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Influence of a Social Gradient on a Swarm of Agents Controlled by the BEECLUST Algorithm

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Abstract

Agents controlled by a swarm algorithm interact with each other so that they have collective capabilities that a single agent does not have. The bio-inspired swarm-algorithm "BEECLUST" has the aim to aggregate a swarm at the global optimum even if there are several local optima (of the same type) present. But what about gradients produced of different stimulus types? In this paper, we present the concept of "social stimuli". We investigate how robots controlled by the BEECLUST-algorithm react to a social stimulus which is created by placing immobilized robots in the environment. It shows that the robots controlled by the BEECLUST-algorithm are able to react on a social stimulus within an environment with a global and a local optimum.

Background & Motivation

A swarm intelligent system is based only on a few simple rules which lead to a complex collective behaviour (Beni, 2005). Nature provides many swarm intelligent systems for us, where we can adopt algorithms. In earlier experiments such swarm intelligent behaviour of young honeybees was investigated. The preferred temperature of young honeybees is 36°C which is also the main temperature in the brood nest of a bee-hive (Grodzicki and Caputa, 2005; Heran, 1952). This temperature is very important for the development of young honeybees and can be interpreted as a natural mechanism to confine them to the brood nest.

In previous experiments it was found that a single young honeybee (*Apis mellifera*) is mostly not able to locate the area with its preferred temperature, whereas a group of young honeybees is able to find the right spot collectively (Kernbach et al., 2009; Schmickl et al., 2008). Figure 1(a) and 1(b) show example-results from such experiments. Similar pictures are shown in (Bodi et al., 2012).
From this swarm-intelligent behaviour an algorithm was derived: the BEECLUST algorithm (Kernbach et al., 2009). This algorithm is used in autonomous swarmrobots to find the global optimum out of several local optima. Such optimum could be a light gradient or - in our case - a temperature gradient. What makes the BEECLUST algorithm special is that it has only a few requirements: The robot needs infrared sensors for distance-measurement and a sensor for measuring the gradient (eg. light- or temperature-sensors). Thus, robots controlled by the BEECLUST algorithm do not need or use abilities that are essential for many other robot-algorithms (table 1).

Not Needed	Requirements
no explicit communication	sensors for distance-measurement
no permanent measurement of the gradient	one single non-directional sensor for measuring the gradient
no memory	
no ego-positioning	
no knowledge of the environment	
no complex navigation (only random-walk)	

Table 1: Requirements and non-requirements of the BEECLUST algorithm

As there are only a few requirements, the algorithm is used more often in robot swarms in the last years (Schmickl et al., 2008; Kernbach et al., 2009; Kengyel et al., 2011; Arvin et al., 2011). The algorithm is also analysed very well by theoretical models (Hamann et al., 2012; Schmickl and Hamann, 2011; Schmickl et al., 2009; Hereford, 2010).

This paper deals with another feature of the BEECLUST algorithm: "Can the decision-making be influenced by an additional kind of gradient?" An easy way to create a second kind of gradient is to place immobilized agents into the arena and thus creating something we define as "social gradient". In the BEECLUST algorithm there is only a minimal social component modelled which is the discrimination of an obstacle and another agent. However, we assume that the system reacts on the social stimulus without changing the original algorithm and therefore the minimal social component plays an important role.

(Acerbi et al., 2007) showed that a social component can improve the success of algorithms based on genetic evolution or individual learning. An experimental setup was created artificially to analyze the social component in the BEECLUST-algorithm: Although the optima are typically not known a priori, immobilized agents were placed into the suboptimum allowing us to understand the effects of the social component of the algorithm. By investigating this behaviour our goal is to create new hypotheses for the swarm research of young honeybees and other social species. Please note, that these experiments aim for an improved understanding of the BEECLUST algorithm and not improvement of the efficiency.

