Auton Agent Multi-Agent Syst (2009) 18:133–155
DOI 10.1007/s10458-008-9058-5

Get in touch: cooperative decision making based on robot-to-robot collisions

Thomas Schmickl · Ronald Thenius · Christoph Moeslinger · Gerald Radspieler · Serge Kernbach · Marc Szymanski · Karl Crailsheim

Published online: 8 August 2008

Abstract We demonstrate the ability of a swarm of autonomous micro-robots to perform collective decision making in a dynamic environment. This decision making is an emergent property of decentralized self-organization, which results from executing a very simple bio-inspired algorithm. This algorithm allows the robotic swarm to choose from several distinct light sources in the environment and to aggregate in the area with the highest illuminance. Interestingly, these decisions are formed by the collective, although no information is exchanged by the robots. The only communicative act is the detection of robot-to-robot encounters. We studied the performance of the robotic swarm under four environmental conditions and investigated the dynamics of the aggregation behaviour as well as the flexibility and the robustness of the solutions. In summary, we can report that the tested robotic swarm showed two main characteristic features of swarm systems: it behaved flexible and the achieved solutions were very robust. This was achieved with limited individual sensor abilities and with low computational effort on each single robot in the swarm.

Keywords Swarm robotics · Collective decision · Swarm intelligence · Honey bees · Heterogeneous environment

T. Schmickl (✉) · R. Thenius · G. Radspieler · K. Crailsheim
Department for Zoology, Karl-Franzens-University Graz, Graz, Austria
e-mail: thomas.schmickl@uni-graz.at

C. Moeslinger
University of Applied Sciences St. Poelten, St. Poelten, Austria

S. Kernbach
Institute of Parallel and Distributed Systems, University of Stuttgart, Stuttgart, Germany

M. Szymanski
Institute for Process Control and Robotics, University Karlsruhe (TH), Karlsruhe, Germany

1 Introduction

The science of "swarm robotics" focuses on the idea to create "intelligent" systems by forming cooperative swarms of autonomous robotic units. The main aim of this approach is the idea that collective intelligence can arise from the interaction of a high number of relatively simple units [5]. This approach is inspired by many findings of collective intelligence in biological organisms, such as fish, birds, ants, termites, bees and slime moulds. The relevant properties of many of these biological systems are reviewed in [6,7], describing the key aspects of these biological systems by the term "self-organized". While "self-organization" describes systems that tend to approach a state of a higher degree of order, also another term is often used in conjunction with those biological systems: "swarm intelligence" [23]. The required key features that have to be present to identify a system as being "swarm intelligent" are summarized by Millonas [29] and (in other terms) also by Şahin [32], who states the following five principles for swarm-intelligent systems, which we will further use to categorize the features of our swarm robotic algorithm:

1. The *proximity principle* refers to a direct and local behavioural response to a given local stimulus, leading to a collective space-and-time computation.
2. The *quality principle* demands, that the collective has to be able to respond to certain quality factors in the environment.
3. The *principle of diverse response* demands that the swarm should not narrow down its behavioural repertoire excessively, to allow the exploration of several alternative solving models. This can be achieved by the locality of noise in the environment, but also by the heterogeneity of the swarm members.
4. The *principle of stability* refers to the fact that the swarm should not switch its behavioural state in reaction to every (small) environmental fluctuation, because such volatility will prevent the swarm's conversion towards near-optimal solutions.
5. In contrast to that, the *principle of adaptability* demands the swarm's ability to change its behavioural state in reaction to more prominent environmental changes. Obviously, a good swarm system will be configured in a way to achieve a well-balanced mixture of the fourth and the fifth principles, as is discussed in [29].

Millonas [29] refers to some sort of utility underlying these principles, which, for us as biologists, do not have to be mentioned explicitly: Only swarm-forming organisms which show individual behaviours that lead also to a gain of the collective have survived natural selection. Thus we can assume, that today's swarm organisms all show at least one kind of utility concerning their swarm behaviours. In social insects, the primary unit of selection is the whole colony, so we can assume that individual behaviours are automatically selected for their utility for the whole group. This is important, because nature offers a huge variety of well-optimized swarm systems as a possible source of inspiration for technical systems, e.g., swarm robotic systems. Although there are many swarm systems described in the biological world, a plethora of behavioural programs (algorithms) has been proposed which were all inspired by collective behaviour of ants, especially by ants' foraging behaviour [27], task allocation mechanisms [28] and collective sorting behaviour [21]. In recent years, the scientific focus of swarm robotics has shifted from mimicking biological behaviours to animal-to-robot interaction [10,14,19,40], as well as to the understanding of the underlying principles of swarm behaviours [8,38]. Interestingly, this coincided with a decrease of the complexity of the swarm systems that were studied, because in both cases very simple behavioural programs like "aggregation" or "dispersion" [30,38] were frequently studied. One reason for that can be that bio-mimicking often leads to complex and not very generalized algorithms which are hard to analyse.

1.1 Motivation and prior studies

Within the swarm robotic project I-Swarm [37], we developed a set of bio-inspired algorithms which were inspired by slime mould behaviour [34] and by honeybee behaviour [35]. We analysed these algorithms in computer simulations of robotic swarms. These first bio-inspired algorithms of the I-Swarm project have a high order of complexity, thus we looked for another swarm algorithm that was able to produce "intelligent" swarm-level behaviour with a minimum of algorithmic complexity. One low-complexity algorithm we found was inspired by some properties of honeybees' aggregation behaviour in a temperature gradient field, which was translated into the physical world of a Jasmine robot. In addition to computer simulation we used a swarm of Jasmine-III robots [24,25], which are a spin-off product of the I-Swarm project, to analyse bio-inspired swarm algorithms in real physical hardware.

In [26], we describe how we derived a swarm robotic algorithm, which is able to enable aggregation behaviour of robots at a single and stable light source without any robot-to-robot communication. Our pervious studies [26] focussed on describing the interesting honeybee behaviour that inspired us to the swarm robotic algorithm, as well as on analysing the algorithm by macroscopic models. Based on the results found in [26], we wanted to know whether or not our algorithm could also successfully control a robotic swarm in a complex environment, consisting of multiple light sources (aggregation targets) which alter their attractiveness in a fluctuating way. In [26], we concentrated on finding an optimal swarm density (number of robots per area unit of the arena). In the study at hand, we used a swarm close to this optimal density and investigated the decision making abilities of such a robotic swarm.

In the following, we give a short description of the corresponding honeybee behaviour as well as of the deduced control algorithm. Figure 1 shows two selected exemplary sequences that show honeybee aggregation behaviour. A detailed ethological analysis of these behaviours is beyond the scope of this article at hand and will be published separately.

It is known from previous studies that bees show temperature preferences and tend to position themselves in a comfortable area [9,18]. For young honeybees, such areas have a temperature range between 34 and 38°C. In preceding experiments with single bees and groups of bees, an interesting behaviour was observed. In these experiments, a single bee moved almost randomly around the arena, with a slight bias towards warmer areas, but it often left the warm spot again (Fig. 1a). Thus the single bee was not able to find a "stable solution" and to stay in the warm area. In contrast to that, a collective of 15 bees was able to converge to a stable solution and to aggregate near the optimal temperature spot: Throughout the course of these experiments (Fig. 1b–d), the bees moved again without significant preference of direction and formed clusters (often pairs) with other bees. Those clusters that were accidentally formed in warm areas lasted longer than those formed in colder areas. Finally, all bees rested in or close to the warm spot.

Based on these interesting phenomena of collective behaviours observable in honeybees (see Fig. 1), we implemented a control algorithm for swarm robots. Based on our observations, we assumed that no higher-level communication among the bees is happening except reactions to bee-to-bee collisions. It is possible that short-range chemical communication via volatile pheromones is happening among the bees, but so far it could not be shown that such a mechanism plays an important part in the collective aggregation behaviour. This fact makes the collective aggregation behaviour of honeybees different from the mechanisms underlying

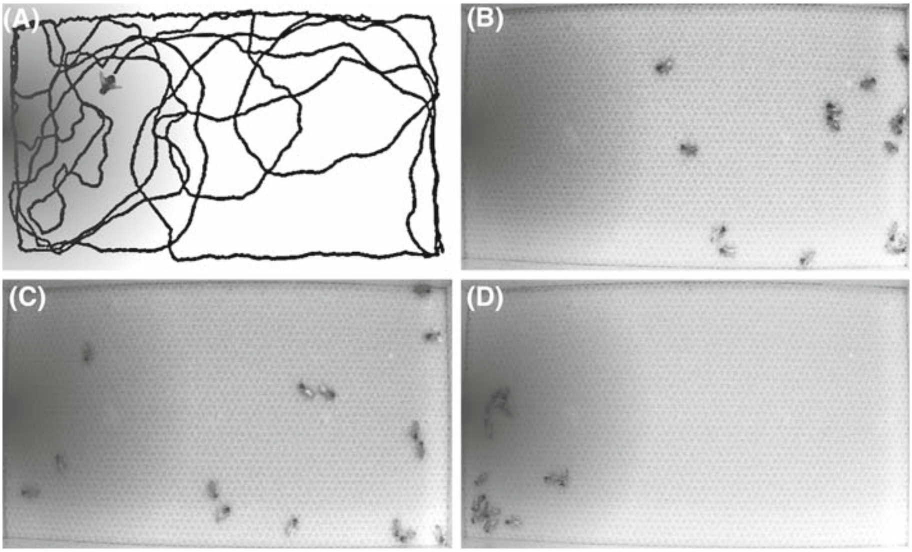

Fig. 1 Navigation behaviour of young bees (1 day old) in a temperature gradient. All figures: The warm area (approx. 38°C) is on the left side of the arena, as indicated by the dark spot. The right side of the arena had a temperature of 31°C. Young honeybees prefer temperature between 34°C and 38°C [9]. (**a**) Trajectory of one single bee for 8 min. (**b–d**) Time lapse of the same experiment with 15 bees (30 s, 1 min, and 10 min after the release of the bees in the arena). Bees were released in the colder area on the right side of the arena

the aggregation of other social animals, e.g., the chain formation of some ant species [11]. The assumed lack of involvement of significant chemical communication makes the collective optimum-finding of honeybees a valuable source of inspiration for a swarm robotic control algorithm, because swarm robots often have only limited abilities of sensing and of communication. Thus, an algorithm that can produce interesting swarm-level behaviours without higher-level communication is of high relevance in this field of robot science.

