Cooperation of two different swarms controlled by BEECLUST algorithm

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Abstract

In this work we investigate how two autonomous agent swarms, controlled by the BEECLUST algorithm are able to cooperate. The task is to locate two different target areas, which are located near each other. Therefore we developed an individual-based NetLogo model to simulate two different agent swarms moving in a temperature gradient. Both agent swarms are controlled by the BEECLUST algorithm, which is inspired by honeybee behavior. We found out that the two cooperating agent swarms are able to locate the target areas, independent of the ratio of the agents.

Introduction

An eusocial insect colony, which consist of large numbers of individuals can be interpreted as a "superorganism" (Oster and Wilson, 1979). This superorganism is able to solve more complex tasks than the single individual members of the superorganism. The thermal reaction of worker honeybees (Ohtani, 1992), which leads to thermal homeostasis in the honeybee colony, is an example for the self-organisation and the swarm-intelligent behavior (Millonas, 1992) of social insects and one main inspiration for the experiments described in this paper. Several studies (Heran, 1952; Ohtani, 1992) have shown that young honeybees prefer to aggregate in, or near an area with a surrounding temperature of 36°C. The bees move randomly and form longer lasting clusters in warmer, than in cooler zones. We use this simple, but efficient behaviour of honeybees for our experiments. The algorithm derived from this behaviour is called BEECLUST (Bodi et al., 2012, 2011; Schmickl and Hamann, 2011). It is based on the following simple rules:

(1) The agents move randomly through the arena. Whenever an agent detects an obstacle, it stops and checks whether the obstacle is another agent or a wall.
(2) If the obstacle is a wall, the agent turns randomly and continues with step 1.
(3) If the obstacle is another agent, the agent measures the local temperature and calculates his individual waiting time, dependent on the local temperature, according to a sigmoidal function.
(4) After the waiting time is over, the agent continues with step 1.

These simple actions of individual agents lead to resource-saving behaviour. Recent works (Kengyel et al., 2011; Kernbach et al., 2009) have shown that artificial agents controlled by this algorithm react flexible regarding environmental changes. In the work at hand we investigate how honey bees age polyethism influences this system. Age polyethism means that in a honeybee colony individuals of the same age perform the same task, and that a given task is often associated with a given age. Examples for such tasks are, collecting nectar in the environment, brood care and the cleaning of the honeycombs. The location of these tasks are not always spatially separated, but can be located near each other, or even within the same area, e.g., broodcare and wax manipulation. It was shown by Bodi et al. (2012) that agents, controlled by BEECLUST, that have identical sensors, but differ regarding their temperature optimum, are able to cooperate well in a complex environment. The question we raise here is, how good can two different groups of agents, that have different sensors (and therefore different tasks) cooperate, if the tasks are located near each other. Based on the results of Bodi et al. (2012), who described the negative influence of jamming effects on groups of agents operating in the same area, and the positive affects of cooperation subgroups we formulated the following hypothesis: Two non-identical agent swarms controlled by BEECLUST are able to cooperate for a given ratio of the agents in the two groups.

Materials and Methods

To answer this question we performed and simulated our experiments in NetLogo (Wilensky, 1999). The simulated area has a size of 16x16 patches. We implemented two different task-areas with a distance of 5 patches and two different agent-swarms A and B, acting parallel in the same environment. Both swarms had the same properties and comply with the rules of the BEECLUST algorithm. The two differ-

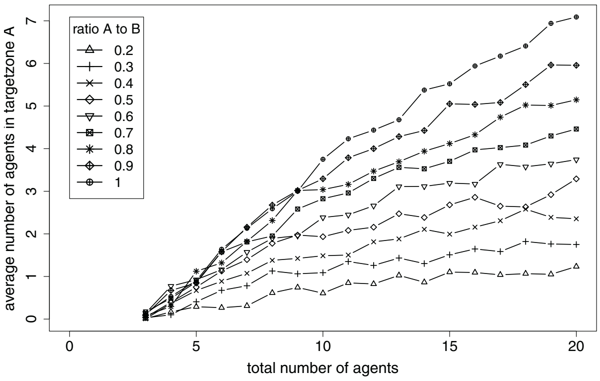

Figure 1: Absolute number of A agents, aggregated in T_A; $n = 100$.

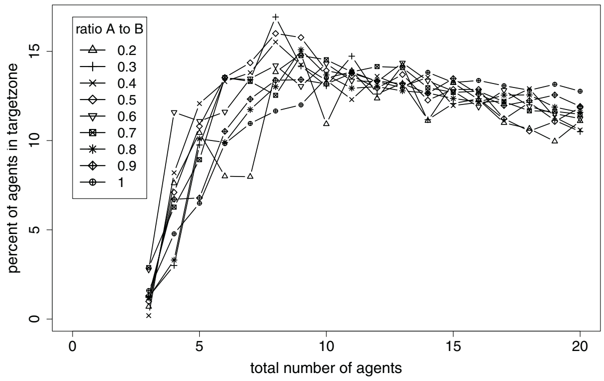

Figure 2: Average percentage of A agents, aggregated in T_A; $n = 100$.

ent task-areas T_A and T_B were implemented as gradients in the environment, scaling from a value of 1 in the maximum to 0 in the environment. The size of T_A was the quater of the size of T_B to simulate a highly specialised task near an area of a more general task.

As mentioned above the length of the waiting time of a single agent is determined by the local value of the gradient. The sigmoidal waiting-curve was identical for both agent-swarms A and B. The maximum waiting time for both swarms was 1000 timesteps.

We observed and analysed the percentage of agents of A aggregated at T_A. The tested population size, including A and B, ranged from 3 to 20 individuals. The ratio of A to B was varied from 0.2 to 1, rounding was always done towards the next bigger number of A. Each experiment ran for 3600 timesteps and was repeated 100 times.

Results and Discussion

It showed, that, by increasing the total amount of agents, the average number of A increased linearly in the target area T_A (see figure 1). Surprisingly it further showed, that, in contrast to our hypothesis (mentioned above), the relative amount of A in the target zone was highly stable against changes of the ratio of A to B (see figure 2). This means, that even a single agent can operate within a group of agents with another task (or even another sensory system) without any loss of efficiency. Due to this we can falsify our hypothesis, that the cooperation of two BEECLUST controlled groups of agents is depending on the ratio of these two groups. To which degree these results can be used in the field of swarm robotics to develop selforganised heterogeneous robot swarms based on BEECLUST is the topic of ongoing research at the moment.

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