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Self-organizing flocking in behaviorally heterogeneous swarms

Alessandro Stranieri

Promoteur:
Prof. Marco DORIGO

Co-promoteur:
Dr. Mauro BIRATTARI

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Abstract

In this dissertation, we study self-organized flocking in a swarm of behaviorally heterogeneous mobile robots: aligning and non-aligning robots. Aligning robots are capable of agreeing on a common heading direction with other neighboring aligning robots. Conversely, non-aligning robots lack this capability. Studying this type of heterogeneity in self-organized flocking is important as it can support the design of a swarm with minimal hardware requirements. Through systematic simulations, we show that a heterogeneous group of aligning and non-aligning robots can achieve good performance in flocking behavior. We further show that the performance is affected not only by the proportion of aligning robots, but also by the way they integrate information about their neighbors as well as the motion control employed by the robots.

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Chapter 1

Introduction

The aim of the work described in this dissertation is to present the study conducted on the possibility for a swarm of robots to move cohesively, to *flock*, even when not all of them are able to align with their neighbors. This chapter constitutes an introduction to this work. In Section 1.1 we introduce flocking as an object of study in robotics and we motivate our proposed study. Section 1.2 is dedicated to the works in flocking that are related to the one presented here.

1.1 Flocking

Flocking is the cohesive and aligned motion of a group of animals along a common direction. The most striking characteristic of flocking is probably the fact that, although the fluid and coordinated motion may seem under the control of a single mind, evidence actually supports the idea that each individual acts according to simple behavioral rules and exploits only local information. Figure 1.1 provides a beautiful example of a formation of birds moving cohesively in formation, as a single entity.

It is no wonder that this emergent behavior has attracted the attention of researchers in the computer science crowd, as well as in the robotics one. Modeling the simple behaviors that enable a group of animals to move in very elegant coordinated fashion, can in fact allow the design of groups of artificial agents which are able to move along the same direction, without the need of central coordination.

All studies about flocking within computer science and robotics root

Figure 1.1: Birds flocking in formation.

back to the seminal work of Reynolds (1987). He was the first to simulate flocking of birds based on three behaviors: *separation* — individuals try to keep a minimum distance between their neighbors, *cohesion* — individuals try to stay together with their neighbors, and *alignment* — individuals try to match their velocities to the average speed of their neighbors. The vast majority of the studies about flocking assume that all the robots in the swarm are behaviorally identical and exploit the three behaviors described above.

In this dissertation, we consider flocking in a behaviorally heterogeneous swarm of robots. All robots in the swarm use the separation and the cohesion behavioral rule. However, only a fraction of the robots, which we call the *aligning* robots, uses the alignment behavior. The rest of the robots, which we call the *non-aligning* robots, do not use the alignment behavior.

The motivation that inspired this work derives from the idea that studying heterogeneity in alignment in self-organized flocking is very important from the practical point of view. The alignment behavior is more demanding in terms of robotics hardware requirements than the separation and cohesion behaviors. In fact, it requires either an elaborate sensing device, through which robots can detect the orientation of neighboring robots or, as explained in this dissertation, a communication device. Therefore, understanding if a swarm can achieve flocking with only a few aligning robots can support the design of swarms with minimal hardware requirements. A