A short description of the BEECLUST algorithm is provided here, for details see (Kernbach et al., 2009; Schmickl et al., 2008). The algorithm works as follows:

1. The agents move around randomly until the agent detects an object in the front.
2. If there is an object, the agent has to distinguish between a collision with an obstacle or another agent:
   (a) If the agent collided with an obstacle, the agent turns around and moves randomly again.
   (b) If this is an agent-to-agent-approach, both agents measure the temperature and calculate the waiting-time which is dependent on the temperature.
3. If the waiting-time is over, the agents move around randomly again.

In the experiments described in (Kengyel et al., 2011; Kernbach et al., 2009; Schmickl et al., 2008), the BEECLUST algorithm was derived and tested with a single kind of gradient: a light- or temperature-gradient. The agents, regardless of the type of agents, were always able to determine the global optimum. In (Schmickl et al., 2008) the algorithm is also tested with two gradients of different intensity and also in dynamically changing environments, showing that the algorithm is flexible enough to react on these dynamic changes of the environment.
The cooperation of two swarms with different waiting time curves is investigated: It is shown that the two swarms benefit from the cooperation with each other if there is only a small swarm (Bodi et al., 2012).

In this work we present the results of experiments in which we investigate how a second, different kind of gradient influences the decision-making of the bio-inspired swarm-algorithm. This paper deals with the following questions:

1. Is the clustering behaviour of the BEECLUST algorithm sensitive to a social gradient?
2. Does a swarm have to trade off between two different gradients?
3. How many social agents are necessary to influence the aggregation behaviour?

Material & Method

We implemented the BEECLUST algorithm in a simulation environment and designed experimental settings that allows us to answer the questions.

Implementation of the Algorithm

For the simulation we used a free multiagent simulation-platform in which we modelled the bio-inspired swarm-algorithm simulating the individual honeybees as autonomous agents. In this work we use a simplified simulation of a robot swarm controlled by the BEECLUST algorithm.

Sensormodel As the algorithm is derived from the behaviour of young honeybees we modelled their antennae for the measurement of temperature as follows: Each position in the arena has a specific temperature assigned (see section “Experimental Setup”). If an agent has to measure the temperature, it has to interrogate the temperature of its current position. This ensures an easy and efficient way to map a temperature and its measurement from an agent’s point of view. See section “Calculation of Waiting-time” for more detailed information.

As BEECLUST experiments were conducted with robots in (Schmickl et al., 2008) we modelled robots’ sensors for the distance measurement. Each simulated robot has three sensors: one in the front, one on the left and one on the right side. Each sensor has an aperture angle of 90°, so that the agent has a field-of-view of 270°. One robot has a diameter of 8 cm. To simulate the distance-measurement of robots we convert the measured distance into integer-values from 0 to 255. The visibilty-range of an agent is about 1.5 robot-diameters. According to this a distance of 1.5 robot-diameters is mapped to a value of 0 and a distance of 0 robot-diameters results in a value of 255. A uniformly distributed random noise of [0;10] is added to the measurement.

Temperature	Waiting-time
<26°C	0s - 10s
26°C - 29°C	18s - 40s
29°C - 33°C	18s - 80s
>33°C	90s - 130s

Table 2: Dependency of local temperature and the waiting-time of the agent

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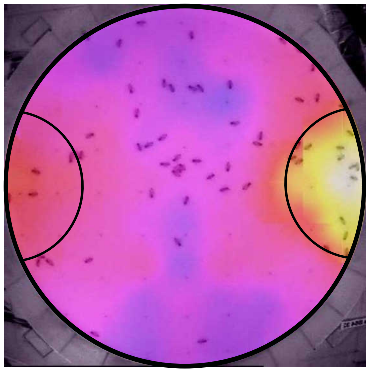
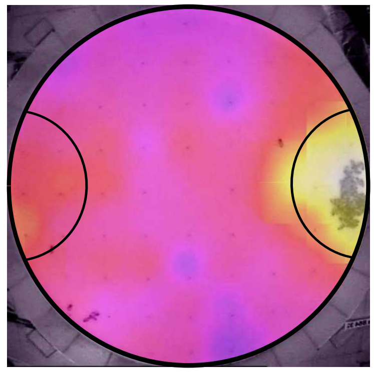
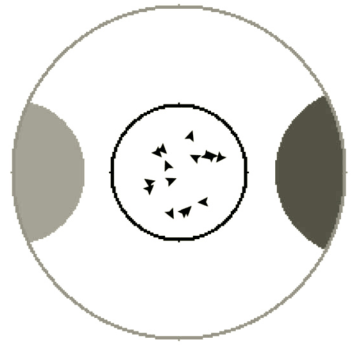


