Chapter Fifteen

A General Methodology for the Control of Mixed Natural-Artificial Societies

Francesco Mondada, José Halloy, Alcherio Martinoli, Nikolaus Correll,
Alexey Gribovskiy, Grégory Sempo, Roland Siegwart, Jean-Louis Deneubourg

15.1 Introduction

The use of lures for interacting with animals has a long history, for instance, the scarecrow in agriculture or decoys for hunting. These lures are often the result of a tradition, evolved in a trial-and-error fashion, rather than of a systematical study of animal behavior. Moreover, classically lures do not interact with each other and do not have any adaptive capabilities.

At the individual level, behavioral sciences have shown [Tinbergen (1951, 1953)] that animal communication could be based on rather simple signals, and that it is possible to interact with animals not only by mimicking their behavior, but also by making specifically designed artifacts that generate and exploit only some signals that are relevant for social behavior. In most existing examples, the lure sends a relevant signal to the animal that reacts to it; then the interaction stops. One way to sustain interactions is to robotize the lure and to teleoperate it. Many examples of recent lures are build along that methodology.

Here we discuss another approach that is based on the design of a lure capable of sending relevant cues to the animal, of sensing the animal response and of adapting its behavior to it. Thus, this design framework implies closing the loop of interaction between the animal and the robot. Moreover, we focus on the social level, i.e., our methodology is designed for animals living in groups and presenting some form of a social structure. Models based on self-organization applied to animal societies shows that simple, but numerous, interactions taking place between individuals may ensure complex performances at the level of the group and produce collective capabilities [Camazine *et al.* (2001)]. The robotic design that we would like to present here allows numerous interactions among individuals of a mixed society composed of robots and animals.

The exploitation of these properties allows the development of robots that interact with animals and can participate in their social activity thus forming a mixed robot-animal society, which is coherent at the collective level. Based on an experience made during the European project Leurre[1] and the Swiss National Science Foundation project "Mixed Society of Robots and Vertebrates"[2] (later will be referenced to as the "Leurre-chickens" project) those aim at developing and investigating artificial lures for cockroaches, sheep, and chickens, we have developed a methodology for the design of mixed societies that relies in part on self-organization phenomenon. We will illustrate our methodology with two examples of mixed societies: cockroaches and small insect-like "InsBot" robots, and chickens and "PoulBot" robots, and specify the steps necessary for designing artificially induced collective responses based on behavioral animal studies.

15.1.1 *Motivation*

The scientific field of *animal-machine interaction* at the collective level has been barely explored. Only a few research projects that follow a formal methodology and involve quantitative modeling have been carried out. Therefore both Leurre projects represent a progress beyond the current state-of-the-art of the interaction between living and artificial agents [Halloy *et al.* (2007); Gribovskiy *et al.* (2010)]. This chapter focuses on the information and tasks processing in living and artificial populations and cooperation between them. By combining advantages of living systems and robotic technology, our approach contrasts with bio-inspired projects, and demonstrates new forms of animal-machine interaction.

We expect our methodology to have a major impact on the design of this new type of intelligent systems, having many perspectives for applications. Recent progress in bioengineering shows that more and more living systems will be used for various types of production, ranging from comestible goods to supply for the chemical industry, or for landscape conservation (e.g., sheep as natural lawn mowers).

In animal production, breeding, development, reproduction and well-being of each animal are critically important for a profitable enterprise [Munack (2002); Nääs (2002)]. Therefore, it is not surprising that information technology (IT) in Agriculture, Food and the Environment and the precision agriculture are growing fields. Current technologies allow producers to monitor individual animal metrics such as feed consumption, milk production or heart rate without any human intervention. This involves not only data collection, but also data analysis. However, the area related to behavior, or the coordination and the control of groups, the subject of Leurre, is still little explored. In agriculture, the possibility to control some parameters of animal behavior could bring a significant improvement in ecologic breeding. Social control of chicken societies could solve some problems, which require today the use of antibiotic or other methods less respectful for the animal and the consumer. Optimal management of such systems could be achieved in synergy

[1] Started on September 1, 2002, finished on August 31, 2005, was sponsored by the Future and Emerging Technologies program of the European Community (IST-2001-35506)

[2] Started on November 1, 2006, Swiss National Science Foundation grants 112150 and 122148

with IT.

Although this project shows similarities with the field of *human-robot interaction*, its scientific challenges are completely different: in Leurre, emphasis is on *collective* intelligence (and not only the individual one), and on designing cooperation based on non-symbolic communication (e.g., pheromones). Therefore the problems that must be solved and a large part of the solution are unconventional, and will bring new development fields for IT.

15.1.2 *State of the Art*

Research in behavioral biology and ethology has shown that interaction with animals can be realized using rather simple signals that are socially relevant for the animal. More concretely, interacting with an animal can be achieved by specially designed and often simple artifacts [De Schutter *et al.* (2001)]. Lures and decoys are common man-made examples of such tools.

Nowadays, there is a growing number of research projects using robotic devices in behavioral studies [Patricelli *et al.* (2002, 2006); Taylor *et al.* (2008); Narins *et al.* (2005); Goth and Evans (2004)], however, as a rule, once the animal has performed the selected behavior, the interaction stops because the lure can not reply to the animal. The challenge is now to build artificial systems that not only stimulate but respond and adapt to the animal behavior. Moreover, for social animals, such systems should be able to deal with groups of animals and not only be limited to one-robot-to-one-animal interactions. Very few research projects deal with such type of scientific questions. The W-M6 rat-like robot [Ishii *et al.* (2006)] attempts to teach a rat to push a lever to access a food source. In this case the animal-robot interaction is one-to-one and is based on imitation and operant conditioning. One of the first example of collective behavior is the Robot Sheepdog Project that was concerned with a mobile robot designed to gather a flock of ducks and to lead them safely to a specified position [Vaughan *et al.* (2000)]. In this project, the robot was endowed with a limited on-board intelligence and relied on the external vision system. The aim was to lead a flock of ducks by an autonomous system inspired by sheepdog behavior. This project included a model for duck flocking in order to be able to design and predict the global behavior. It showed how a robotic system can use animal group behavior to obtain a possibly useful task. Another example is the use of smart collars to study and potentially control the herding behavior of cattle [Butler *et al.* (2006); Correll *et al.* (2008)]. Cows are equipped with collars containing an embedded computer with wireless communication capabilities, a GPS system for positioning the animals, and some devices sending stimuli to the cow. These systems can be used to study different animal behavior such as collective grazing in large open fields. The application considered is building virtual fencing systems based on the interactions between the animals and the network of smart collars formed by the group. This study also exploits some social behavior of cows.

15.2 The Concept of 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. The individual capabilities of the artificial agents and their interactions with the living ones may be very diverse: each category of agents, living or artificial, may react to signals or perform tasks that the other category does not detect or perform; the artificial agents may increase the range of interactions between natural agents or the natural agent may induce new interactions between artificial ones.

The artificial agents interacting with the living units may be autonomous mobile robots mixed and moving with the living units, *mobile nodes*, distributed immobile sensors-actuators, *static nodes*, or sensors-actuators mounted on the living agents and conferring them new capabilities, *mounted nodes*. These three concepts are illustrated in Figure 15.1. and are described in detail below.

Mobile robotic nodes have the advantage to deeply penetrate the animal community and to have a very close interaction with the animals. The challenge in designing these robots is (i) to make them accepted by the animal society and (ii) to understand which parameters allow to control some social properties. The experimental demonstration that robots can be designed to be fully accepted in an animal society and cooperate with animals was the main challenge of the Leurre and Leurre-chickens projects. Such mixed societies are self-organized: while no agent (artificial or natural) is aware of the alternatives collective patterns, they reach together an "unconscious" decision resulting of their multiple interactions. Each robot and animal emits signals and has receptors. Basically, each agent obeys the simple rule which determines how it reacts as a function of the signals it receives from the other robots or animals. Its decision, position and movement thus affect the decision, position and movement of other members of the group, animals or robots.

In a general case, *static nodes* constitute a network of distributed immobile sensors-actuators capable of real-time monitoring of the environmental features and variables characterizing the collective behavior of the society as a whole. Dedicated algorithms are able to process the input information flow in an intelligent way and to govern the population of actuators and devices emitting adequate signals (e.g., sounds or pheromones) in order to modulate the activity of animals by modifying the physical environment (e.g., temperature, light, humidity, food availability, etc.) and by controlling the access of the individuals to different parts of the environment.

Mounted nodes are extensively used to monitor the animal activities; two classical examples are GPS and RFID tags. The challenge with mounted devices is to develop a system able to manage individuals interacting with each other and to govern the response of the artificial systems to environmental changes.

However, despite this diversity of these three approaches, the main character-

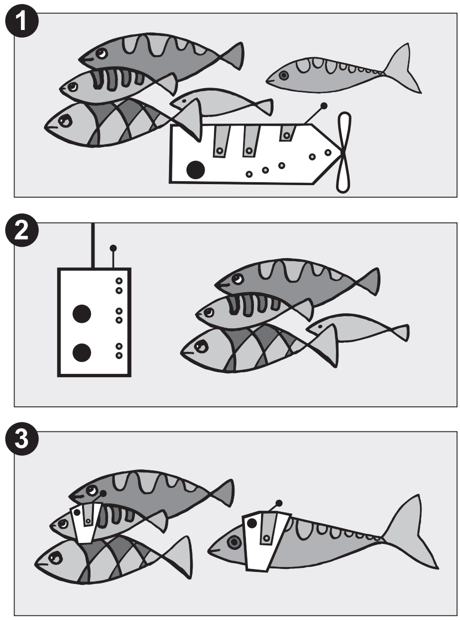


Figure 15.1. Abstract illustration of artificial mobile nodes (1), static nodes (2) and mounted nodes (3) interacting with animal societies

istic of mixed societies is that both animals and artificial agents are able to influence each other. In particular, the artificial agents must be able to use the natural communication channels of the animals (to emit signals and to respond to them) and/or to modify the environmental variables that influence the animal behavior. The technological challenges are to identify the physical input and output the artificial agents should provide to ensure an interaction with the animals and find an implementation for it.