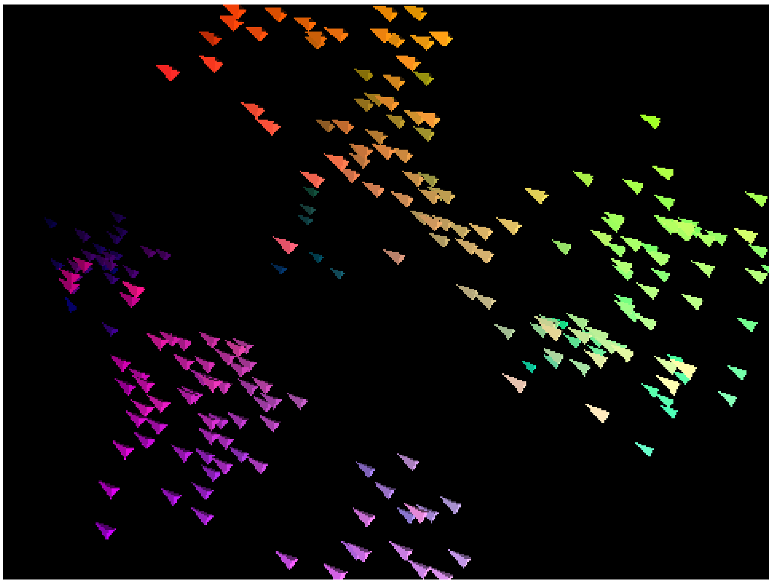

Figure 1.2: Flocking boids-like artificial agents.

long-term vision of this work involves in fact the possibility of having a reduced set of robots capable of sophisticated navigation which lead through unknown and complex environments a larger group of robots specialized on a different task.

The idea presented in this dissertation is tested by conducting simulation-based experiments and we measure self-organized flocking performance in terms of the degree of group order, group cohesiveness and average group speed. With respect to these criteria, we found that the swarm achieves good flocking performance when the proportion of aligning robots is high. Conversely, this performance decreases as the proportion gets lower. To tackle this problem, we propose a new model of robot motion. In the new model, non-aligning robots modulate their forward speed, instead of moving at a fixed forward speed as the other robots.

1.2 Related Works

Flocking is a widely observed phenomenon in social animals (Camazine et al. 2001) such as locusts (Buhl et al. 2006), birds (Ballerini et al. 2007) or human beings (Dyer et al. 2008). Animal groups show a great diversity in their population due to the differences in age, morphology (Krause et al.

1998), nutritional state (Krause 1993), personality (Michelena et al. 2010), and leadership status (Reebs 2000) of the individuals. This diversity mainly results in behavioral differences among the individuals. Couzin et al. (2002) showed that behavioral differences between the individuals in a group change both the dynamics and the organization of the group. Subsequently, Couzin et al. (2005) conducted a seminal study about leadership in animal groups. They modeled a heterogeneous group of individuals of which only a few are aware of a target direction. They showed that the few informed individuals are able to move the whole group along the target direction. In Janson et al. (2005), the authors propose a model to explain how scouts bees are able to direct large swarms of uninformed bees towards a new nesting site. Even when the proportion of scout bees is low, they are able to lead the swarm by flying through it at a slightly faster speed. Sayama (2009) presented the preliminary results obtained in simulation using the Swarm Chemistry framework. They studied the movement of a swarm consisting of two different chemical species, and found that a chaser-escapee relationship between the two different populations of agents is established. More recently, Diwold et al. (2011) showed how a swarm can still fly towards a common direction even when the agents are not all aligned, and when the location of the nesting site is not known with precision.

In robotics, most of the studies about flocking assume a homogeneous set of behaviorally equivalent individuals. One of the earliest studies in robotics was performed by Matarić (1994). She devised a set of "basis behaviors" to implement flocking in a group of robots: safe-wandering, aggregation, dispersion and homing. With the proposed set of behaviors, robots are able to move cohesively towards a homing direction. Kelly & Keating (1996), following a behavior-based approach, designed a leader-following behavior to realize flocking. Hayes & Dormiani-Tabatabaei (2002) proposed a flocking behavior having collision avoidance and alignment behaviors based on local range and bearing measurements. Spears et al. (2004) proposed a framework based on artificial physics. The robots were able to form a regular lattice structure using attraction/repulsion virtual forces and move along a direction indicated by a light source in the environment. Holland et al. (2005) proposed a flocking behavior for unmanned ground vehicles based on separation, cohesion and alignment behaviors. Turgut et al. (2008) proposed a flocking behavior based on separation/cohesion and alignment behaviors.

They implemented this behavior in robots with limited sensing capabilities and conducted a systematic study on the effect of sensing noise in heading measurement on flocking. In a recent study, Moeslinger (2011) proposed a flocking behavior for robots with limited sensing capabilities. It is based on only attraction and repulsion behaviors. By adjusting the sizes of attraction and repulsion zones, they achieved flocking for a small group in a constrained environment.

