The Embodiment of Cockroach Aggregation Behavior in a Group of Micro-robots

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Abstract We report the faithful reproduction of the self-organized aggregation behavior of the German cockroach *Blattella germanica* with a group of robots. We describe the implementation of the biological model provided by Jeanson et al. in Alice robots, and we compare the behaviors of the cockroaches and the robots using the same experimental and analytical methodology. We show that the aggregation behavior of the German cockroach was successfully transferred to the Alice robot despite strong differences between robots and animals at the perceptual, actuatorial, and computational levels. This article highlights some of the major constraints one may encounter during such a work and proposes general principles to ensure that the behavioral model is accurately transferred to the artificial agents.

Keywords
Swarm robotics, autonomous robots, self-organization, biomimetic robotics, aggregation

1 Introduction

Collective behaviors in social animals can be very impressive. They range from the coordinated displacement of thousands of individuals [25, 52] to the building of complex structures [31, 44] and to the proper allocation of tasks among the members of a group [8, 18, 36]. During the last forty years, a growing body of studies has been interested in understanding the mechanisms underlying

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[§] Autonomous Systems Lab, ETH Zürich, ETH Zentrum CLA E31, Tannenstrasse 3, CH-8092 Zürich, Switzerland. E-mail: g.caprari@ieee.org these biological systems. We now know that most of these collective behaviors can be seen as due to decentralized systems made of autonomous units that are distributed in the environment and that can be described as following simple probabilistic stimulus-response behaviors [9]. This peculiar mode of organization, often based on self-organized processes, combines efficiency with flexibility, robustness, and distributedness [7].

For about 20 years, such features have attracted people who are working on research topics far from the study of animal behavior [9]. Probably the best-known example is the development during the 1990s, by Dorigo and his colleagues [22, 23], of the so-called *ant algorithms* for routing optimization. But other research fields are now tightly linked with the study of collective behaviors in social animals, collective robotics being one of them [2]. Aiming at controlling the behaviors of groups of robots, swarm robotics was often inspired by the collective abilities demonstrated by social animals, and particularly by social insects [56]. Indeed, social animals represent promising models for the decentralized organization and coordination of many autonomous robots [7]. For 15 years, several studies have used bio-inspired robot controllers to deal with collective behaviors as manifold as aggregation [46], foraging [57], task allocation [40], stick pulling [35], and site selection [28].

Nevertheless, robotics also offers interesting tools for the study of animal behavior [62]. A recent review by Webb [63] lists several works that studied animal behavior through robotic embodiments and argues that a robotic implementation of a biological mechanism provides a strong "proof in principle" (stronger than any computer simulation) that this mechanism really works as suggested.

Most of these works were concerned with motor and sensorimotor control, navigation, or learning in animals. Only a few of them dealt with biological self-organized behaviors or addressed questions about collective behaviors in animals. For instance, Beckers et al. [4], Holland and Melhuish [34], and Melhuish et al. [48] led a series of studies about ant-inspired object clustering and sorting by groups of robots. Their main goal was to design robot controllers, but they also discuss their results in the context of biological stigmergic processes (stigmergy is a coordination process in which the result of the previously accomplished work guides the animal's next tasks [30, 58]). The work by Kube and Bonabeau [41] on cooperative transport of objects by a group of robots can certainly be considered as more biology-oriented. Though their results did not display very effective collective transport, their robotic embodiment nevertheless was intended to display the first formalized model of cooperative transport of prey by ants. Finally, whatever the main purpose of a robotic embodiment of an animal collective behavior is, it remains an interesting means to test and to explore its properties, since it shares with the animal the physics, constraints, and opportunities of the real world [62, 63].

In the context of collective behaviors a robotics embodiment may fulfill an additional function. Embodied agents could be used to "infiltrate" groups of animals and influence their individual and collective behaviors [17]. Some recent works point in that direction. For instance, Michelsen et al. [49] designed a mechanical model of a dancing bee to investigate the role of various components of the waggle dance in the transfer of information to follower bees. Böehlen [6] performed a cohabitation experiment between a robot and three chickens and identified cues that can be used to increase the acceptance of the robot by the birds. As another example, Vaughan et al. [61] proposed a behavioral algorithm for a robot that is able to control the displacement of a group of ducks inside a closed arena. Fernandez-Juricic et al. [27] used birdlike robots to manipulate the behavior of individuals and study the responses of flock members under different ecological and social conditions. As a last example, the recent LEURRE project[1] has proposed to provide a general methodology for the design and control of mixed societies made up of real animals and autonomous artificial agents [11].

Getting a robot to become accepted by an animal as its conspecific does not necessarily require a perfect matching between the artificial and the biological agents. An artificial decoy mimicking some particular stimuli is often sufficient to induce a specific behavior in the animal [17]. However, in the case of a mixed society that relies on self-organized behaviors, it can be necessary to accurately

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[1] `http://leurre.ulb.ac.be`

imitate with robots the relevant individual and collective animal behaviors in a qualitative as well as in a quantitative sense. Indeed, in a recent theoretical study, Gautrais et al. [29] showed that it is sufficient to modify the quantitative behavior of five individuals within a group of twenty cockroaches in order to change profoundly their self-organized aggregation pattern. This result emphasizes the need for precise compatibility between animal's and artificial agent's individual behaviors.

In this article, we thus address the problem of accurately reproducing a self-organized biological behavior with a group of small autonomous robots. We choose to study a grouping behavior, which is probably the most common collective behavior among living organisms. Grouping occurs in a wide range of taxa, including bacteria, arthropods, fish, birds, and mammals [19, 50, 51]. More precisely, we report here a detailed description of the quantitative reproduction of the self-enhanced aggregation behavior of the German cockroach *Blattella germanica* with groups of 10 and 20 robots.

The behavioral model we used to perform this embodiment was described by Jeanson et al. [37, 38]. They characterized the individual and collective behaviors of *B. germanica* within a descriptive framework that considers almost all behaviors as probabilistic. This descriptive methodology is common in studies of self-organized behaviors in biology [9] and offers a great advantage for our work: Because it describes the behavioral output of animals, it is independent of the perceptual and cognitive process underlying such output. It therefore becomes possible to implement a self-organized behavior in an artificial system with perceptual and cognitive abilities that can be very different from the biological model, provided that the artificial system has access to the information required for the behavioral model to work.

In this article, we will first summarize the biological model of aggregation we used and then explain in detail how this model was implemented in Alice mini-robots (Section 2). We will also emphasize the difficulties encountered during the embodiment process and the solutions applied to solve these problems. In a second part, we will report the experimental validation of this implementation (Section 3). In particular we will compare the measurements of individual and collective behaviors of robots with the same measurements made by Jeanson et al. [37, 38] on cockroaches. We will precisely describe the analytical tools used to quantify behaviors in both insects and robots. Finally, we will discuss the general problems we encountered when porting the animal behavior to the robots.

2 Materials and Methods

In this section, we summarily describe the biological and artificial systems used in our work, followed by an overview of our experimental setup and a detailed description of the behavioral model of aggregation and its implementation in the robots.

2.1 The Biological System: First-Instar Larvae of *Blattella germanica*

The German cockroach, *B. germanica*, is a worldwide urban pest, which lives in close association with humans [55]. It is commonly found in kitchens, restaurants, and supermarkets. This species presents a rudimentary type of social organization and thus could be qualified as presocial. *B. germanica* commonly forages at night. During the day, this insect rests hidden (under kitchen appliances, sinks, behind baseboards, etc.), forming mixed and dense aggregates of individuals of both sexes and all developmental stages, especially at low external humidity [16, 43].