Basic principles of our algorithm are described in [26] in detail. In the study presented here, we investigated the resulting emergent properties of the collective behaviours of our proposed control algorithm. We especially focussed on the ability of the robotic swarm to perform collective decisions and to preserve the found solutions over time (collective memory). Note that these features are resulting from a control algorithm that does not involve higher-level robot-to-robot communication. Nor does it involve any individual memory storage that keeps explicit information about environmental factors. In contrast to that, in our experiments the clusters that are formed as well as the formed robot constellations and distributions act as a collective memory, which does not reside inside of one individual robot but within the whole swarm. We interpret the abilities of the robot swarm to perform collective decisions without individual adaptation as a form of "swarm intelligence". Like neurons inside an animal's brain change their connectivity during a learning process, the network of (weak) robot-to-robot interactions, which are actually just collisions,[1] lead to specific spatial constellations that promote a collective decision.

[1] Throughout this article, the term "collision" is used synonymously for close robot-to-robot encounters (3–5 cm) and not physical collisions of the robots' bodies.

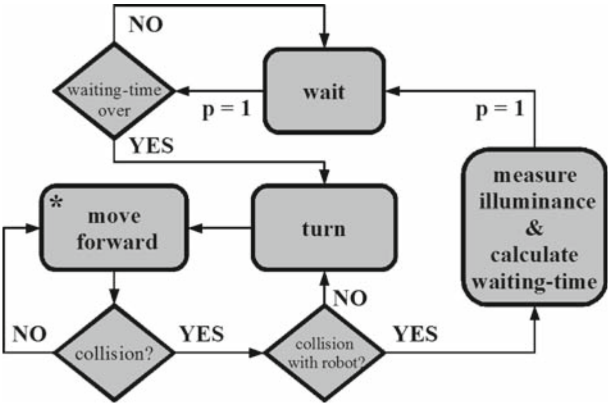

Fig. 2 State-diagram of our control algorithm BEECLUST. Rounded boxes represent behavioural states of a robot, diamonds identify control structures (if-else) and arrows indicate state transitions. Texts at the arrows indicate probabilities of these transitions (p-values) or events that trigger a transition

1.2 The bio-inspired robot control algorithm BEECLUST

For our robot swarm algorithm (further called BEECLUST), we performed several steps of abstraction and simplified the behaviour of individual bees as far as possible. These simplified bee behaviours were then translated into a robot control algorithm. The resulting robot behaviour can be described by the following aspects:

1. All robots move randomly in the arena. Whenever a robot detects an obstacle in front, it stops and listens for possible collision-avoidance signals. If such signals are detected, the robot assumes that the obstacle is another robot. If no such signals are detected, the robot assumes that the obstacle is a wall.
2. After a robot encounters a non-robotic obstacle, it turns randomly and continues with step 1.
3. After a robot encounters another robot, it stops and measures the local illuminance.
4. The higher the local illuminance, the longer the robot waits on the place. After the robot has finished its waiting term, it rotates randomly and proceeds with step 1.

The states, transitions and control structures of the algorithm are depicted in the state diagram in Fig. 2. The diagram depicts the basic random walk behaviour as two states “turn” and “move forward”. The measurement phase of local illuminance and the calculation of the duration of the waiting phase are depicted as one combined state. This robot behaviour leads to clusters of robots resting in the “wait” state, as was demonstrated in [26]. Further details of our algorithm (e.g., specific parameterisation) are described in detail in Sect. 2.

1.3 The focal research questions

For our studies, we assumed that the emerging collective behaviours are complex and allow the swarm to perform a variety of collective decisions. To investigate these abilities, we tested a swarm of 15 robots in an arena that was partially illuminated by two light spots that differed in their emitted light intensity. This “choice experiment” is very similar to typical behavioural experiments performed in ethology to test choice preferences in real animals. We measured the number of robots that clustered below each of these light spots. By varying the intensity of the light spots or by turning off one light spot, we tested the following focal questions:

1. Do the robots cluster below a light?
2. Is the clustering behaviour affected by the light intensity? Does the number of aggregated robots change? Does the constellation of aggregated robots change?
3. In the case of two simultaneous lights of different intensity: Will the robots preferentially aggregate at one of these light sources?
4. Can the collective decision be altered in response to an environmental fluctuation?
5. Is the collective state preserved for some time in the environment?
6. Is there competition among the lights for the available robots?

We conducted two series of experiments that were designed to test the six questions listed above. Some of these questions depend on the answers to other questions, thus it was very important for us to verify or falsify each one of these theses.

2 Materials and methods

To test our hypotheses we used a swarm consisting of 15 robots of the type Jasmine-III (Fig. 9, left image). Each robot was equipped with identical sets of illuminance sensors and collision-avoidance sensors (for details see Sect. 2.4), as well as with identical software controllers. Thus, our robotic swarm was homogeneous concerning the controller software and concerning the basic design of the robots. As preliminary experiments showed, our robotic swarm was heterogeneous concerning the sensory units of the robots (see Fig. 10b) as well as concerning the precision of motion (see Fig. 10a). The robotic swarm was tested in a rectangular arena that was equipped with two light sources; each of them was able to produce different levels of illuminance. For details, please see the next subsection below. The collective behaviour of the robotic swarm was observed under a set of differing environmental conditions (concerning local illuminance) and the experiments were recorded via a video camera from a point above the centre of the arena. The positions of the aggregated robots were sampled in intervals of 15 s. For details, please see Sect. 2.2.

2.1 The arena setup

All experiments were performed in a flat, obstacle free, rectangular arena of 150 cm × 100 cm (see Fig. 3). The arena was equipped with two dimmable light sources, which emitted light in a wavelength which was well detectable for the light-sensor-boards of the robots. The

Fig. 3 Picture of the arena setup used for the robotic experiment

light sources were positioned above the left and the right side of the arena. By dimming or switching off a light, different distributions of illuminance were generated (see also Sects. 3.1 and 3.2).

2.2 The experiments

2.2.1 Measurements

For our analyses, we counted all robots in the behavioural state "wait" (see Fig. 2) and classified them first into two groups, depending on which of the two lights the robots were closer to. To get a finer resolution of our results, we classified the robots also into four categories, depending on their distance to the point with the maximum illuminance, which was always directly below the centre of the corresponding light. For categorisation, we defined four areas (A, B, C, and D), forming four concentric ring-shaped areas around the brightest spot below the corresponding light (see Fig. 4). Radii of these zones are described in Table 1.

2.2.2 Experimental design I: static environment

Before we tested our robot swarm in a dynamic environment, we investigated the aggregation behaviour of robots below a light spot in a static environment. In this experimental setup, which was repeated six times, we tested the swarm with either one bright light (1,100 lux, see Fig. 5b) or with one dimmed light (390 lux, see Fig. 5a) or without any light source (ambient illumination of <10 lux) in the arena. The results of these three experiments were used also as references for the following experiments in dynamic environments.

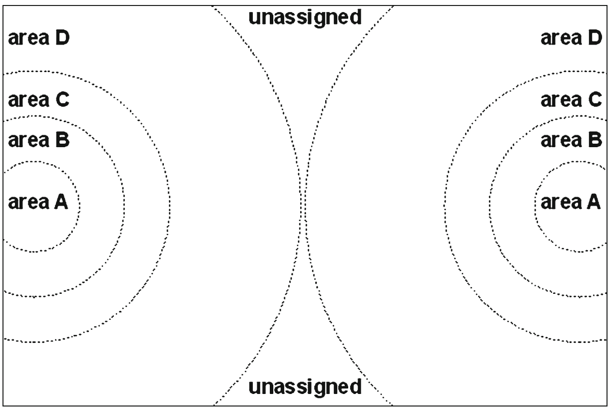

Fig. 4 Sketch of the four different areas that were used to classify how close each aggregated robot had approached the spot with the highest illuminance below the corresponding light

Table 1 Radii of the areas measured from the point of maximum illuminance

Area	Radius
A	$r < 11$ cm
B	$11 \leq r < 22$ cm
C	$22 \leq r < 33$ cm
D	$33 \leq r < 66$ cm