Other works in robotics considered a group of behaviorally heterogeneous robots. Momen et al. (2007) studied flocking with a heterogeneous robotic swarm inspired by mixed-species foraging flocks of birds (Graves & Gotelli 1993). Using simulations, they showed some aspects of mixed-species flocking, such as behavioral differences in their attraction and repulsion rules. Çelikkanat & Şahin (2010), inspired by Couzin et al. (2005) extended the flocking behavior proposed by Turgut et al. (2008) and created a heterogeneous robot swarm by informing some of the robots about a target direction. Recently, in another follow-up study, Ferrante et al. (2010) introduced a new communication strategy to improve flocking performance in case of both static and changing target directions.

Most of the studies in swarm robotics about self-organized flocking have not considered diversity in alignment capabilities.

The rest of this dissertation is organized as follows. Chapter 2 contains the description of the flocking model and the robots used to implement it. In Chapter 3, we describe the simulation environment used to run our experiments, the experimental setup and the results obtained. Finally, we draw the conclusions of this work and propose future directions of research in Chapter 4.

Chapter 2

Method

This section is dedicated to the description of the method used to carry out the proposed study. In Section 2.1, we first describe the framework used to model the behaviors employed by the robots. Section 2.2 describes how we compute linear and angular speed of the robots. Section 2.3 contains the description of how the behaviors are implemented on the robots.

2.1 Artificial physics

We follow a design method based on the artificial physics framework introduced by Spears et al. (2004). According to this method, robots exert virtual forces on each other. In Figure 2.1 we try to give an idea of how the framework is used in this work. At each time step a robot computes the force acting on it. The robot then converts this force into linear and angular speed, which are sent to the wheel actuators.

In order to explain how we implement heterogeneous flocking, we start with the description of our flocking model in the homogeneous case. Using this framework, an homogeneous swarm consists of robots employing both alignment, cohesion and separation behaviors. Figure 2.2 provides a visual representation of the behaviors.

In the homogeneous case, all robots compute the forces according to the same rule:

$$\mathbf{f} = \alpha\mathbf{p} + \beta\mathbf{h},$$

We define $\mathbf{p}$ as the *proximal control vector* and $\mathbf{h}$ as the *alignment control*

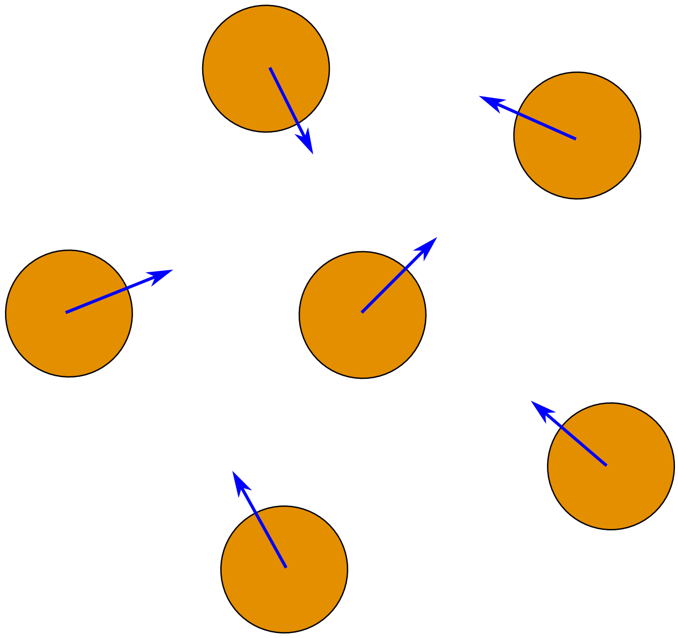

Figure 2.1: In the artificial physics framework used in this work, robots exert forces on each other and move according to the resulting forces acting on them, represented here by the blue arrows.

vector. The proximal control vector $\mathbf{p}$ accounts for attraction and repulsion rules, that is for keeping the robot together with its neighbors and to avoid collisions. The alignment control vector $\mathbf{h}$ is used to make the aligning robots match the average heading direction of its neighboring aligning robots. The parameters α and β are used to adjust the contribution of the corresponding vectors.