(a) Bee-arena with bees at the beginning of the experiment. Left side: local optimum with 32°C, right side: global optimum with 36°C.



(b) Bee-arena with bees at the end of the experiment. Bees are clustering at the global optimum at 36°C on the right side.



(c) Setup of the arena. The left light-gray area is the local optimum with 30°C - 32°C and on the right side the dark-gray area indicates the global optimum with a temperature of 30°C - 36°C. The black circle inside of the arena shows the area where the agents (black triangles) are released at the beginning of the experiment.

Figure 1: Experimental setup of bee experiments (left and middle) and similar experimental setup for robots (right).

Calculation of Waiting-time Choosing the right waiting time for specific temperatures is one of the most important parts of the BEECLUST algorithm. Kernbach et.al. (Kernbach et al., 2009) measured the waiting-time of bees after a bee-to-bee-approach dependent on the temperature of the bees' current position. Based on these measurements the waiting-time in the simulation is chosen as follows: For a temperature less than 26°C, the waiting-time is chosen randomly between 0s and 10s, for temperatures between 26°C and 29°C the agents' waiting-time is between 18s and 40s and for temperatures between 29°C and 33°C a waiting-time from 18s to 80s is chosen. For temperatures above 33°C the calculated waiting-time is between 90s and 130s (table 2).

Experimental Setup The experimental setup is based on an arena that was built for monitoring the behaviour of young honeybees in a complex temperature gradient (Szopek et al., 2008; Bodi et al., 2012). Figure 1(a) and 1(b) show the setup of the bee-arena. Figure 1(c) shows the robot-arena which has similar experimental setup. The arena has a diameter of 25 agent-lengths. It is surrounded by a wall in which the agents are able to perform their movements. On the left and on the right side there are two heat sources which create two different temperature-gradients (light- and dark-gray areas in figure 1(c)): The global optimum with a maximum of 36°C is located on the right side of the arena and occupies an area of about 11% of the arena. The temperature gradient ranges from the right side with 36°C to the middle of the arena with 22°C. The local optimum is located on the left side of the arena and occupies as well 11% of the arena. Here the maximum temperature is 32°C on the left side and ranges to the middle of the arena with 22°C. The 30°C threshold is defined as the border of the local and the global optimum. 78% of the area (white area inside of the arena in figure 1(c)) is defined as the pessimum and has a temperature of 22°C in the middle of the arena.

To test the hypotheses we designed four different experiments (figure 2):

(1) This experiment is used as a reference-experiment. Here we test the BEECLUST algorithm for the given arena with the global optimum on the right side and without the suboptimum on the left side (figure 2(a)).

(2) In this experiment we additionally provide the suboptimum on the left side of the arena (figure 2(b)).

(3) To test how a social stimulus affects the behaviour of aggregation in experiment 3 we place immobilized agents in the suboptimum with 32°C and a dummy-agent in the global optimum with 36°C to avoid side-effects (e.g. jamming-effects) (figure 2(c) and 2(d)). This experiment is conducted with different numbers of social agents to demonstrate how the system reacts to different sizes of a social gradient:
   (a) with 1 agent acting as a social gradient (as depicted in figure 2(c)).
   (b) with 2 agents
   (c) with 3 agents and
   (d) with 4 agents (as depicted in figure 2(d)).