Here we focus on a methodology to mix animals and specifically designed mobile robots that interact and communicate to form a coherent society based on the structure of the animal society. Our hypothesis is that in design of mixed societies, 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 an unique methodology could be developed, based on formal models.

15.3 Methodology Overview

Predicting the properties of complex systems, such as animal groups, which are comprised of multiple components with dynamic interactions is difficult. Observation from a naturalistic point of view is a very useful first step that provide a lot of intuitive elements about how a group works, but it is not sufficient for the creation of a useful society model. Testing the accuracy and completeness of a conjecture requires a further stage in the analysis: formulating a rigorous model which *embodies* hypotheses of how the group works. The mathematical equations and the corresponding computer simulations that compose this model enable one to predict the properties of complex systems, and thus provide a means of evaluating conjectures about a group internal machinery (see, for instance, [Amé *et al.* (2006)]). The starting point for the creation of the model is often given by information on global patterns arising at macroscopic level. The refinement of the model can be achieved by incrementally changing the level of model abstraction (from mathematical equations to realistic simulations) with a real system implementation as a ultimate validation.

The methodology described in the following sections is based on the formalization of the approach used in the Leurre and the Leurre-chickens projects for the design and control of mixed cockroach-robot and chick-robot societies. This methodology generalizes our experience and aims at outlining key invariants that can be applied to species other than those used in the Leurre projects.

The methodology is graphically formalized in Figure 15.2.. On the left side of this graph we can see the starting point of the process, the *animal society*, and the final result, the *modulated* animal-robot *mixed society*. To achieve this result, we suggest an iterative approach based on three main axes, which are graphically represented by three horizontal blocks: *behavioral animal study*, *robot design* and *society modulation*. The *behavioral animal study* analysis axis, going from left to right on the graph, includes extensive experimental studies involving the animal society (Boxes 1 and 2), and aims at contributing to the *multi-level formal society model*.

The resulting formal model of the animal society is a central concept in this methodology and is the starting point for two other synthesis axes: *robot design* and *society modulation*.

Every axis is divided into key processes, each of them is participating in local iterative loops and is thus generating feedback for other processes. These local loops are not strongly outlined in this graphical representation but play a key role in the whole process.

Two processes are common in the overall design methodology: development of *experimental tests and monitoring tools* (Box 1) and that of *modeling and simulation* tools (Box 4), in other words, both natural and man-made systems are tested, modeled, and monitored using the *same* tools.

In the following sections, we will present the main concepts of our methodology, starting with its core element, the multi-level formal model of the society taking into account the interactions among its members (Section 15.4). This model is generated by the study of the animal behavior (Section 15.5). The behavioral study consists of systematic experiments using appropriate monitoring tools (Section 15.5.1), as well as of the identification of key channels of communication between the animals (Section 15.5.2) and their formalization. These models provide an important input for the *robot design* process (Section 15.6) and allow to identify parameters that can be used to modulate the mixed society (Section 15.7).

15.4 The Formal Society Model: Analytical Models and Simulations

Formal model is a mathematical representation of the concept of interest and a basis of scientific rigorous investigation. Among formal models, an *analytical model* is

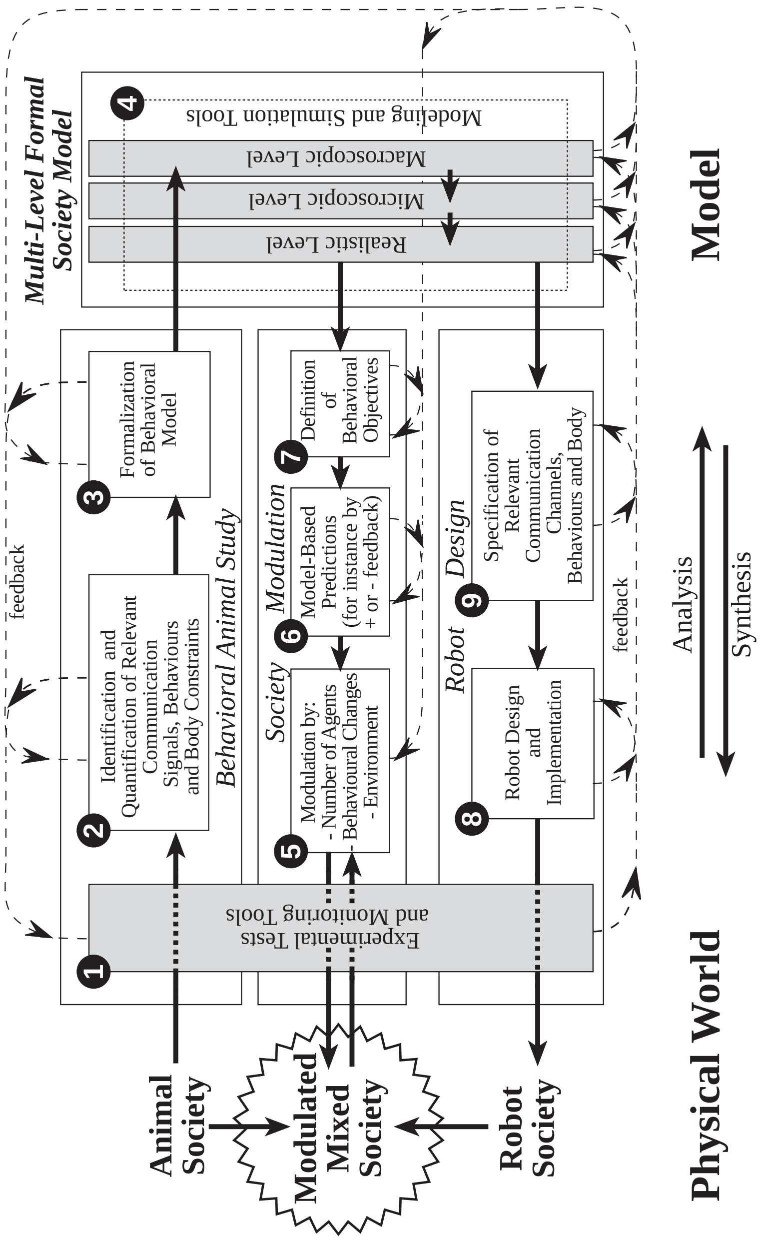


Figure 15.2. Graphical representation of the methodology

formed by explicit equations and may permit to find analytical or numerical solutions. A *simulation* corresponds to the case, where the solution is obtained by numerical experiments on the model rather than by an explicit solution algorithm.

Our formal society models are causal, i.e., they reflect cause-effect relationships and dynamical, i.e., they can describe the time-spread phenomena in a society. The effort to formalize a society model has three main goals. First, the model allows to understand the collective behavior mechanisms as it makes a link between the individual and collective capabilities. A lot of collective behavior can be explained by a certain level of self-organization that produces collective patterns.

The global patterns emerge naturally from the interactions between the individuals and their environment. Second, the model allows to understand the functionality of the collective patterns and their utility for the individuals and the group as a whole. In gregarious animals the collective pattern represents a function that serves for group benefits. One has to clearly understand a link between this collective function and the individual behavior and benefits. Third, the model allows analyzing the level of adaptability and optimality of the collective response. The collective functions that are produced by biological systems usually present an adaptive value and include a certain level of optimality. For mixed societies the optimality can be understood as improving the quality and reliability of the results desired by the designers.

Societies are non-linear dynamical systems with a large number of events corresponding to the actions of the individuals or their changes of behavior. Moreover, individual actions include an element of intrinsic randomness; at each time step each individual is characterized by a probability to change its state and/or to perform a task. Most of these probabilities depend on the activity of the other individuals as they are socially modulated (e.g. in the project Leurre case study, the probability that a cockroach leaves the shelter depends on the number of cockroaches under the shelter).

15.4.1 *Advantages of Mathematical Formalization*

Formal modeling is often considered as an unnecessary aesthetic or academic burden. However, besides the main goals stated above, formal modeling brings other advantages for mixed societies design. First of all, it allows the identification of structural network of interactions in terms of regulating feedback loops, and even a qualitative formal model of this type can be useful and presents a good level of predictability for a global view of the system. Modeling requires expressing and framing hypotheses in a rigorous manner. This also allows to find a domain of validity of the observed patterns that often are bounded in parameters space. Mathematical descriptions often encompass different level of complexity and give a valuable simplified and unified description of the system.

Last but not the least, formal modeling makes it possible to predict the behavior of the systems in a given framework and can then reduce the experimental cost. Those predictions also permit to explore the limits of the system in extreme cases that could be difficult to realize empirically.

Finally, models can have very different levels of refinement and can span between (i) a *qualitative* description of a mechanism that presents an analogy with observed patterns, where variables may not be explicit or experimentally clearly defined and parameters are not measured, and (ii) *quantitative* models, where solutions are compared with variables measured experimentally and parameters have been experimentally calibrated.

Quantitative modeling implies quantitative biology and is of particular importance for the design of the experimental set-up and the type of data gathered. At the level of the control and monitoring of biological systems, models are important tools: they help identifying the environmental conditions modulating the behavior of the units. In the case of robotic systems or mixed societies, they help to make the bridge between animal studies and hardware engineering and provide an efficient common language that can be used by engineers as a specification for the design of the artificial agents and their behaviors. For example, in the Leurre project the formal cockroach model was translated in behavioral software modules [Asadpour *et al.* (2006)].

15.4.2 *Multi-level Modeling*

Given a distributed system with its practically infinite parameter space, ranging from individual physiology, controller and body morphology to features of the environment that influence the society, we need to identify key parameters that allow to describe a particular metric of interest with a sufficient accuracy. Following the principle of parsimony (Occam's razor), the amount of detail at different model abstraction levels should be gradually lowered, allowing a significant decrease of the computation and simulation time at each abstraction step, and increasing generalization while producing forecast according to the same metric(s) at all levels. Moreover, an important characteristic of a good model is to be based on the variables and parameters that can be experimentally measured. Models with a large number of parameters that are not well quantified are not useful for studying the properties of a system. Of course, depending on the abstraction level, the number of modeling parameters and variable varies, the lower levels being richer from this perspective than the higher ones. In addition to the common metric, models at different levels might share a subset of design parameters of particular interest (e.g., the number of individual in the system or a key control parameter). Dynamical models of multi-unit systems have their roots in physics and chemistry. However, nowadays they are classical tools in many other fields such as biology, economy, traffic engineering, etc. These models are frequently categorized in two large groups: *macroscopic* and *microscopic*. There is a vast literature, mainly in physics, devoted to the tools and methods of both categories and the relations between them.