The behavioral model was developed from experiments conducted with first-instar larvae of *B. germanica* (24 h old). At this developmental stage, the body is about 3 mm long (excluding the antennae) and 2 mm wide, and the antenna length is 3 mm. The individuals do not present any polymorphism (i.e., the existence of two or more forms of individuals within the same animal species) or any sexual attraction. See [37, 38] for more details about the origin and the breeding of the animals.

2.2 The Artificial System: Alice Micro-robots

The Alice micro-robots were designed at the EPFL (Lausanne, Switzerland) [12]. They are very small robots (22 × 21 × 20 mm) with a maximum speed of 40 mm s^{-1}. They are equipped with two watch motors with wheels and tires. Four infrared sensors and transmitters are used for obstacle detection and local communication among Alices. Energy is provided by a nickel metal hydride rechargeable battery allowing an autonomy of about 6 h in the configuration used during this study. The Alice robots have a microcontroller PIC16LF877 with 8 Kb of flash EPROM memory, 368 bytes of RAM, and no built-in float operations. The implementation of the behavioral model should thus be as parsimonious as possible, rely on integer operations, and avoid floating point operations. Programming is done with the integrated development environment of the CCS-C compiler, and the compiled programs are downloaded in the Alice memory with the PIC-downloader software.[2]

2.3 Experimental Setup

The behavioral model was built from experiments performed in a uniform environment to avoid any spatial heterogeneities that might bias the behavior of the cockroaches. The experimental setup used with cockroaches consisted of a circular arena with diameter 11 cm and height 3 mm, covered by a glass plate (see [37, 38] for further details).

Experiments with robots were conducted in the same kind of experimental setup. At this point we have to consider the scale difference between a cockroach larva and the robot. A cockroach larva is about 3 mm long, while the Alice robot is 22 mm long. Also, cockroaches move at approximately 10 mm s^{-1}, while the Alice robot has a maximal speed of 40 mm s^{-1}. We choose to scale up from the experimental system used with cockroaches by a factor of four: the Alice moves at maximal speed, the arena has a diameter of 50 cm, and all parameters with length units will be multiplied by four. Note that on this scale the Alice robots are still double the size of a cockroach.

2.4 The Behavioral Model

This section summarizes the individual behavioral model reported in Jeanson et al. [37, 38]. For further details, refer to the cited articles.

The radial distribution of cockroaches during the experiments showed that the larvae (which were dropped in the center of the arena) tended to reach the periphery of the arena and stay in an external ring (0.5 cm wide) for more than 50% of their time (see Figure 1). This is an example of thigmotactic behavior, that is, a tendency to decelerate upon contact with the arena wall and remain in antennal contact with it. We can thus subdivide the arena into a central zone and a peripheral zone. The analysis in Jeanson et al. [37] showed that cockroaches move at approximately constant speed in the central zone. Their movement in that zone is a correlated random walk characterized by a constant rate per unit time of changing direction and a forward-oriented turning-angle distribution. In the peripheral zone, cockroaches follow the arena wall at approximately constant speed with a constant rate of leaving and reentering the central zone. In addition, cockroaches can stop at any moment, stay motionless for some time, and then move again.

Most of these processes are memoryless, that is, the cockroaches have a constant probability per unit time of changing state (from moving straight to turning, from moving to stopping, or leaving the periphery): In other words, the probability of changing from state a to state b between time t and time $t + dt$ is constant and independent of the time already spent in state a. Thus, the time to remain in a given state is exponentially distributed, and the rate of change can be estimated by survival curve analysis [32]. A survival curve analysis consists of plotting on a log-linear scale the proportion of individuals that remain in a given state as a function of the time (or distance) elapsed since the beginning of this state. On this log-linear scale (provided that the process is truly memoryless), the decay of the proportion will follow a straight line (see Figure 2):

$$f(t) = \log\left(e^{-kt}\right) = -kt.$$

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[2] `http://www.ehl.cz/pic/`

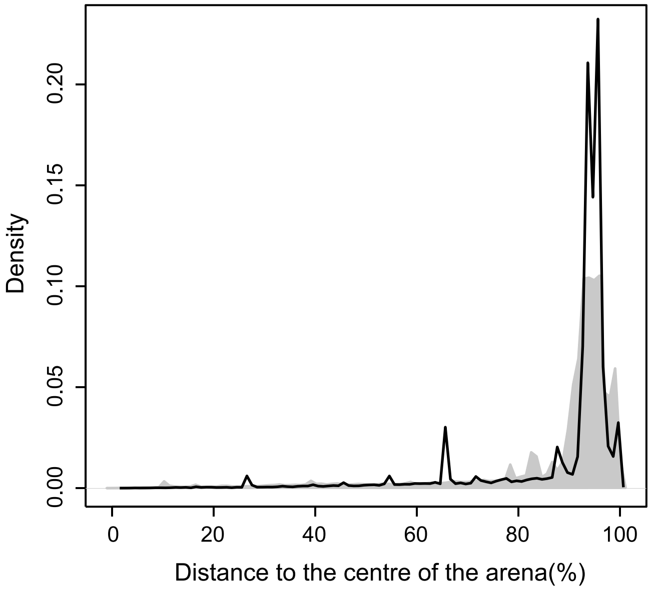

Figure 1. Radial distribution of Alice robots (black line) and cockroaches (gray polygon) in the arena during 60 min of free walking.

The slope k of this straight line will give us the rate of changing state, and its reciprocal $\frac{1}{k}$ will give us the mean time (or distance) to remain in the given state.

In contrast to the simple exponential distributions mentioned above, the stop times (either in the center or in the periphery) followed a distribution that can be described as the sum of two exponential distributions (we call such a distribution a *biexponential* distribution). On a log-linear scale the decay of the proportion of individuals that remain stopped is described by (see Figure 3)

$$f(t) = \log\left(p\mathrm{e}^{-k_1 t} + (1-p)e^{-k_2 t}\right)$$

This distribution can be explained by the cockroach's being in either one of two stop states: a short one (with mean stop time $1/k_1$, the animal shows some activity) and a long one (with mean stop time $1/k_2$, the animal does not show any activity), with probability p of being in the short state [37, 38].

Interactions between individuals were studied by Jeanson et al. [38]. The stopping behavior of a cockroach was obtained by analyzing the fraction of moving cockroaches that stopped when encountering a group of N stopped cockroaches ($1 \leq N \leq 3$). Note that the moving cockroach only perceives its conspecifics in its immediate neighborhood. The fraction of stops increased with the number of stopped cockroaches in the neighborhood. The spontaneous rate of starting to move for a cockroach stopped in a cluster was deduced from the survival curves of aggregate lifetimes. These lifetimes also followed a biexponential distribution (again interpreted as two stop states), and the rates of leaving an aggregate (k_1 and k_2), as well as the probability of being in a short stop state (p), decreased with increasing number of neighbors.

The model (see Figure 4 for a schematic description of the behavioral model and Tables 1 and 2 for parameter values) was first implemented in computer simulations. Details about the simulation can be found in [37] for the individual movement, and in [38] for the collective implementation. In short, a spatially explicit individual-based model was designed to explore model predictions by Monte Carlo simulations. In order to assess the model validity, a comparison between model predictions and real experiments was performed. Collective behaviors were studied by putting 10 or

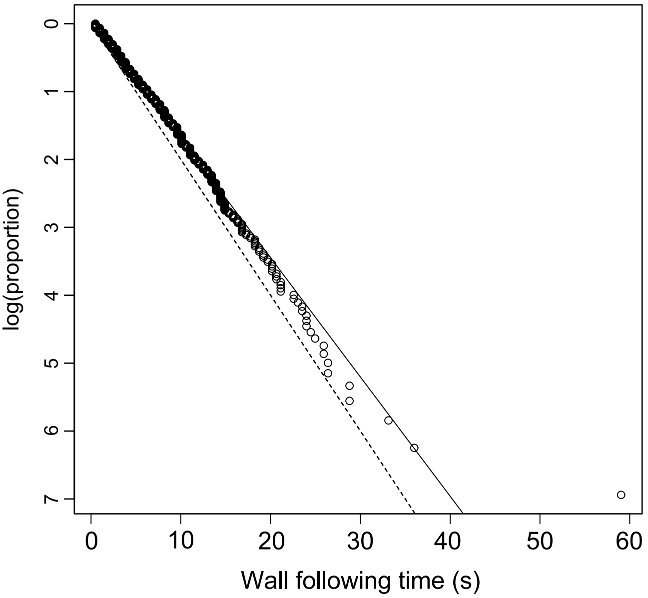

Figure 2. Survival curve of the Alice wall-following times, with the fitted regression line (solid) and the original cockroach regression line (dashed).

