Self-organized flocking with conflicting target directions

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Année Académique 2010/2011
Abstract

In this thesis, we study the self-organized flocking of a swarm of robots that is informed about two target directions. We already know that a small proportion of informed robots can lead the whole group to the given target direction. In some cases, the informed individual may differ in their preferred direction because of the quality and the quantity of food source, or because of age and experience difference. The group should agree on a specific target direction after negotiation. So as to investigate the possible results, we set two subsets of informed robots. A proportion of robots are given the information of goal direction 1. Another proportion of robots are informed of goal direction 2. The rest of robots are known neither of the two goal directions. The flocking behavior is organized in three components: proximal control, alignment control, goal-following control. The implement of the alignment control is based on heading control strategy which consists in local communication with their own heading information in global coordinate system.

We launch simulated-based experiments to evaluate the performance of flocking using an evaluation criteria of probability of splitting and average group direction. We calculate split probability and average direction under different ratios of informed robots for each goal direction. The difference between two preferred directions is also under study in the experiments.

We calculate the split probability and average group direction in experiments. Results show that in most of the cases the swarm doesn’t split and follow expected average direction. This conclusion coincides with some research work.
Acknowledgments

First, I would show my great appreciation to my supervisor, Mauro Birattari, for giving me the opportunity to work in IRIDIA, one of the leading labs in artificial intelligence field. Your serious attitude towards research teaches me a lot.

Second, I would like to express my gratitude to my co-supervisors, Eliseo Ferrante and Dr. Ali Emre Turgut. You are rather my best friends than my co-supervisors. Upon the research, you give me huge help patiently. Your warm encouragement companies my growth. It is you who make my life abroad easier and brighter.

Further, thank you to all my colleagues in IRIDIA. It is you who build a warm and comfortable atmosphere in IRIDIA.

I am grateful to all my Chinese friends here including Eric, Qunyan, Tianjun, Yongxiang, Yulong, Fang. I will never forget the scene that everyday we eat together and share happiness and sadness in our restaurant. I will never forget your active and selfless help without hesitation when I was in trouble.

I also want to say thank you for friends who give me spirit support from remote China.

Finally, I would like to cook one meal for my family once I return home. I miss you so much.
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Chapter 1

Introduction

In chapter 1, we introduce the term of artificial intelligence and swarm intelligence, robotics and swarm robotics, flocking and overall goal of this thesis. Then we present the frame of the thesis.

1.1 Artificial intelligence and Swarm intelligence

Artificial intelligence (AI), a hot topic in science fiction, also attracts attention of researches since its birth. Marvin Minsky had given a definition for artificial intelligence that is “The science of making machines do things that would require intelligence if done by men” [Minsky, 2005]. Herbert Simon had a optimistic prediction in 1976 that “machines will be capable, within twenty years, of doing any work a man can do” [Simon, 2011]. Actually, even now, the development of AI is still on its way. The difficulty of developing artificial intelligence is the complex mechanisms of human-being brain and our thinking process. Strictly speaking, we have got large achievement in artificial intelligence comparing to the 1970s.

During the 1970s, the first winter of AI, limited computer ability once was a big bottleneck for AI. Ross Quillian’s successful work on natural language was demonstrated with a vocabulary of only twenty words [Wikipedia, 2011]. The success of AI nowadays, at one side, is due to the increase of computation ability following the Moore’s law. At another side, it relies on the researchers’ great effort on each subproblem to simulate intelligence and cross-field cooperation to solve problems. The traits described below attracts most attention: deduction, reasoning, problem resolving, knowledge representation, planning, learning, natural language processing, social intelligence, motion and manipulation.

In nature, not only advanced animals achieve a certain level of intelligence, but also some low level living-being such as insects show the trace of intelligence by collective behavior. Although their intelligence level couldn’t match up to humans’ intelligence, we still benefit from the research of these beings. For example, the structure of bee hive contains so many mathematic knowledges and perfect design from where architects learn a lot. The cooper-
CHAPTER 1. INTRODUCTION

The study of swarm in nature provides insights in our lives. The term of swarm intelligence was born.

Swarm intelligence is an artificial intelligence technique based on the study of collective behavior in self-organized system. One definition from Eric Bonabeau, Marco Dorigo and Guy Theraulaz [Bonabeau et al., 1999] is that the design of algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies. This system is made up of a swarm of simple individuals which have to accomplish a relatively difficult task which is beyond the capability of a single individual. A important characteristic of swarm intelligence is the lack of centralized control in the system. Each individual in a swarm has only: a) limited sensing ability and simple equipment; b) local communication either direct or indirect. c) stochastic behavior, positive and negative feedback mechanisms. Ant colonies, bird flocking, animal herding, and fish schooling are examples for social insects with swarm intelligence.