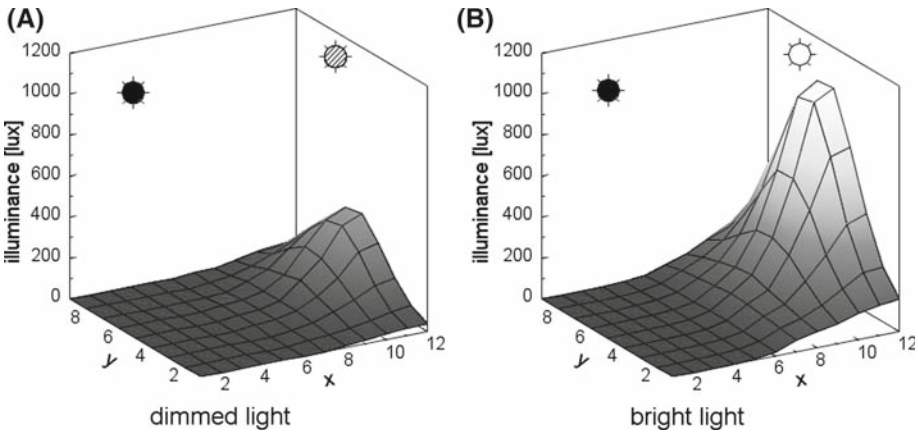

Fig. 5 Spatial distribution of illuminance in the arena during the two experiments that focussed on the collective behaviour of the robotic swarm in a static environment. (**a**) Spatial distribution of illuminance within the arena with one dimmed light (390 lux). (**b**) Spatial distribution of illuminance within the arena with one bright light (1,100 lux). The third setup with no light in the arena is not shown in the figure. The small sun-like symbols in the upper sections of the graphs represent the lights' intensities at the respective side. A striped sun indicates that the light was dimmed; a white sun indicates that the light was bright and the black sun indicates that the light was switched off

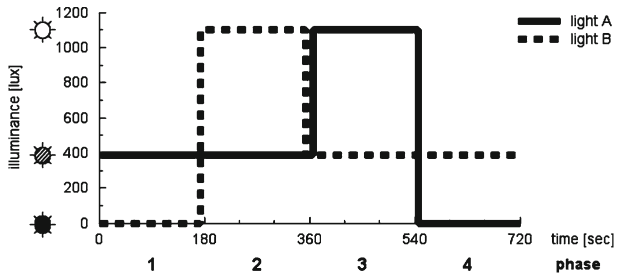

Fig. 6 Timing of our experiments focussing on the behaviour of the robotic swarm in a dynamic environment. Every 180 s the lights' intensities were modified, thus changing the environmental conditions for the robotic swarm

2.2.3 Experimental design II: dynamic environment

This experimental setup, which was repeated six times, consisted of five phases (four experimental phases and one control phase). At the beginning of each phase we altered the light intensities of the two lights. Figure 6 shows the timings of these environmental changes. The experiments started with an initial phase with one dimmed light A (3 min). During the second phase an additional bright light was introduced on the opposite side of the arena (light B for 3 min). During the third phase another change in the environment took place: The light intensity of both lights was switched, so that the bright light was now located on the right side and the dimmed light was located on the left side. During the fourth phase, the bright light on the right side of the arena was turned off and the dimmed light was continued (3 min). Shapes of the light gradients of these four phases are depicted in Fig. 7. In a final fifth phase (not shown in Figs. 6 and 7), all lights were shut off, to test whether or not the robots switched back to random movement, to ensure that clusters were not formed by "malfunctioning" robots.

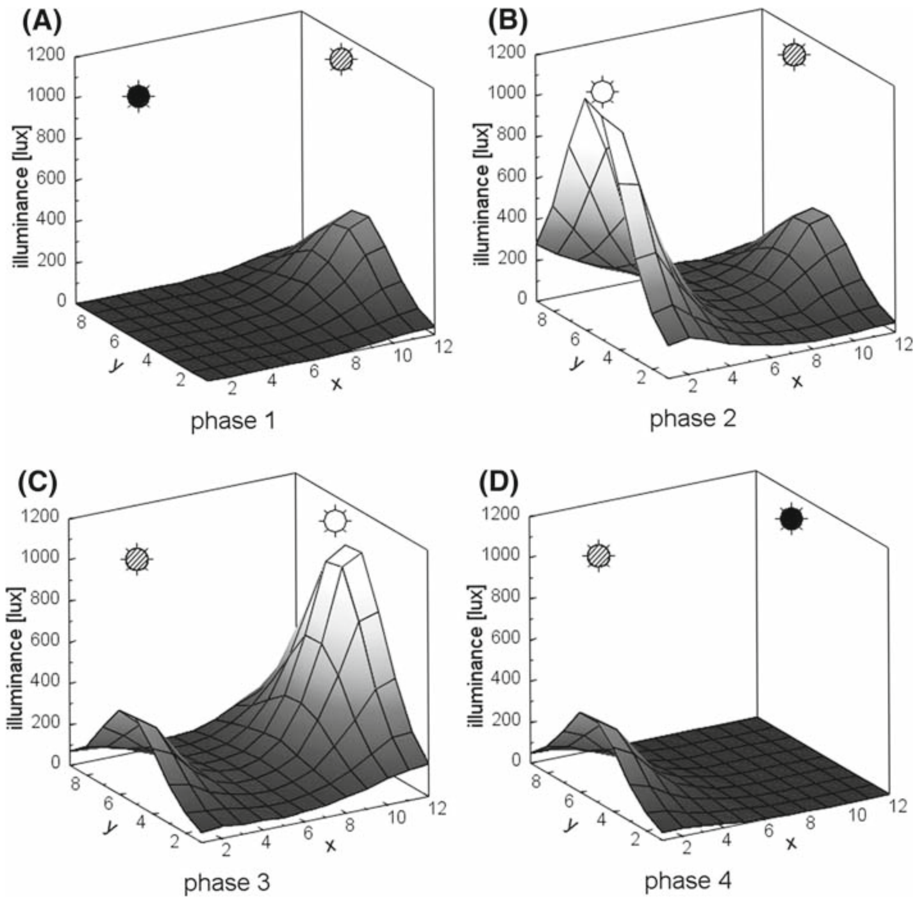

Fig. 7 Spatial distribution of illuminance in the arena during the four distinct phases of our experiments in the dynamic environment. The small sun-like symbols in the upper sections of the graphs represent the lights' intensities at the respective light. A striped sun indicates that the light was dimmed; a white sun indicates that the light was bright and the black sun indicates that the light was switched off

2.3 The controller BEECLUST

As mentioned in Sect. 1, the BEECLUST algorithm can be described by a finite state automaton that was inspired by the behaviour of honeybees navigating in a temperature gradient. The key property of the algorithm, which governs the emergent collective behaviour, is the function that maps the measured local illuminance to a waiting time after each robot-to-robot collision. The function is defined by Eq. 1.

$$w\,(t) = w_{\max} \cdot \frac{s\,(t)^2}{s\,(t)^2 + \theta} \qquad (1)$$

In Eq. 1, the variable $w(t)$ represents the waiting-time of a robot in seconds, and the variable $s(t)$ represents the sensor value reported by the light-sensor mounted atop the robot (for more detail see Sect. 2.4). The parameter $w_{\max}$ expresses the maximum waiting time of a robot at locations of maximum (infinite) luminance. The parameter Θ models the steepness

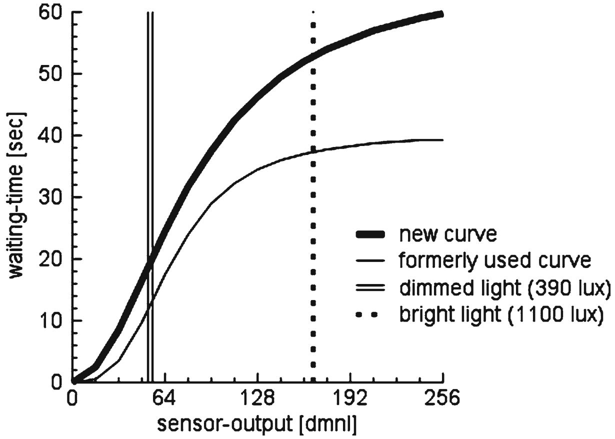

Fig. 8 Dependency of the duration of the state *"wait"* on the local illuminance measured by the robot. The bold curve indicates the function used in the experiments described in this article, the thin curve depicts the function used in [26]. The dotted vertical line indicates the median illuminance measured by the robots directly below a bright light; the vertical parallel line indicates the medium illuminance measured by the robots directly below a dimmed light

of the stimulus-response curve, that his how "fast" the waiting time increases with increasing luminance in the steep part of the sigmoid curve.

In previous experiments [26], we used the values of $w_{\max} = 40$ and $\Theta = 343000$. We found (in preliminary experiments), that we can achieve faster aggregation of robots at the target zones by using values of $w_{\max} = 66$ and $\Theta = 7000$, what we did in the studies presented here. A comparison between these two parameterizations can be seen in Fig. 8. The modification of the "waiting-curve" was necessary to improve aggregation behaviour in the arena setup we used in the experiments described here and is mainly dependent on the shape of the light gradients that are formed by the lamps.

2.4 General robot design

The Jasmine-III robot (Fig. 9, top image) is a two-wheeled robot of the size of about $30\times30\times25$ mm. It is equipped with an ATMEGA168 microprocessor, which is programmable in C [26,41]. It has six IR-sensors for distance measurement and for collision avoidance. The sensors range is approx. 60 mm (see Fig. 9, bottom image). The average speed of a robot in our experiments was approx. 300 mm/s. A more detailed description of the robot hardware can be found in [26], building instructions are given in [41].

