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RESEARCH ARTICLE

Towards Swarm Level Optimisation: The Role of Different Movement Patterns in Swarm Systems

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In a swarm system, for example in a beehive, group decision is based on interactions and interferences of all individuals without a central unit that decides for everybody. When making experiments with young honeybees (*Apis mellifera*), a swarm algorithm, called BEECLUST, was derived [25, 37]. The algorithm enables swarms to locate the "Global-Goal" out of several local optima. There were also four different behavioural types discovered during the experiments: *Random-Walker*, *Goal-Finder*, *Wall-Follower* and the Immobile Bee. In this paper, we introduce the four behavioural types to the BEECLUST algorithm and analyse how the decision making process of the swarm can be influenced. We show how the different types can be used to optimise the decision making for a certain setup of the arena and discuss about Swarm Level Optimisation.

Keywords: autonomous agents; self-organisation; behavioural patterns; honeybees; search; swarm systems

1. Introduction

In many swarm intelligent systems the individuals show behaviours that can be resembled by simple reactive agents but the whole swarm is able to achieve a complex task without a centralized unit that decides. Ants or honeybees are classical swarm systems that have been used as sources of inspiration for artificial swarm intelligent systems, for example, in division of labor in robotic swarms [16, 51, 52]. In addition to the classic swarm systems like the beehives or ant colonies, nature provides many more demonstrations of swarm intelligence. The brain - for example - consists of a very high number of individual neurons that have an action potential threshold. If this threshold is exceeded, the neurons are firing. The interplay of the individual neurons then produces the complex behaviour which we interpret as intelligence [45]. Another example is the swarm behavior in plants. The many branches of a plant act as individual agents in a swarm competing for common resources provided at the roots. The adaptive morphology of the plant is a result of the branch competitions along with the genetic characteristics of the plant [53]. There exist ideas to use swarm intelligence to engineer solutions for traffic issues. If we have autonomous cars that follow only a few rules there might be no need for traffic signs and the traffic itself will be more fluent and safe [49, 50]. Many different approaches have been also taken in the domain of swarm robotics

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e.g. [8, 27, 31]. The human society is another example for collective intelligence or a superorganism. A society can be seen as a multi-cellular organism where the individuals are operating as cells. The network of different communication channels are then acting as a nervous system of the superorganism [20]. The connectivity of single individuals (or neurons) also plays an important role in such a superorganism (not necessarily a physical connection) [41]. In consequence, it is the connectivity that is responsible for the robustness of a collective decentralized control of the system.

Heterogeneous systems can be even more complex. It is especially interesting how the composition of such systems affects global behaviour. Gaining insights and developing methods of composing heterogenous systems can be helpful in many fields: neuroscience [45], logistics [6], society [20], traffic [14, 49] or servicerobotics [12, 30].

These are examples of systems where the research of swarm intelligent systems can contribute to further develop new ideas on how the research can be integrated in our everyday life or how it can be improved.

In swarm systems the performance of the group is built from individual decisions, actions and interactions of single agents. Especially in systems consisting of many mobile agents different movement patterns of single agents are crucial for the organisation of the overall movement. Different patterns of movement have been discovered in various species of animals: e.g. bees [29, 32, 33, 35, 48], bumble bees [17, 54], fish [21, 34], ants [10, 11, 46], termites [7, 22] or birds [13, 15, 26]. Couzin et al. used a simple model to show that only a small number of individuals needs to be informed to guide the whole group [9]. In honeybee swarms only approx. 5% of bees need to be informed to guide the group to a new nest site [38]. Beekman et al. showed, that the small minority of informed scouts indicates the swarm's flight direction visually by streaking through the swarm cloud [5].

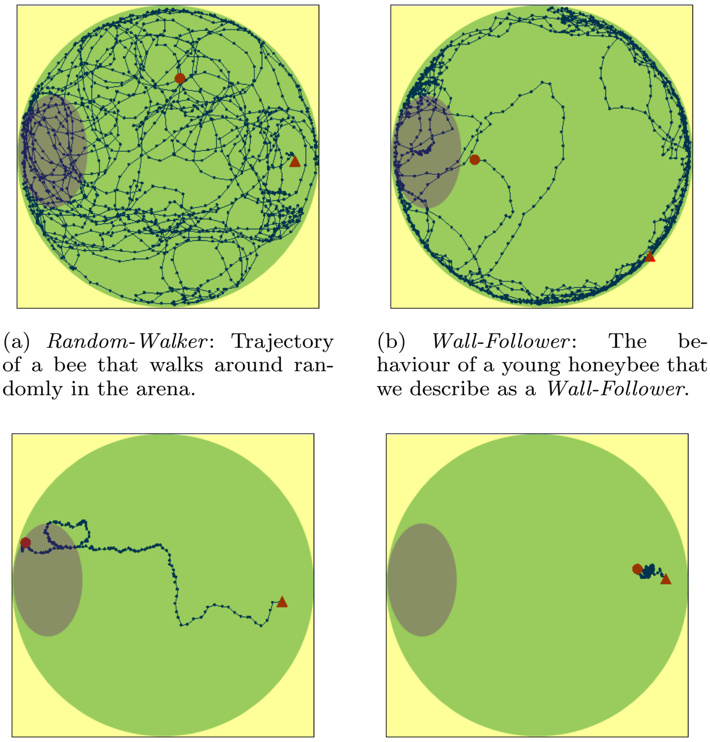
Also, several studies have been done investigating different behaviors of honeybees including their waggle dance, clustering, and search strategies. For example, a mechanical model was used to investigate how a honeybee perceives communication dances of other individuals [28]. In order to study the movement of individual honeybees in a thermoregulating cluster in a hive, a multiagent-model was used [42]. In [33] it is shown that honeybees perform flight patterns with Lévy-flight characteristics as a searching strategy. Lévy flights are random walks with a levy distribution of the length of the motion steps (or speed) that have been shown as optimal strategies for sparsely, randomly distributed targets [47] and used as the motion models of many animals. Bartumeus et al. show an analysis of different random-walk models: a correlated random-walk and Lévy walks and propose a new model which combines correlated random-walks with Lévy walks [4].

Honeybees younger than 24 hours cannot fly. They can locomote in their arena and they have some preferred temperature that is necessary for their development. Although the individual bees seem to be not very successful in positioning themselves in the spots with the preferred temperature, the bees collectively find those spots and aggregate there. In previous experiments with young honeybees [44], four different kinds of movement behaviour in an arena with a temperature gradient were observed (as mentioned in [36]), which can be classified into the following cases: *Random-Walker*, *Wall-Follower*, *Goal-Finder* and Immobile Bee. Figure 1 shows example trajectories of these four classes.

When these different movements of bees were discovered, several questions arose: What effect do the different movements have on other agents or on the swarm? Why are there different behavioural types although just a random-walking-behaviour is enough to reach the goal? What is the role of each behavioural type and how could it be used to predict or modulate the resulting aggregation-behaviour of the swarm?

To investigate these questions we introduce four behavioural types to the BEECLUST-algorithm [37], that is a state-of-the-art algorithm for robot swarms and is derived from the aggregation behaviour of young honeybees. Those bees are able to find a spot with their preferred temperature collectively, although this spot cannot be found by most individual bees [44]. Agents controlled by this algorithm are able to find a certain point of interest in an area without using explicit communication, memory, ego-positioning and permanent measurements of the environment [24, 25, 37]. Thus, it can be used for swarm robots with very limited actuation and sensing capabilities. This algorithm is very simple but the swarm is still able to find a certain predefined point of interest (e.g. hottest or brightest spot in the arena).

