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Abstract. 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.

Keywords: collective behavior, decision-making, multi-level modeling, mixed-societies, multi-objective optimization

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 [12]. 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 [12, 10, 11].

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 [10], cockroaches in [21, 12], fruit flies in [22], honeybees in [16], guppies in [15] and zebrafish in [3, 20, 5, 4].

In particular, Halloy *et al.* ([12]) 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 intricately 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 [12]), this process is often done empirically. Ways of handling different levels of descriptions is investigated in [19, 17, 18], 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 [12]. 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 [12]); 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.

2 Multi-level Models

We use the same experimental setup as [12] (cf Fig. 1): 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 imply a trade-off between competition for resources with limited carrying capacity (the shelters) and cooperation (aggregation of the individuals).

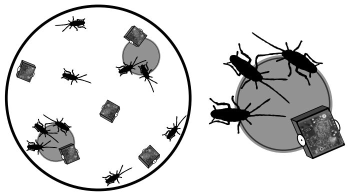


Fig. 1. Experimental setup used in [12] includes two identical shelters (150 mm) and both cockroaches (*P. americana*, approximate size: $\sim 4cm$, surface: $600mm^2$) and robots (surface: $1230mm^2$) in a circular arena (diameter: 1 m). The setup is symmetric.

2.1 Ordinary Differential Equation Model

A mathematical model describing the collective dynamics of mixed groups of robots and cockroaches was developed in [12] (based on [1]). 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):

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

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

$$C = x_e + x_1 + x_2, \quad M = r_e + r_1 + r_2, \quad N = M + C \tag{3}$$

Table 2 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. 3, a bifurcation diagram of the occupation of the first shelter, as function of σ. Represented results are obtained by resolution of Eq. 1 using the Gillespie method [9]. A resolution using the Gillespie method allows to take into account experimental fluctuations. Figure 3 only represents results with population of 50 cockroaches, but similar dynamics are observed with different population sizes.

Parameter for *P. americana*	Parameter for robots	Value for *P. americana*	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

Fig. 2. Parameters list of the ODE model. Cockroaches (*P. americana*) parameter values are from [12]. 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 [12]: the assumption is made that this parameter is imposed by biology, and can't be changed in experiments.

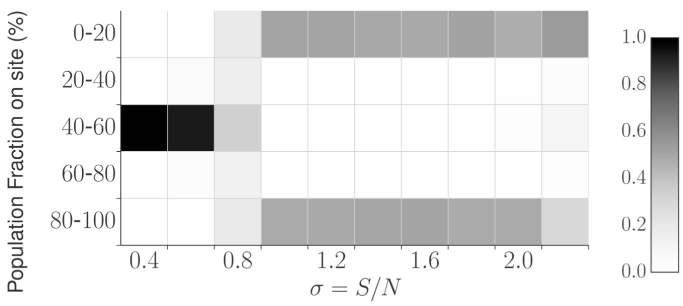


Fig. 3. Bifurcation diagram and distribution of $N = 50$ *P. americana* cockroaches in the first shelter, as function of σ. The bifurcation diagram is represented as bi-dimensional histograms of the results using 1000 solutions by parameter sets. The color of each bin of the histogram corresponds to 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 $\sigma = 0.8$.

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.

2.2 Finite State Machine Model

We define a 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 [13, 8] to describe the collective behavior of cockroaches in a similar setup.

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 [8], this probability depends on the number of present agents. Figure 4 provides a description of this model, with the relevant model parameters.
In our model (as opposed to [13, 8]), 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.

3 Results

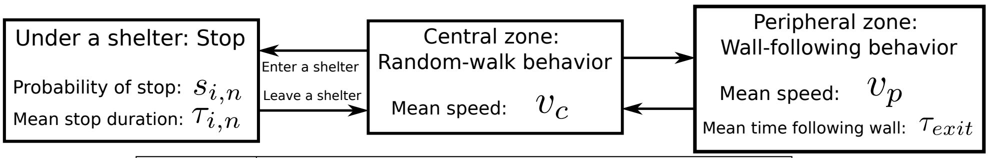
3.1 Numerical Computation

All results from the ODE model were obtained by resolving Eq. 1 and 2 using the Gillespie method ([9]). Results from the FSM model were obtained from simulations of 28800 time steps, of a setup similar to Fig. 1 (used in [12]): a circular arena (diameter $1m$) with two identical shelters (diameter $150mm$).
For both models, only populations of 50 individuals were considered.