In a macroscopic description, the highest abstraction level, we use a number of collective variables X_i to define the instantaneous state of the society [Camazine *et al.* (2001)]. The variables can correspond to the number of individuals demonstrating the same behavior, to a concentration of chemical signals, etc. The dynamics of the society is captured by a set of rate equations: *ordinary differential* or *partial differential equations* (or *difference equations*). The rate depends on the type of process taking place in the system:

$$\frac{\partial X_i}{\partial t} = F_i(X_j, r, t) \qquad \text{or} \qquad X_i(t+1) = X_i(t) + F_i(X_j, r, t), \tag{15.1}$$

here X_i is the mean population exhibiting behavior i.

Note that a macroscopic approach predicts the most probable dynamical states of the system over a large number of experiments. The macroscopic models have

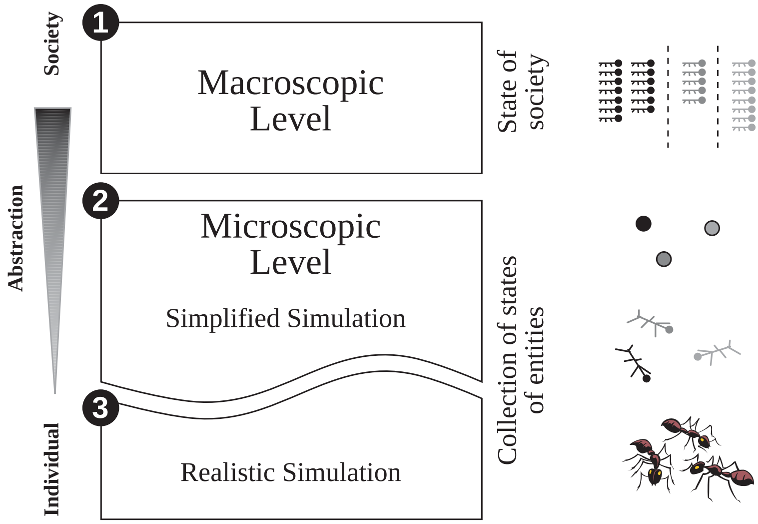


Figure 15.3. Levels of abstraction of the multi-level model

in common that the experiment is governed by a series of stochastic events modifying the different population. A stochastic description of the society can be done by using *master equations* to take into account the fluctuation characterizing such systems. A master equation is a phenomenological first-order differential equation describing the time-evolution of the probability of a system to occupy each of possible states:

$$\frac{dP_k}{dt} = \sum_{l=1}^{N} Q_{lk} P_l - \sum_{l=1}^{N} Q_{kl} P_k, \tag{15.2}$$

where N is the number of states, P_k is the probability for the system to be in the state k, while Q_{lk} is the matrix of transition-rate values. Each state corresponds to X_i individuals exhibiting behavior i. The transition probabilities between states are related to the individual probabilities of behavioral changes and therefore are functions of the number of individuals in the different behavior.

In *agent-based modeling* (ABM) or *microscopic modeling*, a system is modeled as a collection of decision-making autonomous entities. For each entity, at each time step, a set of variables characterizes each individual (its position, speed, physiological variables, etc.). An agent-based model is a set of differential equations, each describing the dynamics of one agent [Bonabeau (2002)]; by solving these equations we obtain various variables configurations. The equations of motion for a body system interacting through a particular potential function is an example of deterministic model:

$$m\frac{d^2x}{dt^2} = -\nabla(V(x(t)). \tag{15.3}$$

These equations can also be probabilistic: the individual behavior can be described by a *finite state automaton* (FSA, or *finite state machine*), whose transitions occur probabilistically. The study of analytical models (microscopic or macroscopic) often requires numerical methods. Difference and differential equations can be solved or analyzed by numeric integration (see Matlab, Mathematica, or other tools). However due to the complexity of the agents and the difficulties to write analytical models, the numerical simulations or numerical experiments are often used in ABM. They can also have different levels of complications.

At a highest level, we consider multi-agent simulations, where some properties of an individual unit are intentionally replaced by simplified versions (e.g., a kinematic point model) or by average quantities in space and time domain. For instance, the agent speed together with its sensorial range and the morphology of an obstacle can be abstracted by a constant probability of encountering this obstacle at every time step of the simulation. At the microscopic level the state of an individual agent and the probability to change its state are represented by a *probabilistic finite state machine* (PFSM).

At the lowest abstraction level we consider realistic, embodied simulation, which faithfully reproduces body morphology, as well as physical constraints of the units and the environment in a 3D multi-unit simulator. For example, in the Leurre projects we have chosen the Webots simulator [Michel (2004)] (Figures 15.4.(a),15.4.(b)), that allows capturing intra-unit details such as body morphology, sensor and actuator placement, spatial characteristics (e.g., sensor aperture, range), and noise (e.g., amplitude, distribution); for fast simulations the Enki 2D simulator [Magnenat *et al.* (2007)] can be used either as a Webots plug-in or as a standalone application (Figure 15.4.(c)). In case of completely artificial systems, results obtained with Webots can be considered to come very close to those observed on a real system [Martinoli *et al.* (2004); Michel (2004)]. Webots is commercially available from Cyberbotics S.A.; an alternative is the Player/Gazebo package [Koenig and Howard (2004)] that is freely available. We notice that the boundary between microscopic and realistic levels of modeling is fuzzy. As a rule of thumb, we consider realistic models to take into account the embodiment details of the agent or, in case of biological units, their physiology.

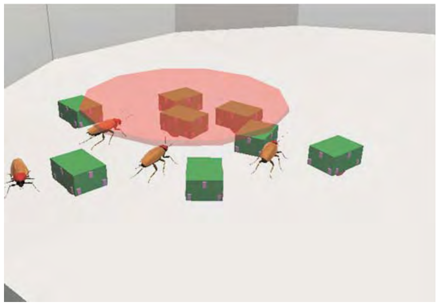
15.4.3 *Relation and Synergy Between the Levels of Description*

Different approaches to modeling (macroscopic vs microscopic; analytical vs simulation) are strongly linked and complementary. They provide tools to numerically solve formal models and allow creating, refining and verification of models generated along the axis of *behavioral animal study*; in addition they deliver data necessary for the *robot design* process and for the predictions used for the *society modulation*.

15.5 Behavioral Animal Studies

Our goal is to understand how behavioral patterns arise from actions and interactions of the members of an animal group, and, more generally, how phenomena at one level of biological organization emerges from the properties of lower-level units. Once its done, we will be able to design artificial agents that can be integrated in the biological system to become a part of a mixed society.

(a) Realistic (sensor and actuator based) simulation of aggregation and collective choice in a swarm of cockroaches (Webots simulator)



(b) Simulated mixed society comprising InsBots and cockroaches (Webots simulator)

(c) Chick-PoulBot mixed group in the Enki simulator

Figure 15.4. Simulation of mixed societies of animals and robots

As shown in Figure 15.5., our approach is based on a blend of experimental and modeling studies, which characterizes the group-level pattern in detail and gives a clear picture of the basic phenomenon to be explained. The first stage is to gather a large body of observations and experimental facts about the system including individual capabilities, the nature of interactions between the individuals and the global patterns that are present at the collective level. At the same level one needs to determine the pathways of information flowing among the subunits and their behavioral rules of thumb.

Although already this stage yields strong suggestions about how an animal group works, testing the accuracy and completeness of the understanding requires a further analysis stage: formulating a rigorous model which embodies one's current knowledge about the system. We take a bottom-up approach to build a model, using empirical findings to shape it. This requires translating a verbal understanding about the interactions among the group members into a mathematical form such as a simulation or a set of equations. Here we focus on the model as a mathematical description of the system. The mathematical description has to be understood in a broad sense, as it can encompass deterministic or stochastic equations and stochastic agent based computer simulations. We mainly use the framework of non-linear dynamical systems and in a broader but fuzzier sense complexity sci-

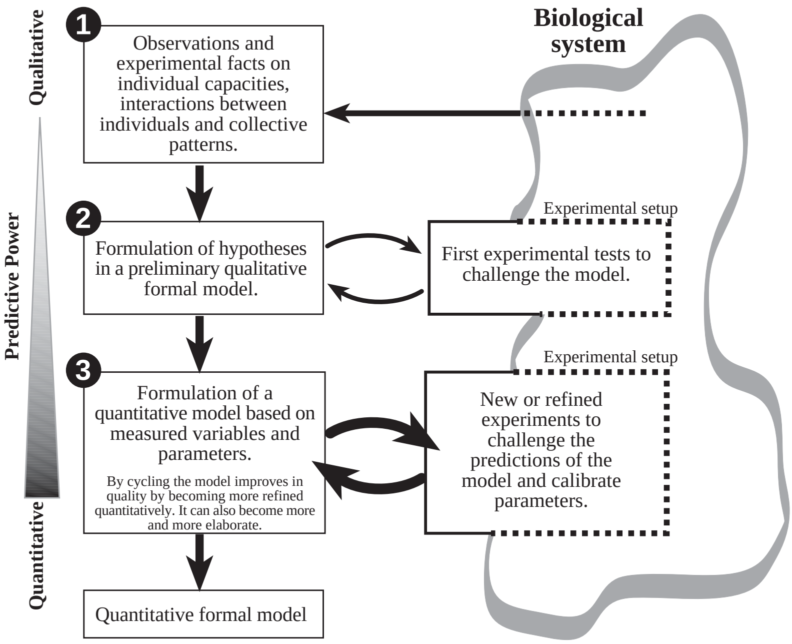


Figure 15.5. Three main stages of building a quantitative behavioral model. Stage 1 implies gathering information of what is known about the considered biological system. Stage 2 could be skipped; it is used to build the first experimental studies and qualitative formal model. Stage 3 is the main and 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 that the final destination that is the model itself, as it ensures a deep understanding of the biological system considered

ence. This exercise is itself useful, since it adds a rigor to the often loosely defined initial hypotheses of the mechanism.

