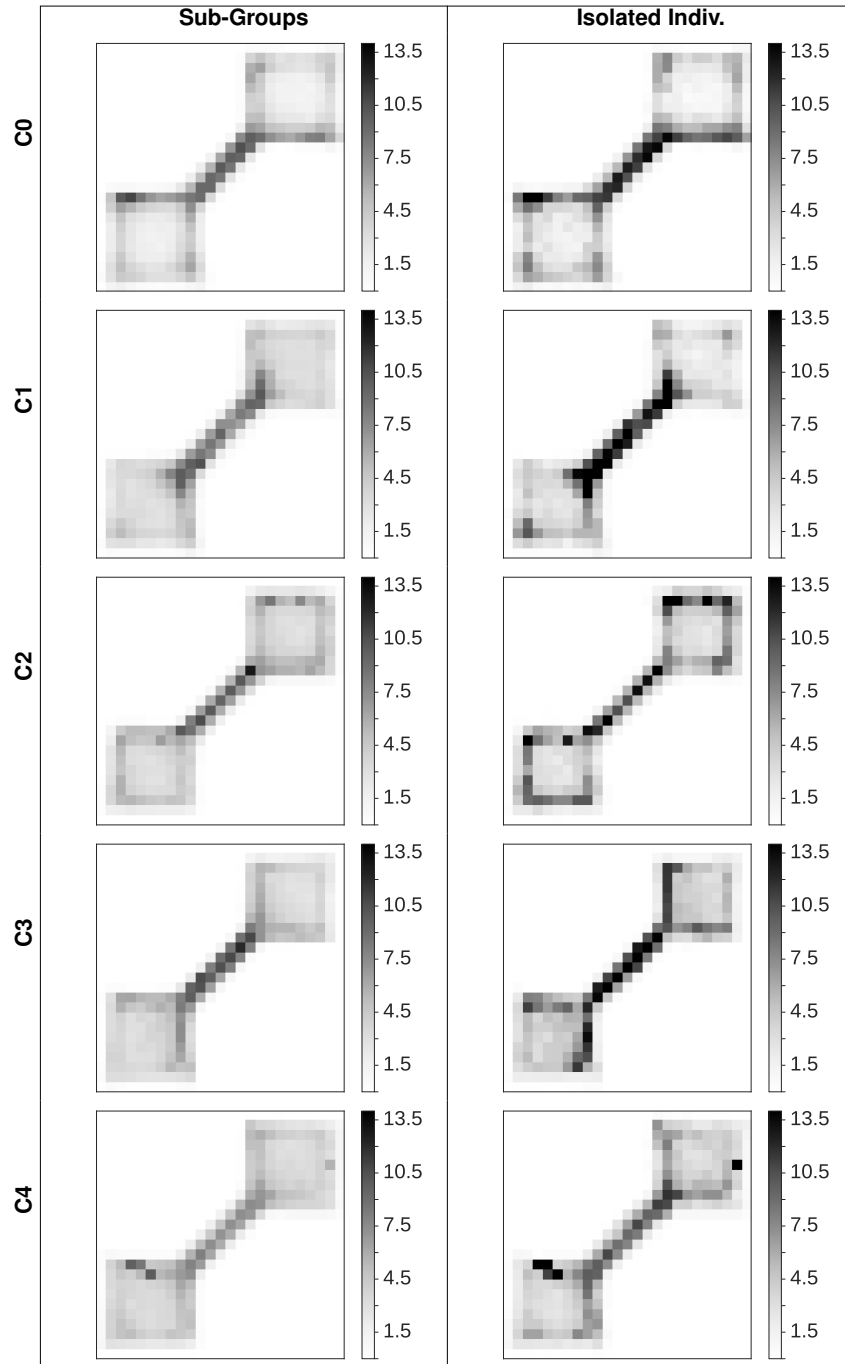


Figure B.3 – Mean probability of presence for all experiments. Results are obtained in 30 minutes experiments using groups of AB strain zebrafish. Each experiment is reiterated 10 times.