There exist various analysis and implementations of the BEECLUST algorithm. For example, the behavior of the algorithm is modelled based on a probability control mechanism [1], or using a birth and death Markov chain [18, 19]. In [2], the parameters of the algorithm are analysed and modifications of the original algorithm is introduced. In [3], the behavior of the swarm is compared with a fuzzy-based aggregation algorithm. Influence of social gradient on the behavior is investigated in [24]. In [23] the combination of the BEECLUST algorithm and a mathematical model describing different individual behaviors is investigated and the distribution of the different behaviors are evolved for particular tasks. The hardware implementation of the algorithm in hardware is presented for a swarm



(a) *Random-Walker*: Trajectory of a bee that walks around randomly in the arena.

(b) *Wall-Follower*: The behaviour of a young honeybee that we describe as a *Wall-Follower*.

(c) *Goal-Finder*: This bee is able to find the area with its preferred temperature.

(d) Immobile Bee: This bee moves in the arena rarely.

Figure 1. Behaviour of young honeybees: typical trajectories of the different types. The large green circle represents the arena. The grey ellipse represents the goal area. The small red triangle and the small red circle indicate the starting position and final positions of the bee respectively. The diameter of the arena is 60 cm and the goal area covers 11% of the whole arena.

of micro robots [25].

We assume that individual behavioural patterns contribute to different attributes of global swarm behaviour and can be used to optimise the swarm's decision making process. We want to optimise a swarm system by composing the swarm from a selection of members with specific behavioural traits. We call this concept "Swarm Level Optimisation": like type setters in former days, who were picking letters from boxes to compose a journal page, a swarm engineer could "engineer" a swarm by picking specific agents and arranging them to a specific goal-tailored swarm system.

We aim for a swarm system that can be optimised for a specific experimental setting by choosing the accurate swarm composition. Here we present the first experiments and results of a whole set of swarm composition experiments. In the end we want to have a set of swarm compositions to pick from according to how the environment looks like. For example, there could be an optimal swarm composition for experiments with one goal, another optimal composition for two or more goals, another one if the goals are located in the middle of the arena or at the walls and so on.

To achieve this goal, we show here how different types of motion behaviour can change the overall swarm-behaviour. Therefore we formulate the following hypotheses:

H1 The *Goal-Finder* is able to locate itself at different goals in the given arena, but is not able to discriminate between a Local and a Global-Goal.
H2 Introducing the Wall-Following-Behaviour to a swarm of *Random-Walker*s raises the success of aggregation for the given setup.
H3 *Immobile-Agent*s have an attractive effect on other swarm members just as Social Agents [24] have.
H4 *Immobile-Agent*s have an effect on the success of aggregation depending on their position.

In the rest of the paper we tackle these four research hypotheses. For this purpose, we first discuss the prerequisites including the behavioural types, the BEECLUST algorithm, and the experimental setup. Afterwards in Section 3 we present the obtained experimental results. In Section 4 we discuss these results and answer the four research hypotheses. Finally, we conclude the paper and outline future research work.

2. Prerequisites

In this section we first describe the four behavioural types in detail. Afterwards - and in order to be self-contained - we briefly recall the BEECLUST algorithm. Finally, we introduce the experimental setup used to answer the stated research hypotheses.

2.1 Implementation of Behavioural Types

We implemented 4 behavioural types according to the trajectories created from the movement of young honeybees shown in figure 1:

Wall-Follower: Once a *Wall-Follower* reaches a wall, it follows the wall at a certain distance. To achieve this the sensor-input has to be between two thresholds. If the sensor-input exceeds the thresholds, the agent makes a small turn either left or right depending on which side the threshold is exceeded. We provided three different implementations of the *Wall-Follower*s in terms of their behavior far from the walls as well as when they meet each other:

(a) When the agent is far from the wall or when it meets another agent, it moves randomly until it finds the wall again (figure 2(a)). We use the acronym "WFrw" for this implementation.

(b) When the agent is far from the wall it moves straight forward. If it meets another agent at a wall, it turns 90° to the inside of the arena (figure 2(b)). We use the acronym "WF90" for this implementation.

(c) When the agent is far from the wall it moves straight forward. If it meets another agent at a wall, it turns 180° and follows the wall in the other direction (figure 2(c)). We use the acronym "WF180" for this implementation.

Goal-Finder: The *Goal-Finder* is implemented like a greedy uphill walker meaning that it moves in the direction of gradient towards the higher temperatures. It compares the temperature on its front left side with the temperature on its front right side and moves in the direction of the higher temperature. If both temperatures are equal, the agents move forward (figure 2(d) shows an example behaviour).

Random-Walker: In each step the *Random-Walker* is moving, it simultaneously makes a randomly generated turn between -35° and +35°. This leads to a trajectory as shown in figure 2(e).

Immobile-Agent: In figure 2(f) it can be seen that this behavioural type does not move very far from its origin and is thus called "*Immobile-Agent*". This trajectory is created by agents with a high turning-angle between -180° and +180°and with a slow speed (a quarter of the speed of the other behavioural types).

Apart from the motion pattern the agents execute the normal BEECLUST algorithm which we will describe in the next section.

2.2 BEECLUST Algorithm

The BEECLUST algorithm is very simple. It is derived from the swarm-behaviour of young honeybees. It is implemented as follows:

(1) Each agent moves around in the arena according to its behavioural type until there is a collision with another agent or an obstacle.
  a) If the agent collides with an obstacle it makes a random turn and moves again according to its behavioural type.
  b) If the agent meets another agent it stops, measures the temperature once and calculates a waiting-time depending on the measured temperature.

(2) If the calculated waiting-time is over, the agent turns and moves around again according to its behavioural type. The turn is always random for all types except for the *Wall-Follower*s (see the details in section 2.1).

A state-machine of the algorithm is shown in figure 3. For more details about the algorithm see [25, 37].

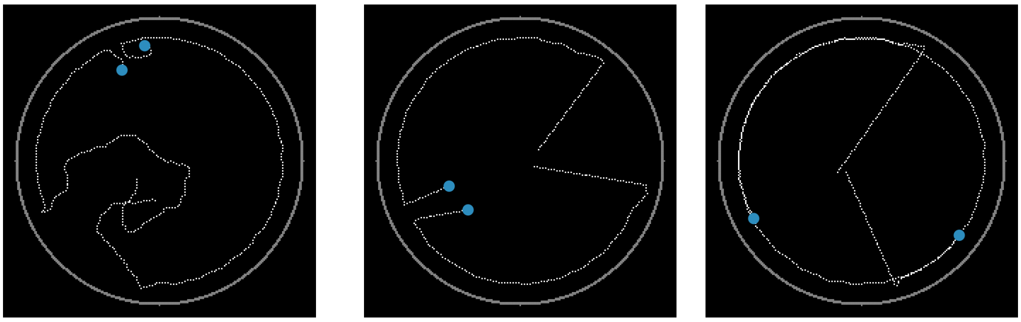
2.3 Setup of the Experimental Arena

To test our hypotheses we used a classical binary choice setup that is often used to investigate swarm-intelligent behaviours and algorithms ([19, 37, 39, 40, 43]). In this choice experiment, two options with different qualities are presented to the swarm and it is supposed to pick the option with higher quality. In this setup, we place two different heat sources (one with the optimal and one with a suboptimal temperature) in the arena. Figure 4 shows the setup of the arena: The gray circle represents the wall of the arena and the agents are allowed only to move inside the wall. On the left side of the arena we modelled a heat source which creates a temperature gradient ranging from 32° C underneath the heat source to 30° C at the border of the semi circle inside the arena. We define the area of 32° C to 30° C as the "Local-Goal". To create a binary choice-experiment we place a second heat source on the right side of the arena. This heat source creates a temperature gradient from 36° C underneath the heat source to 30° C at the border of the semi circle inside the arena. The area ranging from 36° C to 30° C is defined as "Global-Goal". The black area inside of the arena is called "Pessimum" (area that is neither the "Global-Goal" nor the "Local-Goal" inside the arena). The heat sources of the goals create a temperature gradient of 30°C to 20°C from the border of the goals to the middle of the arena. The agents (dots) have a size of $\frac{1}{25}$ arena-size and are released within the white circle randomly.