However, the principal goal of modeling is to check whether the set of processes identified through empirical analysis, interacting as supposed, do indeed produces the actual performance of the intact group. Another important aim of the model is to have a strong predictive power that will be used in designing the artificial agents and will allow forecasting the mixed society global behavior in given conditions. To achieve these goals we then proceed to the second and the third stages that eventually produce a quantitative formal model (see Figure 15.5.). The second stage aims at formulating a qualitative formal model that will be rapidly tested experimentally. This stage is not necessary done as one can have enough information to start immediately the third stage that is the classical working loop between modeling and experiments, where after each cycle the accuracy and predictive power of the model increase.

Such studies are seldom done, because they are time consuming and costly, moreover they require to address engineering and technological challenges for data acquisition and analysis and environment control, which have only recently become available.

15.5.1 *Experimental Tests*

The experimental tests on animals are often based on collective choices made by the animal society in patchy environments often found in natural conditions. Classically, two types of choices can be investigated:

Choices between identical options: groups of animals are proposed to choose between several identical items such as food sources, shelters, paths or other natural resources.

In this binary or multi-choice framework, the aim is to test the existence of potential positive feedbacks that will produce social amplification of the response. **Choices between different options:** groups of animal will be proposed to choose between several items quantitatively different (e.g., shelters size, food quality, path length).

Using the case studies of different options allows to demonstrate the possible group amplification of individual discrimination capabilities. This enhanced group discrimination capability is the consequence of the social amplification by positive feedbacks revealed in the previous framework.

These choices are measured in the context of an experimental methodology, chosen depending on the property to be tracked. In the case of dynamical studies of groups, possible experimental metrics are:

- time series of populations dynamics built by acquiring individual positions and activities;
- influence of social or environmental factors on these dynamics;
- the response functions of the individual to their environment built by estimating parameters like resting times, probabilities of response to stimulus, etc.

This experimental framework also allows:

- testing for the existence and contribution of potential leadership and hierarchy, i.e., the social structure of the group;
- detecting the existence and the nature of the collective non-linear interactions such as activation, mimetism, social or environmental inhibitions, etc.;
- obtaining a quantitative image of the individual discrimination capabilities and their eventual amplification through social interactions;
- estimating the level of optimality and adaptive value of the collective choice, based on the chosen solutions by the animals.

This quantitative methodology requires extensive replication of the same well defined experimental conditions (in the laboratory or in semi-open conditions) to acquire a large body of data to gain statistical significance on the observed dynamics in time and space. This type of experimental procedures and framework go beyond classical naturalistic observations and pushes strongly the need for efficient automated monitoring tools. The monitoring activity and the corresponding engineering effort are often neglected in this type of research project, because monitoring tools are not the goal of the project. However, monitoring tools play a crucial role in the definition of the model and the verification of the results.

15.5.1.1 *Monitoring tools*

In order to achieve quantitative models for predicting metrics at the collective level (for instance, the amount of agents under a certain shelter in the case of collective decisions in cockroach-InsBot societies or the number of chicks following the robot for chick-PoulBot groups), precise understanding of the individual behavior that leads to the collective metric of interest is needed. By observing the natural society we are able to identify behavioral rules that produce certain phenomena at the collective level. For this, measurements of the above described metrics at the collective level are necessary.

The main challenge lies in evaluating which details at the individual level are relevant for the collective response of interest, and which are not. After it has been defined, appropriate monitoring tools are needed to be designed [Noldus *et al.* (2002)]. They are essential to produce automated high-throughput ethograms [Branson *et al.* (2009); Dankert *et al.* (2009); Reiser (2009); Anonymous (2007)]. These ethograms are then used to formulate a behavioral model for the animal that can be further used to program the robots.

15.5.2 *Identification and Quantification of Relevant Behaviors Communication Signals*

In order to better understand the nature of the link between individual and collective behavior, it is important to identify the communication signals that are relevant for the social interactions; afterwards, the influence of each communication channel can be studied separately. These communication channels can be, for example, chemical, tactile, auditory or visual. It is also important to understand how relevant these signals are. Some of them play an essential role, some could be irrelevant.

This process has to be seen in interaction with the whole *behavioral animal study* analysis axis and might imply new experiments, modifications of a potential model, or verification on the animal society. We also note, that the final output of this process is a key element for the *robot design* synthesis axis, as the robot needs to be able to use the communication channels provided by the animals.

15.5.3 *Formalization of Biological Behavioral Model*

As it was already mentioned, experimental and theoretical studies of animal societies demonstrated that numerous interactions between individuals may produce collective intelligence [Deneubourg and Goss (1989); Bonabeau *et al.* (1999); Detrain *et al.* (1999); Parrish and Edelstein-Keshet (1999); Camazine *et al.* (2001); Sumpter (2006)]. The collective solution is progressively build-up by the individuals, and the system remains flexible and is capable to respond to environmental or social changes. The mechanisms producing such emergent collective behaviors are based on self-organization. Not all collective behavior are self-organized, self-organization can coexist with other types of mechanisms including templates, networks of privileged interactions between individuals, various forms of leadership or pre-existing individual specialization.

Self-organization contrasts with blueprint design and centralized information. The individuals do not act according to a detailed blueprint of the collective pattern that they have innate or learned but follow local rules based on incomplete information [Camazine *et al.* (2001)]. Neither an individual is aware of all the alternatives, nor the global collective solution is pre-programmed. What is somehow "encoded" are the individual rules that produce emergent behavior at the social level.

Collective intelligence does not necessarily imply a large number of individuals but rather a large number of interactions and actions between the individuals and the environment. Experiments show that even small groups of animals ($\sim$10) are able to exhibit self-organized behavioral patterns [Amé *et al.* (2006); Halloy *et al.* (2007)]. A self-organized collective behavior emerges at the level of the group from the numerous interactions between the individuals and their environment. Our current understanding of self-organized behavior in biological systems points to the existence of a limited number of simple behavioral modules based on regulatory loops (positive and negative feedbacks) that produce effective emergent collective patterns for resources and work allocation, social differentiation, synchronization or de-synchronization without external pacemaker, clustering and sorting. In such systems, the problems are self-solved collectively and in real-time. The units are mixed with the environment and the groups exhibit organizational structures that are functional, robust, and adaptive [Detrain and Deneubourg (2002); Amé *et al.* (2006)].

Mechanisms based on self-organization include as essential features: non-linearity, incomplete information and randomness [Deneubourg *et al.* (1986)]. These features lead to the design of specific experiments and to statistical analysis to reveal and quantify them. Many collective decisions result from a competition between different information sources that can be amplified by various positive feedbacks (for social insects and gregarious arthropods, see, e.g., [Pasteels *et al.* (1987); Dussutour *et al.* (2004); Amé *et al.* (2006); Camazine *et al.* (2001)]). These positive feedbacks are produced by the numerous repetition of an individual behavior. On the one hand the positive feedback can correspond to the increase of the individual probability of adopting a behavior according to the number of individuals performing this behavior; on the other hand the individual probability of leaving a behavior decreases with the number of individuals exhibiting this behavior. In both cases the necessary but not sufficient condition is that the response of the individuals to the stimuli is non-linear.

In self-organized systems, the same behavioral rule may produce a diversity of patterns depending on the parameter values, the environmental constraints or the population size (see, e.g., [Deneubourg and Goss (1989); Nicolis and Deneubourg (1999); Detrain *et al.* (1991)]). Indeed, in many situations, populations are influenced by the environment that becomes a kind of a particular agent in the system [Deneubourg and Goss (1989); Detrain *et al.* (1999, 2001); Detrain and Deneubourg

(2002)]. Nevertheless, global properties of the environment do not need to be encoded explicitly in the individuals level neither do the agents need a global view of their environment. Individual actions and communication events include a level of intrinsic randomness because animal behavior are seldom deterministic. Randomness and fluctuations play an important role in search by the system of its efficient solutions. This efficiency is largely due to a balance between the fluctuations leading to innovations and the accuracy of the communication or behaviors. One of the strengths of collective intelligence results from both the tolerance to this type of randomness, and its use to solve problems, especially in situations where the team is blocked in a sub-optimal solution [Deneubourg *et al.* (1983); Pasteels *et al.* (1987); Nicolis *et al.* (2003)].

15.5.4 *Lessons Learned from Leurre*

In the Leurre project, we studied the cockroach behavior by a series of collective choice experiments [Amé *et al.* (2004)], that delivered sufficient quantitative information for validating conjectures about a behavioral model. This set of experiments represent a huge amount of data that has to be collected and processed. To achieve this task, automated monitoring tools are absolutely necessary and their development needs an important and often underestimated engineering effort. For quantifying experimental observations, for instance, we developed the tracking software *Swistrack* [3] [Correll *et al.* (2006)] (Figure 15.6.) allowing to analyze video data and to track the trajectories of cockroaches and InsBots within the arena. Using this data, we were able to obtain the number of agents under a shelter and the number of clusters in the arena at a given time. In the chick-robot experiments we also used SwisTrack to track displacements of chicks and PoulBots (Figure 15.7.).

As discussed above, emerging collective behavior is not only a function of the individual motion but also of communication among group members, sensorial characteristics and embodiment, as well as environmental parameters. In the case of cockroach-InsBot interactions, the trajectory data is only a subset of the data necessary to understand completely the interactions. For example, communication via pheromones has an important impact on collective behavior [Amé *et al.* (2004)]. Due to the complexity of monitoring the interplay of chemical communication, individual behavior, and embodiment, these quantities were studied separately in systematic experiments. For instance, through the cockroach experimentation we first discovered the nature and right amount of pheromone to be deployed on the InsBot to have it accepted as a congener [Said *et al.* (2004)] but not as a supernormal stimulus. After the cockroach behavior appeared to remain unaltered under presence of the manipulated InsBot, we could focus exclusively on the monitoring of trajectories.

In the case of chickens sounds emitted by the animals are of interest when investigating the animal behavioral model. To detect the calls emitted by chicks we used a microphone array that can be mounted on the robot or placed on the arena [Gribovskiy and Mondada (2009)].