As said, local communication is a key component of a swarm. The communication mechanism depends on the species. There are two main type of communication mechanisms: direct and indirect. The direct mechanism includes antennae, trophallaxis (food or liquid exchange), mandibular contact, visual contact, etc. An example is that the motion of the swarm of bee is lead by scouts. When they find a new food source, they use different kinds of dance to indicate the orientation and the distance of the source. One of indirect mechanisms of communication is called stigmergy. In stigmergy, individuals in swarm communicate indirectly through the changes in the environment, when one of the individuals modifies the environment. As an example, we will tell about pheromone trails of ants. While walking, ants and termites may deposit a pheromone on the ground. At the same time, they follow with high probability pheromone trails they sense on the ground.

1.2 Robotics and Swarm robotics

Robotics has a much longer history compared to artificial intelligence and the thought of creating humanoid machine traces back to fifteen centuries. One notebook, which was rediscovered in the 1950s and owned by Leonardo da Vinci, revealed that early to 1495 year, Leonardo da Vinci imaged and drew the detail of a mechanical knight now known as Leonardo’s robot, able to sit up, wave its arms and move its head and jaw.

Before eighteen centuries, the development of robotics relies on the ingenious mechanism which is constrained by the level of technique at that decade. Once electronic industry merges into the production, robotics came into a new age of high-speed development. The aim of freeing human from heavy work is a strong motivation for development of this area. And also the military is always the first beneficiary of a new invention. Now the application
of robots cover a large domains such as education, health care, and research.

Swarm robotics is a newly developing subject which combines robotics and swarm intelligence. A large number of autonomous robots, which interact and influence each other locally, cooperatively accomplish a given complex task which is beyond the capabilities of a single robot. During the process of accomplishing a task, without leadership or external control, swarm of robots only relies on local communication and limited sensing ability.

The sought characteristics of a swarm robotics system is robustness, flexibility and scalability [Sahin, 2005].

- **Robustness** is the continual operation capability, maybe at lower performance, when some individuals are out of order or there exists disturbance in the environment. Four factors ensure robustness: redundancy, decentralized coordination, simplicity of individuals, multiplicity of sensing.

- **Flexibility** is the capability to adapt to new, different, changed requirement of the environment. One factor affects flexibility: diversity of strategies. When resolving different tasks, the swarm system should offer corresponding solution by using diverse coordination strategies based on the change of environment.

- **Scalability** is the possibility of continual operation under a large population of group. One factor guarantees scalability: coordination mechanism. In Detail, the coordination mechanism should scale well whatever group size.

Robustness, scalability and flexibility is especially significant for large-scale task or dangerous environment such as environmental monitoring of a lake or a forest, search for survivals after earthquake, detecting harmful gas in an accident and collecting samples of earth on the surface of the moon.

### 1.3 Flocking

In swarm intelligence, several collective behaviors are studied. For instance, pattern formation, aggregation, chain formation, self-assembly, coordinated movement, hole avoidance, foraging, self-deployment and so on. One of them is flocking. The flocking behavior is exhibited when a group of birds is flying or foraging. The similarities happen in shoaling behavior of fish and the herd behavior of animals. It means a large number of individuals assemble together and act coordinately towards a common direction as if they are a super being [Camazine et al., 2001].

This behavior has a significant meaning for one species. It can increase the survival rate for whole species. First, when an individual is in a group, the risk of being captured by a predator decreases [Partridge, 1982]. Because their local sensing and communication range
extends as a super sensor which can detect the predators easily and quickly. Also a single member or small groups are easier to be captured than members belonging to large and cohesive swarm [Ballerini et al., 2008]. Second, it will save the energy of each individual due to less exploration needs. In addition to these, when migrating, birds who follow leader and other companions can save energy by utilizing the streamlines formed by the individuals ahead. [Turgut et al., 2008].

The collective behavior in nature is similar to what we want a swarm of robots do. The biology decision strategy of the swarm provides insight to the study of swarm robotics. Because of the above advantages, flocking becomes a new research direction in swarm robotics to improve the collective capability of accomplishing one task for swarm robots.

In flocking, one of the interesting issue is the mechanism to spread the information of a food source or a migration route. Only a proportion of individuals in the swarm has this information. How does the naive individuals recognize the individuals that have information? Is it necessary to have a recognition ability when communicating? How would the group achieve a common decision if informed individuals have preference? In some species, the elder and experienced ones play more important role than the naive ones. Latest researches on biology show that a swarm of individuals can achieve flocking even if only a minority know the position of food source. The minority is enough to influence the whole group to move along the goal direction without explicit leader, where an implicit mechanism is used to spread the information to the whole group [Couzin et al., 2005].