20 cockroaches into an experimental arena. A camera placed above the arena was coupled with a computer, and image-processing software computed the position of each individual every 10 s during 60 min. Two cockroaches were assumed to belong to the same aggregate if their interindividual distance was less than or equal to 1 cm. The experimental data and the simulation data were then processed to obtain the size of the largest aggregate every 10 s. The comparison between experimental results and simulation results showed good agreement between the model and the biological system on the individual level as well as on the collective level [37, 38].

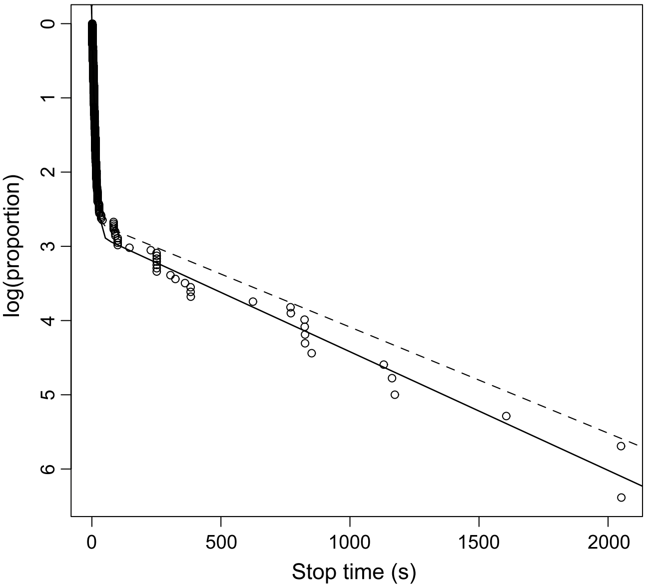

Figure 3. Survival curve of the Alice stop times, with the fitted regression line (solid) and the original cockroach regression line (dashed). These stop times are for a single Alice robot (without neighbors).

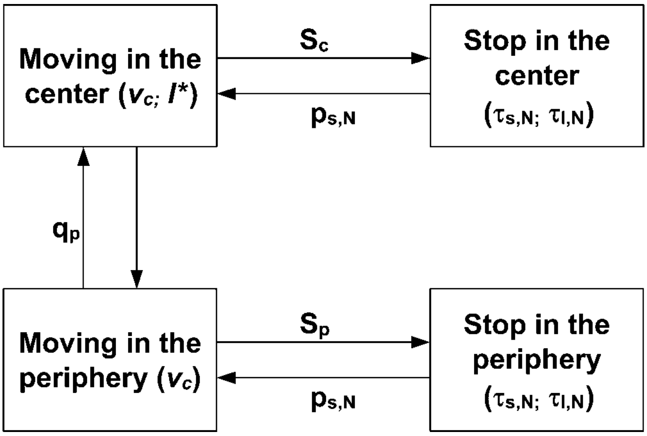

Figure 4. The behavioral model of cockroach displacement. Parameters are: speed in the center, v_c; speed in the periphery, v_p; mean free transport path l^*; rate to quit the periphery, q_p; rate of stopping in the center (s_c) or periphery (s_p); probability of being in the short stop state, $p_{s,N}$, with mean short stopping time $\tau_{s,N}$ and mean long stopping time $\tau_{l,N}$ (as a function of the number N of stopped neighbors). The probability of transition from moving in the center to moving in the periphery is not directly encoded in the model, since it is a direct consequence of the random walk in the center. The parameter values for the cockroaches [37, 38] are listed in Tables 1 and 2.

2.5 Implementation in the Alice Robots

The implementation of the behavioral model described above may be broken down into two parts: displacement and stopping behavior. In the displacement part, we describe the behaviors involved in the dispersal of the robots inside the arena; the stopping behavior part contains a description of the core of the self-organized aggregation process.

Table 1. Individual displacement parameters of the cockroaches [37] and their estimation from the analysis of the Alice's paths (mean ± s.e.m.). Here * indicates that the standard error was estimated from a nonparametric bootstrap (200 iterations); † indicates that the standard error was computed from the measured fraction and the sample size with the formula given by Zar [64].

	Value	
Parameter	Cockroach	Alice
v_c (cm s^{-1})	1.1 ± 0.12*	3.97 ± 0.01*
v_p (cm s^{-1})	1.06 ± 0.09*	3.68 ± 0.01*
s_c (s^{-1})	0.033 ± 0.002†	0.026 ± 0.001*
s_p (s^{-1})	0.084 ± 0.003†	0.074 ± 0.004*
l^* (cm)	2.32	11.35
$p_{s,0}$	0.93 ± 0.018*	0.943 ± 0.010*
$\tau_{s,0}$ (s)	5.87 ± 0.16*	7.52 ± 0.28*
$\tau_{l,0}$ (s)	700 ± 233*	626 ± 103*
τ_{exit} (s)	0.130 ± 0.003†	0.108 ± 0.006*

Table 2. Interaction parameters among cockroaches [38] and their estimation from the analysis of the Alice robot's interactions (mean ± s.e.m.). Each parameter is given for the three tested group sizes (2, 3, and 4). Here * indicates that the standard error was estimated from a nonparametric bootstrap (200 iterations); ‡ indicates that the standard error was computed from the α-trimmed (α = 0.05) values. The meaning of the parentheses is discussed in Section 3.2.2.

Parameter	Value	
	Cockroach	Alice
$F_{\mathrm{Stop},1}$	0.42	0.41 ± 0.03
$F_{\mathrm{Stop},2}$	0.50	0.54 ± 0.05
$F_{\mathrm{Stop},3}$	0.51	(0.72)
$\tau_{s,1}$ (s)	16 ± 2.9*	11.39 ± 1.75*
$\tau_{l,1}$ (s)	1248 ± 712*‡	733 ± 150*
$p_{s,1}$	0.66 ± 0.3*	0.62 ± 0.07*
$\tau_{s,2}$ (s)	18.5 ± 2.5*	9.98 ± 9.90*
$\tau_{l,2}$ (s)	1062 ± 354*‡	713 ± 94*
$p_{s,2}$	0.34 ± 0.04*	0.27 ± 0.12*
$\tau_{s,3}$ (s)	34.1 ± 10.2*	(6.64)
$\tau_{l,3}$ (s)	1719 ± 956*‡	(910)
$p_{s,3}$	0.24 ± 0.06*	(0.09)

2.5.1 Displacement

The correlated random walk used to describe the cockroach displacements [37] is characterized by a series of straight moves (also called free paths) and turns. The lengths of straight moves are exponentially distributed with a mean free path of length l. The distribution of turning angles was found to be bell-shaped. One could implement this random walk in the Alice robot by repeatedly drawing a random free path from an exponential distribution of mean l, with a random turning angle from a fitted bell-shaped curve.