2.4 Experiments

Experiment 1: In order to test Hypothesis 1 we used 12 agents of the type "*Goal-Finder*" performing the BEECLUST algorithm and released them in the middle of the arena.

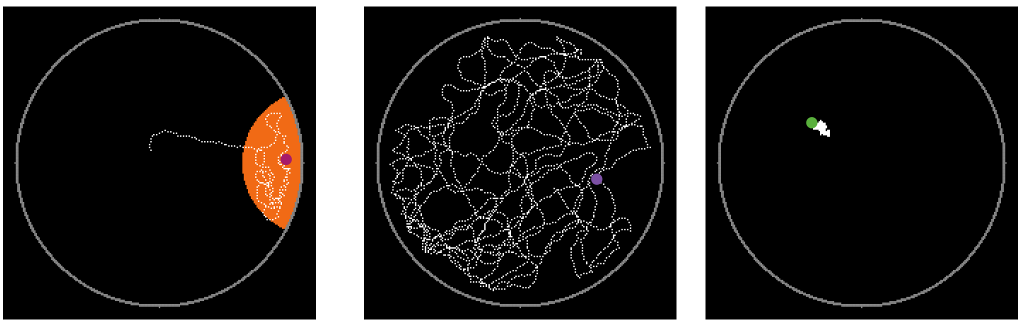
Experiment 2: To investigate the influence of the Wall-Following behaviour to a swarm of *Random-Walkers* (Hypothesis 2), 3 *Wall-Followers* and 9 *Random-Walkers* (in total 12 agents) were released in the middle of the arena. The experiment is repeated for all the three different implementations of the *Wall-Followers*.



(a) Typical trajectory of a *Wall-Follower* with a Random-Walk in the middle of the arena.

(b) Typical trajectory of a *Wall-Follower* with a 90° turn after meeting another agent.

(c) Typical trajectory of a *Wall-Follower* with a 180° turn after meeting another agent.



(d) Typical trajectory of a *Goal-Finder*. The orange area indicates the source of the temperature gradient.

(e) Typical trajectory of a *Random-Walker*.

(f) Typical trajectory of an *Immobile-Agent*.

Figure 2. Typical trajectories of the different implemented behavioural types in simulation.

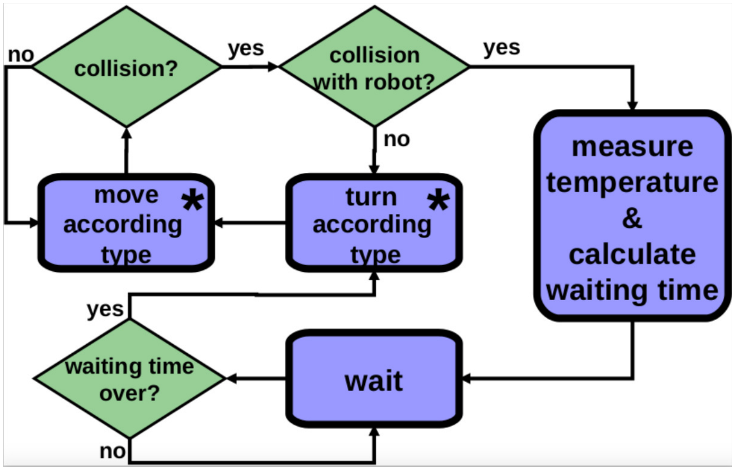


Figure 3. BEECLUST algorithm derived from the behaviour of young honeybees.

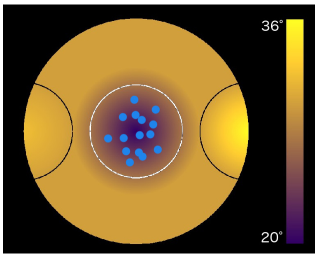


Figure 4. The experimental setup of the circular arena. On the left side is the Local-Goal with a gradient from 32°C to 30°C. On the right side there is a heat source which creates a gradient from 36°C to 30°C ("Global-Goal"). The rest of arena is called "Pessimum" and has a temperature gradient of 30°C (at the border to the goals) to 20°C in the middle of the arena. The agents (dots) are released within the white circle randomly. The agents have a radius of 4% of the arena radius. Each of the Global-Goal and the Local-Goal cover 11% of the arena.

Experiment 3: To test Hypotheses 3 and 4 the influence of the *Immobile-Agent* has to be analyzed. In the first experiment (Hypothesis 3) the goal was to compare the effects of *Immobile-Agents* with the effects of Social Agents defined in [24]. Social Agents are similar to the *Immobile-Agents* except they are fully immobilized (do not turn or move at all). Even though they are fully immobilized, their social effect on other agents (as defined in BEECLUST algorithm in section 2.2) still holds: the reaction of other agents that collide with them is not a reaction to an obstacle but an agent. To compare the behaviors, we created an experimental setup similar to what was used in [24]. Three *Immobile-Agents* were placed in the "Local-Goal" on the left side of the arena and in the Global-Goal we placed three dummy-agents which are perceived as obstacles. In the middle of the arena 9 *Random-Walkers* are released, so that we have 12 agents in total.

Experiment 4: A series of experiments was made to test Hypothesis 4. First 12 *Random-Walkers* were used in an arena with a Global and a Local-Goal and no *Immobile-Agents* are placed in the arena. Then three *Immobile-Agents* were placed in the Global-Goal, in the Local-Goal and in the middle of the arena consecutively. In all three cases 9 *Random-Walkers* were released in the middle of the arena. The same series of experiments was done with *Wall-Followers* (WF180) and *Immobile-Agents* instead of *Random-Walkers* and *Immobile-Agents*.

We also made a set of experiments for exhaustive analysis with (in total) 15 agents. We start with 15 agents of one type and then replace the agents one by one with another type. In this set of experiments, we release all the agents (including *Immobile-Agents* if they exist) in the middle of the arena. The results of these experiments provide a swarm-designer with a guideline how the composition of the swarm with different types shall be engineered.

All experiments were repeated with "number of repetitions $n = 100$". The simulated time is 30 minutes per experiment and repetition.

3. Results

The success of aggregation was measured by counting the median number of agents over time in the Global, in the Local-Goal and in the Pessimum. On the y-axis the figures show the median number of agents and the x-axis show the different areas for every tested behavioural type. All significances were tested with the Wilcoxon-Test (Global-Goal tested against Local-Goal) and the Mann-Whitney U-Test (Global-Goal of one experiment against Global-Goal of another experiment) with $p < 0.05$.

Figure 5 shows the median aggregation count for a swarm of only *Goal-Finder*s, only *Random-Walker*s, and a swarm of 9 *Random-Walker*s and 3 *Wall-Follower*s with the three different implementations of the wall following behaviors. In the case of a swarm consisting only of *Goal-Finder*s, half of the agents in the swarm locate themselves in the Local-Goal and half in the Global-Goal. In the case of all *Random-Walker*s, half of the swarm stays in the Pessimum. From the rest, most agents aggregate in the Global-Goal. In the experiments with the *Wall-Follower*s, most of the agents either aggregate in the Global-Goal or locate themselves in the Pessimum. Yet, there is a slight difference between the WFrw (*Wall-Follower*s that do a random walk when not at a wall), and the two other implementations (moving straight when not at a wall). In the case of WFrw, the number of agents aggregated in the Global-Goal is higher than the number of agents in the Pessimum, while this is opposite in the other two implementations. The behavior of the WFrw case is also significantly different than the experiment with all *Random-Walker*s where more agents locate themselves in the Pessimum than in the Global-Goal. For significances and the exact values see table 1.

