Emergent Flocking with Low-End Swarm Robots

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Abstract. This article analyses a flocking algorithm that was developed specifically for small and simple swarm robots. It is similar to traditional flocking algorithms for swarm robots, however it does not need communication nor global information. Its only requirements are at least 4 circumferential distance sensors which can have very limited range. This is possible because our algorithm generates *emergent* alignment of flock members. We show an analysis of our simulations and a short overview of a real robot experiment.

Keywords: swarm robots, emergent behaviour, flocking.

1 Introduction

The phenomenon of flocks, herds and schools is a prime example of emergent behaviour. The elegant movement of flocking birds or a fish school seems highly coordinated, yet it is solely the result of the interactions within the swarm. There have been lots of speculations as to why this complex behaviour might have evolved. Most explanations state that it is advantageous for the individual to be part of a flock to better avoid predators or to increase the foraging success. However, there have been few quantitative investigations of the real animal behaviour because measurements of a moving, 3-dimensional swarm seem almost impossible. Since the proposed advantages of flocking can only be achieved by the swarm and not the individual, flocking can be described as being *swarm-intelligent* [3]. Such swarm-intelligent behaviours are highly interesting and can, for example, be used in the field of *swarm robotics* [5], where a high number of rather simple robots should reach a goal collectively. Flocking algorithms for autonomous agents have been introduced by Craig Reynolds [17] who tried to emulate this behaviour for computer animations. His 'boids' display stunningly natural group movements which are a result of these three simple behaviours:

- *Collision Avoidance* is a basic behaviour for embodied agents.
- *Flock Centering* makes boids stay close to their (nearby) flock mates.
- *Matching of Velocity and Heading* leads to a common direction of movement.

These standard flocking rules also apply to schools of fish and the effects of different attraction and repulsion forces, group sizes and heterogeneity of the groups have been investigated in [18]. Since the introduction of swarm robotics,

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these behaviours have also been implemented numerous times in both simulations of swarms and real robot swarms. However, all approaches presented for the *Matching of Velocity and Heading* behaviour in real robot swarms included either communication between the robots to exchange positions and headings [11,23,7,1] or (dynamic) leaders [9]. Such communication requires special robotic hardware (e.g. *Bluetooth*, a stable communication channel, a digital compass or even a global positioning system). The implementations of the aforementioned flocking algorithms are not very nature-like because they require communication among the flock neighbors or even the whole swarm. This complexity renders these algorithms unfeasible for a swarm of small and simple robots. The difference to real flocking behaviour is that in real swarms the animals can align because they can identify the heading of each other. Robots usually do not have the possibility to visually derive the heading of their flock mates from the body form unless they use multiple on-board cameras and complex image recognition. Another alignment method in animals is the use of a specialized *lateral line organ* [14] which is present in most fish species, however an emulation of such an organ for robots is very complicated. There are very few communication-less approaches to robot flocking (e.g. [2,4]) who generated a flocking swarm by using an arena with a light beacon and making robots that are illuminated by this beacon behave differently than the robots they cast a shadow on, which results in a common movement towards the light beacon. Although this solution is quite clever, its downside is that it requires a special arena setup. Another communication-less algorithm was introduced by [15] who evolved controllers for a group of 3 minimally equipped robots with a view to generate formation movement. The simulated evolution could indeed produce controllers that allowed 3 robots to engage in different roles (leader or follower) depending on the position in the small 'flock'. However, the evolved controllers only work on a group size of 3 robots and it does not seem like this solution is applicable for bigger swarms.

For us, the requirements of traditional flocking algorithms are in conflict with the concept of swarm robotics where the individual robot is usually small and expected to have very limited abilities [19]. We are interested in working with minimalistic swarm robots which are not capable of long range communication and do not have global information like position and heading. These constraints limit the potential of robot swarms and thus reaching a common goal, like forming an aggregation, is not an easy task. In swarm robotics, such aggregated swarms could be used for collective transport [22] or assembly [21,16]. Therefore it is interesting to research the flocking potential of such minimalistic swarms.

We have shown in [13] that a swarm of such simple robots can flock without communication, which means that the individual robot does not need to know and communicate the exact positions and headings of its neighbours. Instead, our approach is more nature-oriented and relies purely on the sensory perception of the robots. A robot does not need information of all neighboring robots, but only uses the estimated distance of the nearest neighbour in each of its sensor fields. We discretized the robots' sensor fields into different zones (similar to [10]) which either lead to *attraction to* or *repulsion from* other robots. In this paper we will investigate the sizes of these zones to show that an asymmetric composition can generate *emergent* alignment which negates the need for complex communication or image recognition to achieve alignment and therefore flocking in small robot swarms.