However, since the final goal will be experiments with several robots at the same time, there is a simpler solution. In fact, when averaged over many individuals and after a few diffusive events, a random walk as described above is equivalent to one where the turning angles are distributed uniformly in $[-180; 180]$ deg (isotropic distribution) and the straight moves are exponentially distributed with mean l^* [13]. Here l^* corresponds to the transport mean free path and is computed from l and the asymmetry parameter $g \in (-1, 1)$ by the equation $l^* = \frac{l}{1-g}$. It represents the distance beyond which the random walk becomes uncorrelated. g corresponds to the mean of the cosine of the turning angle. It characterizes the tendency of the individual to continue in the same general direction (majority of turning angles in $[0; +90[$ and $]-90; 0]$ deg, $1 \geq g > 0$) or to make U-turns (majority of turning angles in $]+90; +180]$ and $[-180; -90[$ deg, $-1 \leq g < 0$). See [37] for a more detailed description. Given the limited computing capacities of the Alice robots, we choose to implement this simplified random walk.

Uniform random numbers were generated with a Quick & Dirty algorithm (Press et al. [53]). Exponential random numbers with mean l^* were created from a uniform random number $r \in (0, 1)$

transformed to $-(\log r)/*$ with an algorithm using only integers (see Ahrens and Dieter [1] for the algorithm). Letting the robot move or turn at maximum speed, we computed from these random numbers the time (in milliseconds, the unit of the internal clock in the Alice robot) that it should move straight forward or turn. This random walk is continued until the robot detects an arena wall with its infrared sensors.

When the robot detects a wall, it switches into wall-following behavior (provided with the preprogrammed sensory-motor behaviors of Alice robots; see Caprari [10]). The time an Alice robot follows the wall is also exponentially distributed with mean τ_{Exit} [37] and was computed as described above. Upon completion of this wall-following path the robot returns to the central zone with a random angle drawn uniformly between 17 and 78 deg (as an approximation to the log-normal angle distribution measured in [37]).

2.5.2 Stopping Behavior

The rate of stopping is constant per unit time (memoryless process); the above displacement is thus interrupted every 500 ms, and a random number uniformly distributed between 0 and 100 is drawn to decide whether or not the robot should stop. This probability is different when the robot is in the center (s_c) than when it is in the periphery (s_p). It also varies with the number N of neighbors that an Alice robot detects through its local infrared communication (s_N, $0 \le N \le 3$). Each robot broadcasts with its infrared emitters two robot-specific identification numbers: an odd one if it is moving (movement number) and an even one if it is stopped (stop number). This emission can be read by other robots up to a distance of ≈ 4 cm. Each robot can thus detect the number of stopped robots in its immediate neighborhood. In agreement with the behavioral model, the maximum number of stopped robots that an Alice could detect at the same time was limited to three [38].

The stop duration has a biexponential distribution that varies according to the number N of neighbors an Alice robot can detect ($1 \le N \le 3$; see above). This biexponential distribution is generated by the superposition of two exponential distributions, one for short stops and one for long stops. The robot thus first draws a random number uniformly distributed between 0 and 100 to decide whether it will be a short stop (probability $p_{s,N}$) or a long stop, and then draws an exponential stop time that is either short (mean $\tau_{s,N}$) or long (mean $\tau_{l,N}$).

If the number of stopped neighbors changes during a robot's stop, the robot has to modify the duration of its halt according to the new number of neighbors. Because we deal with a memoryless process, the time the robot has to remain stopped is independent of the time it has already spent in this state. Consequently, when the number of stopped neighbors changes, the robot only draws a new stop time from the appropriate exponential distribution. Note that the robot retains whether the stop state is short or long.

Once the stop time has elapsed, the robot continues its displacement with either a random walk (center) or a wall-following behavior (periphery).

3 Analysis and Comparison with Cockroach Behavior

In order to validate the implementation of the cockroach aggregation behavior in an Alice robot, we performed the analysis of robot behaviors in conditions similar to those used for the characterization of cockroach behaviors. This analysis is broken down into three different parts. The first (behavior of an isolated robot) and second (local interactions) parts validate the implementation at the individual level; the third part focuses on the collective output of the system. In each of these parts, the data collected with robots are compared with the data collected with cockroaches in [37, 38].

3.1 Path Analysis for an Individual Robot

Individual displacements of robots were studied by letting a single individual move during 60 min in the experimental arena. This experiment was repeated 10 times with 10 different robots.

Displacements were recorded with a high-definition camera (Sony CDR-VX 2000 E), and the paths were digitized with automatic tracking software (Ethovision®, version 1.90, Noldus Information Technology, 1 pixel = 0.278 × 0.219 cm). The sampling rate was chosen according to Tourtellot et al. [59]: The time interval between two successive points should let an individual move approximately its own body length. Thus, the sampling rate was set to one point every 0.48 s for the robots. The analysis of the different paths followed the procedures explained in [37]. These procedures were implemented in the open-source software R [54] (scripts can be obtained from the authors upon request). The paths over a whole hour were divided into the pieces in the central zone and the pieces in the peripheral zone (all coordinates less than 2.75 cm from arena walls). Then these pieces were again subdivided into subpieces where the Alice robot moved and where it was at a stop (defined as less than 7-mm distance between two successive coordinates for at least 0.96 s [14]). Standard errors for all parameters were estimated by a nonparametric bootstrap method [26].

3.1.1 Central Zone

The speed in the center was computed as the total length of a path subpiece divided by the total time it took the robot to pass through it. The mean (v_c) of these velocities gave 3.97 ± 0.01 cm s^{-1} (mean ± s.e.m.).

To assess the random walk of the robots in the central zone, we computed the transport mean free path l^*. One could compute this value by means of the equation $l^* = \frac{l}{1-g}$ given in Section 2.5.1. But to compute l and g, one would need an unbiased criterion to compute the distribution of turning angles, that is, to establish accurately at which moment the individual significantly changed the direction of its path [59, 60]. To compute the value of l^* we rather used the same method as in Jeanson et al. [37], which does not require the characterization of the distribution of turning angles. The net squared displacement of a moving individual is given by [39]

$$\langle R_n^2 \rangle \approx n\int_0^{+\infty} l^2 p(l)\ \mathrm{d}l$$

where $p(l)\ \mathrm{d}l$ is the probability that the length of each path has a value between l and $l + \mathrm{d}l$. Thus $\langle R_n^2 \rangle$ corresponds to the square of the straight line distance between the beginning of a path and the position of the individual after n consecutive steps. In the case of a diffusive random walk, assume an exponential distribution of the path lengths with a characteristic length l^*:

$$p(l) = \frac{1}{l^*} e^{l/l^*}$$

Then

$$\langle R_n^2 \rangle \approx n\int_0^{+\infty} l^2 \frac{1}{l^*} e^{l/l^*}\ \mathrm{d}l \approx 2n(l^*)^2 \tag{1}$$

Assuming that the velocity v is constant, at time t we have

$$n = \frac{tv}{l^*} \tag{2}$$

and substituting Equation 1 in Equation 2, we finally get

$$\left\langle R_n^2 \right\rangle \approx 2 v_c l^* t \quad \Rightarrow \quad l^* \approx \frac{\left\langle R_n^2 \right\rangle}{2 v_c t} \tag{3}$$

For each path and each time step, we calculated the square of the distance R_n between the beginning of the path (x_0, y_0) and the position (x_n, y_n) of the robot after n steps:

$$\left\langle R_n^2 \right\rangle = (x_n - x_0)^2 + (y_n - y_0)^2$$

Figure 5 shows the average squared distance $\langle R_n^2 \rangle$ as a function of time for all paths recorded in the central zone of the arena. During the diffusive regime, the mean squared net displacement increases linearly with time and then reaches a plateau due to the finite space provided by the arena, which prevents robots from diffusing further away. Fitting the initial linear part of the curve to get the slope, we obtained (Figure 5)

$$\left\langle R_n^2 \right\rangle = 90.14t - 150.24, \qquad r = 0.998 \tag{4}$$

With $v_c = 3.97$ cm s^{-1}, Equations 3 and 4 predict a transport mean free path $l^* \approx 11.35$ cm, which is of the same order as the expected value 9.28 cm corresponding to the transport mean free path of cockroaches, 2.32 cm, scaled by a factor 4 (see Section 2.3).