The results for comparing the effects of *Immobile-Agent*s with the effects of Social Agents in [24] are shown in figure 6. On the x-axis the different areas of the arena in which the agents are counted are shown. The y-axis shows the median and quartiles of the time the agents spent in the respective area. In both cases, 3 Social Agents or *Immobile-Agent*s were placed in the Local-Goal. In the experiment with Social Agents, the median time that agents spent in the Global-Goal was 27% and in the Local-Goal 29.2%. In the case of *Immobile-Agent*s instead of Social

Experiments	Significance	p-value
Goal-Finder GG - LG	n.s.	0.743
Random-Walker GG - LG	s.	< 0.01
Wall-Follower RW GG - LG	s.	< 0.01
Wall-Follower 90 GG - LG	s.	< 0.01
Wall-Follower 180 GG - LG	s.	< 0.01
RW GG - WFrw GG	s.	< 0.01
RW GG - WF90 GG	n.s.	0.5595
RW GG - WF180 GG	n.s.	< 0.01

Table 1. Significance-values for the different behavioural types tested in figure 5. WF = *Wall-Follower*, RW = *Random-Walker*, GF = *Goal-Finder*.

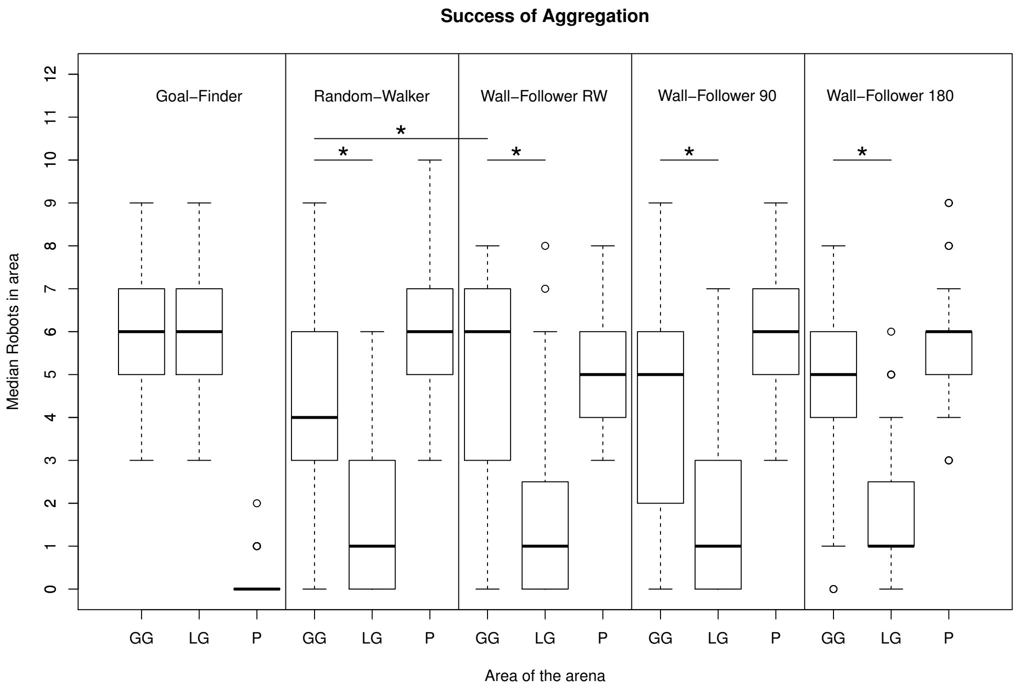


Figure 5. Success of aggregation for different behavioural types. "GG", "LG" and "P" refers to the "Global-Goal", "Local-Goal" and "Pessimum", respectively. X-axis shows the different areas for every tested behavioural type. The y-axis shows the median number of agents in the respective area. Significances are tested with the Wilcoxon-Test (Global-Goal tested against Local-Goal) and the Mann-Whitney U-Test (Global-Goal of one experiment against Global-Goal of another experiment) with $p < 0.05$.

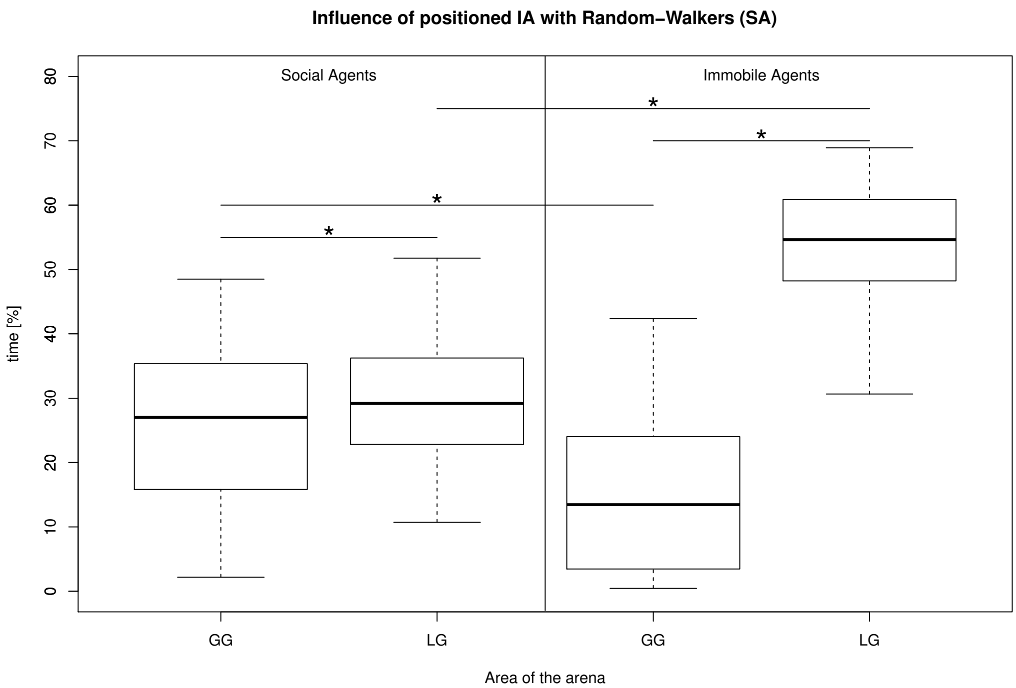


Figure 6. The figure compares the influence of Social Agents [24] with the influence of *Immobile-Agents* to a swarm performing the BEECLUST algorithm. X-axis shows the different areas of the arena: "GG" and "LG" refers to the "Global-Goal" and "Local-Goal", respectively. Y-axis shows the median amount of time the agents spent in the respective area. Significances are tested with the Wilcoxon-Test (Global-Goal tested against Local-Goal) and the Mann-Whitney U-Test (Global-Goal of one experiment against Global-Goal of another experiment) with $p < 0.05$.

Experiments	Significance	p-value
SA GG - IA GG	s.	< 0.01
Social Agents GG - LG	s.	0.02142
SA LG - IA LG	s.	< 0.01
Immobile-Agents GG - LG	s.	< 0.01

Table 2. Significance-values of the comparison of Social Agents (SA) and *Immobile-Agents* (IA) in figure 6.

Agents, the median time the agents spent in the respective area was 13.45% in the Global-Goal and 54.64% in the Local-Goal. The significantly longer time period spent by the swarm in the Local-Goal when the *Immobile-Agents* are positioned there (comparing the same case with Social Agents in the Local-Goal) represents a higher attraction effect of the *Immobile-Agents* than Social Agents. All the results are significantly different ($p < 0.05$). For significances and the exact p-values see table 2.