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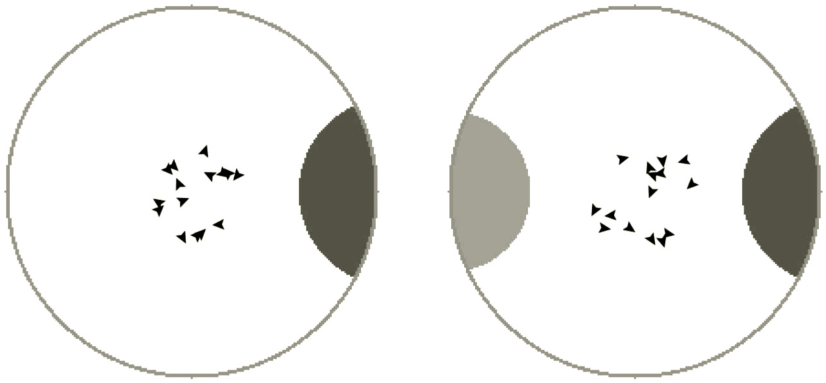
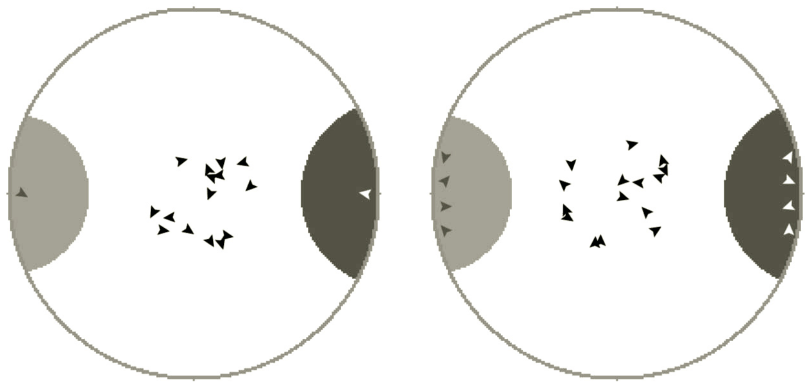


(a) Arena with global optimum

(b) Arena with local and global optimum



(c) Arena with one social agent placed in the suboptimum on the left side (dark-gray triangle) and a dummy-agent in the global optimum (light-gray triangle) which is perceived as an obstacle by the other agents.

(d) Arena with four social agents placed in the suboptimum on the left side (dark-gray triangles) and four dummy-agents in the global optimum (light-gray triangles) which are perceived as obstacles by the other agents.

Figure 2: Different experimental settings. The dark-gray area on the right side of the arena indicates the global optimum with a temperature of 30°C - 36°C. The light-gray area on the left side is the local optimum with 30°C - 32°C. The black triangles indicate agents that are controlled by the BEECLUST algorithm.

Each experiment was repeated 100 times. At the beginning of each experiment the agents are placed randomly inside a central area which has a diameter of 10 agent-lengths and is located in the middle of the arena (figure 1(c)). In all six experiments 15 agents perform the BEECLUST algorithm with identical parameter settings. The agents move around in the arena with a speed of two agent-lengths per second. Agents which generate the social stimuli are immobile and do not perform the BEECLUST algorithm. To ensure that placing agents into the suboptimum has no side-effects (e.g. regarding jamming-effects due to overcrowding of an optimum) we also place dummy-agents into the global optimum which are perceived as obstacles and not as an agent.

Changes to the original BEECLUST Algorithm as published in (Schmickl et al., 2008) The BEECLUST algorithm is not changed in its sequence, only the input values for calculating the waiting time mentioned in table 2 where taken from a temperature gradient instead of a light gradient. We didn't have to adapt the algorithm so that it responds to the social gradient.

Results

On the x-axes of figure 3 and 6 the abbreviation "LO" is referring to experiment (2) with only a global and a local optimum. "1SA", "2SA", "3SA" and "4SA" are referring to experiments with a social gradient with 1, 2, 3 or 4 social agents, respectively.