In this study, we consider a behaviorally heterogeneous swarm of robots and we now refer to two different kinds of robots: *aligning* and *non-aligning* robots. Given the model above, as one can intuitively imagine, the rule according to which non-aligning robots compute the force acting on them becomes simpler:

$$\mathbf{f} = \alpha\mathbf{p}.$$

Furthermore, the modified model can then be represented as in Figure 2.3. In the two following sub-sections we describe how the two force components, $\mathbf{p}$ and $\mathbf{h}$ are computed.

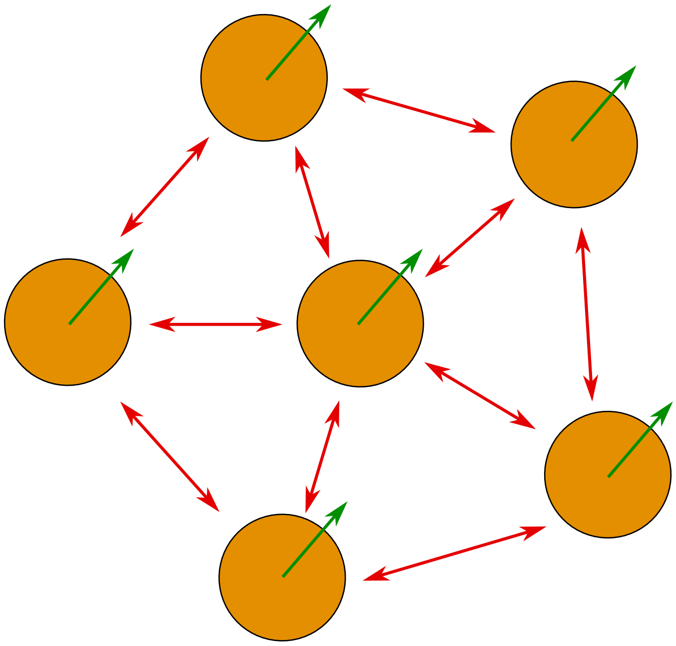

Figure 2.2: Behaviorally homogeneous flocking in the virtual physics framework.

2.1.1 Proximal control

Let m_p denote the number of neighbors of a robot within a range D_p. Let also d_i and ϕ_i denote the relative range and bearing of the i^{th} neighbor, respectively. The proximal control vector $\mathbf{p}$ is given by:

$$\mathbf{p} = \sum_{i=1}^{m_p} p_i(d_i) e^{j\phi_i}.$$

p_i is calculated as a function of d_i using a force function derived from the Lennard-Jones potential function, which results in the formation of regular structures as shown in Hettiarachchi & Spears (2009):

$$p_i(d_i) = 12\epsilon \left[\frac{{d_{des}}^{12}}{d_i^{13}} - \frac{{d_{des}}^{6}}{d_i^{7}} \right].$$

The parameter ϵ determines the strength of the attractive and repulsive force, and d_{des} is the desired distance between the robots. Figure 2.4 provides an example of how a robot computes the proximal vector.