The results of the experiments with *Immobile-Agents* positioned in different areas are shown in figure 7. The x-axis shows the position of *Immobile-Agents* and different areas of the arena, whereas the y-axis shows the median of agents in the corresponding area. The results are grouped into three boxplots corresponding to each setup. The first setup shows the median aggregation count without any *Immobile-Agents* and is used as a reference to the other setups. Here, half of the swarm stay in the Pessimum and from the rest of the swarm, a higher fraction aggregate in the Global-Goal. In the setup with *Immobile-Agents* positioning in the Global-Goal, the decision of the swarm is clear with most of the agents aggregating in the Global-Goal and no agents (in terms of the median of the repetitions) in the Local-Goal. In the case of positioning the *Immobile-Agents* in the Local-

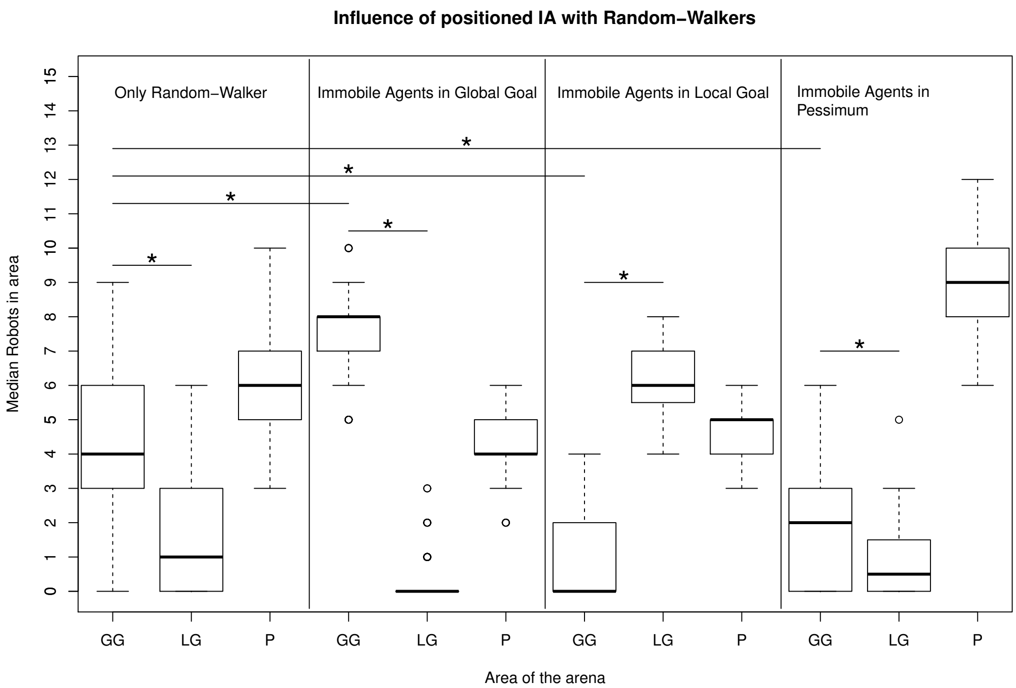


Figure 7. Influence of *Immobile-Agents* positioned in different areas of the arena on a swarm of *Random-Walkers*. X-axis shows the different areas of the arena: “GG”, “LG” and “P” refers to the “Global-Goal”, “Local-Goal” and “Pessimum”, respectively. The y-axis shows the median number of agents in the respective area. Significances are tested with the Wilcoxon-Test (Global-Goal tested against Local-Goal) and the Mann-Whitney U-Test (Global-Goal of one experiment against Global-Goal of another experiment) with $p < 0.05$.

Experiments	Significance	p-value
Random-Walker GG - LG	s.	< 0.01
IA in GG: GG - LG	s.	< 0.01
IA in LG: GG - LG	s.	< 0.01
IA in P: GG - LG	s.	< 0.01
RW GG - IA in GG: GG	s.	< 0.01
RW GG - IA in LG: GG	s.	< 0.01
RW GG - IA in P: gg	s.	< 0.01

Table 3. Significance-values of the influence of *Immobile-Agents* (IA) on a swarm of *Random-Walkers* (RW) in figure 7.

Goal, the majority of the swarm is attracted to the Local-Goal. Finally, the effect of positioning the *Immobile-Agents* in the Pessimum is to attract the swarm into the Pessimum area. For the statistical significances between the different results ($p < 0.05$), see table 3.

Figure 8 shows the results of how *Wall-Followers* (WF180) are influenced by *Immobile-Agents*. The x-axis shows the position of *Immobile-Agents* and different areas of the arena, whereas the y-axis shows the median number of agents in the corresponding area. The first group of boxplots represent the results of 12 *Wall-Followers* (WF180) without *Immobile-Agents* and is used as a reference. It shows that the swarm is mostly positioned in the Pessimum when it only consists of the *Wall-Followers*. In this case, the number of agents in the Global-Goal is slightly higher than the Local-Goal. The second group of boxplots represents the results for the setup with *Immobile-Agents* being positioned in the Global-Goal. In this case, half of the swarm aggregates in the Global-Goal and the other half are

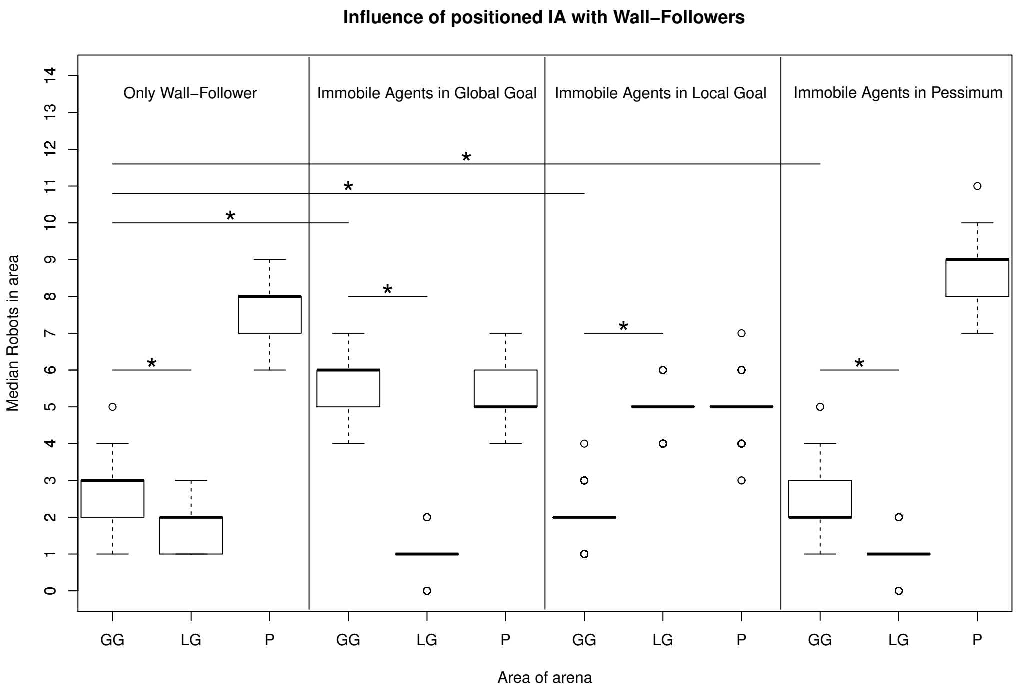


Figure 8. Influence of *Immobile-Agents* positioned in different areas of the arena on a swarm of *Wall-Followers* (WF180). X-axis shows the different areas of the arena: “GG”, “LG” and “P” refers to the “Global-Goal”, “Local-Goal” and “Pessimum”, respectively. The y-axis shows the median number of agents in the respective area. Significances are tested with the Wilcoxon-Test (Global-Goal tested against Local-Goal) and the Mann-Whitney U-Test (Global-Goal of one experiment against Global-Goal of another experiment) with $p < 0.05$.