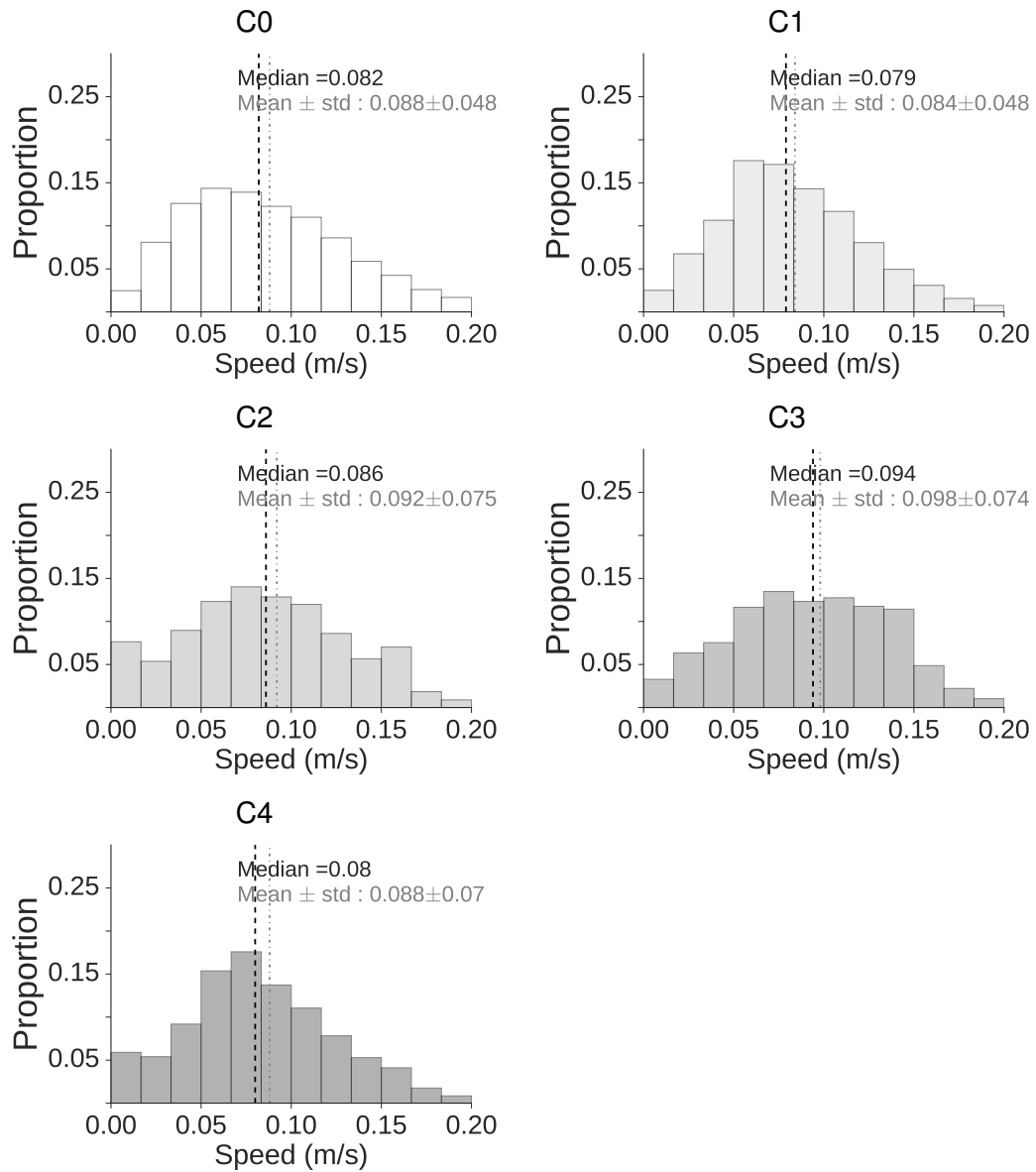


Figure B.4 – *Distribution of linear speed of agents in the rooms, for all experiments. Results are obtained in 30 minutes experiments using groups of AB strain zebrafish. Each experiment is reiterated 10 times. The distributions differ significantly (Two-sample Kolmogorov–Smirnov test, with p -values < 0.05).*