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.



Parameter	Description
l	Mean size of path
a	Geometric mean for angle departure
τ_{exit}	Mean time an agent follow a wall
v_c	Mean speed in central zone
v_p	Mean speed in peripheral zone
$s_{i,n}$	Probability of stop in shelter i with n neighbors
$\tau_{i,n}$	Mean stop duration in shelter i with n neighbors

Fig. 4. 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.

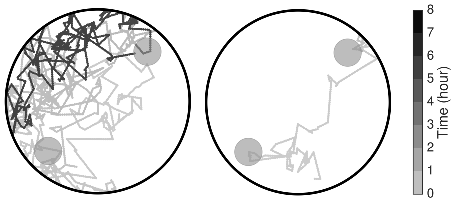


Fig. 5. Examples of the trajectory of an artificial insect, using the FSM model. The arena is circular and contains two shelters. Gray lines represents the trajectory of one agent. The brightness of the line reflects to simulation time. All experiments last 28800 time steps (corresponding to 8 hours). 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.

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. 3.

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 ([2], population size is 20, maximal number of generations is 500).

The fitness, 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:

$$\text{Fitness}_{\text{calibration}}(x) = D_{\text{Hellinger}}(B_{\text{optimized}}/Nu, B_{\text{reference}}/Nu) \tag{4}$$

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 ([7]) is defined by the equation:

$$D_{\text{Hellinger}}(P, Q) = \sqrt{2 \sum_{i=1}^{d} (\sqrt{P_i} - \sqrt{Q_i})^2} \tag{5}$$

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 ([7]).

Figure 7 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. 3 are tested, and Fig. 7 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 [8] (results not shown).

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. 8. 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 3.2.

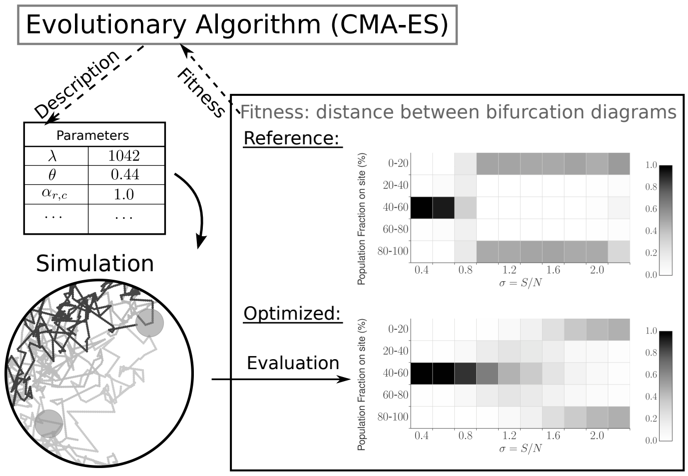


Fig. 6. Workflow of the Automated model calibration task by optimization. The optimized bifurcation diagram and the reference bifurcation diagram are both converted to one-dimensional histograms, by normalizing the sum of all bin values to 1.0. We use CMA-ES ([2]) as optimizer. The optimizer minimizes the fitness, which is computed by the formula: $\text{Fitness}_{\text{calibration}}(x) = D_{\text{Hellinger}}(B_{\text{optimized}}/N_u, B_{\text{reference}}/N_u)$ where x is the optimized parameter set, N_u is the number of histograms 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. $D_{\text{Hellinger}}(P, Q) = \sqrt{2 \sum_{i=1}^{d} (\sqrt{P_i} - \sqrt{Q_i})^2}$ is the Hellinger distance ([7])

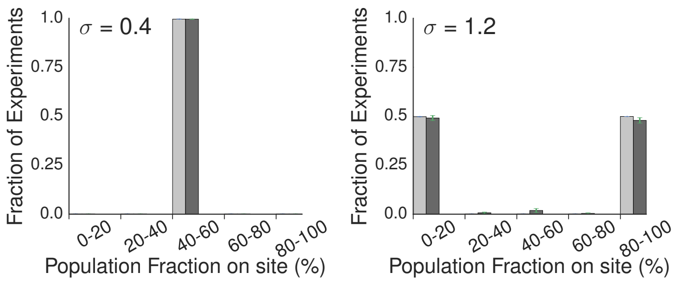


Fig. 7. Distribution of 50 cockroaches in the first shelter for chosen values of σ, using two different models: ODE (in dark grey) and FSM (in light grey). The parameter σ values are chosen before the bifurcation point ($\sigma = 0.4$), and just after the bifurcation point ($\sigma = 1.2$). Similar results are obtained for the range of values of σ present in Fig. 3. 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 $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).