Experiments	Significance	p-value
Wall-Follower GG - LG	s.	< 0.01
IA in GG: GG - LG	s.	< 0.01
IA in LG: GG - LG	s.	< 0.01
IA in P: GG - LG	s.	< 0.01
WF GG - IA in GG: GG	s.	< 0.01
WF GG - IA in LG: GG	s.	< 0.01
WF GG - IA in P: GG	s.	< 0.01

Table 4. Significance-values of the influence of *Immobile-Agents* (IA) on a swarm of *Wall-Followers* (WF) in figure 8.

mostly positioned in the Pessimum. In the third case when the *Immobile-Agents* are positioned in the Local-Goal, almost half of the swarm are attracted to the Local-Goal and the most of the rest are positioned in the Pessimum. Finally, when the *Immobile-Agents* are placed in the Pessimum, the majority of the swarm stays in the Pessimum. The number of agents in the Global-Goal is slightly higher than the Local-Goal. For the significances of the differences in each case, see table 4.

Figure 9 and 10 depict the results of the experiments for exhaustive analysis. For a better representation of the swarms' decision making process, here we define a fitness function indicating the performance of the swarm for aggregating in the Global-Goal area:

$$F = G - L \tag{1}$$

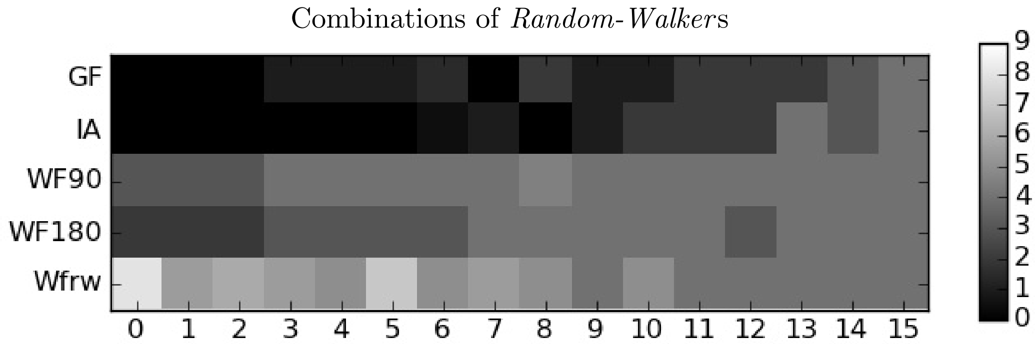
where G is the number of agents within the Global-Goal area and L is the number of agents within the Local-Goal area. Note that some results are plotted twice in reversed order to have a better overview (for example line 1 of figure 9(a) and line 5 of figure 9(b)).

In figure 9(a) the x-axis shows the number of *Random-Walker* of the swarm, whereas the total number of agents used is always 15 agents. Black means low fitness and white means high fitness. As indicated by the figure, the swarm achieves a high fitness in aggregating in the Global-Goal if many WFrw are used (left lower corner). If many *Goal-Finders* or *Immobile-Agents* are used, the swarm achieves a low fitness (left upper corner).

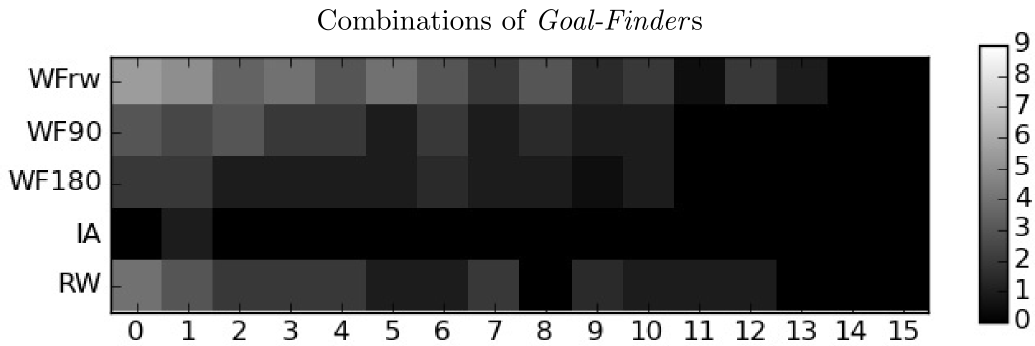
The next subfigure shows combinations of *Goal-Finders* with the other types. Here we can see that the introduction a high number of *Goal-Finders* to the swarm decreases the performance of the swarm for the binary choice setup in all combinations. Figure 9(c) shows combinations of *Immobile-Agents* with all other types.

Figure 10 shows combinations with *Wall-Followers*. Here we show only three different combinations with the *Wall-Follower*, because WFrw, WF90 and WF180 are only variations of the wall-following behaviour and not three totally different behaviour types. It can be seen, that with an increasing number of *Wall-Followers* the variation of WFrw is the only type that improves the performance of the swarm. An increase of the number of WF90 or WF180 leads in both cases to a decrease of the performance when combined with the *Random-Walker* (figure 10(b) and 10(c)).

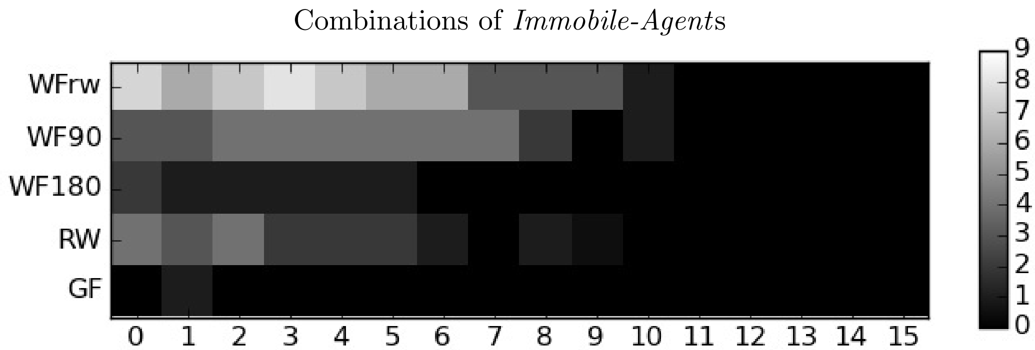
Timelines of 5 example compositions of behavioural types are shown in figure 11 ($n = 100$). Figure 11(a) shows 3 combinations of *Random-Walker* and *Goal-Finder*: The fitness of a swarm with 15 *Goal-Finders* and 0 *Random-Walkers* (solid line) increases in the first 5 minutes sligthly, but then decreases again and stays at 0 until the experiment ends. At a ratio of 7 *Random-Walker*s and 8 *Goal-Finder*s (dashed line), the fitness of the swarm starts to increase during the experiment, although the fitness is still very low in the end. When removing all *Goal-Finder*s (0 *Goal-Finder* and 15 *Random-Walker*, dotted line), the fitness increases from the beginning of the experiment until 25 minutes are over. Then the fitness stays the same for the last 5 minutes of the experiment. In figure 11(b) the timeline of combinations with *Random-Walker*s and WFrw are depicted. The dotted line shows the fitness of 15 *Random-Walker*s (same as in figure 11(a)). The dashed line shows a combination of 7 *Random-Walker*s and 8 WFrw. Here, the fitness rises faster compared to the homogeneous swarm with 15 *Random-Walker*s. 15 agents of WFrw are used to create the solid line. In the first 15 minutes, the fitness of this swarm (solid line) and the one with 7 RW and 8 WFrw (dashed line) is almost the same. After 15 minutes, the fitness of the swarm with 15 WFrw increases more and has a slightly better fitness at the end of the experiment.



(a) X-axis shows the number of *Random-Walker*s used.



(b) The x-axis shows the number of *Goal-Finder*s.



(c) The x-axis shows the number of *Immobile-Agent*s.

Figure 9. Results of exhaustive analysis with *Random-Walker*s, *Goal-Finder*s and *Immobile-Agent*s. The agents of a swarm of 15 of one type were replaced one by one with another behavioural type. We always used 15 agents in total. Black = low fitness, white = high fitness.