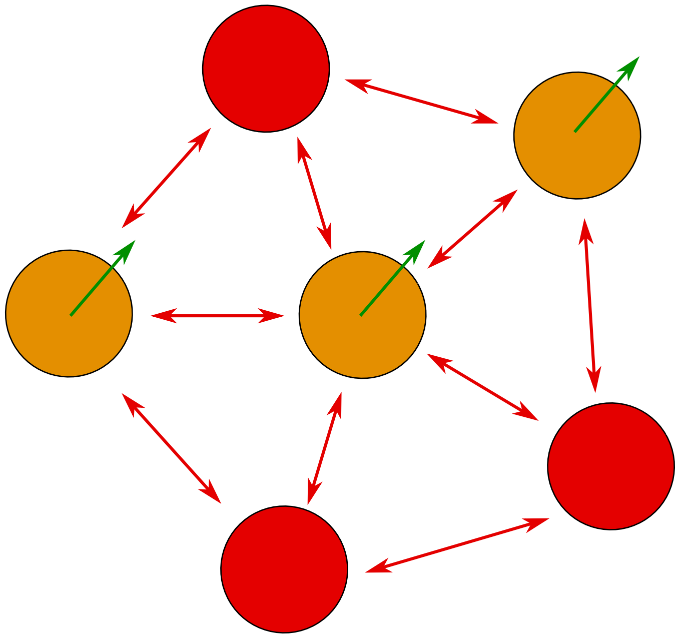

Figure 2.3: Behaviorally heterogeneous flocking. A fraction of the agents (in red) employs the sole proximal control behavior.

2.1.2 Alignment control

Let θ_0 denote the orientation of a given robot. Furthermore, let m_a denote the number of aligning robots within the range D_a of this robot, and $\theta_i, i \in \{1, \ldots, m_a\}$ their orientation. All orientations are expressed in the body-fixed reference frame of the robot under consideration[1]. The robot calculates the alignment control vector, that is, the average orientation of the m_a robots, including its own:

$$\mathbf{h} = \frac{\sum_{i=0}^{m_a} e^{j\theta_i}}{\| \sum_{i=0}^{m_a} e^{j\theta_i} \|},$$

where $\| \cdot \|$ denotes the norm of a vector. Figure 2.5 provides an example of how a robot computes the alignment vector.

[1]In our study, we define two reference frames, both of which use the right-hand convention. One is the reference frame common to all of the robots, which is available due to the light source. The other is the body-fixed reference frame specific to each robot. The body-fixed reference frame is fixed to the center of a robot: its x-axis points to the front of the robot and its y-axis is coincident with the rotation axis of the wheels.

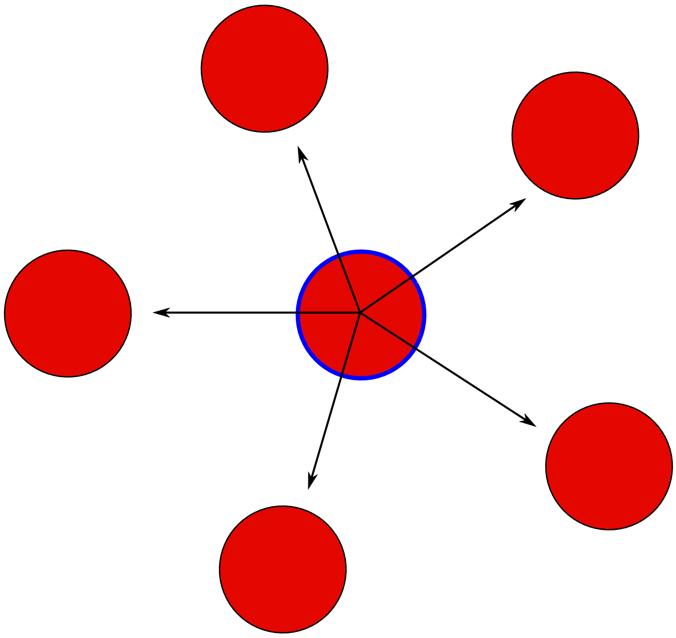

Figure 2.4: Proximal control behavior representation.

2.2 Motion control

The force computed with the rules described in the previous section must then be converted in forward and angular speed. For this study we consider two motion control rules. The two rules differ in the way the forward speed u and the angular speed ω are determined. This section is dedicated to the description of these two rules.

2.2.1 CMC

The first rule is denoted as *constant forward speed motion control* (henceforth CMC). In CMC, robots are always moving at a constant forward speed, but can change their angular speed.