To assess the probability of a robot to stop spontaneously (that is, without any interactions with another robot) in the central zone, we used only the paths of the robots that started in the peripheral zone of the arena and that either stopped spontaneously in the central zone or returned to the

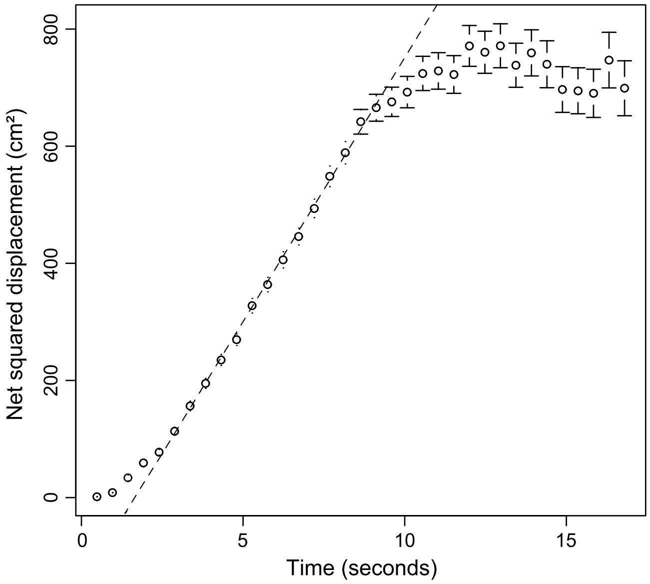

Figure 5. Mean net squared displacement $\langle R_n^2 \rangle$ of robots as a function of time. Each dot represents the mean ± s.e.m. The dashed line represents the linear regression based on the linear part of the curve ($\langle R_n^2 \rangle = 90.14t - 150.24$, $r^2 = 0.998$).

periphery. We computed the fraction $F_{\mathrm{Stop,c}}$ of paths that ended in a spontaneous stop in the central zone. Assuming that the speed v_{c} in the center of the arena is constant, knowing the diameter d of the central zone, and using a recent result from Blanco and Fournier [5], the probability for a robot to spontaneously stop in the central zone can be computed from the following equation (see [37] for the detailed mathematics):

$$s_{\mathrm{c}} = \frac{4v_{\mathrm{c}}(F_{\mathrm{Stop,c}})}{\pi d}$$

In the central zone of the arena, the fraction $F_{\mathrm{Stop,c}}$ was 22.7% ($n = 616$) for the robots. Thus, the probability per unit time of spontaneously stopping in the central zone of the arena is $s_{\mathrm{c}} = 0.026 \pm 0.001\ \mathrm{s}^{-1}$ for the robots.

3.1.2 Peripheral Zone

The speed in the periphery was computed as detailed above, giving a mean speed $v_{\mathrm{p}} = 3.68 \pm 0.01\ \mathrm{cm\ s}^{-1}$. The rates to stop spontaneously in or to quit the periphery were estimated together by first drawing the survival curve of all the times during which a robot followed the arena wall before either spontaneously stopping or quitting it (see Figure 2). Given the proportion of these wall-following path pieces that ended in a spontaneous stop in the periphery, one can decompose the slope of this survival curve into the rate of quitting the periphery ($q_p = 1/\tau_{\mathrm{Exit}}$) and the rate of spontaneously stopping ($s_{\mathrm{p}} = 1/\tau_{\mathrm{Stop}}$) in it (see Jeanson et al. [37] for the details). This procedure gave a quitting rate of $0.102 \pm 0.006\ \mathrm{s}^{-1}$ and a spontaneous stopping rate of $0.074 \pm 0.004\ \mathrm{s}^{-1}$.

3.1.3 Spontaneous Stopping Times

Spontaneous stopping times were also analyzed with a survival curve, and they showed, like the cockroach data, a biexponential distribution (see Figure 3). We estimated the probability $p_{\mathrm{s},0}$ for a spontaneous stop to be of the short type and the mean duration of short ($\tau_{\mathrm{s},0}$) and long ($\tau_{\mathrm{l},0}$) stops by fitting the following equation to the fraction of robots, $F(t)$, still motionless at time t (using the least squares method):

$$F(t) = p_{\mathrm{s},N}\mathrm{e}^{-t/\tau_{s,N}} + (1 - p_{\mathrm{s},N})\mathrm{e}^{-t/\tau_{l,N}}, \qquad N = 0 \tag{5}$$

The best fit was obtained with $p_{\mathrm{s},0} = 0.94 \pm 0.01$, $\tau_{\mathrm{s},0} = 7.52 \pm 0.28$ s, and $\tau_{l,0} = 626 \pm 103$ s.

3.2 Interactions among Robots

In order to quantify interactions among robots we must determine when one individual detects another. This was done by estimating the detection area of a single robot. A robot *A* was programmed to report the presence of neighbors in its vicinity. Another robot *B* was drawn near to *A* from several different directions and orientations: parallel to the incoming direction with the front toward *A*, parallel to the incoming direction with the back toward *A*, and perpendicular to the incoming direction (Figure 6). For each of these directions and orientations we then measured the maximal distance from which *A* detected the approaching robot *B*. This gave us an estimate of the neighbor detection area of *A* for each orientation of *B* (Figure 6). We finally defined the maximal detection area of *A* as the superposition of the previous detection areas. In the rest of the analysis we considered that a stopped robot was a neighbor of another one, and hence belonged to the same aggregate, if its body crossed the maximal detection area of the other one, whatever its incoming orientation.

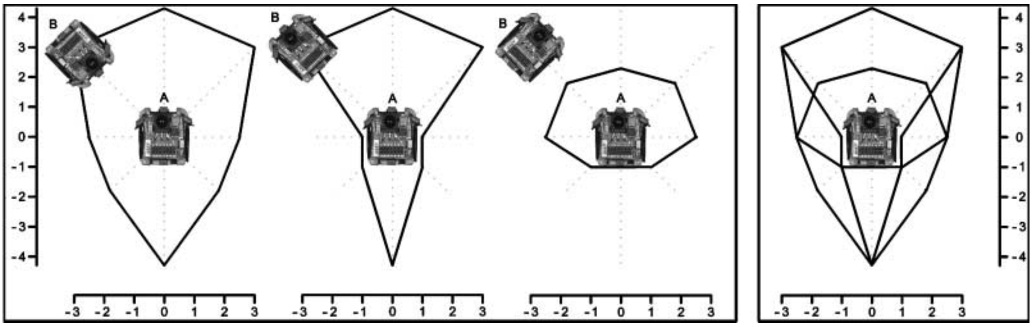

Figure 6. Left box: Estimated neighbor detection areas (scales are in centimeters) of a single robot *A* for different orientations of the neighbor *B*. From the left to the right: neighbor front, neighbor back, and neighbor side aim at the robot *A*. Right box: The estimated maximum neighbor detection area is the superposition of the three previous estimated neighbor detection areas.

3.2.1 Probabilities of Joining and Leaving an Aggregate

To analyze the interactions among individuals, that is, to determine the behavioral rules based on local information, we introduced several aggregates of N stopped robots in the arena ($1 \leq N \leq 3$), and then we let a single robot move between them. Forty experiments lasting 60 min were performed.