2.5 Robot heterogeneity

Some of the robots tended to have a (slight) drift aside (Fig. 10a), even when the software controller instructed the robots to drive straight ahead. This individual attribute of each robot was evident in all experiments described here. For our experiments, this motion heterogeneity was actually not a problem, since it allowed us to test the stability of the collective behaviour.

Our robots were equipped with light-sensor boards mounted on top to measure the local light conditions. For details about the light board design, please refer to [41]. Due to manufacturing reasons, these sensor-boards slightly differed in their response to a given environmental

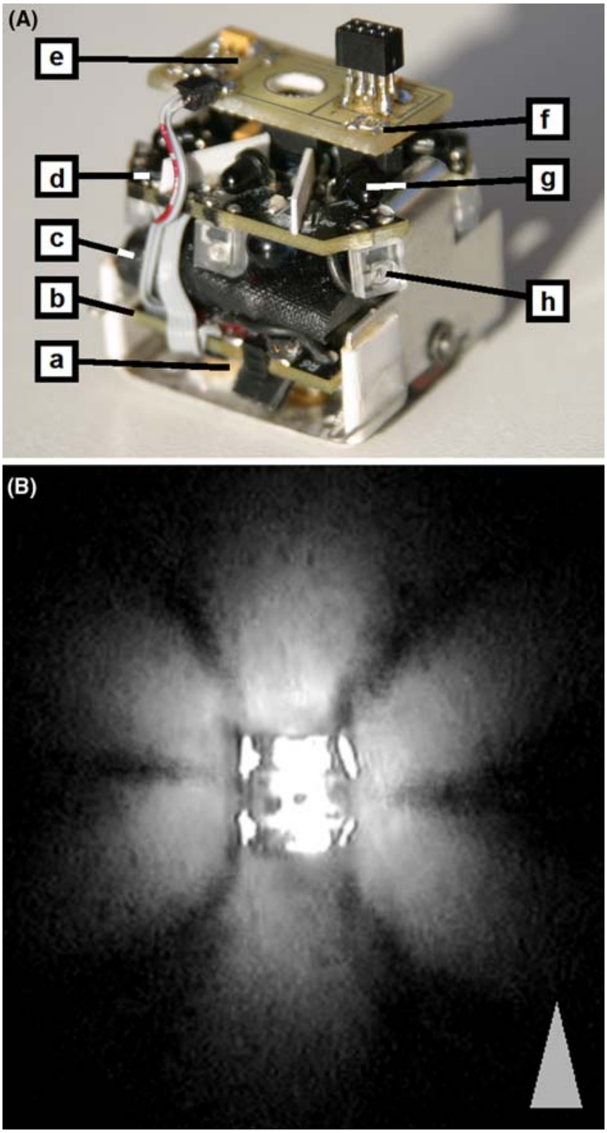

Fig. 9 Top: The Jasmine-III robot, front side: (a) one of the two motors; (b) motion-control-board for compensating manufacturing differences of the motors; (c) lithium-polymer accumulator; (d) main board; (e) illuminance-sensor-board; (f) single light sensor on light-board; (g) IR-sensor for distance measurement; (h) IR-emitter, corresponding with IR-sensor. Bottom: IR-image of a single robot. Arrow indicates heading of robot

illuminance (see Fig. 10b). Again, this sensorial heterogeneity was a positive feature, as it allowed us to investigate the stability of our bio-inspired algorithm.

2.6 Sampling, data evaluation & statistics

For our analyses we repeated each experimental setup 6 times. We sampled the number of aggregated robots (non-moving robots in the "wait" state) in intervals of 15 s. In each environmental condition (experimental phase, 180 s duration), we excluded the first three intervals of the 12 samples from our data sets that were evaluated. This was done to eliminate

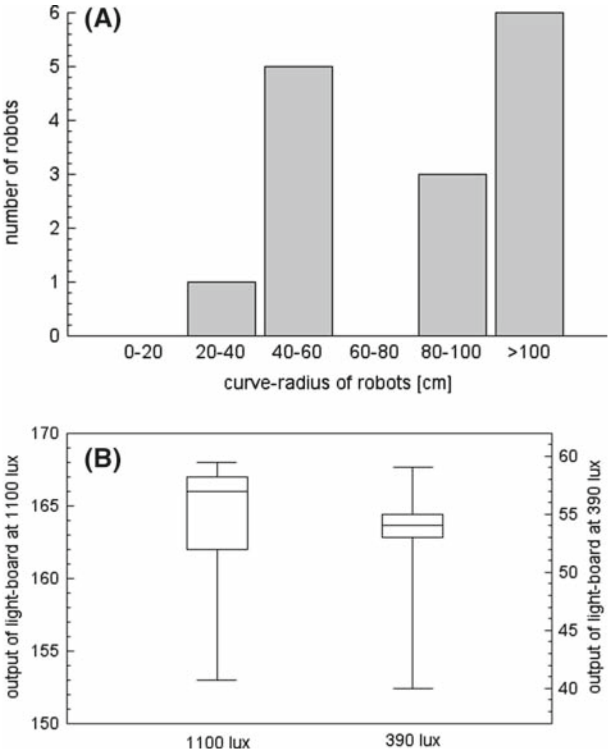

Fig. 10 (**a**) Distribution of the robots' side-drifts. Most robots (9 of 15) had no, or only a very slight drift aside with curve-radii greater than 80 cm. Some robots (6 of 15) had a curve radius of less then 60 cm and more than 20 cm. No robot had a curve radius below 20 cm. (**b**) Median, quartiles and extreme values of measured light intensities (reported sensor values) under constant controlled conditions (1,100 and 390 lux)

the transitional periods from our data and to consider just the "final solutions" the swarm converged to.

For statistical tests we used one-way ANOVA (completely randomized blocks) to test whether or not the environmental conditions significantly affected the observed aggregation behaviour of the robots. Comparison of means was performed with Student–Newman–Keuls post-hoc test after the ANOVA analyses. Pair-wise comparisons of means were performed as paired Wilcoxon signed rank test with continuity correction. Figures depict medians, quartiles and extreme values throughout this article, except where mentioned differently.

3 Results

3.1 Static environment

As shown in Fig. 11, the environmental conditions affected the aggregation behaviour of the robot swarm significantly (ANOVA, $F_{1,106} = 238.9$, $p < 0.00001$). Under conditions of one bright light (1,100 lux) in the arena, 9.4 ± 1.8 robots aggregated below the bright light. In contrast to that, fewer (4.3 ± 1.6) robots aggregated if the light was dimmed to 390 lux. No robots aggregated anywhere in the arena (control setup), when the light was

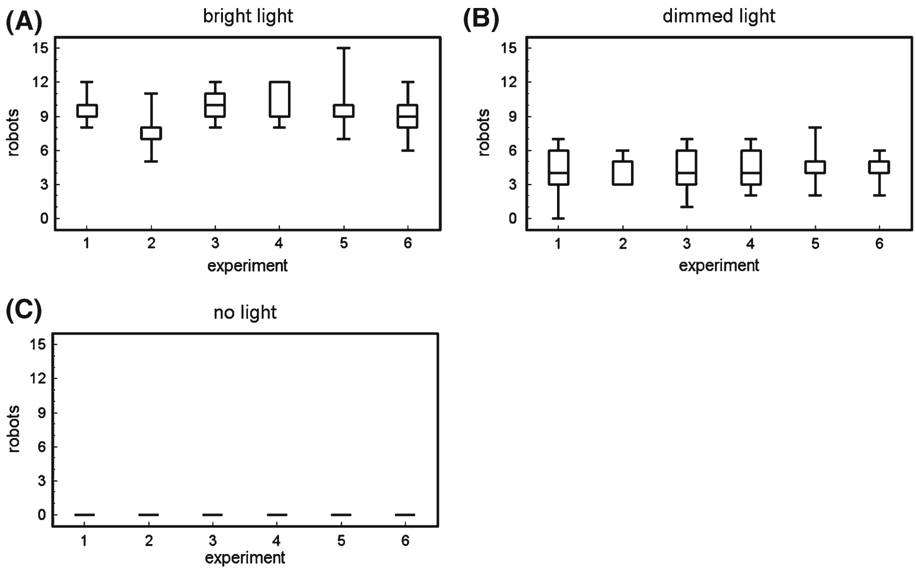

Fig. 11 (**a**) Number of aggregated robots per interval in a static environment with one bright light (1,100 lux) in the arena. Approx. 60% of all robots aggregated under this environmental condition. (**b**) Number of aggregated robots per interval in a static environment with one dimmed light (390 lux) in the arena. Approx. 30% of all robots aggregated under this environmental condition. (**c**) Number of aggregated robots per interval in a static environment without any light source. This environmental condition always resulted in no aggregation of robots. Medians, quartiles, and extremes are depicted. $N = 6$ repetitions with nine sampling intervals each

turned off. Statistical analyses showed, that the results gained in all six repetitions of the same environmental setting were not statistically differentiable (ANOVA, bright light: $F_{5,49} = 2.1$, n.s.; dimmed light: $F_{5,49} = 0.1$, n.s.).

By classifying the robots' locations into four areas (see Sect. 2), we analysed the spatial distributions of the aggregated robots. Area A was the area around the brightest spot (below the light), the areas B, C, and D were defined by concentric rings around area A. Area D was the furthest away from the light (see Fig. 4). Our experiments with one dimmed light resulted in different robot distributions than experiments with one bright light (Fig. 12). To demonstrate how our algorithm changes the swarm behaviour compared to the basic random movement, a simple mathematical model was constructed to predict the expected distributions for randomly aggregating robots.