[3] http://swistrack.sourceforge.net

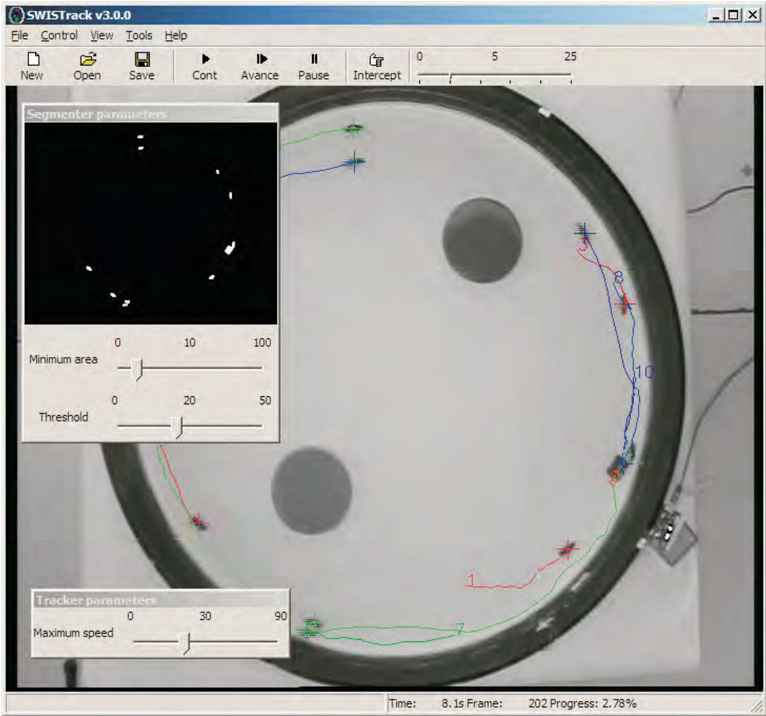


Figure 15.6. Screenshot of the freely available software *SwisTrack* tracking of mixed animal-robot societies. The arena is populated with cockroaches and one InsBot

15.6 Robot Design

The design of the robot is based on the communication channels that have been identified in the animal study and formalized in the model. The design process does not consist in copying the animal in all its aspects. Instead, to be efficient and functional in the context of social interactions, the design has to consider only the relevant communication channels, the relevant behaviors, and the relevant body constraints (Box 9), which can be identified by means of modeling at different abstraction levels. It is not useful to implement body or behavior characteristics that are not relevant for the social interactions.

Robot design in itself is a classical engineering process based on specifications and iterating between a design, a prototyping and a test phase. Figure 15.8. illustrates this process; we can see that its the constructive counterpart of the analysis process described in Section 15.5 and presented in Figure 15.5.. Note that the Figure 15.8. is an alternative vision of the Robot Design axis of Figure 15.2., better emphasizing the iterative nature of the robot design process.

The main difficulties in the robot design are situated at the level of the technical specifications of the robot (Figure 15.2.,Box 9), which represents the phase 1 in Figure 15.8.. These specifications are part of the interface between the model coming from the animal behavior and the technological world, especially at the hardware level. At the software level most of the interfacing effort is done while defining the

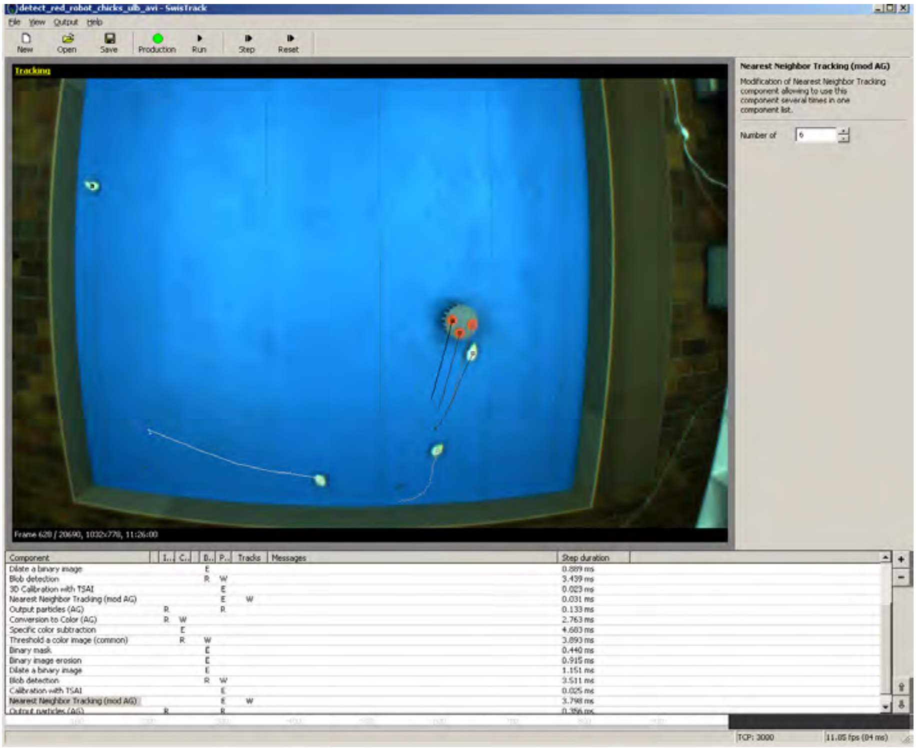


Figure 15.7. The *SwisTrack* software is used to track chicks and a PoulBot robot

models, generating a common language between animal study and engineering.

As for the experimentation with animals, tests are the final key element of robot design following the prototyping. There are two levels of tests: (i) a technical verification of functionalities and (ii) an experimentation on the interaction with animals. The first type of tests is a classical engineering process that takes places mostly before experimentation and represents the phase 2 in Figure 15.8.. When the robot has most functionalities working, the experimentation (phase 3 in Figure 15.8.) can start. To ensure a coherence in the project, the robotic experimental process has to take place with the same tools and procedures as in biological behavioral studies (Section 15.5). Part of the technical tests continues during the phase 3, where we iteratively improve the design of the robot based on the experimental results and new inputs from the animal study and the modeling.

15.6.1 *Specifications of Relevant Communication Channels, Behaviors and Body*

This step of the process is in charge of making a bridge between the communication channels identified in biology, formalized in the multi-level model and tested using simulation tools on one side, and the robotic technology on the other side. Even after one has identified relevant communication channels on the biological side, has formalized and simulated it, this still does not give a complete indication

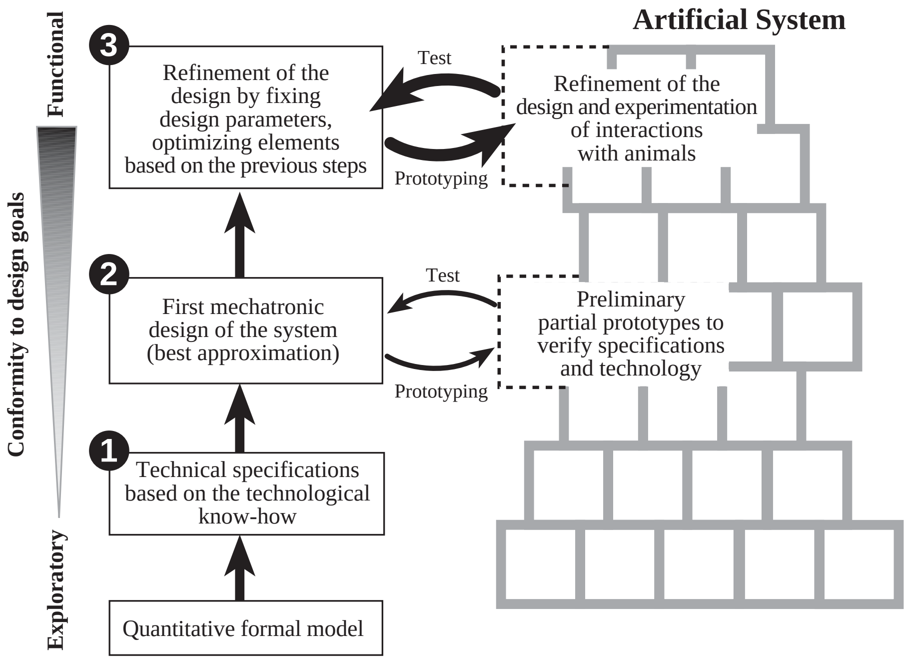


Figure 15.8. Main phases of the robot design process

on its technological implementation on the artificial system. Some features can be modulated at the software level of the implementation. At the hardware level, however, this is generally not the case. Moreover, the hardware implementation of communication is usually different from the one found in nature. This means that this step is strongly linked to the technology available as well as to the design and the implementation of the specifications, and to the final testing, which is the only possible validation of the specifications.

Therefore, the definition of the specifications of the robot is an interactive process, involving Boxes 1 and 8 from Figure 15.2., and strongly exploiting the feedback information coming from design, implementation and tests (Figure 15.9.). The specifications are built up gradually, starting from some generic features and going into more and more details. This local iterative process interacts with the global iterative process of looking for solutions. Therefore, some results of local iterations could give feedbacks to the whole process and, in particular, introduce new elements in the formal multi-level model.

15.6.2 *Robot Design and Implementation*

As it was said above, the robot design and implementation is a classical element of engineering. The only particular aspect of this step is its stronger link with the definition of the specification and the experimental phase than in classical engineering projects. This is due to the difficulties to clearly define the goal in a classical engi-

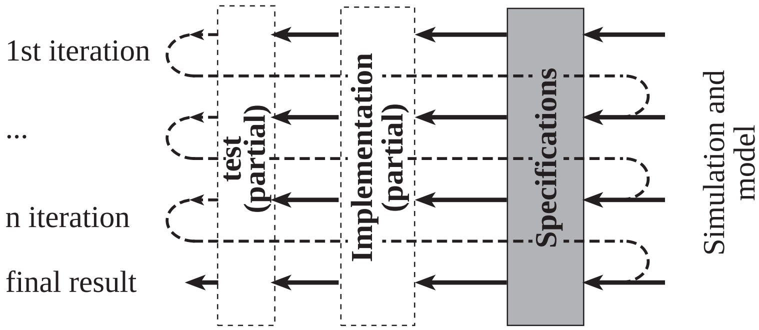


Figure 15.9. Iterative process of the definition of the robot specifications

neering form by establishing clear and final specifications. These interactions and the strong iterative process pushes to have faster prototyping phases, flexible prototypes and intensive tests. Partial prototyping, which is often used in industry, is also a key element of this process.

