How Two Cooperating Robot Swarms Are Affected by Two Conflictive Aggregation Spots

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Abstract. Previous studies showed that two swarms of autonomous robots pursuing two conflicting goals can cooperate efficiently, especially at small swarm sizes. In this study we investigate how the spatial separation of the two conflictive aggregation spots affect the cooperation behaviour. The swarms are controlled by the BEECLUST algorithm, which is a robot control algorithm inspired by honeybee behaviour. We found that the spatial separation of the optima does not affect the aggregation efficiency of swarm sizes of 9 individuals or more. In contrast smaller cooperating swarms take advantage in their aggregation efficiency. Heterogeneous swarms are a big challenge in swarm robotics. When several tasks have to be achieved in parallel, swarms have to split up in task-related sub-swarms. Then efficiency enhancement by cooperation and the exploitation of side effects are a successful recipe for developing swarm intelligent algorithms.

1 Introduction

In social insects (e.g. honeybees) a huge number of individuals form a superorganism which shows self-organisation and swarm intelligent behaviour [1]. Even if all individuals exhibit "simple" behaviour, the swarm as a whole is able to solve complex challenges. Honeybees for example exploit rich foods sources more massively than poorer ones [2]. In the field of swarm robotics it is very important to keep individuals as simple as possible because resources are limited (e.g. memory or energy). For this reason social insects are a perfect source of inspiration for the field of swarm robotics [3] [4]. In swarm robotics the aggregation of agents is a very common goal but the approaches are very diverse. Dorigo et al. used an evolving neural network which consisted of 12 neurons for robot aggregation [5]. Other aggregation experiments were made with cockroach-like robots in simulation experiments as well as in real world, whereas an unique ID was required and communicated between the robots [6].

In this work we made experiments with robots controlled by the BEECLUST algorithm which is inspired by honeybee behaviour [7]. This algorithm consists of four simple rules (see Fig. 1):

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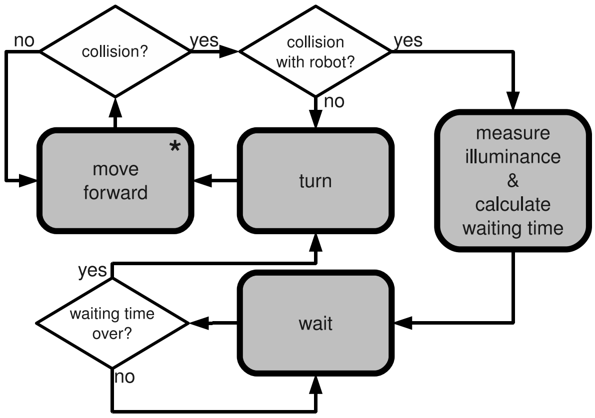

Fig. 1. Finite state machine of the BEECLUST algorithm. Boxes represent the different states of the robots. Diamonds represent if-else decisions. The asterisk (*) indicates the starting state of the controller.

1. The robots move straight forward through the arena. Whenever a robot detects an obstacle it checks whether the obstacle is a wall or another robot.
2. If this obstacle is a wall, the robot turns and continues with step 1.
3. If the obstacle is another robot, the robot measures the local illuminance and calculates a waiting time, depending on the illuminance.
4. When the waiting time is over, the robot turns and continues with step 1.

In [7] it has been shown that a swarm of Jasmine III robots, controlled by this algorithm, is able to find a spot of highest illuminance in an arena. A swarm of robots controlled by this algorithm responds dynamically on spontaneous environmental changes and satisfies all needs for being classified as swarm intelligent [1] [7]. The reasons for this intelligent behaviour are the feedback loops which emerge from within the swarm [8]. In [9] we showed that swarms of robots controlled by this algorithm act robust against disturbances induced by other swarms. Small swarms can even take advantage in their ability to aggregate if another swarm is present, even if the other swarm is performing a different task. Elaborating on this work, we wanted to find out if the spatial separation of two conflicting target sites for both swarms has an influence on the aggregation efficiency.

2 Methods

We performed our experiments in SMARS which is a simulation environment for experiments with Jasmine III robots, written in NetLogo [10]. We implemented two different swarms which act in parallel within the same environment: One swarm waits longer at places of high illuminance and is further called “light finders”. The other swarm waits longer at places of low illuminance and is called “shadow finders”. So the only difference between the two swarms is that a