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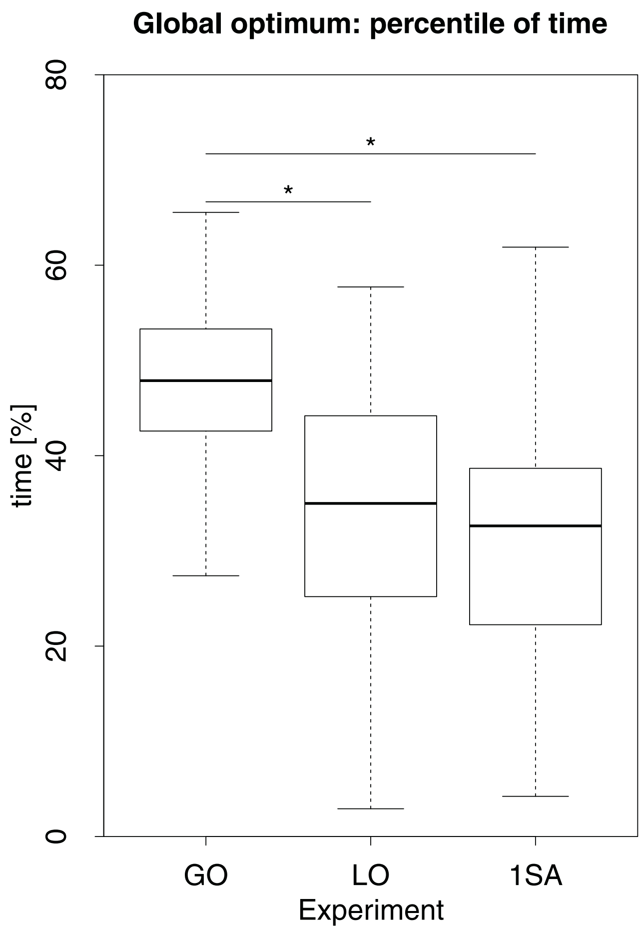

Figure 3: Percentile of time the agents spent in the global optimum. The plot shows the median with 1st and 3rd quartile. n=100. The bars with asterisks indicate significances at a significance-level of p=0.05 and were tested with the Wilcoxon-Mann-Whitney-U test (nominal scaled).

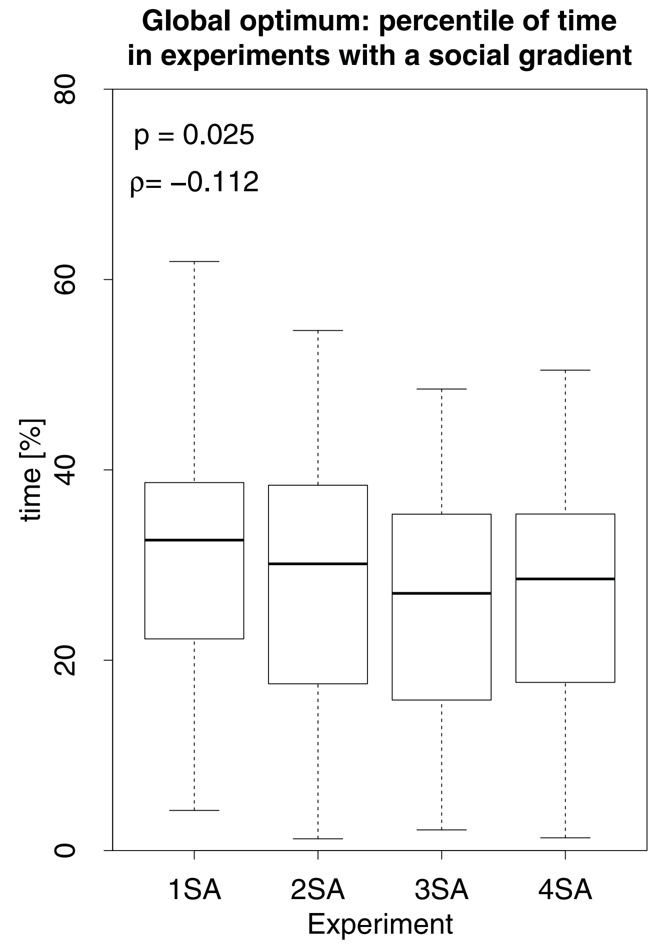

Figure 4: Percentile of time the agents spent in the global optimum in experiments with an increasing amount of social agents. The statistics is made with Spearman-statistics (ordinal scaled).