Couzin et al. [Couzin et al., 2005] made a research on the above problems using a swarm of robots. When the information of target direction is given to one robot, this robot is informed of that direction. They demonstrate the accuracy of the robots on the condition that preferences exist in the informed robots. Preferences mean with respect to natural world, some individuals are aware of one target information and some ones are aware of another target information. They found that the bigger of the size of group, the smaller proportion of informed robots is needed to achieve the same accuracy of flocking. When preferences exist, if the number of individuals who are aware of each preference is equal, the motion depend on the difference in two preferences. Once reaching a certain degree, the motion direction of the group will change from average direction of the preferences to random one of the preferences. If the number of individuals who are aware of each preference differ, the motion trend will change from average direction of the preferences to the preference of the majority possess under a certain value of difference between preferences. Once importing positive and negative feedback for the weight of preference, the difference which brings the break point of motion direction is smaller than without feedback.
1.4 Overall goals

In some cases, the goal direction may not be static and unique during the flocking. Unexpected factors such as presence of obstacles or enemies may force the group to deviate the initial direction. Another example is when foraging, several food sources may be discovered at the same time. Because of the disparity of quality, quantity and distance, the preference differ in the informed individuals and more than one goal direction exist in the whole swarm.

In this thesis we study self-organized flocking of swarm robots under two goal directions. We set two subsets of informed robots. A proportion of robots are given the information of goal direction 1. Another proportion of robots are informed of goal direction 2. The rest of robots in the swarm are naive and know neither of the two directions. The movement trend of the whole group becomes difficult to predict. In this setting the swarm don’t split and move together as a group towards a common direction after negotiating. This common direction can be either equal to one of the two given goal directions or a third direction which is the average of the two directions present. Another possibility is that during the move they split into several groups and move towards their own informed direction.

The flocking behavior has three components: proximal control, alignment control, and goal-following control. Proximal control which combines separation and attraction towards the neighboring robots, aims at making each robot keep an appropriate distance to the others. Alignment control is to let the robots match each others’ direction after perceiving the neighbors’ heading. We makes an analysis on the relation between ratios of informed robots for each direction and the performance of flocking. The metrics of flocking performance are probability of splitting and average direction. We design a series of experiments to measure the flocking.

The rest of the thesis is organized as follows: In chapter 2 we introduce the related work on flocking in robotics and biology. In chapter 3 we present our control model to simulate the flocking behavior for robots. In chapter 4 we show the simulator platform to develop the controller of robot motion and the physical implement of control model. In chapter 5 we present the design, the metrics, results of the experiments and explanation of the results . In chapter 6 we make a conclusion for the future research emphasis. All other plots which is not showed in the content will be attached in appendix.
Chapter 2

State of the Art of Flocking

Reynolds [Reynolds, 1987] did the first study of flocking in computer science. He thought it is inefficacy and rigid to decide each individual’s route separately. He use particle system to simulate the flocking of birds. He proposed three individual-based behaviors: separation, alignment, cohesion. Separation is to prevent individuals collision with their neighbors. Alignment is let individuals match its neighbors’ heading. Cohesion is to stay close to neighbors. All these behaviors rely on local sensing and local decision rule. He not only simulates the behavior of single bird, but also simulates the perceptual mechanism and physics of aerodynamic flight. The results of his work is similar to the natural flocking in nature. However, he assumes that all the individuals can detect velocity of its neighbors in order to alignment. This is hard to accomplish in robotics due to limited sensing capability utilized in robots.

In robotics, one of the earliest attempt to realize flocking was by Mataric [Mataric, 1994]. She created a set of “basic behaviors” including safe-wandering, aggregation, dispersion and homing to implement flocking. The robots were able to sense obstacles, perceive their own position with respect to static beacons present in the environment and broadcast this information to others. The group of robots were able to move cohesively towards a homing direction, avoiding collision with companions and obstacles.

Kelley and Keating [Kelly and Keating, 1996] proposed flocking based on leader-following behavior to realize flocking with real robots. The robots use ultrasound sensors to sense the obstacles in the environment and an active infrared(IR) system to perceive the relative range and bearing of neighbors. One robot was elected as a leader on-line using an off-the-shelf radio frequency (RF) to guide the movement of whole group. The IR system was used in generating attractive/repulsive forces towards other robots. The ultrasound sensors were utilized to generate a repulsive force against obstacles in the environment.

Hayes et al. [Hayes and Dormiani-Tabatabaei, 2002] proposed a flocking algorithm based on two behaviors: collision avoidance and velocity-matching flock centering. Each robot was able to sense the range and bearing of other robots and according to this information
it calculated the center-of-mass (CoM) which was used for flocking cohesion. The change of CoM indicated the robot motion direction in next step and used to align the individual within the group. When doing experiment on Webots simulator, he realized the algorithm and optimized the parameters, which was verified later with the real robots. When launching experiments on physical robots, he had to use overhead camera system to track the robot and broadcast their range and bearing information.