The probability of stopping in an aggregate is defined in [38] as follows:

$$P_{\mathrm{Stop},N} = \frac{v \log(1 - F_{\mathrm{Stop},N})}{d}$$

with v the speed of the cockroach (either v_{c} or v_{p}, depending on the position of the animal in the arena), d the maximum distance at which a moving cockroach could perceive a stopped one, and $F_{\mathrm{Stop},N}$ the fraction of cockroaches that stopped when encountering N ($1 \leq N \leq 3$) stopped neighbors. d strongly depends on the size and shape of the maximal detection area of the cockroach, which was defined as a disk of diameter 6 mm centered on the head of the animal. This disk corresponds to the area around the head of the cockroaches within which an antennal contact with another cockroach can happen (antennae are 3 mm long). Because the maximal detection area measured for robots does not match the size and shape of the one for cockroaches, we did not compute $P_{\mathrm{Stop},N}$ in robots, but we rather chose $F_{\mathrm{Stop},N}$ to compare robots' stopping behavior with cockroaches' stopping behavior. We thus recorded the number of encounters a moving robot made with N stopped robots within its maximal detection area and the number of these encounters that ended in a stop of the moving robot.

Once a robot was stopped near N robots, we computed the duration of that stop. We then drew log-linear plots of the stop-time survival curve for each group size (2 to 4, counting the observed robot). As with the cockroaches, all the survival curves showed a bilinear pattern (biexponential on a normal scale). Since in our setup only one robot could leave the aggregate, we could estimate the stopping parameters for each group size [probability of being in the short stopping state ($p_{\mathrm{s},N}$), mean duration of short stops ($\tau_{\mathrm{s},N}$), and mean duration of long stops ($\tau_{l,N}$)] by directly fitting Equation 5.

3.2.2 Calibration of Interaction Parameters

Interactions among robots and neighbor detection are based on local communication through infrared transmitters and sensors. However, the quality of this local communication is somewhat restricted, particularly in the case of bad alignment or multiple robots emitting at the same time in the same place [10]. In our experiments, a robot could obtain the following false identification numbers: a stop number from a moving robot, a movement number from a stopped robot, or two different numbers from the same robot (identification numbers are sent every 50 ms and stored in memory for at most 1 s). This noisy perception of the number of stopped neighbors had to be taken into account during the implementation of the behavioral model.

At the behavioral level, the major consequence was a discrepancy between the stopping probability (estimated by $F_{\mathrm{Stop},N}$) and time (estimated by $p_{s,N}$, $\tau_{s,N}$, and $\tau_{l,N}$) measured in experiments and those coded in a robot's controller. Thus, the hardware constraints have altered the behavioral output of the robot in comparison with the programmed behavioral algorithm. To correct for this hardware problem, we decided to calibrate the interaction parameters programmed in the robots by a modified bisection method. More precisely, we ran a first set of 40 experiments to assess the initial discrepancy between implemented and observed interaction values. If this discrepancy was negative (implemented < observed), the implemented value was excessively increased; if it was positive, the implemented value was excessively decreased. Another set of 40 experiments gave us a new assessment of the discrepancy with an opposite sign: positive if it was formerly negative, and negative if it was formerly positive. This gave us a first interval that contained the set of implementation parameters that would result in the correct behavioral values (those of the cockroaches). We then reduced this interval by a dichotomous process. For each parameter we computed the mean of the upper and lower bounds of the interval and implemented it in the robots' controller. We then ran a new set of 40 experiments, and we checked whether the correct behavioral values were below or above this mean. If the correct values were below the mean, it became the upper bound of the interval. Otherwise, it became the lower bound. This process was repeated until no statistical difference was observed between robots' and cockroaches' interaction behaviors.

After the last set of 40 experiments, we obtained interaction parameter values with robots in agreement with those found in cockroaches, except for $N = 3$: Stop events in these experiments with at least three robots inside the maximal detection area were too scarce to confidently estimate the interaction values. Thus, the values of the different interaction parameters for more than two neighbors are given without any confidence interval and are displayed in parentheses in Table 2.

$F_{\mathrm{Stop},N}$, the fraction of cockroaches that stopped when encountering N ($1 \leq N \leq 3$) stopped neighbors, increased with the number of stopped neighbors (Table 2). Thus, the probability for a robot to join an aggregate increased with the number of neighbors, as in cockroaches. Regarding $p_{s,N}$, $\tau_{s,N}$, and $\tau_{l,N}$, the results (see Figure 7 and Tables 1 and 2) indicated that the stop times, either

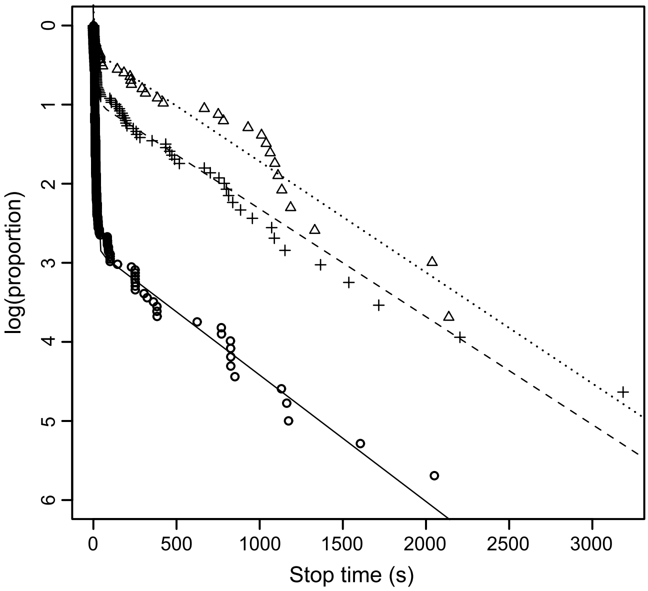

Figure 7. Survival curves of robot stop times near 0 (circles), 1 (plus signs), or 2 (triangles) neighbors, with their fitted regression lines.

short ($\tau_{s,N}$) or long ($\tau_{l,N}$), remained inside the confidence interval of cockroach values. The probability of belonging to short stop durations ($p_{s,N}$) decreased as the number of neighbors increased and remained in the confidence interval of cockroach values.

3.3 Collective Behaviors

For the final validation of our implementation of the cockroach aggregation behavior in Alice robots, we compared the collective structures that resulted from this self-organized clustering process between robots and cockroaches. The movement of 10 robots (10 replications) or 20 robots (10 replications) was recorded over 60 min with a high-definition camera (Sony CDR-VX 2000 E). Every minute, we computed three collective behavioral measures: the number of aggregates, the size of the largest one, and the number of isolated robots. An example experiment can be seen in Figure 8.

The results of the collective experiments with the robots were compared with the results of the same experiments made with 10 (20 replications) or 20 (22 replications) cockroaches by Jeanson et al. [38]. This comparison is shown in Figure 9. Note that the cockroaches are introduced at the center of the experimental arena under CO_2 narcosis [37, 38]. After recovery from this narcosis, cockroaches first ran around in an excited way. Furthermore, all the cockroaches in a group introduced into the arena did not wake up simultaneously. Therefore, to compare the dynamics of aggregation, one should not take into account the first 5 min of the experiments with cockroaches.

Qualitatively, the curves of robots and cockroaches display a similar shape whatever the observed measure. All the curves have reached a stationary state after 40 min. We then computed for each experiment and each behavioral measurement the mean over the last 20 min and compared, using an exact Wilcoxon rank sum test for nonpaired data, the set of robot experiments with the set of cockroach experiments.

Regarding the number of aggregates, experiments with 10 agents resulted in 1.905 ± 0.174 robot aggregates versus 1.590 ± 0.109 cockroach aggregates (NS, $W = 134.5$, $p = 0.13$). Experiments with 20 agents resulted in 3.160 ± 0.210 robot aggregates versus 2.502 ± 0.250 cockroach aggregates (NS, $W = 158$, $p = 0.051$).