2 Material and Methods

2.1 Algorithm Requirements

Our flocking algorithm has minimal requirements, which means that it can be implemented on simple and therefore very small swarm robots. The algorithm does not require global information about positions or headings, memory, elaborate robot-to-robot recognition or communication. It only needs at least 4 distance sensors with circumferential vision. In swarm robotics, such distance sensors are usually IR-sensors which are used for obstacle detection and collision avoidance. The sensors can be used in *active mode* and *passive mode*. Active mode means that the robot activates the IR-LED at the position of the IR-sensors and checks for reflected light from obstacles. The range of this active IR-sensing is very limited, depending on the LED strength and on the reflecting surface. In passive mode, the robot checks the sensor without emitting light and can thus detect other IR-emitting sources like other robots. This mode of sensing can have a longer range, depending on the light-emitting source. Other distance measuring sensors, like ultrasonic sensors, can be used for our algorithm as well. In preliminary tests we measured the maximum active and passive IR-sensing ranges of two of our real swarm robot types [20,6] to use realistic constraints in our simulations. In our case the maximum sensor ranges were 1 robot-diameter for active obstacle sensing and about 5 robot-diameters for passive robot sensing. This means that in our experiments each robot only has a very limited perception of its surroundings.

2.2 Simulator

We conducted our experiments using a simulator (see Fig. 2B) developed in the multi-agent programmable modeling environment NetLogo [24]. The simulations are mainly used for a *proof-of-concept* and do not incorporate physical properties like sensor or actuator characteristics. What we aim at with this work is to demonstrate the *usability* of our algorithm. Therefore, we simulated a minimalist 4 sensors model (similar to the I-Swarm robot [19]). In our simulations we use a wrapped arena, i.e. there are no boundaries that could hinder the flock. Other simulation parameters are: robot speed (3 robot-diameters per second), sensor measurements (60 per second), sensor errors (5%, random-normal), turn angle (10 degrees), maximum active sensor range (1 robot-diameter), maximum passive sensor range (5 robot-diameters).

2.3 Flocking Algorithm

At first we define what *aggregate* or *flock* means in this paper: If two or more robots are within the passive IR-sensor range of each other they are considered as being *connected*, because they can react on each other. All robots that are *directly* or *indirectly connected* (i.e. there are other connected robots in between) are considered as being part of an aggregate. If the robots in this aggregate are non-randomly aligned and the centre-of-mass of this aggregate moves in a general direction we define that as a flock.

Our algorithm can be represented as a simple finite state machine. All robots periodically emit IR-light from their distance sensors in order to be perceived by other robots. They also poll their active and passive IR-sensors to measure their distance to objects or other robots. In contrast to a camera, IR-sensing has the constraint that a robot can only distinguish one robot per sensor. Since the IR-sensors return the highest value, that means that the robot can only perceive the nearest neighbor in each sensor field. The returned distances are checked against various *thresholds*, depending on the direction of the IR-sensor. Please see [13] for a depiction of the resulting zones. The 3 layers of our algorithm are as follows:

1. First, the sensor in front is polled actively. This is to check if there are close obstacles in front. If the active sensor returns a distance value which means that there is an obstacle in front that is closer than 1 robot-diameter, the robot turns away from that obstacle. This layer leads to basic *collision avoidance*.
2. If there are no objects in the way, the passive sensors in front and at the sides are polled. This is to check if other robots are too close. If the passive sensor returns a low distance value, which means that there is another robot in front that is closer than 1 robot-diameter, the robot turns away from that other robot. This layer is the *flock separation* part of our flocking algorithm.
3. If there are no other robots in close range, the robot polls its passive sensors at the side and rear positions. This is to check if there are other robots around which are too far away. For every sensor that returns a certain distance value, which means that another robot is inside the passive sensor range but too far away, the robot adds up all resulting turns. For example, if another robot is too far away on the left side of the robot and also another robot is too far on the right side of the robot, the robot does not turn. This layer is the *flock cohesion* part of our flocking algorithm.

In the end the robot always moves forward the predefined distance, leading to a continuous movement.