Concerning the fraction of the robot swarm that aggregated in the four areas, the following picture was found: Under dimmed light conditions, a higher fraction of aggregated robots was located in areas A, B, and C compared to the random aggregation model (see Fig. 12a). Under bright light conditions, a higher fraction of aggregated robots was found in areas B and C, compared to the random aggregation model (see Fig. 12a).

Concerning the expected density of aggregated robots within a square zone of 1 dm^2 within each of these areas, a different picture was observed: With dimmed light, the areas A and B showed the highest positive deviation from the random aggregation model, which means that robots preferentially aggregated in the areas A and B (see Fig. 12b). Under conditions of bright light, the robots preferentially aggregated in the areas B and C, compared to the random aggregation model (see Fig. 12b).

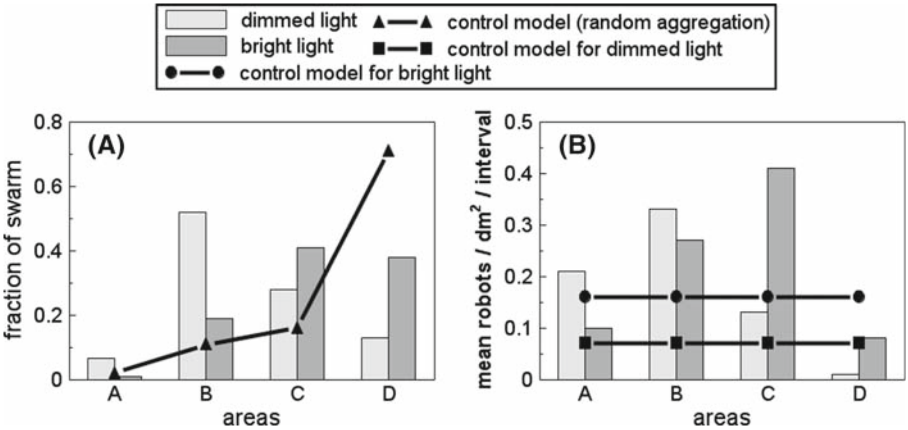

Fig. 12 (**a**) Allocation of all aggregated robots to the four areas. Bars indicate the fractions of all aggregated robots measured during our experiments with either a dimmed light or a bright light. The line indicates the numbers of aggregated robots predicted by a model of random-walk and random aggregation. (**b**) Mean number of robots per measured interval, normalized according to the different area sizes. Bars indicate the mean of the number of robots observed in the corresponding area during our experiments with either a dimmed light or a bright light. Lines indicate the number of aggregated robots predicted by a model of random-walk and of equivalent mean waiting times as was measured in the real robots for each light condition. $N = 6$ repetitions with nine sampling intervals each

In summary, the robots approached the centre of the light spot closer under conditions of the dimmed light compared with conditions of a bright light in the arena.

3.2 Dynamic environment

In a second experimental setup, we examined the robotic swarm in a changing environment. Our robotic swarm always reconfigured itself according to the environmental condition that was present in each experimental phase (see Fig. 13). During the first 4 experimental phases, we altered the intensities of two lights. In the first phase, approx. 30% of the robots aggregated at the dimmed light A and no robots aggregated at light B, which was switched off (Fig. 14a,b). In the second phase, the dimmed light A did not change, but light B was switched on with full intensity. Throughout this second phase there was a constant decrease in the number of robots which previously aggregated at the dimmed light A and a constant increase in the number of robots which now aggregated at the bright light B. Finally, approx. 55% of all robots clustered at the brighter light B, while the number of robots clustered at the dimmed light decreased below 15% of the whole swarm (Fig. 14a,b). At the beginning of the third phase the conditions changed again as the dimmed light A was switched to full intensity, whereas the bright light B was dimmed. Throughout this third phase there was a constant increase in the number of robots which aggregated at the (now) bright light A and a constant decrease in the number of robots which had aggregated at the dimmed light B. At the end of this phase, approx. 60% of all robots clustered at the (now) bright light A and approx. 20% of the robots clustered at the dimmed light B, which had been bright in the preceding phase (Fig. 14a,b). During the fourth phase, the previously bright light A was switched off, which led to an increase of the number of aggregated robots at the dimmed light B (30% of all robots). No robots clustered below light A, which was switched off. In a final fifth (control) phase, all lights were switched off, which led to no aggregation of robots at all (data

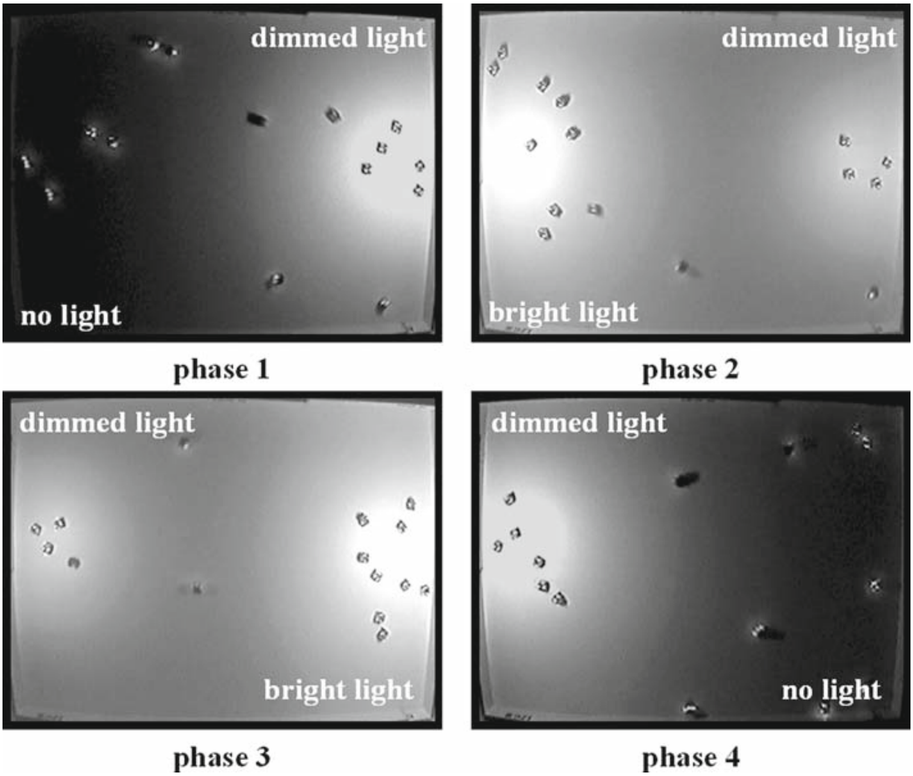

Fig. 13 Photographs of typical final swarm configurations at the end of each of the four phases in the dynamic experiment

not shown). This fifth phase showed that clusters were 100% light-induced and not artefacts, as malfunctioning robots could also cause clustering. Also the total number of aggregated robots changed significantly (ANOVA, $F_{1,22} = 189.8$, $p < 0.00001$) depending on the light condition: In the phases with just one dimmed light (phase 1 and 4), the mean number of aggregated robots (4.6 ± 1.9) was significantly lower than the mean number of aggregated robots (10.5 ± 1.9) in the phases with one dimmed and one bright light (phase 2 and 3).

In all four phases of the experiment, the mean number of robots aggregating at the brighter light spot was significantly higher (paired Wilcoxon signed rank test with continuity correction, $n = 6$ repetitions with nine intervals for each light for each phase, $p < 0.001$) than on the light with lower illuminance (or no illuminance in phase 1 and 4).

We tested the hypothesis that the observed differences in the robots' allocations below the lights were induced by the lights' settings in the four phases. Figure 15a compares the median observed number of aggregated robots during the four experimental phases. It was found that at light A as well as at light B, the mean number of aggregated robots was different between the experimental phases, but not between the repetitions of each phase. Table 2 gives the summarized statistical results for these analyses.

Figure 15b shows that a lower number of robots aggregated at the dimmed light in phases when also a bright light was present in the arena (2.7 ± 1.8), compared to phases without any other light (4.6 ± 1.9; ANOVA, $F_{1,10} = 11.6$, $p < 0.01$).