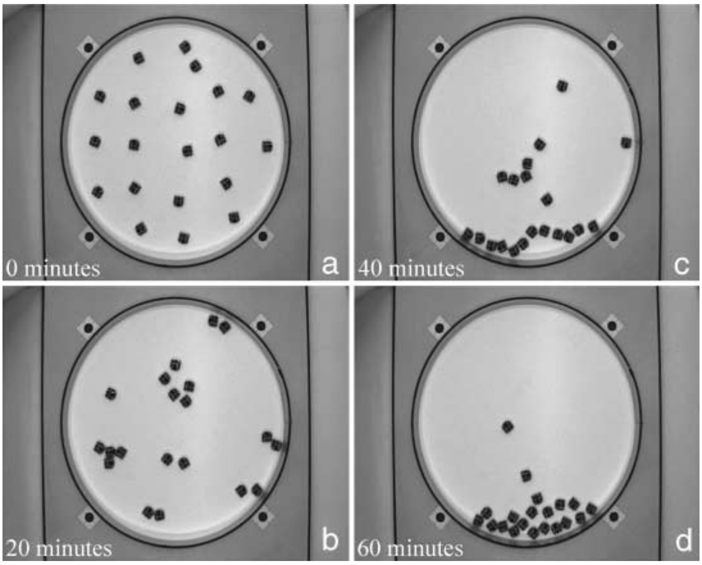

Figure 8. An example of a collective experiment with 20 robots that ends with a single large aggregate. Snapshots were done (a) at the beginning of the experiment, (b) after 20 min, (c) after 40 min, and (d) at the end of the experiment.

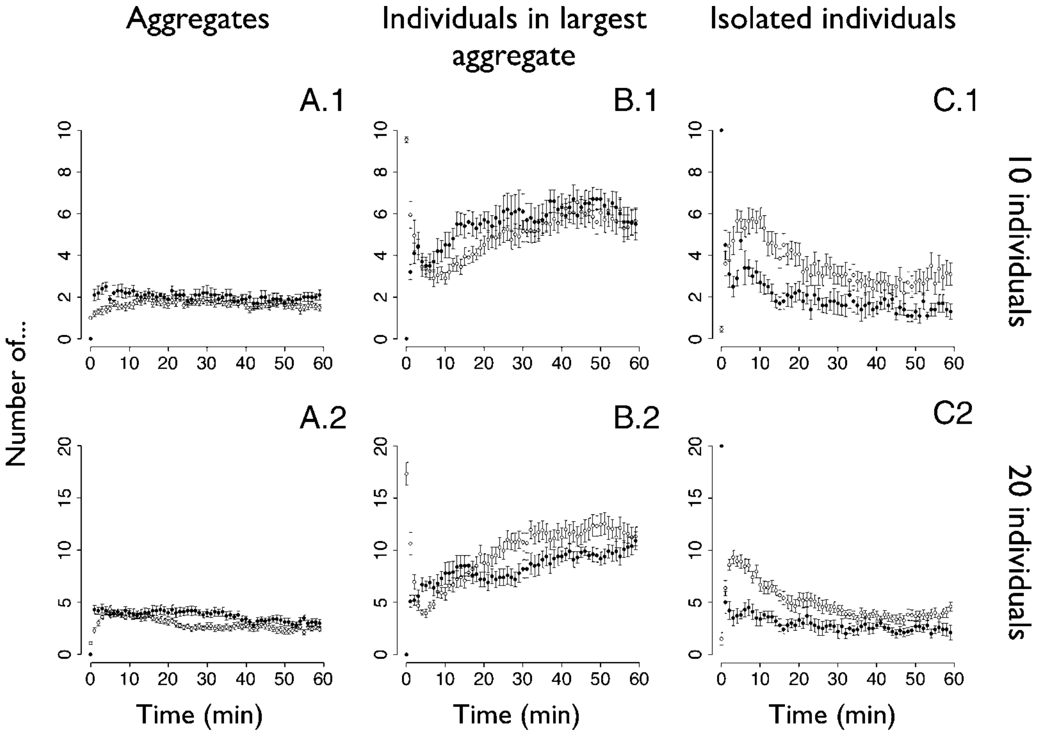

Figure 9. Dynamics of aggregation in robots (black dots) and cockroaches (white dots; data from [38]). Data points represent the mean ± s.e.m. Row 1 represents experiments with 10 individuals (10 replications with robots, 20 replications with cockroaches). Row 2 represents experiments with 20 individuals (10 replications with robots, 22 replications with cockroaches). Column A represents the mean number of aggregates as a function of time. Column B represents the mean size of the largest aggregate as a function of time. Column C represents the mean number of isolated individuals as a function of time.

In experiments with 10 agents, the size of the largest cluster was 6.200 ± 0.489 in robots and 5.895 ± 0.480 in cockroaches (NS, $W = 109, p = 0.71$). In experiments with 20 agents, the size of the largest cluster was 9.740 ± 0.538 in robots and 11.818 ± 0.900 in cockroaches (NS, $W = 74, p = 0.15$).

At the end, the number of isolated individuals in experiments with 10 agents was 1.455 ± 0.143 in robots and 2.7675 ± 0.447 in cockroaches (NS, $W = 60$, $p = 0.08$). The number of isolated individuals in experiments with 20 agents was 2.430 ± 0.232 in robots and 3.723 ± 0.342 in cockroaches (significant difference, $W = 53, p = 0.02$).

Quantitatively, experiments with 10 robots showed very good agreement with the biological system all along the experiment. Experiments with 20 robots also showed good agreement with the cockroaches, except for the number of isolated individuals, which is significantly higher in cockroaches than in robots.

4 Discussion

To build a realistic representation of an animal behavior with robots raises several problems. The very first of them is to determine which level of description is required to capture the main explanatory mechanisms underlying a given behavior. Should we study the group level, the individual level, the cognitive level, the physiological level? Actually, this problem is not specific to a robotics model of animal behaviors. It is rather a general concern for all people involved in modeling animal behavior, whatever their analytical and modeling tools are. Yet, it can have major implications for the design of the robot architecture and controller. This level of description conditions what part of the biological model has to be faithfully reproduced and what part permits a less accurate implementation because it is only weakly linked with the studied behavior.

For instance, Lambrinos et al. [42] have tested their hypothesis about the navigation behavior of the Saharan ant *Cataglyphis* with a mobile robot called Sahabot. Their main purpose was to gain insight about the way this insect uses the polarized-light pattern of the sky to find its way back home after a foraging trip. Thus, they concentrated their efforts on the robotic embodiment of the detection and the treatment of the polarized light as made by this ant. On the contrary, the other parts of the robot were designed without caring about biological realism: The robot was much larger than the ants, it had wheels instead of legs, it moved on a soft synthetic material in Zürich rather than on sand in the middle of the Sahara desert. However, their Sahabot correctly reproduced the characteristic homing trajectories of the ant *Cataglyphis* and thus strengthened the hypothesis about the major role of the polarized-light pattern of the sky in the navigation abilities of this desert ant.

In the case of a self-organized behavior the level of description focuses on the interactions between the agents and between them and their environment. More precisely, the behavioral hypotheses mainly concentrate on the two following questions:

1. How does an agent's activity evolve in space and/or time in a homogeneous environment and in the absence of other agents?
2. How is this evolution modified by the presence of environmental discontinuities? How is it modified by the activities or the result of the activities of the other agents?