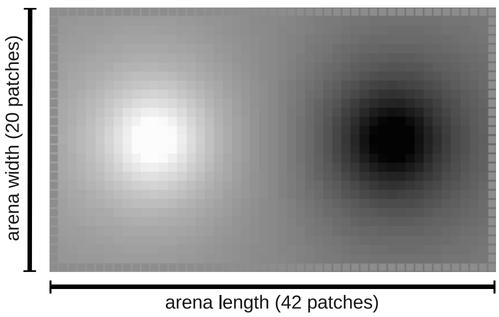

Fig. 2. Screenshot of an empty arena. The white area indicates the light spot, the black area indicates the shadow spot. The arena has the size of 42x20 patches, whereby a patch is a square with the side length of 3 cm.

different waiting time function was implemented (see Fig. 4) whereas the robots do not discriminate between the two swarms. The tested population sizes were 2, 3, 6, 9, 11, 18 and 24 robots per swarm. Each experiment was repeated six times. We implemented the following light distribution: The arena shows an ambient illuminance of 500 lux, one light spot of approx. 1000 lux and one shadow spot of approx. 0 lux. The arena has a size of 46 patches in length and 20 patches in width (see Fig. 2), whereby a patch is a square with a side length of 3 cm. In a first experiment we changed the distance between the light spot and the shadow spot in each run. These spots had a distance of 7, 9, 11 and 13 patches to the arena centre. All tested light distributions are shown in Fig. 3. In a second experiment we tested the response of the robot swarm on spontaneous changes in the environment. For this reason we started the experiments with the same setup as already mentioned above. After four minutes we swapped the positions of the light and the shadow spot. After four more minutes we swapped them again and monitored the following reaction of the robot swarm for four more minutes. In this experiment we compared runs with a distance of 7 patches between the optima and the arena centre to runs with a distance of 13 patches between the optima and the arena centre.

In our analysis we defined a target zone for the “light finders” which includes all patches, on which an illuminance between 600 and 1000 lux was present. This area covers 40% of the maximum light value in the arena. To analyse the aggregation quality we monitored the percentage of “light finders” within the state “wait” in the target zone during the last minute of every repetition. To analyse the aggregation speed of the swarm we monitored the point of time, in which 50% of the “light finders” were aggregated in the target zone (TA_{50}). Each run took 4 minutes. To analyse the swarm’s respond on changes in environment, we monitored the “light finders” in the target zone during the whole experiments. For quantifying possible enhancement of aggregation (% of the total swarm) we defined the index ΔAL as

$$\Delta AL = AL_7 - AL_{13}. \qquad (1)$$

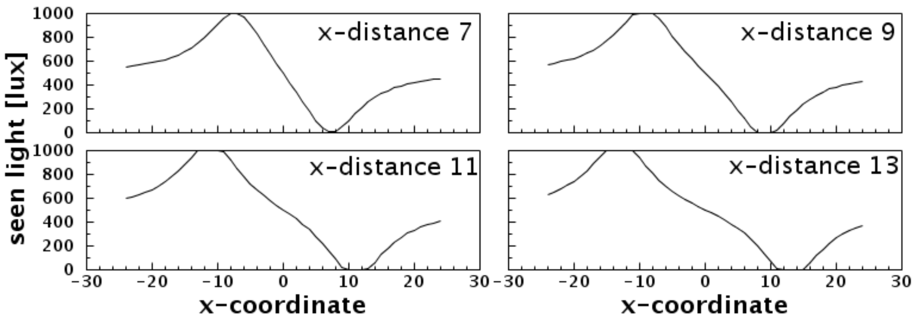

Fig. 3. Tested light distributions. The centres of the extreme spots were located in a distance of 7 (A), 9 (B), 11 (C) and 13 (D) patches from the arena centre.

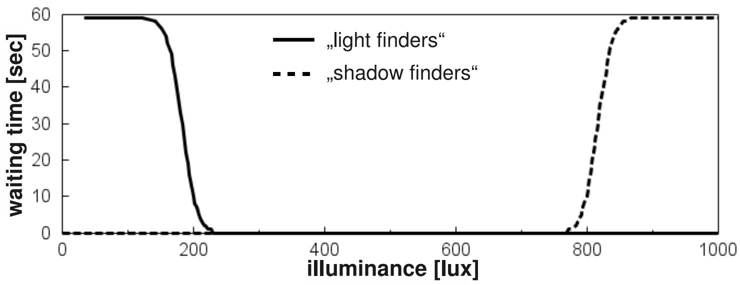

Fig. 4. Dependence of the waiting time on the local illuminance. The solid line shows the function which was implemented in the "light finders", the dashed line represents the same for the "shadow finders".

ΔAL represents the aggregation enhancement of the "light finders". AL_7 is the percentage of aggregated "light finders" when the optimum has a x-distance of 7 patches. AL_{13} is the percentage of aggregated "light finders" when the optimum has a x-distance of 13 patches from the arena centre.