The time the agents spent in the global optimum is shown in figure 3. In experiment 1 ("GO") with just one optimum of 36°C the median time the agents spent in the global optimum is 47.88%. The median time in the experiment (2) with a local optimum ("LO") is 34.98% and with 1 social agent ("1SA") the median time is 32.62%. The results of experiment 1 is significantly different to the results of experiment 2 and 3a. The significances were tested with a level of p=0.05 (Wilcoxon-Mann-Whitney-U test).

Figure 4 shows the time the agents spent in the global optimum of the experiments with a different amount of social agents. The median times of experiments with 1, 2, 3 and 4 social agents are 32.62%, 30.12% , 27.03% and 28.54%, respectively. Here, the significances were tested with Spearman-statistics and showed no significant correlation between the amount of social agents and the time the agents spent in the global optimum (p = 0.025 and ρ = -0.112).

Figure 6 shows the percentage of time the agents spent in the local optimum. The time for experiment 1 ("GO") is calculated with a uniform distribution model, due to the fact that in this experimental setting no local optimum is available. As the defined area of the local optimum covers 11%, the agents would spend 11% of the time in this area. In experiment (2) the median time spent in the local optimum of 32°C was 16.25%. The median time for experiment (3a) with one social agent is 26.50%. The results of the experiments here are all significantly different to each other. The significances were tested with a level of p=0.05 (Wilcoxon-Mann-Whitney-U test).

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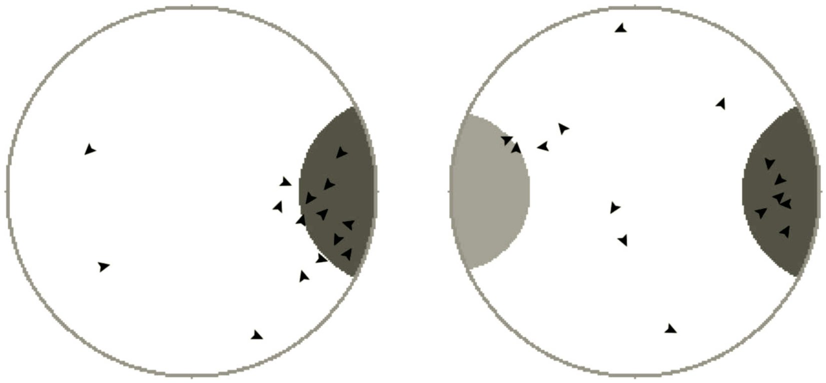
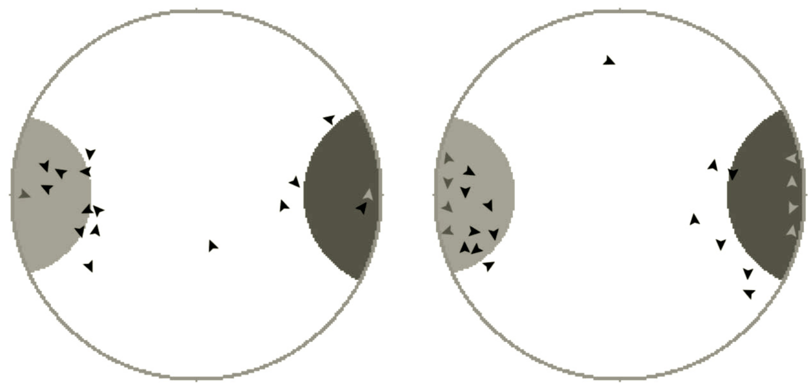


(a) Typical distribution of experiment with global goal

(b) Typical distribution of experiment with global and local goal



(c) Typical distribution of experiment with one agent indicating the social gradient placed in the suboptimum on the left side (dark-gray triangle) and one dummy-agent in the global optimum (light-gray triangle) which are perceived as obstacles by the other agents.