15.6.3 *Robot Design in the Leurre Project*

When starting to deal with cockroaches, some preliminary tests have been done on interactions between animals and the Alice robot [Caprari and Siegwart (2005)], a platform developed in another framework and that was available before the beginning of the project. The results of these experiments, combined with the model resulting from the animal study, have been used as a base to design the first generation of InsBot robots (Figure 15.10.).

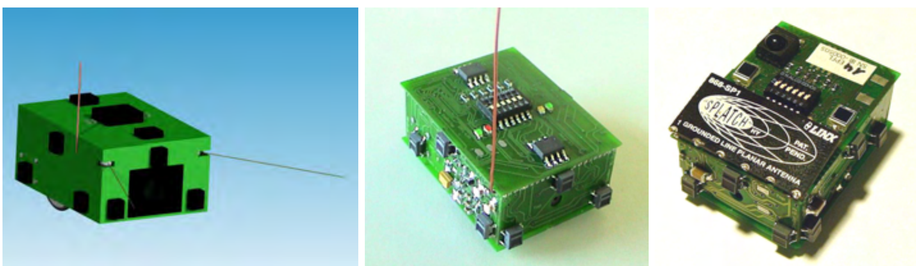


Figure 15.10. The three main versions (in chronological order) of the design of the InsBot robot

As we have already mentioned, certain *specification-implementation-test* iterations can include very important design choices. For example, initially the importance of the cockroach antennas as a communication channel was unclear. At one point of the project there was some evidence pushing the hypothesis that antennas could be a support for a relevant communication channel. Therefore, the specifications had to be modified to include active antennas respecting some size, displacement and controllability. A prototype of antennas was implemented (Figure 15.11.) and tested with real cockroaches. It turned out that these artificial antennas rather than opening a new communication channel were significantly disturbing the behavior of the cockroaches. Moreover, their implementation was not trivial and their energy consumption was prohibitive for this size of system. Eventually, the antennas were removed from the specifications and from the design.

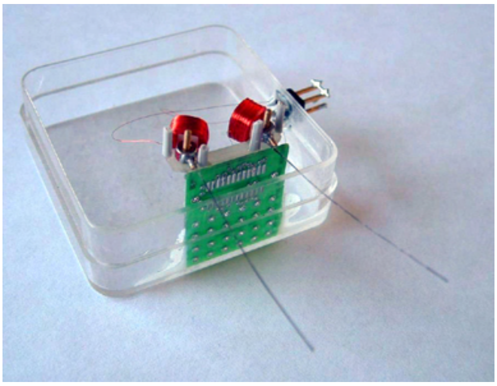


Figure 15.11. Prototype of moving robotic antennas

Later, preparing the experiments with chicks we did the preliminary tests on filial imprinting and collective displacement with the Lego robot. The results of the tests were used to make an initial specification for the PoulBot robot that was designed on the base of the marXbot [Bonani *et al.* (2010)]. The further evolution of the robot is presented in Figure 15.13.; in the course of experiments the robot was equipped with various modules such as a protective bumper, variable color pattern, omnidirectional camera, etc. [Gribovskiy *et al.* (2010)].

Figure 15.12. The Lego robot was used in the preliminary experiments to verify the filial imprinting procedure and basic robotic behaviors

15.7 Society Modulation

This synthesis axis is the last one in the methodology and implies that the mixed society has been implemented at least partially. In mixed societies, the modula-

Figure 15.13. The evolution of the PoulBot robot

tion of the characteristics of the artificial agents (e.g., behavioral rules or number of agents) is the only way to generate the diversity of collective patterns. However, the very first step before the modulation is the definition of the objectives one wants to achieve for the mixed societies. The objectives may be to provoke in the mixed society dynamics or patterns, different from the animal ones either quantitatively (e.g., the reduction of panic frequency in animal groups) or qualitatively (e.g., periodic collective behavior in mixed societies instead of stationary regime in animal societies or task specialization instead of unspecialization).

These objectives are very dependent on the characteristics of the animal society, the technological constraints and the potential interactions between the artificial agents and animals. Therefore, they cannot be established in an abstract way and are based on the multi-level model of the mixed society and the goals of the whole project. This step might appear to be trivial at first glance but is not. In the Leurre project, particularly, this choice of objectives for a mixed cockroach-robot society was established once first models (macroscopic and microscopic) of the cockroach collective behavior had been studied and first biological experiments had been performed.

15.7.1 *Model-based Predictions*

A society is a dynamical network of nodes interacting through positive and negative feedbacks. The nodes correspond to individuals being in the same state and to environmental or social parameters modulating the individual probability of changing behavior (see Figure 15.14. a). This network of individual responses and interactions governs the collective response and its efficiency. In the process of designing mixed societies, we look for new collective responses to the environment, where new feedbacks play a key role. The artificial agents are at the origin of this new sensitivity to environmental parameters but are also the support for new feedbacks (see Figure 15.14. b). Thanks to these non-linear effects a limited change of some control parameter values may induce important changes at the level of the group.

The main challenge is identifying the characteristics of artificial agents and of their interactions with animals. A purely experimental approach is too much time-consuming, hence, the coupling between multi-levels modeling and experimental tests is an efficient way to perform this task.

A first theoretical study (macroscopic and microscopic) is helpful to identify the

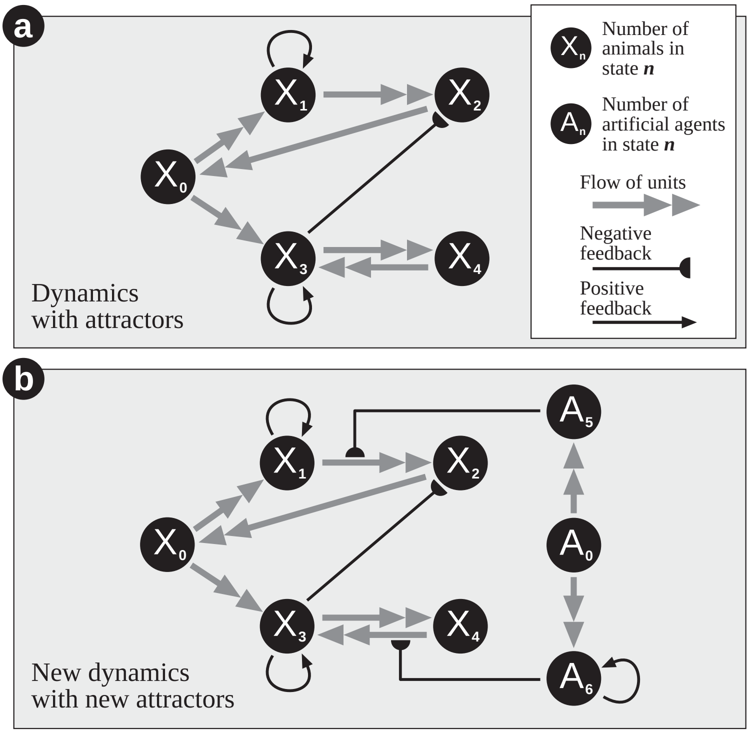


Figure 15.14. Animals society is a network of interactions. The introduction of artificial agents (b) in a society of animals (a) introduces also changes in the dynamic and the attractors of the system.

set of interactions needed to generate the desired collective response of the mixed society. We know that a limited number of simple generic rules (including different feedbacks) produce effective collective patterns in biological systems for work allocation, social differentiation, synchronization, aggregation, etc. These rules are the building blocks for higher collective complexity; some sets of them to be found that are able to produce the desired collective response. Detailed and quantitative theoretical studies, including physical details, give the opportunity to identify the most efficient response. This efficiency can be the robustness of the collective response, the rate at which this response is reached, etc. The implementation of these rules is often challenging and this issue has to be taken into account when selecting rules to implement. It means that sometimes the selected rules are not those predicted to be optimal from the theoretical analysis.

15.7.2 *Parameters Modulation*

The last step of the analysis mainly concerns the modulation of the parameter values, and the effect of this modulation on the collective responses. In non-linear systems, the modulation of the parameter values (while keeping the same behavioral rules) can lead to bifurcations producing qualitatively different patterns. The bifurcation occurs when a small change of the parameter values, *the bifurcation pa-*

rameters, causes a sudden qualitative change in the system long-term dynamical behavior i.e. new solutions appear or disappear. In the context of choosing a rule and the modulation of the response of the mixed societies, an important criteria of selection of the behavioral rule is the number of different patterns that may be produced by modulating the parameters of only one rule.

Two key parameters are the number of agents (animal and artificial) and the intensity of the interactions. In mixed societies, we can modulate only the interaction between the artificial agents and between the artificial agents and animals. The intensity of the signal perceived by the individual controls its response. This intensity depends on the intensity of the emitted signal and physical parameters affecting its propagation and lifetime. Moreover, different intensities of the same signal may induce different behaviors such as attraction at low intensity or fleeing at high intensity.

The non-linearity of the individual response to a signal incorporated in the non-linearity of the associated feedback function is another important bifurcation parameter. For example, a mixed society may be unable to reach its objective due to the fact that some of its feedbacks do not present an appropriate non-linearity.

If the intensity of interaction (between the artificial agents and the animals) is high enough, a small number of artificial agents is able to influence the dynamics of the mixed societies. However, it does not mean that such a small group is as efficient as a large group of artificial agents with a low intensity of interaction.

Moreover, the intensity of interaction is a way to modulate the randomness: a strong interaction between artificial agents and animals is more deterministic than a weak interaction. For the same values of parameters, the mixed societies, as most of the non-linear systems, may exhibit different stable states that are characterized by different efficiency or correspond more or less to the objectives of the mixed society. Randomness is a positive ingredient to explore the different alternatives and to find effective solutions. Therefore, the study of optimality in such systems needs to take into account the stochasticity of the phenomenon and the theoretical models, such as stochastic equations or stochastic simulations, and must be able to take into account the different fluctuations.