Spears et al. [Spears et al., 2004] proposed a framework of artificial physics for distributed control of swarm. The robots were able generate lattice formation using attraction and repulsion virtual forces in two or three dimensions. In their experiments, they use seven robots to form a regular hexagonal lattice, and moved along the light direction while keeping the formation fixed.

Holland et al. [Holland et al., 2005] proposed a flocking algorithm for unmanned ground vehicles (UAV) which is similar to Reynold’s algorithm. A host was used as a intermediate station for receiving each UAV’s range, bearing, velocity and sending them to other UAV to simulate the sensing process of one UAV for perceiving range and bearing and heading of its neighbors.

Moeslinger et al. [C. Moslinger and Crailsheim, 2000] studied in minimalist flocking algorithm in robotics. He found a way to achieve flocking without communication, memory or global information in which way it is especially better for small and communication-incapable robots. They partitioned the sensor field for robot and set different thresholds for attraction and repulsion in sectors. The robots finally result in flocking in a small group in a constrained environment.

Turgut et al. [Turgut et al., 2008] proposed an algorithm based on two behaviors to achieve flocking in real robots, which are proximal control and heading alignment. They introduced a novel sensing system which is called Virtual Heading System to achieve alignment. A compass was installed on each robot to perceive its heading with respect to the North. The robots simulate communicating locally to share their own heading information. The infrared Short-Range Sensing System is used to detect range and bearing of neighboring robots and obstacles in short range. A virtual force is computed then to avoid collision and maintain cohesion among robots in order to get proximal control. They evaluated the noise effect, the number of VHS neighbors and the range of wireless communication. They found that the range of wireless communication determine up to what scale of flocking is achieved.

Çelikkanat et al. [Çelikkanat et al., 2008] followed Turgut et al.’s work and extended the flocking behavior by providing goal direction to some individuals which are called informed robots. They found that only a minority of robots who know the goal direction is enough to guide the whole group to right direction which is similar to the results shown in [Couzin et al., 2005].

Ferrante et al. [Ferrante et al., 2010] introduced a new communication strategy called the
information aware communication for alignment behavior. He provided a goal direction to a minority of the group as in [Çelikkanat et al., 2008] [Couzin et al., 2005] and the rest of the group is uninformed, different than in [Çelikkanat et al., 2008]. When communicating, the communication content for informed robots and uninformed robots were different. Informed robots send the the goal direction, whereas, the uninformed robots send the average direction of its neighbors. They performed simulation-based experiments for this new strategy in stationary and non-stationary environment. Non-stationary environment means that goal direction and the informed individuals are changed over time. Stationary environment means that the goal direction and the informed individuals are fixed during one run. The proposed strategy performs better than heading communication in both stationary and non-stationary environment. It also scales well and was robust against noise.

Further, Ferrante et al. [Ferrante et al.,] performed a comparative study of two flocking controllers. One is with alignment behavior and another is without alignment behavior. They executed simulation-base experiments under different setting of noise, the swarm size and the proportion of informed robots to understand how the settings influence the result of controller. They executed experiments in stationary and non-stationary environment similar to [Ferrante et al., 2010]. They found out that for small group no-alignment controller performs well and for larger group alignment behavior is more accurate. Noise increases accuracy in no-alignment controller for larger group. The proportion of informed robots we need to achieve same accuracy for no-alignment controller is more than the one for alignment controller.

Recently, Stranieri et al. [Stranieri et al., 2011] perform flocking with a swarm of behaviorally heterogeneous mobile robots: aligning and non-aligning robots. Aligning robots were able to negotiate a common heading direction with other aligning robots in close proximity. Non-aligning lack the capability. They also presented two motion control rules. One rule is to make the forward speed of robot fixed and change only their angular speed. The other is that the forward speed and angular speed are both changed. The degree of group order, group cohesiveness and average group speed are computed to evaluate the flocking performance. The results showed that self-organized flocking can be achieved even if some robots in group were not able to communicate with others to agree on a common heading direction. More aligning robots mean better performance and if the number of aligning robots is too small, the only way to make them flocking is let non-aligning robots change their forward speed.
Chapter 3

Methodology

We follow the virtual physics approach in the flocking. At each time step, a virtual force vector is calculated as:

\[ \mathbf{f} = \alpha \mathbf{p} + \beta \mathbf{h} + \gamma \mathbf{g}_i. \]  

(3.1)

where \( \mathbf{f} \) denotes the sum of virtual force vector, \( \mathbf{p} \) denotes the proximal control vector, \( \mathbf{h} \) denotes the alignment control vector, \( \mathbf{g}_i \) where \( i = \{1, 2\} \) denotes the target goal direction. For the uninformed robots, \( \gamma = 0 \). The weights for each component are fixed with \( \alpha = 1, \beta = 4, \gamma = 1 \).