(d) Typical distribution of experiment with four agents indicating the social gradient placed in the suboptimum on the left side (dark-gray triangles) and four dummy-agents in the global optimum (light-gray triangles) which are perceived as obstacles by the other agents.

Figure 5: Examples of results of different experimental settings. The dark-gray area on the right side of the arena indicates the global optimum with a temperature of 30°C - 36°C. The light-gray area on the left side is the local optimum with 30°C - 32°C. The black triangles indicate agents that are controlled by the BEECLUST algorithm.

In figure 7 the time the agents spent in the local optimum are shown for the experiments with an increasing amount of social agents. The median times for 1, 2, 3 and 4 social agents are 26.50%, 27.08%, 29.21% and 30.04%, respectively. The significances were tested with Spearman-statistics and showed no significant correlation between the amount of social agents and the time the agents spent in the local optimum (p = 0.003 and $\rho = 0.148$).

Discussion

The main feature of the BEECLUST algorithm is to find the global optimum within a complex environment, as shown in (Schmickl et al., 2008) experiments with light-gradients in a dynamic environment were conducted. In the following, we will discuss the three questions mentioned in section "Background & Motivation":

Is the clustering behaviour of the BEECLUST algorithm sensitive to a social gradient?
The BEECLUST algorithm as tested in (Schmickl et al., 2008) is able to locate the global optimum in static and dynamic environments robust. In the experiments we showed that this stable decision-making can be influenced by adding another gradient - a social gradient. By just using one additional agent - functioning as a source of a social

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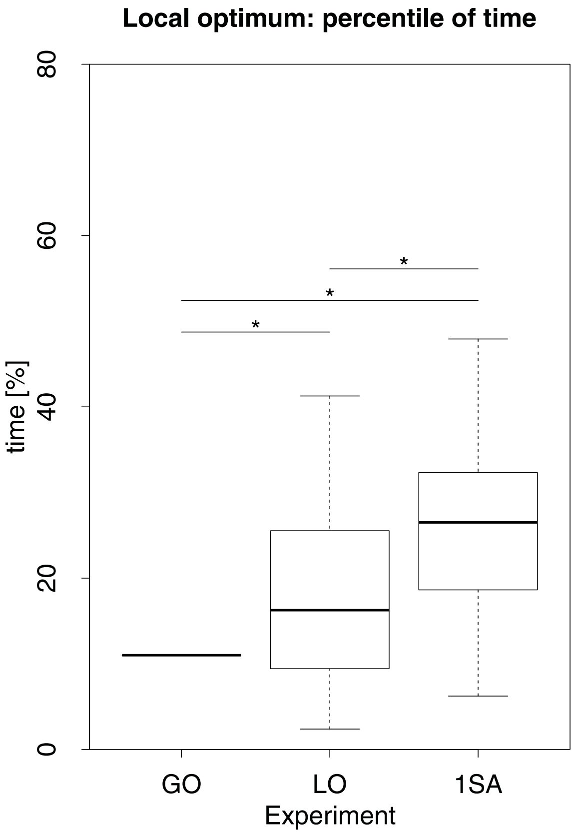

Figure 6: Percentile of time the agents spent in the local optimum. The plot shows the median with 1st and 3rd quartile. n=100. The bars with asterisks indicate significances at a significance-level of p=0.05 and were tested with the Wilcoxon-Mann-Whitney-U test (nominal scaled).