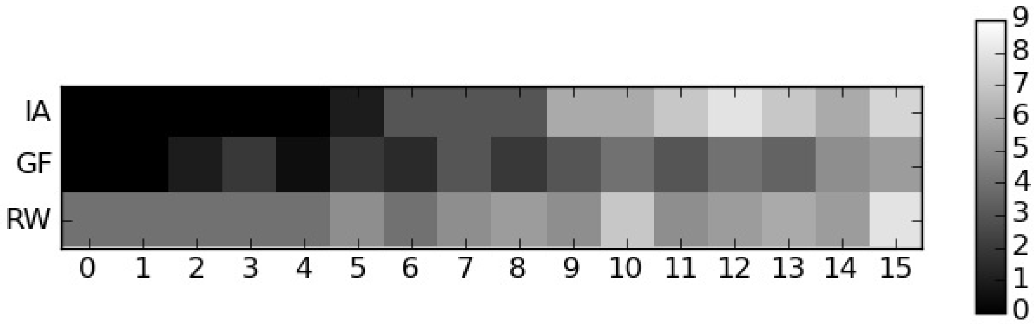
4. Discussion

In the following section, we want to discuss the influence of the four motion patterns to the original BEECLUST algorithm which is only defined by *Random-Walkers* [25].

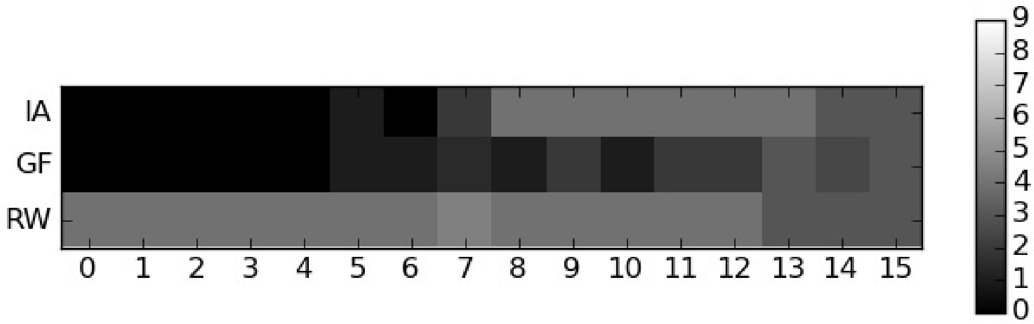
H1: *The Goal-Finder is able to locate itself at different goals in the given arena, but is not able to discriminate between a Local-Goal and a Global-Goal.*

The results of our experiments presented in figure 5 shows that different behavioural types lead to different aggregation-behaviour.

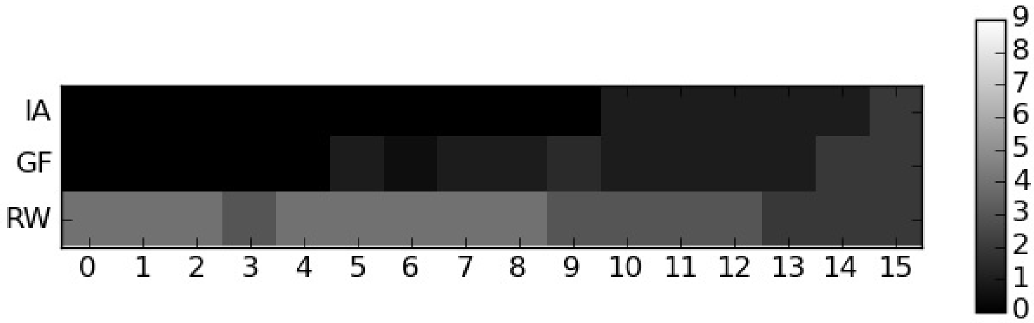
If we look at the results of the *Goal-Finder* setup, half of the agents are located in the Global-Goal and the other half in the Local-Goal. This can be explained by the implementation method used: as a *Goal-Finder* compares the temperature on the left side with the temperature on the right side, those agents always move to the side where it is warmer (locally). The coldest area is in the middle of the arena. If the agents' starting position is slightly left or right of the coldest area,



(a) The x-axis shows the number of WFrw.

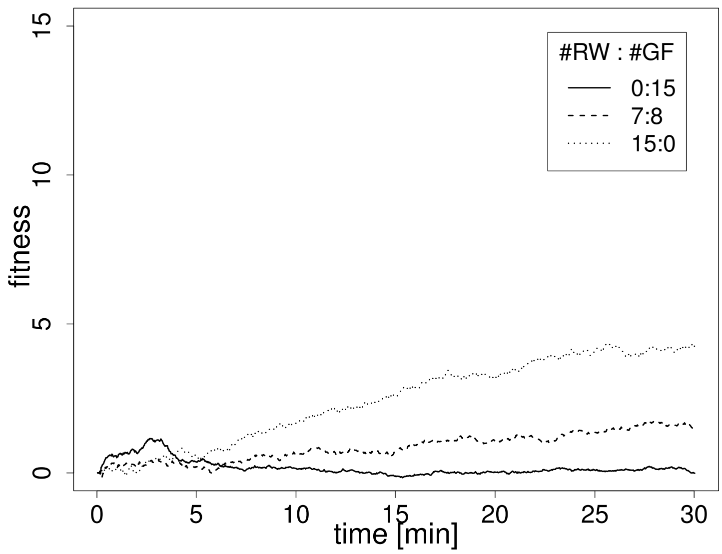


(b) The x-axis shows the number of *Wall-Followers*(90).

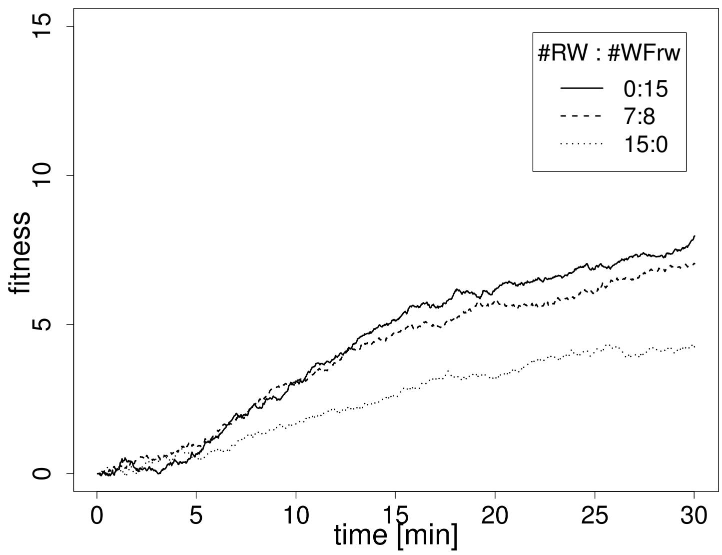


(c) The x-axis shows the number of *Wall-Followers*(180).

Figure 10. Results of exhaustive analysis with *Wall-Follower*. The agents of a swarm of 15 of one type were replaced one by one with another behavioural type. We always used 15 agents in total. Black = low fitness, white = high fitness.



(a) Combinations of *Random-Walker* and *Goal-Finder*. Swarm with 15 *Random-Walker*s (dotted line) achieves the best fitness compared to a swarm with partially *Random-Walker*s and *Goal-Finder*s (dashed line) or only *Goal-Finder*s (solid line).



(b) Combinations of *Random-Walker* and *Wall-Follower*s (WFrw). 15 *Random-Walker* as reference (dotted line). Replacing *Random-Walker* with *Wall-Follower* (WFrw, dashed and solid line) increases fitness of the swarm.