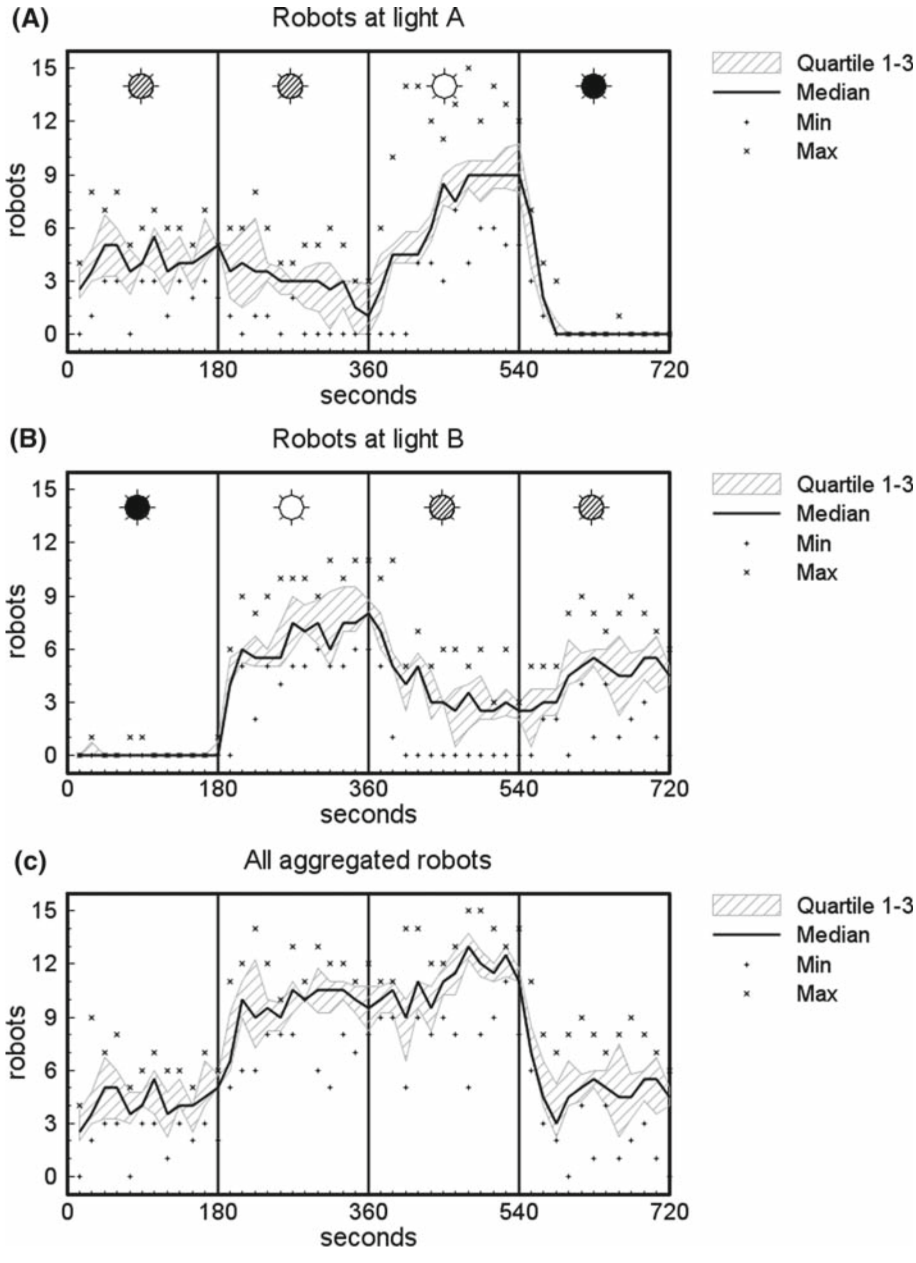

Fig. 14 (**a**) Number of aggregated robots at light A. The three vertical lines indicate the timings of the changes in the environment. (**b**) Number of aggregated robots at light B. (**c**) Total number of aggregated robots, regardless of arena side. $N = 6$ repetitions. The small sun-like symbols in the upper sections of the graphs represent the lights' intensities at the respective light. A striped sun indicates that the light was dimmed during this phase; a white sun indicates that the light was bright and the black sun indicates that the light was switched off

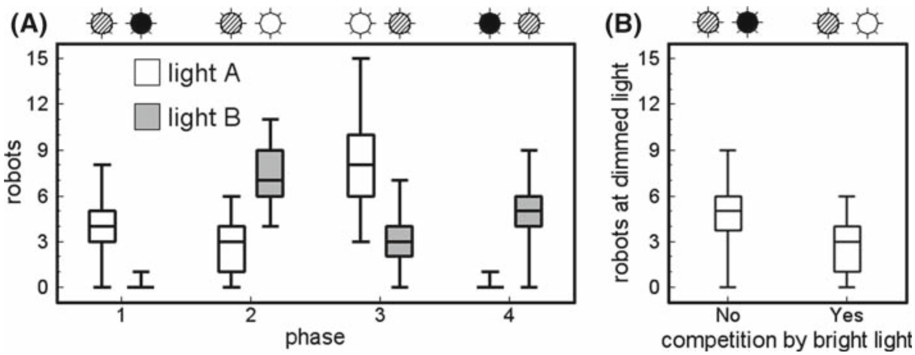

Fig. 15 (**a**) Box & whisker diagram depicting the median number of aggregated robots in each environmental configuration. $N = 6$ repetitions with nine intervals each. (**b**) Box & whisker diagram of those phases that used a dimmed light without any other competing light (phases 1 and 4) versus those phases that used a dimmed light that was competed by a bright light (phases 2 and 3). $N = 12$ per arena competition status with nine intervals each. The small sun-like symbols in the upper sections of the graphs represent the lights' intensities at the respective light. A striped sun indicates that the light was dimmed; a white sun indicates that the light was bright and the black sun indicates that the light was switched off

Table 2 Statistical results of the comparison of the four experimental phases concerning the mean number of aggregated robots

	Phase	Mean number of aggregated robots	Non-significant ranges	$F_{3,20}$	p
Robots at light A	1	4.2	a	40.5	<0.00001
	2	2.5	b		
	3	8.3	c		
	4	0.02	d		
Robots at light B	1	0.1	e	51.8	<0.00001
	2	7.3	f		
	3	2.9	g		
	4	4.8	h		

We used one-way ANOVA (completely randomized blocks) with post-hoc comparisons of the means (Student–Newman–Keuls). $N = 6$ repetitions of each phase. Mean values of the last nine measured intervals in each phase were used

4 Discussion

Our experiments showed that the bio-inspired control algorithm BEECLUST is able to produce a variety of interesting collective behaviours. In all tested circumstances, the swarm of robots was able to collectively converge to solutions and to aggregate close to the brightest available light in the arena. In the following, we will first discuss the gained results in order to clarify which of our focal questions was answered by our experimental results. In addition, we want to discuss the key properties of our algorithm in order to check whether or not it can be classified as being "swarm intelligent", according to the principles stated in [29].

4.1 Did the robots cluster below a light?

The experiments performed in the stable environment showed that the robot swarm was always able to locate the light, thus it was able to perform "space-and-time computations" in the arena (see Fig. 15). This ability was achieved with a very limited sensory range and with almost no actuation. The only form of "actuation" of our robots was "not to move", but this was performed in respect of the local illuminance. Thus, the *proximity principle,* mentioned in [29], was met by our algorithm.

4.2 Was the clustering behaviour affected by the light intensity?

In addition, the robotic swarm modulated its collective behaviour in a way that correlated with the environmental situation (see Fig. 15). The number of aggregated robots was positively correlated with light intensity (=illuminance). Thus, we can conclude that not only the individual robot is able to respond to a quality factor in the environment (see Fig. 8), but also the whole swarm of robots can respond to such quality factors. This is consistent with the demand of the *quality principle* mentioned in [29].

One aspect of the *principle of stability* was already seen in the experiments with the stable environment: In all six repetitions that we performed with each of the three tested environmental conditions, the resulting cluster sizes did not differ significantly, thus, we conclude, that our algorithm leads to precise and stable results.

As can be seen in Fig. 15a and b, the different light conditions led to different cluster constellations in the arena. All of them differed from a random aggregation model, thus it can be interpreted as being a result of our robotic algorithm. With dimmed light, the higher fraction of the robots clustered closer to the point with the highest illuminance. Bright lights attracted more robots, but due to the emerging robot-to-robot constellations, these robots did not approach the light spot as efficiently as it was done with dimmed light. Thus the robot swarm was always able to converge towards clusters close to the optimal light spot, but performed different strategies: Bright light attracts more robots (in total), but dimmed light leads to more precise aggregation. We conclude that this ability satisfies the *principle of diverse response* as it was mentioned in [29].

4.3 In the case of two simultaneous lights with different intensities: did the robots preferentially aggregate at one of these light sources?

This question was answered by the experiments depicted in Fig. 14, which were performed in a dynamic environment. We observed that the robot swarm was stable enough (*principle of stability*) to converge to a desired collective state in each of the environmental conditions and to preserve this state up to the end of the corresponding environmental phase: The robot swarm aggregated mainly on the side of the arena that had the higher light intensity. It is important to know that also the dimmed light was selected by the robot swarm, thus the illuminance caused by the dimmed light was not below a behavioural threshold. But whenever the bright light was present simultaneously, the robotic swarm aggregated preferentially on the brighter side of the arena.

4.4 Could the collective decision be altered in response to an environmental fluctuation?

After each environmental change, the swarm was flexible enough (*principle of adaptability*) to change its collective state and to converge to a new near-optimal solution. The transitional period lasted for approx. 45 s (see Fig. 14), which is resulting from the way we implemented the dependency of the waiting period on the local illuminance (see Fig. 8).

4.5 Was the collective state preserved for some time in the environment?

We observed that the robotic solutions endured in the environment as long as the corresponding stimulus was present. Bigger clusters survived for approx. 45 s. after the environment changed its illuminance configuration (see Fig. 14). Thus, we conclude that short-term fluctuations that last for not longer than approx. 30 s can be compensated by our robotic algorithm. This property can be easily be modified by altering the parameters $w_{\max}$ and Θ used in Eq. 1, which is depicted in Fig. 8.