The forward speed is kept constant at

$$u = U.$$

The angular speed is proportional to the angular component of the total force $\mathbf{f}$. Hence, it ignores the magnitude $\|\mathbf{f}\|$ of the force:

$$\omega = K\angle\mathbf{f}.$$

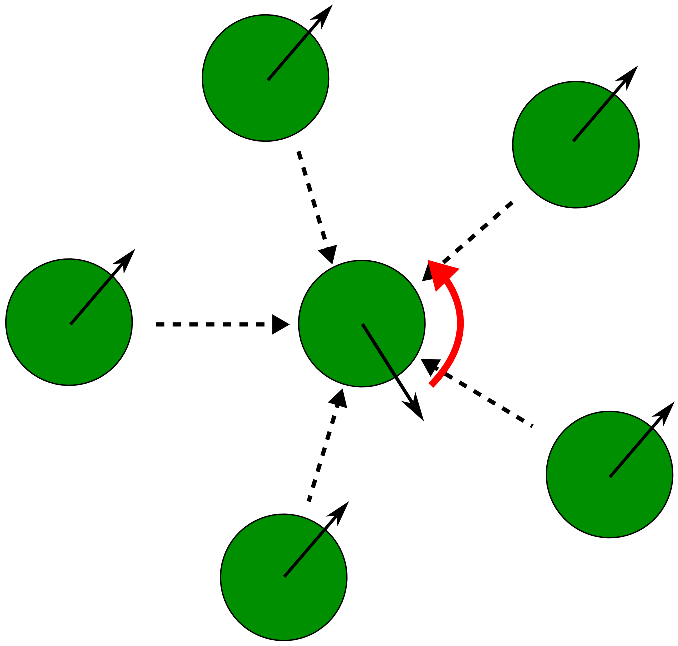

Figure 2.5: Alignment control behavior representation.

It is important to notice, that according to this rule, the values of α and β are not independent, and only their ratio matters. In fact, in this rule the magnitude of the resulting f vector is ignored and adding weighted vectors does not change the angle.

2.2.2 VMC

According to the second rule considered, denoted as *variable forward speed motion control* (henceforth VMC), robots move not only at a variable angular speed but also at a variable forward speed.

First, let $\mathbf{f}_x = \|\mathbf{f}\| \cos(\angle\mathbf{f})$ and $\mathbf{f}_y = \|\mathbf{f}\| \sin(\angle\mathbf{f})$ denote the projection of the total force $\mathbf{f}$ on the x-axis and y-axis of the robot body-fixed reference frame respectively. Accordingly, the forward speed u is directly proportional to the x component of the total force and the angular speed ω is directly proportional to the y component of the force. Hence:

$$u = K_1\mathbf{f}_x$$

$$\omega = K_2\mathbf{f}_y.$$

K, K_1, K_2 are constants, whose values are given in Table 3.1.

Contrarily as the CMC case, here the values of α and β matter, as the magnitude of the force vector as an influence on both linear and angular speed.

In this work, we consider and study two different cases in which we vary the motion control rule applied to the non-aligning robots. In the first case, referred as the *CMC-CMC* case, all robots share the same motion control rule, that is, CMC. In the second case, referred as the *CMC-VMC* case, aligning robots use CMC, whereas non-aligning robots use VMC (Figure 2.6).

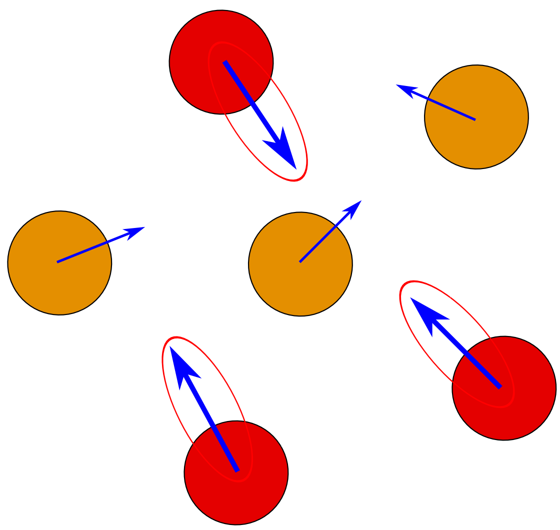

Figure 2.6: Heterogeneity in motion control rule. Non aligning robots here employ the VMC motion control rule.