Figure 11. Timelines of 5 different combinations of behavioural types. Simulated time is 30 minutes (x-axis). The y-axis shows the mean number of agents in the Global-Goal (repetitions $n = 100$). Left side: combinations of *Random-Walker*s and *Goal-Finder*s. Right side: combinations of *Random-Walker*s and *Wall-Follower*s (WFrw).

the starting position is the crucial factor whether the agents are moving to the left side (Local-Goal) or to the right side (Global-Goal). Once an agent has located itself in an optimum, it is stuck there because whatever direction the agent tries to go the temperature gets colder. The results of the *Goal-Finder*s can be interpreted as they are able to mark the different goals although they are not able to make a swarm-decision for the Global-Goal. The ability of marking the goals can be more useful when the initial distribution of the bees is uniform in terms of their initial positioning in relation to the different goals. When a *Goal-Finder* marks a goal, it will not move a lot and behaves relatively similar to *Immobile-Agent*s and can attract other agents. When several goals are marked, it is the task of the swarm to choose the best goal.

The difference between a *Goal-Finder* and a leading- or informed agent is, that the *Goal-Finder* uses no ego-positioning and does not know where the goal is located. Therefore a *Goal-Finder* is an uninformed agent. If a *Goal-Finder* reaches a Local-Goal it is trapped there and does not know if there is a better goal somewhere in the search area. In contrast, a leading agent (or informed agent) knows where the best goal is, where it is located relatively to the goal and thus, where it has to go to reach the goal.

Figure 5 demonstrates that in all cases except the *Goal-Finder* setup, the number of agents located in the Global-Goal is significantly higher than the number of agents in the Local-Goal according to Wilcoxon-test. this can be seen as a clear decision of the swarm for the Global-Goal if we consider the fact that the total area covered by both goals is only 22% of the whole arena and the total number of agents located in either of the goal areas is about 50% of the whole swarm.

H2: *Introducing Wall-Following-Behaviour to a swarm of Random-Walkers raises the success of aggregation for the given setup.*

To investigate this hypothesis, we combined the Wall-Following-Behaviour with the Random-Walking-Behaviour. If the agents have contact with the wall, they follow the wall. But if the agents lose the wall (eg. if they meet another agent and have to avoid a collision) the behaviour switches to a *Random-Walker* until the agent has contact with the wall again. The results in figure 5 (last three boxplots) and figure 9(a) show, that the introduction of the Wall-Following-Behaviour leads to a more distinct decision-making of the swarm regarding the Global-Goal. The number of agents in the Global-Goal is nearly doubled by the combination of these two behavioural types compared to experiments where only *Random-Walker*s were used. Combining the Wall-Following-Behaviour with a 90° or 180° turn if they lose the wall, does not lead to a significant increase regarding the number of agents in the Global-Goal.

However, the introduction of the Wall-Following behaviour could also lead to a deterioration of the median aggregation count. If - for example - the goals are in the center of the arena and the swarm system consists mostly of *Wall-Follower*s, the agents will spend most of the time at the wall and will have problems to detect the goals in the middle of the arena. Therefore, the use and also the number of *Wall-Follower*s in a swarm system has to be wisely chosen considering the goal of the experiment and the swarm-systems' intention.

H3: *Immobile-Agents have similar effects on the swarm as Social Agents.*

In [24] it was shown that the swarm-behaviour of agents controlled by the BEECLUST algorithm is affected by artificially placed agents functioning as a social seed. Figure 6 shows the results of experiments with Social Agents (reprint from [24]) compared to the results of our experiments with the behavioural type "*Immobile-Agent*". Recall that in these experiments, the Social/*Immobile-Agent*s where placed only in the Local-Goal in order to influence the swarm behavior by attracting the swarm towards the Local-Goal. In those experiments with Social Agents it was possible to influence the swarm decision making in a way, that the agents spent significantly more time in the Local-Goal instead of the Global-Goal. If we use *Immobile-Agent*s, the swarm decision gets clearer and it can be seen that the *Immobile-Agent*s have the same but also a bigger effect than the Social Agents. Due to the very limited movement but high turning-angle, the *Immobile-Agent*s are better recognised by other agents than the Social Agents with no movement at all.

H4: *Immobile-Agents can have positive and negative effects on the success of aggregation depending on their position.*

To show the different possible effects a series of experiments is made with *Immobile-Agent*s and *Random-Walker*s (figure 7) and with *Immobile-Agent*s and *Wall-Follower*s (figure 8). In the experiments with *Random-Walker*s, the area where the *Immobile-Agent*s were placed in the beginning was always the region with the highest number of agents at the end of the experiment. Because it is the swarm's intention to locate the Global-Goal, *Immobile-Agent*s have - as expected - a positive influence on *Random-Walker*s if they start in the Global-Goal, but have a negative influence on the swarm decision if they are placed in the Local-Goal or Pessimum.

If we look at the same experiments with *Wall-Follower*s (figure 8), it is not that clear anymore. Using only *Wall-Follower*s most of the agents are located in the Pessimum, but a significant decision between the Local and the Global-Goal can be still made. Placing *Immobile-Agent*s in the Global-Goal leads to a clear decision making. Here, most of the agents locate themselves in the Global-Goal whereas very few agents are located in the Local-Goal. Thus, placing *Immobile-Agent*s in the Global-Goal has in fact - as expected - a positive effect on the median aggregation count compared to the results with only *Wall-Follower*s. As can be seen in figure 8 the swarm always decides (significantly) for the area where the *Immobile-Agent*s are located. Thus, the *Immobile-Agent*s attract other agents to the region where they are located.

As *Immobile-Agent*s do not move but attract other agents, this behavioural type can be used to mark different locations that are possible candidates for Global-Goals. The swarm's task is then to decide which of the marked goals is the best option.

The exhaustive analysis (shown in figures 9(a) - 9(c)) depicts that the decision making of the swarm in a binary choice-experiment deteriorates if *Goal-Finder*s or *Immobile-Agent*s that are positioned in the Pessimum are introduced in a swarm of *Random-Walker*s. Introducing WF90 and WF180 to the swarm do not change the decision-making-process of the swarm significantly, although the exhaustive analysis shows a tendency to decrease the fitness. An improvement and also the best results for the binary choice-experiment can be achieved by only using WFrw.

5. Conclusion & Future Work

We conclude that the behavior of a swarm of agents running a BEECLUST algorithm is influenced by introducing individual behavior types to the algorithm. Furthermore, various global swarm behaviors can be achieved by different combinations of the individual behaviors facilitating the optimization of behaviour in the swarm level. Depending on the behavioural types that we use, the influence can be positive or negative for the given setup. If one composes a swarm of different behavioural types, one should always have the given setup and the goal of the swarm in mind. *Goal-Finder*s - for example - are able to locate goals but are not very useful if a decision about the quality of the goals shall be made by the swarm. However they can be used to "mark" a goal. *Wall-Follower*s should be used to increase the time the agents spend at the wall. If we know that most of the goals are located next to the wall, the decision making process will be influenced positively.

*Immobile-Agent*s have a strong attracting effect. If the swarm shall decide about the quality of marked goals, this behavioural type can be useful. However this type should only be used very carefully as the attracting effect is very strong.

If it is not definitely clear which type has a positive effect for the setup, it is safe to use only *Random-Walker*s because they will cover the whole search space.

In future work we want to - based on this analysis - elaborate the idea of Swarm Level Optimisation and therefore compose different goal-tailored swarms with the four behavioural types. We plan to use genetic algorithms to evolve the composition of a swarm towards optimal adaptation to specific predefined scenarios. This stock of standard scenarios will then provide ready-made solutions for various similar problems. As both - the BEECLUST algorithm and the four behavioural types - are inspired by the behaviour of young honeybees, we plan to make new hypothesis about how their motion influences the swarm behaviour. We also want to use learning agents (online unsupervised learning) to further improve the swarm's decision making process.

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