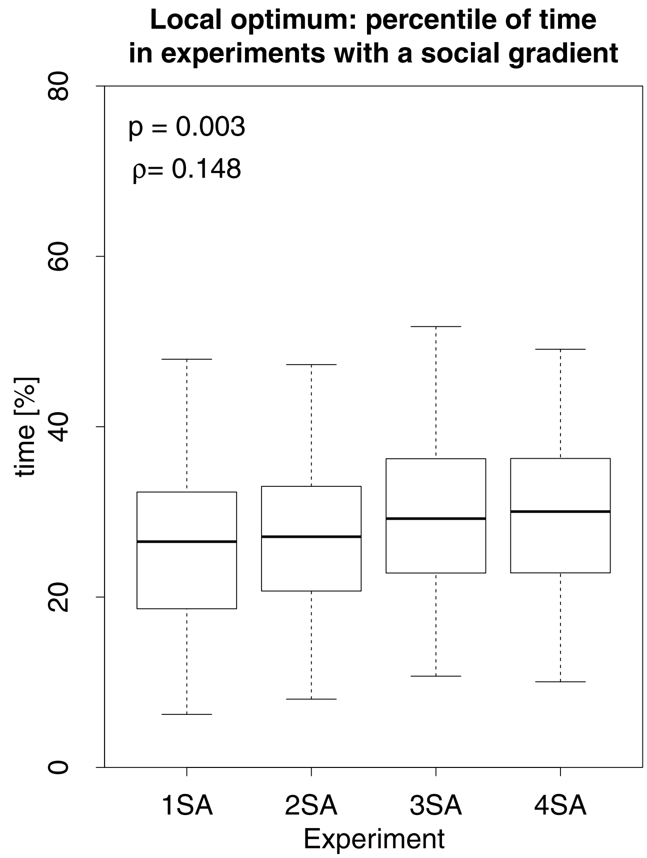

Figure 7: Percentile of time the agents spent in the global optimum in experiments with an increasing amount of social agents. The statistics is made with Spearman-statistics (ordinal scaled).

gradient - we were able to increase the percentage of time in the local optimum from 16.25% to 26.50% (compare figures 5(b) and 5(c).

How many social agents are necessary to influence the aggregation behaviour?
Adding just one single social agent had a huge effect. We were able to bound agents for more than 10% of the time to the suboptimum. To reach the threshold were the agents spend more time in the suboptimum than in the global optimum, three social agents were necessary (see figure 4 and 7). This leads us to the next question:

Does a swarm have to trade off between two different gradients?
A swarm of agents which is controlled by the BEECLUST algorithm always decides for the global optimum even if a second suboptimal gradient of the same type is present. Thus a discrimination of the local and the global optimum is possible. If there is a second gradient of another type, the decision-making of a swarm is not that clear anymore. In a weak gradient, agents which were undecided start to decide for the social gradient, but also agents from the global optimum reconsider their decision. If the social gradient gets stronger, no more agents are bound from the pessimum but some additional agents from the global optimum change their minds (see figure 5).

The percentage of time that agents spent in the pessimum is significantly lower in the experiments with social agents (3a, 3b, 3c) compared to the experiment without a social stimulus (2). Increasing the amount of social agents had no significant effects.

If we compare the results of experiment (3a) with experiment (2) it appears that fewer agents stay in the pessimum or global optimum and more agents stay in the local optimum. We can conclude that agents get bound not only from the global optimum but also from the pessimum (figure 3

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and 6). This effect can also be observed in the results of experiment (3b). Three social agents is the minimum number of agents that are needed so that more agents place themselves in the local optimum than in the global optimum (figure 4 and 7). Adding another social agent - in total 4 social agents - leads to no significant changes in the percentage of time the robots spent in the optima.

Conclusion & Future Work

We conclude that the BEECLUST algorithm can be influenced by using a social gradient induced by immobile agents placed in the suboptimal area of the arena.

As the social gradient had an unexpected big effect, we also want to introduce the social gradient to experiments with real honeybees. As the BEECLUST algorithm is derived from the behaviour of young honeybees, we expect that the decision-making of young honeybees can also be influenced by offering a second, different type of gradient. These results can then be used for further investigations of the swarm-intelligent behaviour of honeybees by creating bio-hybrid systems consisting of real honeybees and artificial autonomous robots (Schmickl et al., 2013).

In (Schmickl et al., 2008) robot-experiments were conducted in light-gradients. We want to implement the BEECLUST algorithm in robots and expose them to a temperature-gradient and a social gradient. With this, we want to get closer to the situation honeybees are faced with and provide feedback for the biological swarm research.

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