To summarize, the control of mixed societies is possible through the modulation of the parameters of the behavioral rules governing the artificial agents. Due to its self-organized dynamics, the mixed society will spontaneously adopt the desired objectives. Due to plasticity of self-organized mechanisms, the modulation of the parameters can result in a large diversity of responses and to adopt various patterns. However, in some situations, changing the value of the parameters is not enough to reach a new objective; in this case, new rules must be adopted and followed by the artificial agents.

15.8 Discussion

This methodology implies a constant and strong interaction between disciplines. Despite the impression of linearity of the diagram in the Figure 15.2., the whole methodology and the approach are strongly iterative. Iterations take place at the level of a single process (for instance, in the Box 8, when designing and implementing a robot), between processes (e.g., between specification, Box 9, and robot design, Box 8), between axis (e.g., *robot design* and *animal behavioral study*) and in the whole process, as illustrated by figure 15.15.. These iterations, which are a usual component of many design or analysis processes, have a strong interdisciplinary nature here, since iterations require participation of researchers from different research fields. Those exchanges take place continuously and on a regular basis that requires a close collaboration of the several teams working on the project.

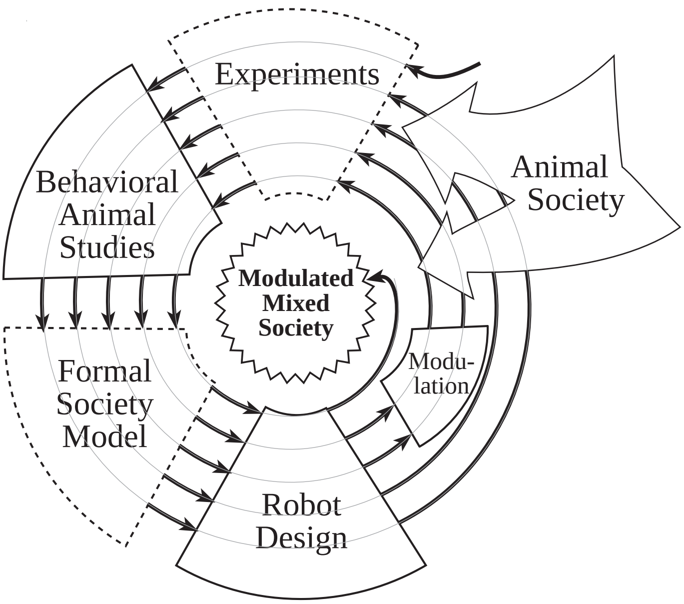


Figure 15.15. Graphical representation of the iterative interactions between the three main axis and the related tools.

Finding a common vocabulary is essential. The interdisciplinary integration of several teams working on the project starts by establishing a reliable communication among them. This seems to be obvious but is not trivial. People coming from different disciplines have often a different vocabulary that is a real obstacle to the mutual understanding. There is obviously a specialized vocabulary, which is not shared between the disciplines, and that has to be partially learned by groups not using it. There is also a set of concepts that are shared by all disciplines, but have different names, or terms that have a completely different meaning in different disciplines. For instance, the term *experimental* has not the same meaning and connotations for people in animal behavioral sciences and engineers. For an engineer the term *experimental* is applied to systems based on untested ideas, not finalized. Researcher working on animals relates this term with the scientific experimentation. Clarifying the terminology and being careful when using new terms is crucial for the success of this type of project.

Monitoring tools is a key element of the experimental setup. Usually computer vision methods is a first choice for indoor experiments, depending on the size of the monitored area and experimental lighting conditions, but they might not be well-suited for field experiments; in this case GPS based systems might be worth being considered. Also, tracking of a large number of considerably small agents that occasionally overlap (as it was the case for our experiments with cockroaches, chickens and sheep), might render extraction of useful data from the video stream unfeasible. In this case, other means to automatically gather the information about the animal behavior need to be leveraged. Using GPS collars for field measurements and RFID for indoor experiments for obtain a trajectory data are interesting alternatives to vision. Behavioral data can be also collected in a classic fashion by using traditional field techniques, ranging from embedded sensors networks [Szewczyk *et al.* (2004)] and classical telemetry techniques to pen and notebook.

Also, conclusions drawn from monitoring such quantities need to be treated with care. Consider the following example: we are interested in measuring the number of cockroaches in the neighborhood of one InsBot during a particular experiment. But the number of cockroaches really perceived by the InsBot itself might be different from one provided by the monitoring and this *egocentric* perception of the InsBot is what finally governs its behavior. In order to quantify individual animal behavior that underlies emergent collective behavior, one needs to monitor the individual's *behavior* as well as its *interactions* with other individuals. Of principal importance is the prior identification of interesting signals, be it a simple object location in the environment or more sophisticated tactile, chemical, or aural clues. Only upon availability of this information, appropriate monitoring tools can be designed. The choice of the monitoring technique should be done to achieve a flexible and an insightful analysis of the target behavior, and in any circumstances it should not bias the results. Thus the engineering of the monitoring tool is an extremely important and time consuming process. This aspect should be considered carefully in the planning of this type of projects.

A formal multi-level model of society is required for robot design and animal behavior understanding. Modeling and simulation tools give the enhanced understanding of the system and its behavior. We believe that a formal model of a mixed society has to be multi-level in order to be the most useful to this purpose. Indeed, while for natural units of the system it is difficult, or even impossible, to obtain accurate microscopic information about the individuals (e.g., controller, sensory details) and thus the tendency is to contribute essentially at the macroscopic level, such information is available for artificial systems and should be considered at one or more levels of the models. Moreover if a model achieves a quantitative match with a reality on given metrics and allows the specific representation of design parameters, it can be used in a model-based approach for optimization and design purposes. Finally, it is worth mentioning that although the estimation of behavioral parameters of the animals is crucial for achieving quantitatively correct predictions, modeling and fitting algorithms can also be used to *estimate* plausible parameters from experimental data [Correll and Martinoli (2006)], and thus yield a valuable insight about the validity of a possible model. More concretely, system identification can be used to induce the necessary behavioral parameters that generate an observed pattern at the collective level, which in turn allows one to draw a conclusion about possible communication channels.

Robot design in the Leurre projects is the iterative process (Section 15.6) that led to several partial implementations and major revisions of the robot, as illustrated in Figures 15.10. and 15.13.. The application of this methodology to more complex animals can need more iterations and many partial implementations and tests.

Another key element in the Leurre projects is a requirement of robotic miniaturization and low power consumption. In the application of this methodology to bigger animals these constraints will be probably replaced by the need of higher computational power and more complex sensors, even if the low power constraint will always play an important role because of the mobility of the device.

15.9 Conclusion and Outlook

We presented a methodology for designing the artificial lures that are able to provoke particular, potentially beyond natural, responses in collective animal societies. The main difficulty in this process is to predict the emergent response at collective level, which is a function of multiple interactions among the animals and lures. To achieve this, we suggest to adhere to an iterative process consisting of deriving a quantitative behavioral model for the individual animals, identification of potential interactions among individuals based on experimental observations, and validation of the model and its assumptions by means of higher level abstract models (realistic, microscopic, and macroscopic models). The resulting formal description of animal behavior and interactions, can then serve as a guideline for developing specifications of potential robotic platforms or lures, whose behavior and interactions are in turn validated by using the same methods and tools used for studying the natural society.

The formally identical abstraction levels for the natural and the artificial societies can then be applied to mixed societies, enabling us to achieve trustworthy predictions for the response of the modulated society, which can be used to explore the parameter space of the system as well as resulting collective responses.

One direct field of application of our methodology is research in animal behavior. A number of monitoring tools was recently developed to produce automated quantitative ethograms [Branson *et al.* (2009); Dankert *et al.* (2009); Reiser (2009); Anonymous (2007)]. Our framework includes such techniques but further developed it to add embedded social robotic lures. By introducing artificial agents into the animal group we can test individual and group reaction to various stimuli; by combining robots with automated ethograms we can achieve an unparalleled automatization of animal behavior experimentation.

Another field of application can be the management of domestic animal stocks. All animal species that are bred are social animals, e.g., poultry, cattle, sheep, goat. The concepts presented here can be applied to animal societies whose behavior and interactions are more complex potentially leading to various agricultural applications such as low-stress management of live-stock [Correll *et al.* (2008)].

On the long term, this methodology could also be put at work to manage wild life animal pests or resources in particular group living species. One can envision artificial intelligent systems capable of interacting and modulating the behavior of unwanted pests to drive them away of specific places. Or, on the contrary, to attract valuable animals used as natural resources, for example, schools of fish. Improving the selectivity and efficiency of fishery is a necessity for sustainable live stock management.

Finally, designing mixed societies of animal and robots open the way to hybrid systems, where the artificial agents are enhanced by the animal capabilities and, in the opposite way, the animals can make use of the artificial agents capabilities. For example, animals have very good perception abilities for sounds, vision and more importantly smell. Artificial agents presenting similar capabilities are still very far from the animal perceptual efficiency. Locomotion in natural and wild environment is very efficiently performed by animals to the contrary of robots for which locomotion in such environment is a challenging task. By embedding artificial agents on the animals (mounted nodes) the locomotion issue could efficiently be solved. One can also envision animals making use of the artificial agent capabilities such as long range communication that is easily performed by robots. This would lead no novel group behavior based on natural short range and artificial long range perception.

Bibliography

Amé, J.-M., Halloy, J., Rivault, C., Detrain, C. and Deneubourg, J. L. (2006). Collegial decision making based on social amplification leads to optimal group formation, *Proceedings of the National Academy of Sciences of the United States of America* **103**, 15, pp. pp. 5835–5840, URL `http://www.jstor.org/stable/30050186`.

Amé, J.-M., Rivault, C. and Deneubourg, J.-L. (2004). Cockroach aggregation based on strain odour recognition, *Animal Behavior* **68**, pp. 793–801.

Anonymous (2007). Geneticist seeks engineer: must like flies and worms, *Nat Meth* **4**, p. 463.