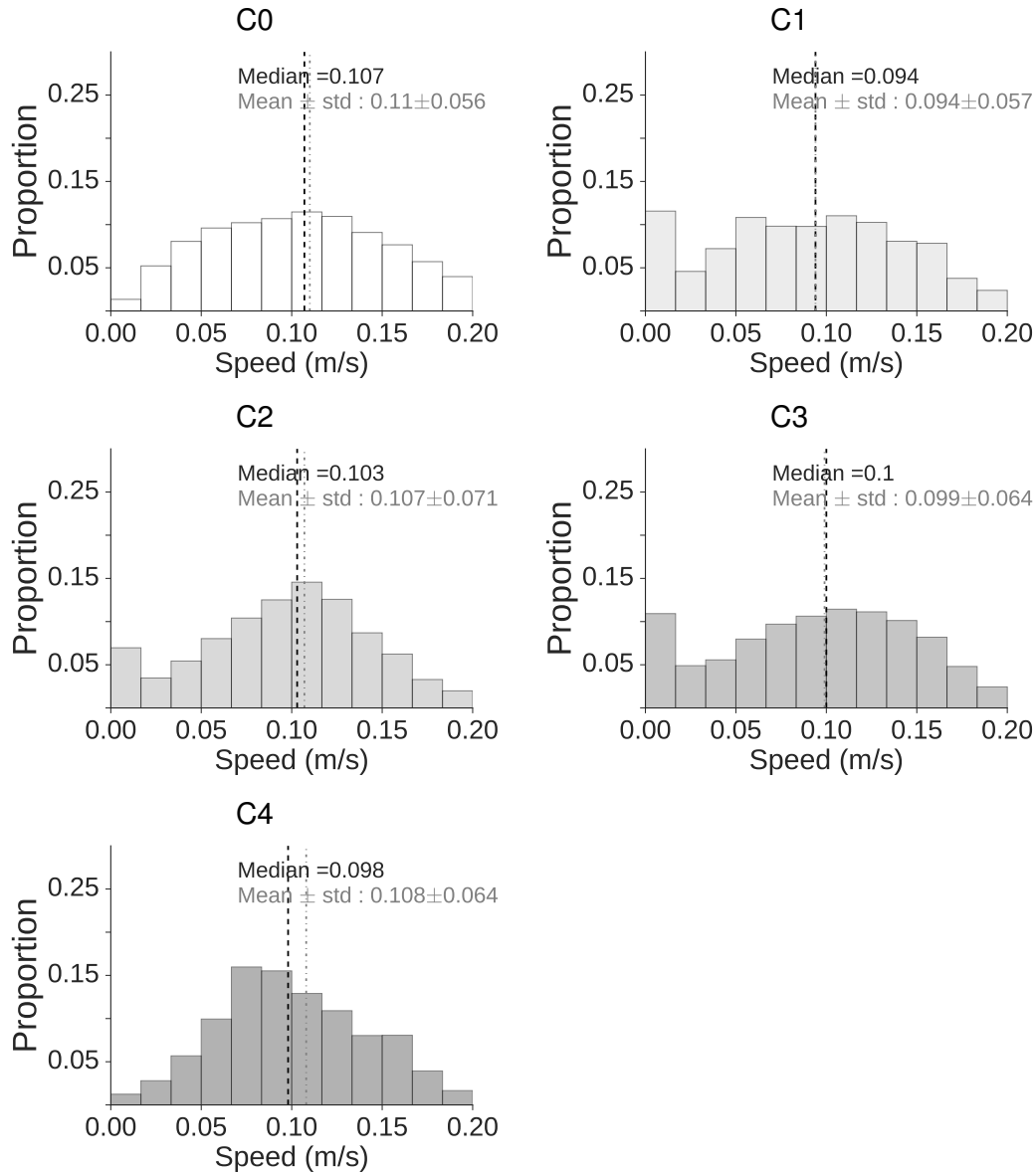


Figure B.5 – Distribution of linear speed of agents in the corridor, for all experiments. Results are obtained in 30 minutes experiments using groups of AB strain zebrafish. Each experiment is reiterated 10 times. The distributions differ significantly (Two-sample Kolmogorov–Smirnov test, with p -values < 0.05).

B.2 Automated optimization of multi-level models of collective behaviour in a mixed society of animals and robots

B.2.1 Simulations

Results from the MC and Hybrid models are obtained from simulations of 28800 time steps. The set-up is as described in [27, 1] (*cf* Fig. 5.2): a circular arena (diameter 1m) containing two identical shelters (diameter 150mm). For all models, only populations of 50 individuals are considered (similar results are observed with populations of 16 and 100).