3 Results and Discussion

In Fig. 5 we show that small swarms (2 and 3 individuals) show a lower aggregation quality than larger swarms. The distance between the two optima has an effect on small swarms by decreasing the fraction of aggregated robots. Larger swarms (9 individuals or more) are not influenced by the distance between the optima. In each case 70% to 80% of the swarm is aggregated under the light spot. Concerning the aggregation speed we found that larger swarms (9 individuals or more) are not affected by the distance between the optima (see Fig. 5). In each case it takes about 30 to 40 seconds to place 50% of the swarm under the light source. But contrary to aggregation quality, small swarms aggregate faster when the optima are close to each other.

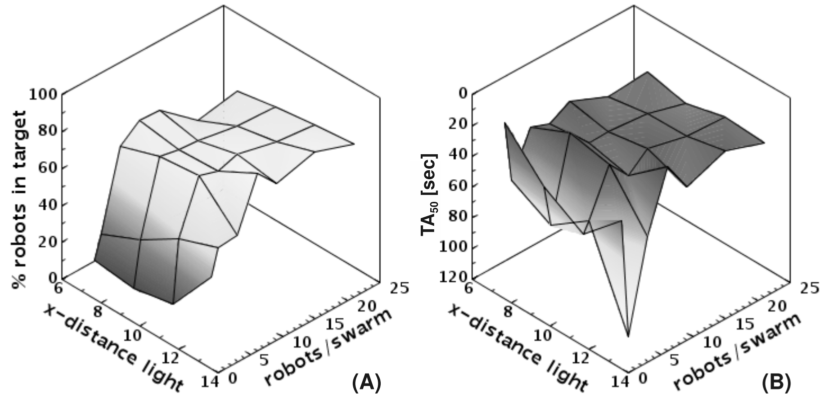

Fig. 5. (A) Percentage of "light finders" aggregated in the target zone within the last minute of the observation. This represents the aggregation quality. (B) Point of time when 50% "light finders" are aggregated in the target zone. This is an indicator for aggregation speed (n = 6 repetitions per experiment).

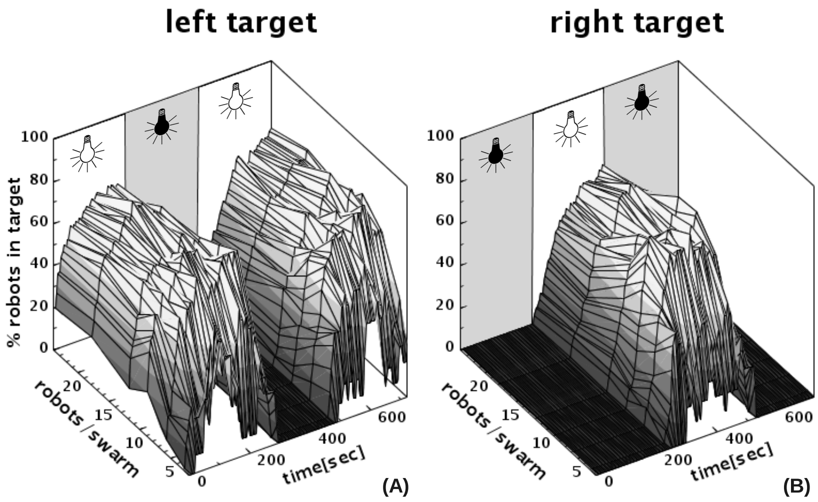

Fig. 6. Percentage of aggregated "light finders" in the target zone. The distance from an optimum to the arena centre (x-distance) is 13 patches. (A) Left target zone. (B) Right target zone.

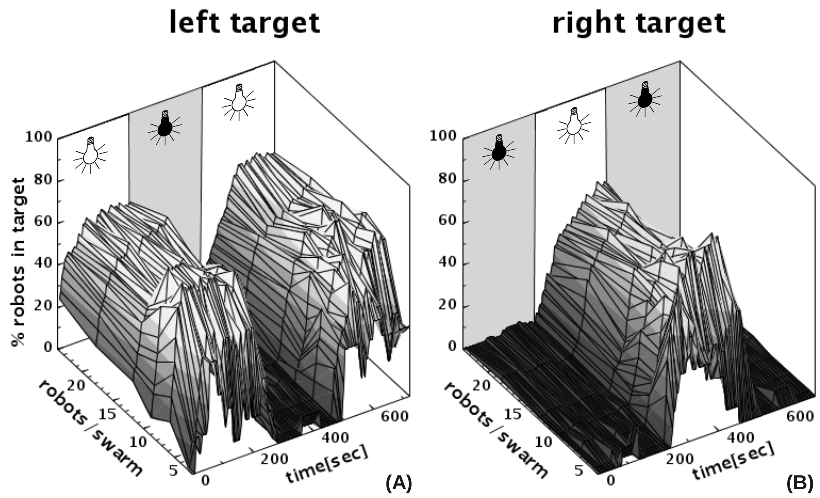

Fig. 7. Percentage of aggregated "light finders" in the target zone. The distance from an optimum to the arena centre (x-distance) is 7 patches. (A) Left target zone. (B) Right target zone.