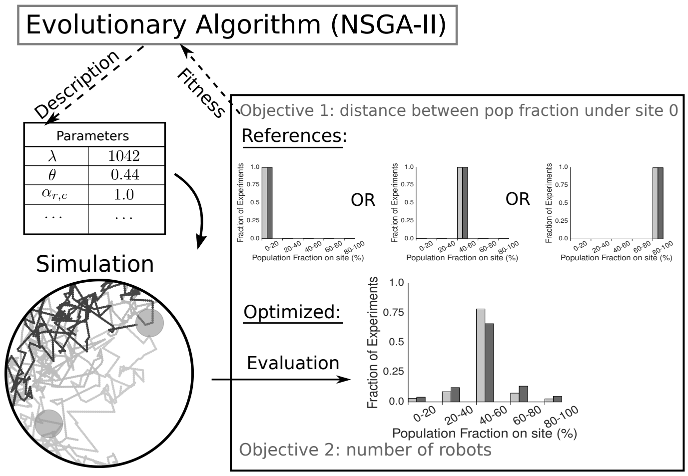


Fig. 8. Workflow of the process of modulating of the collective behavior of a group of cockroaches by robots. We use NSGA-II ([6]) as optimizer. The optimizer minimizes two objectives: (1) the difference between the optimized histogram and the reference histogram using the Hellinger distance ($D_{\mathrm{Hellinger}}(P, Q) = \sqrt{2 \sum_{i=1}^{d} (\sqrt{P_i} - \sqrt{Q_i})^2}$ as described in [7]), (2) the portion of robots in the population. Three reference histograms are considered, resulting of three possible types of modulation.

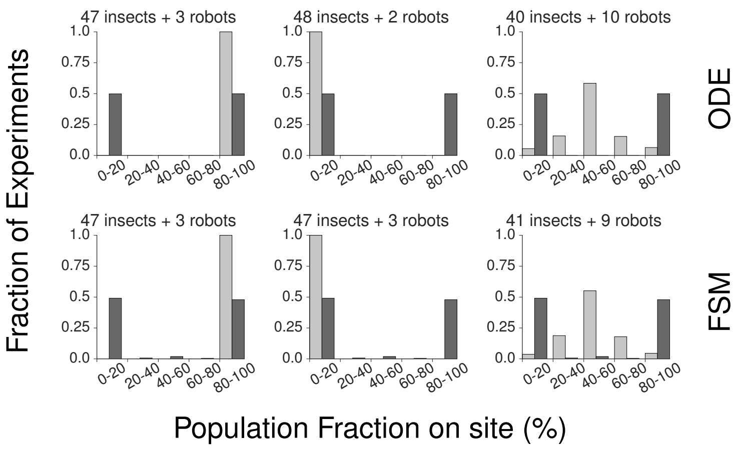


Fig. 9. Instances of results bio-hybrid group behavior when robots are optimized to change the reference behavior of cockroaches alone as much as possible (dark grey: reference animal-only model, light grey: optimized animals-and-robots models). σ values are chosen just after the bifurcation point ($\sigma = 1.2$). 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.

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:

$$\text{Fitness}_1 = D_{\text{Hellinger}}(\text{Hist}_{\text{optimized}}, \text{Hist}_{\text{reference}}) \quad (6)$$

$$\text{Fitness}_2 = M/N \quad (7)$$

with $D_{\text{Hellinger}}$ described in Eq. 5), and M the number of robots, from Eq. 3. We need a multi-objective optimizer to minimize these two objectives: we use the state-of-the-art NSGA-II evolutionary algorithm ([6], 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 9 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 [8] (results not shown).

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 ([12, 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.

The ODE model can describe the collective behavior of cockroaches, by using a parameter set obtained by experimentation with actual insects in [12]. A FSM model of cockroach behavior is introduced, with inspiration from [14, 8]. 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).

Acknowledgments

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