Basically, everyone should keep a safe distance with each other to avoid collision and achieve cohesion, which we call proximal control. Further, they would like to follow the trend of neighbors’ move in order to keep them act coordinately, which is alignment control. The last one is target control which is available for the random selected robots who are informed of goal direction 1 or goal direction 2.

3.1 Proximal control

We use Lennard-Jones Potential to realize the repulsion and attraction forces among robots. Its formula is showed in Hettiaraechchi and Spears (2009):

\[ p_i(d_i) = 12\epsilon\left[\frac{d_{des}^{12}}{d_i^{13}} - \frac{d_{des}^6}{d_i^6}\right] \]  

(3.2)

where \( p_i(d_i) \) denotes the force between two robots, \( d_{des} \) denotes the desired distance at which the force is 0. The parameter \( \epsilon \) defines the strength of the attractive/repulsion force. Each robot measures the range and bearing of its neighbors and these range and bearing
CHAPTER 3. METHODOLOGY

3.2 Alignment control

The core of flocking is to make the swarm move cohesively towards a common direction. This requires that each robot knows its own heading and the heading information from neighbors. We adopt the heading control strategy proposed by Turgut et al. [Turgut et al., 2008]. A robot $r$ detects its own heading $\theta_0$ with respect to the global reference frame, as the angle $\theta_0$ in Figure 3.1 and sends the heading message to neighbors. The robot receive an angle $\hat{\theta}_i$ from $i_{th}$ neighbor, as the angle $\theta_i$ in Figure 3.1. It transforms this angle into its body-fixed reference frame which is $\hat{\theta}_i$ in Figure 3.1. Having received $k$ angles from its $k$ neighbors, it will be calculated as:

$$h = \frac{\sum_{i=0}^{k} e^{j\hat{\theta}_i}}{\| \sum_{i=0}^{k} e^{j\hat{\theta}_i} \|} \tag{3.4}$$

where $\| \cdot \|$ denotes the norm of a vector, $k$ denotes the number of neighbors, $\hat{\theta}_i$ denotes the transformed heading information from $i_{th}$ neighbor. $\hat{\theta}_0$ represents its own heading of a given robot.

Then $h$ joins the calculation in formula 3.1.
3.3 Motion control

The movement of robot is motivated by the virtual force calculated above in equation \(3.1\). Forward and angular speed of the robot is calculated using virtual force \(f\). We calculate the \(x\) component of the force, \(f_x\), and \(y\) component of the force, \(f_y\). The linear and rotational speeds are calculated as:

\[
u = K_1 f_x.\] (3.5)

\[
w = K_2 f_y\] (3.6)

where \(u\) denotes the linear speed, \(w\) denotes the angular speed, \(K_1\) and \(K_2\) are the linear and angular gains, respectively. To avoid excess drive for wheels actuators, we adopt thresholds to limit forward speed and angular speed. \(u \subseteq [0, U_{max}]\), \(w \subseteq [-\Omega_{max}, \Omega_{max}]\).
Chapter 4

The Platform

In this thesis, we use foot-bot robot and ARGoS simulator. They were developed for the Swarmnoid Project whose goal was to design, implementation and control of a novel distribution robotics system. In the following, we explain foot-bot robot and ARGoS simulator.

4.1 Foot-bot Hardware

The foot-bot contains these components: the base of the robots where the wheels actuated by 2W motors are installed; the LED rings around the robot; two cameras, one is the 2.0 mega-pixels UXGA camera which is omnidirectional, and another one is looking-up; the gripper for assembling; 24 proximity sensors situated in a ring facing outside, 8 proximity sensors facing down, 4 contact ground sensor and a rotating long-range infrared distance sensor; it also installs hot-swappable battery for solving a common situation. That is while accomplishing a long-last experiment, robots need to recharge after a while which will waste a lot of time. The super-capacitor keeps a promise that the robot when recharging is still alive. This process is finished automatically thanks to the automatic battery recharge station. In Figure 4.1 we present the foot-bot. In table 4.1 we show main sensors and actuators equipped on the foot-bot.