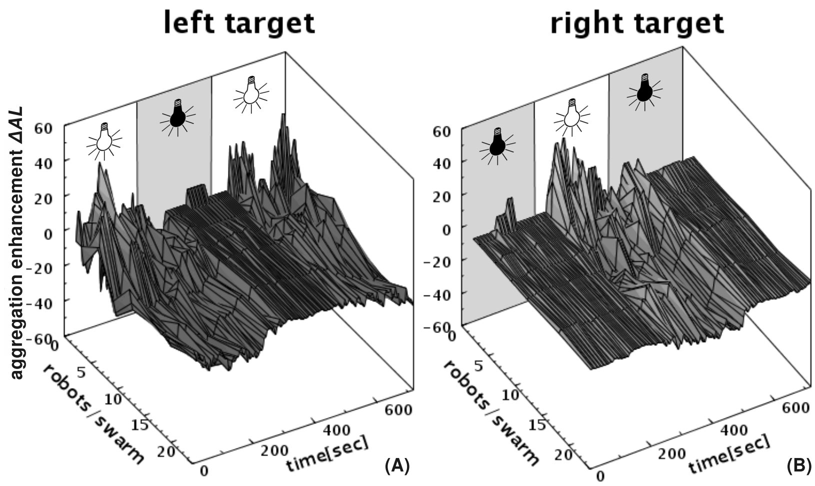

Fig. 8. Shown is the aggregation enhancement ΔAL in percent. For the formulation of ΔAL see equation 1. (A) Left target zone. (B) Right target zone. Please notice, that the y-axis (robots/swarm) is flipped for a more clearly representation in this the figure.

We show that the swarm reacts fast and reliable to spontaneous changes in the environment and follows the light spot in the arena when the two optima are far (x-distance = 13 patches) from each other (see Fig. 6) as well as when the two optima are close (x-distance = 7 patches) to each other (see Fig. 7). In both cases we found that swarms of 9 individuals or more show a robust aggregation efficiency: approx. 60% of the swarm aggregates when the optima are close to each other and 70% of the swarm aggregates when the optima are far from each other. But as it can bee seen in Fig. 7 small swarms (2 and 3 individuals) show a higher aggregation quality than larger swarms when the optima are close but the aggregation quality decreases when the two optima are far from each other (see Fig. 6).

In Fig. 8 we show that small swarms can achieve an aggregation enhancement of 30% after 100 seconds when the two targets are close to each other. After that the enhancement decreases again. This means that small swarm aggregate faster when the two optima are close to each other. The same effect can be seen after the swap of the two optima in second 240 in the right target and second 480 in the left target. This shows that small swarms can take advantage of close optima and are able to react more dynamically on spontaneous environmental changes. Larger swarms on the other hand are not significantly affected by the distance between the two targets.

Our results corroborate our presumption of the BEECLUST algorithm being a robust control algorithm for robot swarms. In Fig. 6 and Fig. 7 we show that the swarm is able to react to spontaneous changes in the environment. This corresponds well with reports in [7]. As it is shown in Fig. 5, the aggregation quality increases with the swarm size until an optimal robot density (9 individuals) is reached. This fits well to the results shown in [9]. Such a "critical minimum swarm density" is characteristic for swarm algorithms. The distance between the two optima affects small swarms (6 individuals and below) significantly in aggregation quality and speed. In contrast large swarms are affected only slightly. Small swarms do not only aggregate faster when the two optima are close to each other (see Fig. 5), they also react faster to environmental changes than larger swarms (see Fig. 8). The reason for better aggregation performance with close targets is that both swarms of aggregated robots build a kind of one big cluster which is shared by both swarms when the two optima are close to each other. This leads to a high number of robot-to-robot encounters near their optima. In large swarms, jamming effects induced by high robot density cancel this benefit out. Nevertheless large swarms show robust aggregation which is not affected significantly by the spatial separation of the optima.

4 Summary and Outlook

In summary, we say that the BEECLUST algorithm works very robust even with two cooperating swarms without discriminating the swarm affiliation. Larger swarms are not affected by the spatial separation of the optima, whereas smaller swarms gain benefit from optima which are close to each other. In future we will investigate whether or not the light gradient steepness in the arena (flat vs. steep vs. discrete steps) has an influence on the aggregation efficiency. Furthermore we will investigate whether or not the BEECLUST algorithm acts dynamically enough to follow moving light spots.

Acknowledgements

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