B.2.2 Mean Field model resolution

The Mean Field model [1] used in this article is defined as follows:

$$\frac{dx_i}{dt} = x_e \mu_i \left(1 - \frac{x_i + \omega r_i}{S_i} \right) - x_i \frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n} \quad (\text{B.1})$$

$$\frac{dr_i}{dt} = r_e \mu_{ri} \left(1 - \frac{x_i + \omega r_i}{S_i} \right) - r_i \frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^{n_r}} \quad (\text{B.2})$$

$$C = x_e + x_1 + x_2, \quad R = r_e + r_1 + r_2, \quad M = R + C \quad (\text{B.3})$$

Results are obtained by solving Eq. B.1 and Eq. B.2 using the Gillespie method [81]. The Gillespie method allows experimental fluctuations to be taken into account. The Gillespie algorithm generates a birth-and-death stochastic process, described by the following master equation:

$$\begin{aligned} \frac{d}{dt} P(x_1, x_2, r_1, r_2, t) = & + W_1(x_1) P(x_1 - 1, x_2, r_1, r_2, t) - W_1(x_1) P(x_1, x_2, r_1, r_2, t) \\ & + W_2(x_1 + 1) P(x_1 + 1, x_2, r_1, r_2, t) - W_2(x_1) P(x_1, x_2, r_1, r_2, t) \\ & + W_3(x_2) P(x_1, x_2 - 1, r_1, r_2, t) - W_3(x_2) P(x_1, x_2, r_1, r_2, t) \\ & + W_4(x_2 + 1) P(x_1, x_2 + 1, r_1, r_2, t) - W_4(x_2) P(x_1, x_2, r_1, r_2, t) \\ & + W_5(r_1) P(x_1, x_2, r_1 - 1, r_2, t) - W_5(r_1) P(x_1, x_2, r_1, r_2, t) \\ & + W_6(r_1 + 1) P(x_1, x_2, r_1 + 1, r_2, t) - W_6(r_1) P(x_1, x_2, r_1, r_2, t) \\ & + W_7(r_2) P(x_1, x_2, r_1, r_2 - 1, t) - W_7(r_2) P(x_1, x_2, r_1, r_2, t) \\ & + W_8(r_2 + 1) P(x_1, x_2, r_1, r_2 + 1, t) - W_8(r_2) P(x_1, x_2, r_1, r_2, t) \end{aligned} \quad (\text{B.4})$$

$$W_1 = x_e \mu_1 \left(1 - \frac{x_1 + \omega r_1}{S_1} \right) \quad W_2 = x_1 \frac{\theta_1}{1 + \rho \frac{x_1 + \beta r_1}{S_1}^n} \quad (\text{B.5})$$

$$W_3 = x_e \mu_2 \left(1 - \frac{x_2 + \omega r_2}{S_2} \right) \quad W_4 = x_2 \frac{\theta_2}{1 + \rho \frac{x_2 + \beta r_2}{S_2}^n} \quad (\text{B.6})$$

$$W_5 = r_e \mu_{r1} \left(1 - \frac{x_1 + \omega r_1}{S_1} \right) \quad W_6 = r_1 \frac{\theta_{r1}}{1 + \rho_r \frac{\gamma x_1 + \delta r_1}{S_1}^{n_r}} \quad (\text{B.7})$$

$$W_7 = r_e \mu_{r2} \left(1 - \frac{x_2 + \omega r_2}{S_2} \right) \quad W_8 = r_2 \frac{\theta_{r2}}{1 + \rho_r \frac{\gamma x_2 + \delta r_2}{S_2}^{n_r}} \quad (\text{B.8})$$

This equation gives the time evolution of probability $\frac{d}{dt}P(x_1, x_2, r_1, r_2, t)$ of finding x_e animals outside the shelters, r_e robots outside the shelters, x_1 animals under the first shelter, r_1 robots under the first shelter, x_2 animals under the second shelter and r_2 robots under the second shelter. As this probability depends only on the previous state of the system, the process is Markovian. The number of agents is taken into account by the Gillespie algorithm, as described in Eq. B.3.

Only populations of 50 individuals are considered. **Similar results are observed with populations of 16 and 100** (results not shown).

Halloy *et al.* [1] only consider cases with two populations and two sites. The model can be generalized to P sites and N populations:

$$\frac{dx_{j,k}}{dt} = x_e \mu_{j,k} \left(1 - \frac{\nu \cdot x_k^\top}{S_k} \right) - x_{j,k} \frac{\theta_{j,k}}{1 + \rho_j \left(\frac{\alpha_j \cdot x_k^\top}{S_j} \right)^{n_j}} \quad (\text{B.9})$$

for $j = 1, \dots, n \quad k = 1, \dots, p$

$$M = x_e + \sum_j^N \sum_k^P x_{j,k} \quad (\text{B.10})$$

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