4.6 Was there competition among the lights for the available robots?

Statistical analysis show that the number of robots aggregated at the dimmed light was significantly lowered in those phases where there was also a bright light present simultaneously. This can be interpreted as a competition between the two clusters of robots formed below the two lights in the arena. The shared limited resource, that the clusters competed for, was the limited number of free moving robots. The fact that we found indications of competition in our experimental data indicates that our swarm robotic system involves a positive feedback, which we interpret as follows: Bigger clusters are hit by randomly moving robots more likely than smaller clusters. Thus bigger clusters "attract" more robots. Higher illumination causes individual robots to wait for a longer period, thus higher illuminance allows clusters to stay big for a longer time, or even to grow faster. The fact that there were still robots aggregated at the dimmed light spot in the presence of the bright light tells us, that the positive feedback in the system is relatively weak. This is an important finding for further improving the algorithm to be more selective for light sources: Increasing the strength of the present positive feedback loops will favour aggregation on brighter lights more over the aggregation at the spots with weaker illuminance. Thus an improved algorithm (future work) that allows modulating the strength of these feedback loops will allow modulating the selectiveness of the collective swarm behaviour.

Interestingly, positive feedback loops that favour collective decisions are frequently described in natural "swarm systems". In ants, the pheromone deposited on ant trails provides the positive feedback to favour shorter paths over longer ones [3,12]. These examples all involve chemical communication, a method that is achievable in swarm robotics only with complex technical devices [39]. In cockroaches, local environmental cues promote the aggregation behaviour, whereby chemical promoters of aggregation are likely not very volatile, thus they act assumedly only at very short range [1,22]. Such short-ranging positive feedback loops were also shown to promote swarm-intelligent honeybee foraging decisions [33,36]. In this case, the positive feedback is not achieved by chemical substances, but it is achieved by behavioural interactions (dances), which only act very locally and, unlike chemical signals, do not persist over longer time. This points us into an interesting direction for further improvements of our swarm robotic algorithm: Can simple behavioural adaptations further increase the positive feedback to improve the selectiveness of the robotic swarm?

4.7 Generality of our approach

We investigated the generality of our approach in various ways. To see, whether or not our findings are closely related to the used robotic hardware, we created a variety of macroscopic models which abstract the majority of the hardware features by treating the robots like gas molecules of an ideal gas or like particles driven by Brownian motion [20,26]. We also implemented bottom-up multi-agent simulations, which model Jasmine robots (6 IR detectors, 2 wheels) as well as I-Swarm robots (4 IR detectors, 3 legs). All these simulations and models showed that our algorithm is predicted to cause aggregation behaviour comparable to the behaviour observed in our real robotic swarm, regardless how much a robot's hardware is abstracted. These studies revealed that the most critical factors for our algorithm are the density of robots in the arena and the probability of robot-to-robot detection. These two factors are critical factors in any swarm robotic system. In future studies, we will investigate our algorithm also with different types of stimuli: Instead of light spots we will test sound fields, temperature gradients and chemical gradients.

4.8 Our work in the context of current swarm robotics research

Many tasks for robotic swarms are based upon aggregation. The importance of this behaviour has led to various approaches in its analysis and utilization. In [38] the probabilistic clustering behaviour of an aggregating robotic swarm is described from a macroscopic point of view and the results compared to simulations. A similar approach is made in [8] using a cockroach-inspired algorithm. An evolutionary algorithm is used in [13] to evolve the neural net controllers of a robotic swarm to achieve aggregation behaviour. In contrast to our real-world experiments, the simulated environments in [8,13,38] are homogenous without any spatial distribution and thus only the probabilistic aggregate sizes are analyzed. The evolutionary algorithm approach described in [13] was also used for simulations with a heterogeneous arena in [2] where a small group of robots utilized an evolved neural network controller that enabled the robots to collectively move towards a light source.

Another approach that, on the first sight, looks rather similar to our approach is described in [15], where a robotic swarm aggregates in an arena with two shaded shelters. The robotic swarm utilizes a "cockroach-derived algorithm" which is based on the very detailed mimicry of cockroach behaviour [22]. However, besides the similar looking result of two aggregates of robots in specific areas, the objectives for [15] are very different from our approach: BEECLUST is an algorithm that is inspired by honeybees and is intended to enable a robotic swarm to collectively choose an optimal site for aggregation. The algorithm used in [15] is aimed to emulate cockroach behaviour as closely as possible and is therefore much more complex concerning its robotic implementation. The BEECLUST algorithm uses a correlated random walk, whereas the cockroach-derived algorithm consists of a correlated random walk in the centre of the arena and a wall-following behaviour at the walls of the arena. In addition, our robots stop and perform measurements of the environment only when encountering other robots, in contrast to the cockroach-derived algorithm where robots stop randomly and the environment is measured frequently. Our arena is different because the luminance under the light source is graduated, which is why we divided that area into four zones. The luminance under the shaded shelters is not graduated. Furthermore, self-enhanced aggregation observed in [15] was achieved by transmitting information between the robots in form of their ID numbers. No sort of signal-transfer is used for the BEECLUST algorithm (not a single bit is communicated from one robot to another robot).

There exist several other algorithms that allow coordination of autonomous agents without direct communication. Firstly, there is a variety of flocking algorithms [31,16], where geometrical rules are used by swarm members to position themselves relatively to their neighbours. In contrast to our algorithm, the flocking task poses very high computational demands and requires very sophisticated sensorial abilities [28] and preceding studies of the same group propose a communication-less algorithm, which enables a swarm of autonomous robots to regulate task performance and to develop task specialization. This topic is not addressed by our algorithm, which focuses on collective decision making in an aggregation scenario. And finally, there is a variety of "stigmergic" algorithms [4,17], where direct communication is replaced by indirect communication, as agents alter the environment by performing a task. In our algorithm, the robots do not alter the environment, except of positioning themselves in the arena. We do not interpret such self-positioning as stigmergic behaviour, because then any form of motion behaviour has to be interpreted as stigmergic" behaviour, what would remove the significance from the stigmergic concept. In addition to that, stigmergic algorithms are not necessarily swarm algorithms, as was demonstrated in [4], which show that stigmergic puck-sorting can be achieved also with one acting robot alone. Our algorithm works only with several robots, whereby the optimal swarm density is approx. 10 Jasmine robots per m^2.

Summing up, we show results from experiments with a real robotic swarm which include all the noise and interferences that would be hard to properly simulate. Besides that, our algorithm is exceedingly simple which allows easy portability to other robotic swarms.

5 Conclusion

The observed collective decisions were an emergent property achieved by the whole group of robots, not by single individuals. No adaptation took place within the individual robot. Nevertheless, we observed a highly adaptive collective behaviour, achieved by the robot-to-robot social network, which was knotted by the weak ties of robot-to-robot collisions. Nevertheless, these weak interactions led to a spatially distributed social network among the robots that allowed them to converge to collective decisions.

Although our algorithm is purely based on undirected motion and has to deal with imprecise sensor and actuator devices, the final results showed a high efficiency of the algorithm: In the phases with two lights in the arena (phase 2 and 3), the average number of aggregated robots varied between 10 and 11 among the repetitions. This means that approx. 70% of all robots successfully converged to a solution. The remaining 4–5 free moving robots performed an important role in the dynamic environment. Similar to "scouts", as they are known from social insects' foraging, these robots constantly explored the arena and started to form new aggregations as soon as light conditions changed. In situations with just one dimmed light available, the dimmed light was "exploited" more precisely (robots aggregated closer to the light source). In these situations, many scouts were searching for other light sources. When we turned on the second (bright) light, this environmental change was detected by the swarm almost immediately and the swarm reacted quickly by recruiting a majority of the robots to the bright light source. In those situations where a bright light was present in the arena, the number of "scouts" was small and more robots exploited the bright light. Such features, like emergent dynamic allocation of scouts and recruits, are usually referred as "swarm intelligent" in the biological examples of social insect foraging.

The results that we gained from our observations reported in this article make us confident that our very simple algorithm covers enough complexity to generate much more collective behaviours and functions. Investing into this algorithm seems to be valuable, because the algorithm impressed us with its accuracy and with its robustness. Although many robots did not move straight and although there was sensorial heterogeneity, the robot swarm always behaved predictable (on the swarm level) and precise. Simultaneously, the experiments with the environmental fluctuations showed that the swarm behaviour was flexible and adaptive. So far we do not know any other control algorithm published and analysed, that achieves this level of accuracy with such little computational efforts, with almost no communication bandwidth and with such little individual accuracy concerning motion and sensory systems in a dynamic and complex environment like the one we used for our studies presented here.

Acknowledgements This study was partially supported by the following research grants: EU-IST FET project I-Swarm, no. 507006 and the research grant “Temperature-induced aggregation of young honeybees”, no. P19478-B16.