The range and bearing system is especially important in our experiments, for it affords not only the detection of range and bearing of other robot but also the communication with others. It is infrared module which allows the robot to compute a rough estimate of the direction and the distance of the neighboring robots. The range of detection is up to 5 m [Bonani et al., 2010]. The package they communicate with is including the following messages: 1) id of the robot sensed; 2) range (=distance) in meters relative to the sensing robot; 3) bearing horizontal (=angle) in signed radians relative to the sensing robot; 4) data (10 bytes) transmitted by the other robot.
ARGoS (Autonomous Robots Go Swarming) is an open-source simulator which is developed by Carlo Pinciroli et al. [Pinciroli et al., 2011]. It is a modular, multi-engine, open-source simulator for heterogeneous swarm robotics. It is extensible and scalable. We use ARGoS to perform experiments with a simulated version of the foot-bot.

One significant characteristic of ARGoS is its multiple engines. In ARGoS, simulated space and physics engine are distinct concepts which makes it realizable to run multiple engines in one experiment. They are linked by the embodied entities. Simulated space is for storing entities and Physics engine is for updating the state of entities. According to the physics engine each entity use, the entities are divided into subsets and different engines are assigned to these subsets. The advantage of this design contains: decrease the range of detecting collision because only the entities with identical physics engine have the possibility of collision, increase the usage of CPU, decrease the run time and so on.

Another characteristic of ARGoS is its multiple-threading. It is embedded in the main loop function in ARGoS. The main loop function is divided into three phases evaluated in
4.3. FLOCKING

<table>
<thead>
<tr>
<th>Type</th>
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<tr>
<td>Proximity Sensor</td>
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<tr>
<td>Contact Group Sensor</td>
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<td>2</td>
</tr>
<tr>
<td>Wheel actuators</td>
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</tr>
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</table>

Table 4.1: The sensor and actuators on foot-bot

Figure 4.2: Overall architecture of the Swarmanoid Simulator [Pincirolli et al., 2011].

order: sensor and control, act, physics. During each phase, there is one master thread and several slave threads which partake part of the jobs of the master thread.

4.3 Flocking

We use the simulated version of the foot-bot robot. The foot-bot contains the following sensors and actuators: i) A light sensor which is used to detect the bearing of a distant light source placed the experimental environment to measure orientation of the robot. It is used for realizing a global reference system. ii) A range and bearing system (RAB) which has
two functions. One is to communicate the heading information of the robots for alignment control. Another is to measure range and bearing of the neighboring robots for proximal control. iii) Two wheels actuators, used to control the speed of left wheel and right wheel independently.

When achieving motion control, we use the drive model in Turgut et al. \cite{Turgut et al., 2008} to convert the forward speed $u$ and the angular speed $w$ into the linear speed of two wheels.

\[ N_L = u + \frac{w}{2}l, \]

\[ N_R = u - \frac{w}{2}l, \]

where $l$ is the distance of two wheels.

The values of the constants and variables in the experiments are showed in Table 4.2.
### 4.3. FLOCKING

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Value(s) / Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>Number of robots</td>
<td>100</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>Goal Direction 1</td>
<td>0</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>Goal Direction 2</td>
<td>${20, 40, 60, 80, 100, 120, 140, 160, 180}$</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Prop. of robot informed of $\theta_1$</td>
<td>${0.001, 0.09, 0.1, 0.19, 0.2, 0.29, 0.3, 0.39, 0.4, 0.49, 0.5}$</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Prop. of robot informed of $\theta_2$</td>
<td>${0.001, 0.1, 0.11, 0.2, 0.21, 0.3, 0.31, 0.4, 0.41, 0.5, 0.51}$</td>
</tr>
<tr>
<td>$U_{max}$</td>
<td>Maximum forward speed</td>
<td>20 cm/s</td>
</tr>
<tr>
<td>$\Omega_{max}$</td>
<td>Max angular speed</td>
<td>$\pi/2$ rad/s</td>
</tr>
<tr>
<td>$K_1$</td>
<td>linear gain</td>
<td>2 s/kg</td>
</tr>
<tr>
<td>$K_2$</td>
<td>angular gain</td>
<td>$2 \text{ s/(kg } \cdot \text{ m)}$</td>
</tr>
<tr>
<td>$l$</td>
<td>Inter-wheel distance</td>
<td>5 cm</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Strength of pot. function</td>
<td>0.5</td>
</tr>
<tr>
<td>$d_{des}$</td>
<td>Inter-robot distance</td>
<td>0.6 m</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Amount of noise</td>
<td>0.00000001</td>
</tr>
<tr>
<td>$T$</td>
<td>Experiment duration</td>
<td>500 secs</td>
</tr>
</tbody>
</table>

Table 4.2: Experimental values or range of values for all constants and variables
Chapter 5

Experiments

In the following we introduce the aim and the setting of these experiments. Subsequently we show the metrics for the performance of flocking. Finally we present the result of the experiments.

5.1 Task and setting of the experiment

The aim of our experiments is to study the flocking performance under different ratios of robots which are informed of different goal directions. Besides the ratios, the difference between the two goal directions is also taken into account as a parameter.