In most cases it is possible to answer these two questions without making any hypothesis about the physiology of the agents, but rather by performing a statistical description (i.e., in terms of mean, confidence interval, and/or probability) of the observable output of the agent, that is, its behavior. For instance, question 1 applied to the aggregation behavior studied in this article is answered by simply tracking the successive positions of the animal in order to obtain characteristic measurements of its displacement: length of free paths, distribution of turning angles, and duration of spontaneous stops. These three measurements are sufficient to reproduce with any moving agent the dispersal of cockroaches in space and time. No additional information is required, for example, about walking mechanisms. Question 2 can be answered as well by simply measuring the modification of the stop duration if the animal is in the presence of a given number of conspecifics. Here again, no additional hypotheses are needed about the way the animal estimates the neighbor density. One can thus reproduce the cockroach aggregation behavior with any agent able to estimate this density. This is in fact what we did with Alice robots, and one could do it again with any kind of robot able to move, to stop, and to detect its conspecifics in a rather limited range. Of course these actions have to be performed with space and time scales properly adapted to the size and speed of the robots, so that the dynamics of the self-organized behavior remain the same.

More generally the models of self-organized animal behaviors can often be considered as independent of the animal's physiology. Their implementation in artificial agents only requires that the agents be able to accomplish the actions stated in the model with corresponding space and time scales. However, if the model is independent of the animal's physiology, its implementation remains conditioned by the artificial agent's "physiology," that is, everything that is involved in the agent's functioning: hardware, firmware, operating system, and so on. The problem of the unstable detection of neighbors met in Section 3.2.2 well illustrates that point.

The infrared local communication between robots was noisy and introduced undesired fluctuations in the neighbor count. Noise of course exists in nature, and its creative role in self-organized biological systems has already been emphasized in many studies (see for instance [9, 20, 21, 33]). But in our case, the variability of cockroach behavior was already considered in the model. Indeed, the description of the animal behavior in terms of probabilities or in terms of means and confidence intervals accommodated the biological noise. Therefore, the noisy infrared communication added an artificial fluctuation over the fluctuations already included in the biological model. This additional fluctuation could have deeply modified the collective output of the model and thus could have jeopardized our main objective, which was to quantitatively reproduce the self-organized aggregation of cockroaches with a group of robots. Indeed we already knew that the self-organized aggregation process implemented in this article can produce a wide variety of aggregation patterns depending on the balance between the tendencies to join and to leave an aggregate [29].

Thus, the "physiology" of the robots can have an important influence on the realistic implementation of a biological model. To achieve this implementation, it is necessary to control the effects of the robot's "physiology" on the output of the biological model. First, the differences between the biological model and its robotic implementation must be evaluated. This has to be done with exactly the same protocol as the one applied to study the animal behavior and to build the biological model. The study of the robot behavior must be done with an experimental environment, an observation methodology, and a procedure of analysis identical to the one used with the animal model. This ensures the realism of the implementation and facilitates the detection of discrepancies. All through the work presented in this article, we observed this principle, which allowed us to detect the implementation flaw introduced by the communication channel of the Alice robots.

After the difference between the model and the robot behavior has been established, it has to be reduced as far as possible. However, this problem has to be handled on a case-by-case basis, since it strongly depends on the hardware part of the robot that is used: Two different kinds of robots with different hardware (or "physiology") but endowed with the same model can display different behavioral output. As regards our work, the effect of the noisy infrared communication on the stop and restart behavior was counterbalanced thanks to a dichotomous calibration of stop and restart probabilities implemented in the robot controller. Although this method looks rather rough and time-consuming, it turned out to be efficient in finding a good set of stop and restart parameters. Moreover, it saved us an exhaustive analysis of infrared communication noise, which could have eventually cost more time.

Once all the mechanisms that constitute the biological model have been correctly reproduced, the last step of the work is to verify that the final output of the implementation acts as the animal does. This final stage is of great importance, since it validates that the model is compatible with the real phenomenon and that its implementation does not suffer a flaw. In the case of self-organized behavior, the final output corresponds to the collective behavior of the agents. In our work, this collective behavior resulted in an aggregation of the robots which was defined through three dynamic measures: number of robots remaining alone, number of clusters formed, and number of robots in the largest cluster. Here again, these measurements were obtained in the same experimental conditions as for cockroaches and allowed a direct comparison between the collective behavior of animals and robots. The results displayed in Section 3.3 show good qualitative agreement between cockroaches and Alice robots for the three measurements. Quantitatively, this agreement remains good, except for an increased tendency of the cockroaches to remain isolated.

Thus, robots seem to slightly overaggregate. This could be consistent with the results in Jeanson et al. [38] that show a higher aggregation intensity in simulated cockroaches than in real ones. However, the discrepancy observed between the simulations and the cockroaches is much more significant than the small discrepancy observed between the cockroaches and the robots. The simulations in [38] did not implement a physical occlusion between the simulated cockroaches. As a consequence a simulated cockroach passing near a given cluster could perceive not only the cockroaches at the periphery of the cluster, but also those inside. Therefore, the resulting aggregation was faster and more stable. Experiments with robots, on the contrary, naturally took the physical occlusion into account. This explains why the collective behavior of the robots was closer to the collective behavior of the cockroaches. It also emphasizes the effect of physical constraints on the regulation of aggregation in cockroaches, and more generally their role in self-organized behavior as a potential source of negative feedback.

Another reason for the slight over-aggregation of robots could be the difference between the maximal perception area of robots and cockroaches. The perception area of cockroaches was estimated by Jeanson et al. [38] as a 6-mm-diameter disk around the head of the cockroach. Scaled by four to match the robot size, this area corresponds to 4.5 cm^2. The perception area of the robots as described in Figure 6 corresponds to 30.7 cm^2. As stated by Martinoli et al. [45], the probability for a moving agent to encounter a conspecific inside a closed arena grows with its perception area. Moreover, with a macroscopic implementation (difference equations) of the aggregation model used in this article, Correll and Martinoli [15] showed that the number of agents in clusters grows with the encounter probability. Together, this could easily explain why robots in our experiments had a tendency to remain more clustered than cockroaches. This also highlights the potential effect of small physiological differences in agents on the dynamics of self-organized behaviors.

5 Conclusion

We report in this article the implementation of self-organized aggregation behavior in a group of small autonomous robots. The main originality of this work lies in the nature of this implementation. Most of the works about self-organized behaviors in collective robotics focus on the design of controllers that solve or that optimize the solving of multi-robot coordination problems (see Matarić [47] for a general discussion; see Baldassarre et al. [3] and Dorigo et al. [24] for examples of self-organized aggregation of robots). On the contrary, our purpose was to realistically reproduce with a group of Alice mini-robots the self-organized aggregation behavior of a social animal, namely the German cockroach *B. germanica*. Thus, this work comes close to other biology-oriented studies like those reviewed by Webb [62, 63], even if these studies are mostly dedicated to the understanding of individual animal behaviors.

To reach our goal, we have used a behavioral model of this biological phenomenon previously studied in Jeanson et al. [37, 38] that described the individual behaviors of the animals in a stochastic framework. Such a description makes the model independent of the animal's physiology and thus allows its implementation in a wide variety of artificial agents. However, at least if the artificial agent is a robot, it should be noted that its "physiology" can have some undesired effects on its individual behaviors that may strongly modify the collective behavior of the group. If these effects cannot be eliminated with a hardware or firmware solution, they can be reduced thanks to a careful implementation of the model driven by an experimental assessment of the behavioral differences.

Finally, the present work provides a basic framework for further thinking and experimental studies about the realistic implementation of biological models in collective robotics:

1. because it highlights the main constraints that one may encounter during the realistic implementation of self-organized behaviors in groups of robots;
2. because it proposes general principles to ensure that the behavioral model is accurately and faithfully transferred to the artificial agents.

It can thus be considered as an important step in the process linking the study of self-organized animal behaviors to their control by groups of biomimetic robots as proposed in Caprari et al. [11].

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