References

1. Ame, J.-M., Rivault, C., & Deneubourg, J.-L. (2004). Cockroach aggregation based on strain odour recognition. *Animal Behaviour, 68*, 793–801. doi:10.1016/j.anbehav.2004.01.009.
2. Baldassarre, G., Nolfi, S., & Parisi, D. (2003). Evolving mobile robots able to display collective behaviour. *Artificial Life, 9*, 255–267. doi:10.1162/106454603322392460.
3. Beckers, R., Deneubourg, J.-L., & Goss, S. (1992). Trails and U-turns in the selection of a path by the ant Lasius niger. *Journal of Theoretical Biology, 159*, 397–415. doi:10.1016/S0022-5193(05)80686-1.
4. Beckers, R., Holland, O. E., & Deneubourg, J.-L. (1994). From local actions to global tasks: Stigmergy and collective robotics. *Artificial Life, IV*, 181–189.
5. Beni, G. (2005). From swarm intelligence to swarm robotics. In E. Şahin & W. Spears (Eds.), *Proceedings of the SAB 2004 Workshop on Swarm Robotics*, Santa Monica, CA, USA, July, 2004. *Lecture Notes in Computer Science 3342*, pp. 1–9.
6. Bonabeau, E., Dorigo, M., & Theraulaz, G. (1999). Swarm intelligence: From natural to artificial systems. In *Santa Fe Institute Studies in the Sciences of Complexity* (306 pp.). New York, NY: Oxford University Press.
7. Camazine, S., Deneubourg, J.-L., Franks, N. R., Sneyd, J., Theraulaz, G., & Bonabeau, E. (2003). *Self-organization in biological systems* (560 pp.). Princeton, NJ: Princeton University Press.
8. Corell, N., & Martinoli, A. (2007). Modeling self-organized aggregation in a swarm of miniature robots. In *IEEE International Conference on Robotics and Automation*, Workshop on collective behaviors inspired by biological and biochemical systems.
9. Crailsheim, K., Eggenreich, U., Ressi, R., & Szolderits, M. J. (1999). Temperature preference of honeybee drones (Hymenoptera: Apidae). *Entomologia Generalis, 24*, 37–47.
10. De Schutter, G., Theraulaz, G., & Deneubourgh, J.-L. (2001). Animal-robots collective intelligence. *Annals of Mathematics and Artificial Intelligence, 31*, 223–238. doi:10.1023/A:1016638723526.
11. Deneubourg, J.-L., Lioni, A., & Detrain, C. (2002). Dynamics of aggregation and emergence of cooperation. *The Biological Bulletin, 202*, 262–267. doi:10.2307/1543477.
12. Depickère, S., Fresneau, D., Detrain, C., & Deneubourg, J.-L. (2004). Marking as a decision factor in the choice of a new resting site in Lasius niger. *Insectes Sociaux, 51*, 243–246.
13. Dorigo, M., Trianni, V., Sahin, E., Gro, R., Labella, T. H., Baldassarre, G., et al. (2004). Evolving self-organizing behaviors for a swarm-bot. *Autonomous Robots, 17*, 223–245. doi:10.1023/B:AURO.0000033973.24945.f3.
14. Garnier, S., Jost, C., Jeanson, R., Gautrais, J., Asadpour, M., Caprari, G., et al. (2005). Collective decision-making by a group of cockroach-like robots. In *IEEE Swarm Intelligence Symposium (SIS'05)*, pp. 233–240.
15. Garnier, S., Tache, F., Combe, M., Grimal, A., & Theraulaz, G. (2007). Alice in pheromone land: An experimental setup for the study of ant-like robots. In *IEEE Swarm Intelligence Symposium*.
16. Gervasi, V., & Prencipe, G. (2004). Coordination without communication: The case of the flocking problem. *Discrete Applied Mathematics, 144*, 324–344. doi:10.1016/j.dam.2003.11.010.
17. Grassé, P. P. (1959). La reconstruction du nid et les coordinations inter-individuelles chez Bellicositermes natalensis et Cubitermes sp. La théorie de la stigmergie: Essai d'interprétation des termites constructeurs. *Insectes Sociaux, 6*, 41–83. doi:10.1007/BF02223791.
18. Grodzicki, P., & Caputa, M. (2005). Social versus individual behaviour: A comparative approach to thermal behaviour of the honeybee (*Apis mellifera* L.) and the American cockroach (*Periplaneta americana* L.). *Journal of Insect Physiology, 51*, 315–322. doi:10.1016/j.jinsphys.2005.01.001.
19. Halloy, J., Sempo, G., Caprari, G., Rivault, C., Asadpour, M., Tâche, F., et al. (2007). Social integration of robots into groups of cockroaches to control self-organized choices. *Science, 318*, 1155–1158. doi:10.1126/science.1144259.
20. Hamann, H., Wörn, H., Crailsheim, K., & Schmickl, T. (2008). Spatial macroscopic models of a bio-inspired robotic swarm algorithm. In *Proceedings of the IEEE/RSJ 2008 International Conference on Intelligent Robots and Systems*.
21. Holland, O., & Melhuish, C. (1999). Stigmergy, self-organization, and sorting in collective robotics. *Artificial Life, 5*, 173–202. doi:10.1162/106454699568737.

22. Jeanson, R., Rivault, C., Deneubourg, J.-L., Blanco, S., Fournier, R., Jost, C., et al. (2005). Self-organized aggregation in cockroaches. *Animal Behaviour, 69*, 169–180. doi:10.1016/j.anbehav.2004.02.009.
23. Kennedy, J., & Eberhart, R. C. (2001). *Swarm intelligence* (512 pp.). San Francisco, CA: Morgan Kaufmann Publishers, Inc.
24. Kornienko, S., Kornienko, O., & Levi, P. (2005). IR-based communication and perception in microrobotic swarms. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'05)*, Edmonton, Canada.
25. Kornienko, S., Kornienko, O., & Levi, P. (2005). Collective AI: Context awareness via communication. In *International Joint Conference on Artificial Intelligence (IJCAI'05)*, Edinburgh, UK.
26. Kornienko, S., Thenius, R., Kornienko, O., & Schmickl, T. (accepted). Re-embodiment of honeybee aggregation behavior in an artificial micro-robotic swarm. Accepted for publication in *Adaptive Behaviour*.
27. Krieger, M. J. B., & Billeter, J.-B. (2000). The call of duty: Self-organised task allocation in a population of up to twelve mobile robots. *Robotics and Autonomous Systems, 30*, 65–84. doi:10.1016/S0921-8890(99)00065-2.
28. Labella, T. H., Dorigo, M., & Deneubourg, J.-L. (2006). Division of labor in a group of robots inspired by ants' foraging behavior. *ACM Transactions on Autonomous and Adaptive Systems, 1*, 4–25. doi:10.1145/1152934.1152936.
29. Millonas, M. M. (1994). Swarms, phase transitions, and collective intelligence. *Artificial Life, 3*, 417–445.
30. Payton, D., Daily, M., Estowski, R., Howard, M., & Lee, C. (2001). Pheromone robotics. *Autonomous Robots, 11*, 319–324. doi:10.1023/A:1012411712038.
31. Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *SIGGRAPH Computer Graphics and Interactive Techniques, 21*, 25–34. doi:10.1145/37402.37406.
32. Şahin E. (2005). Swarm robotics: From sources of inspiration to domains of application. In E. Şahin & W. Spears (Eds.), *Proceedings of the SAB 2004 Workshop on Swarm Robotics*, Santa Monica, CA, USA, July, 2004. *Lecture Notes in Computer Science 3342*, pp. 10–20.
33. Schmickl, T., & Crailsheim, K. (2004). Costs of environmental fluctuations and benefits of dynamic decentralized foraging decisions in honeybees. *Adaptive Behavior, 12*, 263–277. doi:10.1177/105971230401200311.
34. Schmickl, T., & Crailsheim, K. (2007). A navigation algorithm for swarm robotics inspired by slime mold aggregation. In E. Şahin W. Spears, & A. F. T. Winfield (Eds.), *Proceedings of the SAB 2006 Workshop on Swarm Robotics*, Rome, Italy, September, 2006. *Lecture Notes in Computer Science 4433*, pp. 1–13.
35. Schmickl, T., Möslinger, C., & Crailsheim, K. (2007). Collective perception in a robot swarm. In E. Şahin, W. Spears, & A. F. T. Winfield (Eds.), *Proceedings of the SAB 2006 Workshop on Swarm Robotics*, Rome, Italy, September, 2006. *Lecture Notes in Computer Science 4433*, pp. 144–157.
36. Seeley, T. D., Camazine, S., & Sneyd, J. (1991). Collective decision-making in honey bees: How colonies choose among nectar sources. *Behavioral Ecology and Sociobiology, 28*, 277–290. doi:10.1007/BF00175101.
37. Seyfried, J., Szymanski, M., Bender, N., Estana, R., Thiel, M., & Wörn, H. (2005). The I-SWARM project: Intelligent small world autonomous robots for micromanipulation. In E. Şahin, & W. Spears (Eds.), *Proceedings of the SAB 2004 Workshop on Swarm Robotics*, Santa Monica, CA, USA, July, 2004. *Lecture Notes in Computer Science 3342*, pp. 70–83.
38. Soysal, O., & Şahin, E. (2007). A macroscopic model for self-organized aggregation in swarm robotic systems. In E. Şahin, W. Spears, & A. F. T. Winfield (Eds.), *Proceedings of the SAB 2006 Workshop on Swarm Robotics*, Rome, Italy, September, 2006. *Lecture Notes in Computer Science 4433*, pp. 27–42.
39. Sugawara, K., Kazama, T., & Watanabe, T. (2004). Foraging behavior of interacting robots with virtual pheromone. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sendai, Japan, pp. 3074–3079.
40. Tâche, F., Asadpour, M., Caprari, G., Karlen, W., & Siegwart, R. (2005). Perception and behavior of InsBot: Robot–animal interaction issues. In *IEEE International Conference on Robotics and Biomimetics (ROPIO'05)*, Shatin, pp. 517–522.
41. www.swarmrobot.org Accessed 1 August 2008.