We set the group size to be $N$ foot-bots in the arena of $12 \times 12$. At the beginning, all robots are randomly positioned on an area of $5 \times 5$ with random orientation. The orientations are drawn from a uniform distribution range of $[-\pi, \pi]$. $\lambda$ percentage of robots are given the goal direction $\theta_1$, $\mu$ percentage of robots are informed of the goal direction $\theta_2$. The number of robots which are informed of goal direction $\theta_1$ is $N_A = N\lambda$, and the number of robots which are informed of goal direction $\theta_2$ is $N_B = N\mu$. We fix the $\theta_1 = 0$, and only vary $\theta_2$ from 20 degrees to 180 degrees with the interval of 20 degrees. $\theta_2 \subseteq \{20, 40, 60, 80, 100, 120, 140, 160, 180\}$. We also change $\lambda$ and $\mu$ to vary the number of robots with informed direction $\theta_1$ and informed direction $\theta_2$. We repeat each experiment 100 times and we set the duration of each experiment to 500 seconds.

5.2 Metrics

In flocking behavior we require that the whole group acts like a single entity, which means that the individuals should stay together and act cohesively. Given two conflicting goal directions, we calculate the number of group at the end of each experiment to evaluate the splitting probability. We also compute the average direction of the group at the end of each experiment to evaluate how the group moved in the presence of two goal directions.
In order to compute split probability and average direction, we use the interface of simulator to get the coordinates and orientation of each robot from entity map. Then we calculate the distance between any two of them.

5.2.1 Split probability

Split probability is calculated using the number of group at the end of each experiment. We calculate frequency of the number of group which is more than $1$ in $100$ runs, and get the split probability for that certain setting.

The group number is obtained using the definition of equivalence class. In our case, we use maximum sensing range of RAB $d_{\text{max}}$ as the maximum distance between two members in one group. If the distance between two robots is less than $d_{\text{max}}$, they are in the same group. In terms of equivalence class, if the distance of robot A and B is at the range of $[0, d_{\text{max}}]$, A is in the same class as B. And it is a equivalence relation that means if A is in the same class as B and B is in the same class as C, A is in the same class as C.

If the distance between A and B is less than $d_{\text{max}}$, we get a equivalence relation (A,B). Using the same way, we get rid of all the distances between every two robots, and get the set of equivalence relations such as \{ (A,B),(C,D),(A,D) \}. One member in a equivalence relation is called a element. In the following, we get rid of the family number for each element.

We implement the algorithm in [William H. Press and Flannery, 1993]. The core of the algorithm is as follows: Let $F(j)$ be the class or “family” number of element $j$. Start off with each element in its own family, so that $F(j)=j$. Handling each equivalence relation “ $j$ is equivalent to $k$” by (i) tracking $j$ up to its highest ancestor; (ii) tracking $k$ up to its highest ancestor; (iii) giving $j$ to $k$ as a new parent. After processing all the relations, we traverse all the element $j$ and reset their $F(j)$’s to their highest possible ancestors. The elements which have same $F(j)$ is in a equivalence class and they are in one group.

5.2.2 Average direction

The calculation of average direction of all robots’ orientations $\bar{\vartheta}$ in arena is based on vectorial operation.

$$\bar{\vartheta} = \zeta \sum_{i=1}^{N} e^{j \vartheta_i}.$$  

where $\zeta$ means the angle of a vector represented in the complex plane, $N$ is the number of robots in the arena, $\vartheta_i$ denotes the orientation of the $i^{th}$ robot.

We also calculate the theoretical average direction $\hat{\vartheta}$ in total informed robots for reference.

$$\hat{\vartheta} = \zeta (N_A e^{j \vartheta_1} + N_B e^{j \vartheta_2})$$
5.3. Results

The results show that no matter the value of $N_A$, $N_B$ and $|\theta_2 - \theta_1|$, the swarm does not split. Therefore, we present three representation plots and put the rest in appendix. In Figure 5.1, we can see that the split probability is zero.

We discuss the experimental results of average direction in the following order: when $N_A$ and $N_B$ are equal ($N_A = N_B$), when there is a small difference between $N_A$ and $N_B$ ($N_B - N_A = 2$), when there is a large difference between $N_A$ and $N_B$ ($N_B - N_A \geq 10$).
5.3.1 Equality

First, we show the results for $N_A = N_B$ in Figure 5.2. For $\theta_2 \subseteq \{20, 40, 60, 80, 100, 120, 140, 160\}$, they strictly follow the theoretical average direction in total view. It also can be observed that if $N_A = N_B$, with the increase of angle difference, the deviation points appears more and more frequent. If we fix $\theta_2$, the more informed robots for each direction, the more precise of their flocking behavior following theoretical average direction. When $\theta_2 = 180$, their movement direction is near to the goal direction $\theta_1$ rather than the average direction. The explanation for this abnormal point is that once the given directions are opposite, and $N_A$ and $N_B$ are too close to each other, the whole group is in unstable state and they will choose a random direction which may be depends on the initial distribution of orientations.