Asadpour, M., F.Tache, Caprari, G., Karlen, W. and Siegwart, R. (2006). Robot-animal interaction: Perception and behavior of insbot, *Int. Journal of Advanced Robotics Systems* **3**, pp. 93–98.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems, *Proceedings of the National Academy of Sciences* **99**, pp. 7280–7287.

Bonabeau, E., Dorigo, M. and Theraulaz, G. (1999). *Swarm Intelligence - From Natural to Artificial Systems* (Oxford Univ. Press).

Bonani, M., Longchamp, V., Magnenat, S., Rtornaz, P., Burnier, D., Roulet, G., Vaussard, F., Bleuler, H. and Mondada, F. (2010). The marXbot, a miniature mobile robot opening new perspectives for the collective-robotic research, in *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems (IROS 2010)*.

Branson, K., Robie, A. A., Bender, J., Perona, P. and Dickinson, M. H. (2009). High-throughput ethomics in large groups of drosophila, *Nat Meth* **6**, 6, pp. 451–457, URL `http://dx.doi.org/10.1038/nmeth.1328`.

Butler, Z., Corke, P., Peterson, R. and Rus, D. (2006). From robots to animals: Virtual fences for controlling cattle, *International Journal of Robotic Research* **25**, 5-6, pp. 485–508.

Camazine, S., Deneubourg, J., Franks, N., Sneyd, J., Bonabeau, E. and Theraulaz, G. (2001). *Self-Organization in Biological Systems* (Princeton University Press).

Caprari, G. and Siegwart, R. (2005). Mobile micro-robots ready to use: Alice, in *Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 3295–3300.

Correll, N. and Martinoli, A. (2006). System identification of self-organized robotic swarms, in *8th International Symposium on Distributed Autonomous Robotic Systems (DARS)*.

Correll, N., Schager, M. and Rus, D. (2008). Social control of herd animals by integration of artificially controlled congeners, in *Proc. of the 10th International Conference on Simulation of Adaptive Behavior (SAB). Springer Lecture Notes in Artificial Intelligence LNAI 5040* (Osaka, Japan), pp. 437–447, best Paper Award.

Correll, N., Sempo, G., de Meneses, Y. L., Halloy, J., Deneubourg, J.-L. and Martinoli, A. (2006). Swistrack: A tracking tool for multi-unit robotic and biological research, in *IEEE/RSJ Conference on Intelligent Robots and Systems, to appear*.

Dankert, H., Wang, L., Hoopfer, E. D., Anderson, D. J. and Perona, P. (2009). Automated monitoring and analysis of social behavior in drosophila, *Nat Meth* **6**, 4, pp. 297–303, URL `http://dx.doi.org/10.1038/nmeth.1310`.

De Schutter, G., Theraulaz, G. and Deneubourg, J.-L. (2001). Animalrobots collective intelligence, *Annals of Mathematical and Artificial Intelligence* , 31, pp. 223–238.

Deneubourg, J., Aron, S., Goss, S., Pasteels, J. and Duerinck, G. (1986). Random behaviour, amplification processes and number of participants: how they contribute to the foraging properties of ants, *Physica D* **22**, pp. 176–186.

Deneubourg, J. and Goss, S. (1989). Collective patterns and decision-making, *Ethology, Ecol-*

ogy & Evolution **1**, pp. 295–311.

Deneubourg, J., Pasteels, J. and Verhaeghe, J. (1983). Probabilistic behaviour in ants: A strategy of errors? *Journal of Theoretical Biology* **105**, 2, pp. 259 – 271, doi:DOI:10.1016/S0022-5193(83)80007-1.

Detrain, C., Deneubourg, J. and Pasteels, J. (1999). *Information Processing in social Insects* (Birkhäuser).

Detrain, C. and Deneubourg, J.-L. (2002). Complexity of environment and parsimony of decision rules in insect societies, *Biol. Bull.* **202**, pp. 268–274.

Detrain, C., Deneubourg, J.-L., Goss, S. and Quinet, Y. (1991). Dynamics of collective exploration in the ant pheidole pallidula, *Psyche* **98(1)**, pp. 21–31.

Detrain, C., Natan, C. and Deneubourg, J.-L. (2001). The influence of the physical environment on the self-organised foraging patterns of ants, *Naturwissenschaften* **88**, pp. 171–174.

Dussutour, A., Fourcassie, V., Helbing, D. and Deneubourg, J.-L. (2004). Optimal traffic organization in ants under crowded conditions, *Nature* **428**, 6978, pp. 70–73.

Goth, A. and Evans, C. S. (2004). Social responses without early experience: Australian brush-turkey chicks use visual cues to aggregate with conspecifics, *Journal of experimental biology* **207**, pp. 2199–2208.

Gribovskiy, A., Halloy, J., Deneubourg, J.-L., Bleuler, H. and Mondada, F. (2010). Towards mixed societies of chickens and robots, in *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems (IROS 2010)*.

Gribovskiy, A. and Mondada, F. (2009). Real-time audio-visual calls detection system for a chicken robot, in *International Conference on Advanced Robotics, 2009*, pp. 1–6.

Halloy, J., Sempo, G., Caprari, G., Rivault, C., Asadpour, M., Tache, F., Said, I., Durier, V., Canonge, S., Ame, J. M., Detrain, C., Correll, N., Martinoli, A., Mondada, F., Siegwart, R. and Deneubourg, J.-L. (2007). Social integration of robots into groups of cockroaches to control self-organized choices, *Science* **318**, pp. 1155–1158.

Ishii, H., Ogura, M., Kurisu, S., Komura, A., Takanishi, A., Iida, N. and Kimura, H. (2006). Experimental study on task teaching to real rats through interaction with a robotic rat, in *9th International Conference on Simulation of Adaptive Behavior*.

Koenig, N. and Howard, A. (2004). Design and use paradigms for gazebo, an open-source multi-robot simulator, in *IEEE/RSJ International Conference on Intelligent Robots and Systems* (Sendai, Japan), pp. 2149–2154, URL `http://cres.usc.edu/cgi-bin/print_pub_details.pl?pubid=394`.

Magnenat, S., Waibel, M. and Beyeler, A. (2007). Enki: The fast 2d robot simulator, URL `http://lis.epfl.ch/resources/enki`.

Martinoli, A., Easton, K. and Agassounon, W. (2004). Modeling of swarm robotic systems: A case study in collaborative distributed manipulation, *Int. Journal of Robotics Research* **23**, 4, pp. 415–436, special issue on Experimental Robotics, P. Dario and B. Siciliano, editors.

Michel, O. (2004). Webots: Professional mobile robot simulation, *Journal of Advanced Robotic Systems* **1**, 1, pp. 39–42.

Munack, A. (2002). Agriculture and the environment: New challenges for engineers, *CIGR Journal of Scientific Research and Development* **IV**.

Nääs, I. (2002). Application of mechanotronics to animal production, *CIGR Journal of Scientific Research and Development* **IV**.

Narins, P. M., Grabul, D. S., Soma, K. K., Gaucher, P. and Hodl, W. (2005). Cross-modal integration in a dart-poison frog, *Proc. Natl. Acad. Sci. USA* **102(7)**, pp. 2425–2429.

Nicolis, S. and Deneubourg, J.-L. (1999). Emerging patterns and food recruitment in ants: an analytical study, *Journal of Theoretical Biology* **198**, pp. 575–592.

Nicolis, S., Detrain, C., Demolin, D. and Deneubourg, J. (2003). Optimality of collective choices: A stochastic approach, *Bulletin of Mathematical Biology* **65**, pp. 795–808, URL `http://dx.doi.org/10.1016/S0092-8240(03)00040-5`, 10.1016/S0092-8240(03)00040-5.

Noldus, L. P., Spink, A. J. and Tegelenbosch, R. A. (2002). Computerised video tracking, movement analysis and behaviour recognition in insects, *Computers and Electronics in Agriculture* **35**, pp. 201–227.

Parrish, J. K. and Edelstein-Keshet, L. (1999). Complexity, Pattern, and Evolutionary Trade-Offs in Animal Aggregation, *Science* **284**, 5411, pp. 99–101, doi:10.1126/science.284.5411.99, URL `http://www.sciencemag.org/cgi/content/abstract/284/5411/99`.

Pasteels, J. M., Deneubourg, J.-L. and Goss, S. (1987). Self-organization mechanisms in ant societies (i): trail recruitment to newly discovered food sources. *Experientia Supplementum* **54**, p. 155175.

Patricelli, G. L., Coleman, S. W. and Borgia, G. (2006). Male satin bowerbirds, ptilonorhynchus violaceus, adjust their display intensity in response to female startling: an experiment with robotic females, *Animal Behaviour* **71 (1)**, pp. 49–59.

Patricelli, G. L., Uy, J. A. C., Walsh, G. and Borgia, G. (2002). Sexual selection: Male displays adjusted to female's response, *Nature* **415**, pp. 279–280.

Reiser, M. (2009). The ethomics era? *Nat Meth* **6**, 6, pp. 413–414, URL `http://dx.doi.org/10.1038/nmeth0609-413`.

Said, I., Durier, V. and Rivault, C. (2004). European project leurre deliverable d2.1:2 report and demonstration on insbot-cockroach interaction. part i. chemical communication, Tech. rep., EVE group, Université de Rennes I.

Sumpter, D. (2006). The principles of collective animal behaviour, *Philosophical Transactions of the Royal Society B: Biological Sciences* **361**, 1465, pp. 5–22, doi:10.1098/rstb.2005.1733.

Szewczyk, R., Osterweil, E., Polastre, J., Hamilton, M., Mainwaring, A. and Estrin, D. (2004). Habitat monitoring with sensor networks, *Communications of the ACM* **47**, 6, pp. 34–40.

Taylor, R. C., Klein, B. A., Stein, J. and Ryan, M. J. (2008). Faux frogs: multimodal signalling and the value of robotics in animal behaviour, *Animal Behaviour* **76**, 3, pp. 1089 – 1097.

Tinbergen, N. (1951). *The study of instinct* (Oxford UP, Oxford).

Tinbergen, N. (1953). *The herring gulls world* (Collins, London).

Vaughan, R., Sumpter, N., Henderson, J., Frost, A. and Cameron, S. (2000). Experiments in automatic flock control, *Robotics and Autonomous Systems* **31**, pp. 109–117.