3 Results

3.1 Threshold Analysis

Our simulations investigate the thresholds of the 4 sensor model to test our hypothesis that asymmetric zones can lead to emergent alignment and thus generate flocking. A parameter sweep was performed that changed the threshold for the attractive zones on the sides and the threshold for the attractive zone to the rear. The minimal threshold for the zones on the sides was 1 robot-diameter because at distances closer than this the robots turn away from each other. The minimal threshold for the zone on the rear was 0 robot-diameters because robots do not have repulsive zones in the rear. The maximum distance for all thresholds was 5 robot-diameters which is the maximum passive sensor range of our simulated robots. The thresholds were changed at 0.25 robot-diameter intervals resulting in $21x17 = 357$ threshold combinations per swarm size (5, 10 and 15 robots). Each robot swarm started aggregated in the middle of an unbounded arena in a starting area whose size was correlated to the swarm size. The robots' positions inside that starting area and their headings were randomized and 50 repetitions for each threshold combination were made. The centre-of-mass (CoM) of the initially aggregated swarm was calculated and its path logged as long as 80% of the whole swarm were part of the flock.

Fig. 1 shows the path length of the CoM of one exemplary robot swarm size and a superimposed average path length for all swarm sizes after 60 simulated seconds. The measured path length depends on the combinations of the side thresholds (x-axis) and rear thresholds (y-axis) and also on the swarm size. The black lines depict identical threshold values for the sides and rear zones. Ideal flocking with instant alignment would result in a maximum CoM distance of 180 robot-diameters. In these simulation runs we also measured the average global alignment of the swarm during 60 seconds by adding the vectors of all flock members each second. When normalized, the results showed almost identical values as the CoM distance measurements, therefore they are not shown in this paper. Generally, side or rear thresholds greater than 4 robot-diameters lead to incoherent swarms which quickly disperse, resulting in minimal CoM path lengths (see dark areas in Fig. 1). Smaller thresholds generally keep the swarm coherent and result in medium CoM path lengths (see dark grey areas in Fig. 1). Only certain threshold combinations where the rear threshold is greater (= further outside) than the threshold to the sides lead to a relatively long CoM path length (see light grey areas in Fig. 1). The influence of swarm size on the flocking ability is also quite visible, but not shown in this paper. The larger the swarm gets, the worse is its mobility. Flocks of 5 robots can move a distance which is up to 50% of the maximum CoM distance with certain threshold combinations (threshold sides: 1.25 robot-diameters; threshold rear: 2.5 robot-diameters). Flocks of 10 robots can move up to 35% of the maximum CoM distance (threshold sides: 1.75 robot-diameters; threshold rear: 3 robot-diameters) and flocks of 15 robots can move up to 29% of the maximum distance (threshold sides: 2 robot-diameters; threshold rear: 3.25 robot-diameters). By superimposing (and averaging) the results from all three swarm sizes we found out that the best threshold combination for small swarms is 2.25 robot-diameters for the side threshold and 3 robot-diameters for the rear threshold.

3.2 Real Experiments

To attest the usability on real robots, we ported the algorithm to 3 e-puck robots [6]. We emulated the minimalist 4-sensors model by combining 2 of the

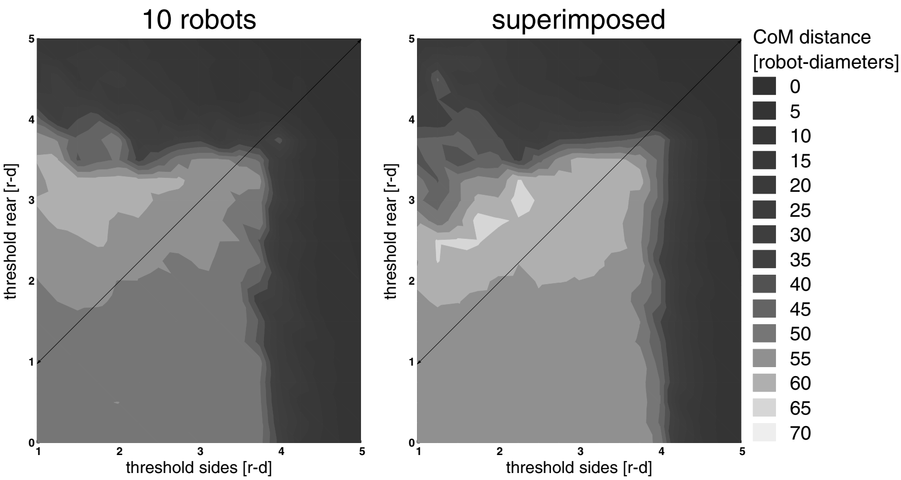

Fig. 1. Results of a parameter sweep which tested the effects of different side and rear threshold combinations on flock coherence and flock mobility. The path length of the centre-of-mass of an initially randomly aggregated swarm is shown as a coloured surface where brighter areas indicate longer path lengths and therefore better flocking of the swarm. Black lines indicate identical threshold values for the side and rear zones. Medians of 50 repetitions for each threshold combination for a swarm size of 10 robots and superimposed results of 5, 10 and 15 robots for 60 seconds.