5.3.2 Small Difference

When $N_B - N_A = 2$, which means there is a small difference between $N_A$ and $N_B$, we can see from Figure 5.3 that for $\theta_2 \subseteq \{20, 40, 60, 80, 100, 120, 140, 160\}$, they strictly follow the theoretical average direction as they do when $N_A = N_B$. With the increase of angle difference, the range of moving direction enlarges. If we fix $\theta_2$, the more informed robots for each direction, the more precise of their flocking behavior following theoretical average direction. When $\theta_2 = 180$, every time they follow a random direction in the range of $[-\pi, \pi]$ when compared to $N_A = N_B$ case.

5.3.3 Large Difference

If there is a wide gap between $N_A$ and $N_B$, the theoretical average direction in total informed robots represents the majority in some sense. From Figure 5.4 we can observe clearly that big disparity in quantity guarantees precise flocking following the expected direction even when $\theta_2 = 180$. So with large difference, no matter the angle difference, the direction of flocking always follow the theoretical average direction.

To summarize, we can say that independent of the value of $N_A$, $N_B$, $|\theta_2 - \theta_1|$, the robots achieve flocking towards a common direction. In most of the settings, the robots follow the theoretical average direction. Only when $\theta_2 = 180$ and $N_A$ and $N_B$ are too close, the swarm emerges a unstable state that the collective motion of the group becomes random.
Figure 5.2: Average Direction Distribution for $N_A = N_B$: (a) 10 vs 10; (b) 30 vs 30; (c) 50 vs 50. Solid black line represents the theoretical average direction in total informed robots.
Figure 5.3: Average Direction Distribution for a small difference between $N_A$ and $N_B$: (a) 9 vs 11; (b) 29 vs 31; (c) 49 vs 51. Solid black line represents the theoretical average direction in total informed robots.
Figure 5.4: Average Direction Distribution for large difference between $N_A$ and $N_B$: (a) 1 vs 20; (b) 1 vs 30; (c) 1 vs 50. Solid black line represents the theoretical average direction in total informed robots.
Chapter 6

Conclusion

In this thesis, we studied self-organized flocking of swarm robots with conflicting target directions. Some the robots are informed about goal direction 1, and the other proportion of robots are informed of goal direction 2. The rest of the robots are naive and know neither of the two goal directions. We use a heading alignment control strategy in which the robots communicate with the average direction of their neighbors. We launch simulator-based experiments to study flocking performance. The metrics of flocking performance is split probability and average direction. We change the number of robots that exhibit each direction and the difference of two given directions to observe it.

Results show that heading alignment strategy performs well under conflicting target direction. In most of the cases the swarm doesn’t split and follows expected average direction. Only when $\theta_2 = 180$ and $N_A$ and $N_B$ are too close, the swarm emerges a unstable state that the collective motion direction of the group becomes random.

In presence of two target directions, from the engineering point of view, we can imagine several macroscopic objectives for the swarm. In conflicting target directions environment, one is to make a swarm go along the average direction, another is to let the swarm follow one of the given goal directions, the third is to make them follow each own direction and the swarm split. We accomplished one of these objectives, that is to make a swarm go along the average direction, by using the alignment strategy in which robots just sense their neighbors orientation. Future work will focus on the other two objectives and we will investigate the usage of other communication strategies.
APPENDIX
Figure 6.1: Average Direction Distribution for $N_A$ and $N_B$. Solid black line represents the theoretical average direction in total informed robots.
Figure 6.2: Average Direction Distribution for $N_A$ and $N_B$. Solid black line represents the theoretical average direction in total informed robots.
CHAPTER 6. CONCLUSION

Figure 6.3: Average Direction Distribution for $N_A$ and $N_B$. Solid black line represents the theoretical average direction in total informed robots.
Figure 6.4: Split Probability for \( N_A \) and \( N_B \).
Figure 6.5: Split Probability for $N_A$ and $N_B$. 

(a) Split probability for 10 vs 10

(b) Split probability for 10 vs 20

(c) Split probability for 10 vs 30

(d) Split probability for 10 vs 40

(e) Split probability for 10 vs 50

(f) Split probability for 19 vs 21
Figure 6.6: Split Probability for $N_A$ and $N_B$. 
Figure 6.7: Split Probability for $N_A$ and $N_B$. 
Bibliography