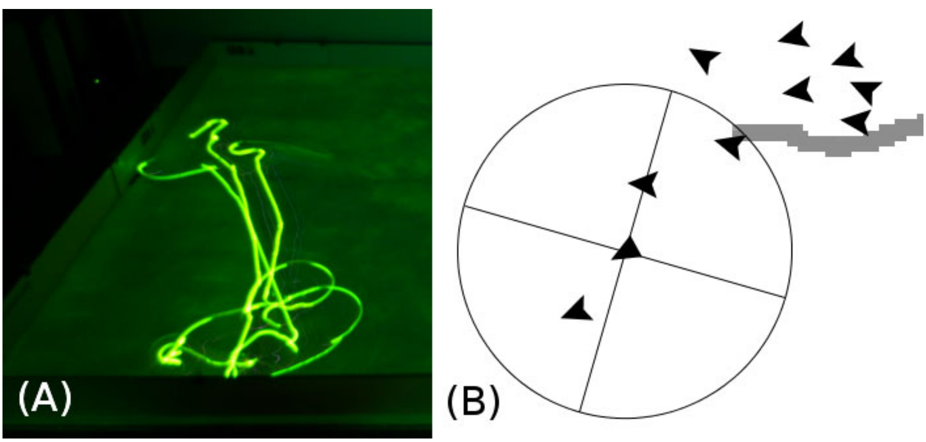

Fig. 2. A: 30 second exposure photo of a test run in a darkened arena in which 3 e-pucks utilised the minimalist flocking algorithm. Each e-puck had 1 green LED, the trails are are visible because of the long exposure. B: Screenshot of a simulated flock of 10 robots (black triangles). The path of the centre-of-mass of the flock is indicated by the grey line on the floor. One of the robots is shown with its sensor range and sensor sectors. A short video of a simulation can be seen at [12].

e-pucks 8 IR-sensors in each direction. Fig. 2A shows a short experiment where the trail of each robot is visible. The small flock managed to stay coherent and also cover a small distance inside the arena. Unfortunately the arena is rather small, so the flock usually reaches a wall very quickly and the arrangement of the flock changes. There are of course a lot of differences to the simulation, mainly sensor characteristics and slower robot speed. Nevertheless we think that our preliminary test runs look promising and we plan on improving the algorithm for the e-pucks and try it with bigger swarms and heterogeneous swarms of e-pucks and Jasmine robots [8].

4 Discussion

In this paper we have analysed a flocking algorithm for swarm robots that works with minimal equipment. This was done by taking a more nature-like approach towards flocking which eliminated the need for communication between the swarm robots. We used the robots' IR-sensors equivalently to a very simple visual perception of an animal and thereby allowed the robots to react on their nearby flock mates. We simulated robots with a minimalist design of 4 distance sensors with a very short passive sensor range of only 5 robot-diameters. Even though flocking algorithms only work if they also have an *alignment* part we did not explicitly implement such a mechanism. In our algorithm, this part is an *emergent* property of the algorithm's 3rd layer. We have shown that if the rear distance threshold (delimiting the attractive zone in the rear) is chosen to be more outward than the side thresholds (delimiting the attractive zones to the sides) this leads to an improved movement of the flock. This improved movement is the effect of the emergent alignment which happens when two robots approach each other. One of these robots will be behind the other robot by chance and due to them sensing each other in different zones the robot behind will turn towards the robot in front. As in natural flocks there are no pre-defined leaders, nevertheless will the robot that is in front 'lead' the robots behind it. If a flock encounters other robots which join the flock, the arrangement of the flock can change instantly and other robots can become the leaders. Our flocking algorithm was also shown to work on real robots. For these experiments we used unmodified, non-communicating e-pucks [6]. One advantage of this flocking algorithm is the adaptability, which means that it can be used on different swarm robot designs. It also allows for heterogeneous robot swarms under the condition that the robots use the same distance-measuring method.

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