2.3 Flocking With Robots

In this section we describe the robotic platform, whose simulated version is used to carry out our study, and how the forces described in the sections above are computed.

2.3.1 The Foot-bot

In this study, the swarm is composed of simulated versions of the foot-bot robot developed by Bonani et al. (2010), which is showed in Figure 2.7.

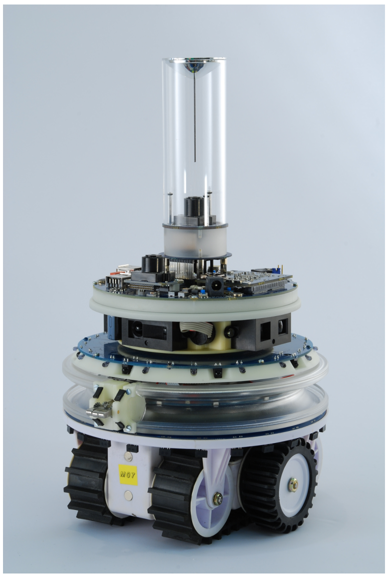

Figure 2.7: The Foot-bot.

The foot-bot is a differentially-driven mobile robot with the following sensors and actuators: i) A light sensor used to measure the orientation of robot (θ_0) with respect to a light source present in the environment perceived by all robots. ii) A range and bearing sensing and communication device (henceforth called RAB), with which a robot can communicate with its neighbors and perceive their range and bearing measurements (Roberts et al. 2009). iii) Two wheels actuators, that are used to control independently the left and right wheels speed of the robot.

At each time-step, each foot-bot performs two behaviors: the proximal control behavior and the alignment control behavior. These behaviors are used to compute the respective force vectors.

To achieve proximal control with the foot-bot, the RAB is used for measuring the relative range and bearing d_i and ϕ_i of the i_{th} neighbor. For achieving alignment control, we use communication to simulate orientation sensing as in Turgut et al. (2008). In particular, each aligning robot sends its orientation, expressed in the global reference frame, using the communication unit present in the RAB. At the same time, it receives the orientation θ_i

of its i^{th} neighboring aligning robot. It transforms this angle into its body-fixed reference frame. In this way, we are able to simulate a robot sensing the orientation of its neighboring aligning robots.

To achieve motion control, we first limit the forward speed within $[0,\ U_{max}]$, and the angular speed within $[-\Omega_{max},\ \Omega_{max}]$. We then use the differential drive model used in Turgut et al. (2008) to convert the forward speed u and the angular speed ω into the linear speeds of the left (N_L) and right (N_R) wheel:

$$N_L = \left(u + \frac{\omega}{2} l\right),$$

$$N_R = \left(u - \frac{\omega}{2} l\right),$$

where l is the distance between the wheels.

The values of the constants that we used in our experiments are given in Table 3.1.

Chapter 3

Experiments and Results

This chapter is dedicated to the description of the results obtained in this study. Section 3.1 describes the simulation framework, the experimental set-up and the metrics used to evaluate the flocking performance. In Section 3.2 we show the results obtained.

3.1 Experiments

3.1.1 The simulator

In robotics, the use of simulation tools is essential for the development of controllers. One of the main reasons is that they allow to test controllers without the risk of damaging the hardware. A simulation environment allows to prevent those situations to happen before they actually happen on the physical robots.

Another characteristic that makes simulations convenient is the speed of execution. In fact, a software can simulate hours of real time in some minutes, removes all the down times (example: time to replace robots' batteries or to set the environment up), and allows parallel execution of the same experiment on different computers. Additionally, figures collection and statistical analysis are usually easier in a simulated environment than in a real one.

As additional benefit for swarm robotics studies, a simulator allows to test algorithms and proof empirically their working principles with a huge amount of robots, which might not be available in reality.

On the downside, the intrinsic complexity of a (multi-)robot system and

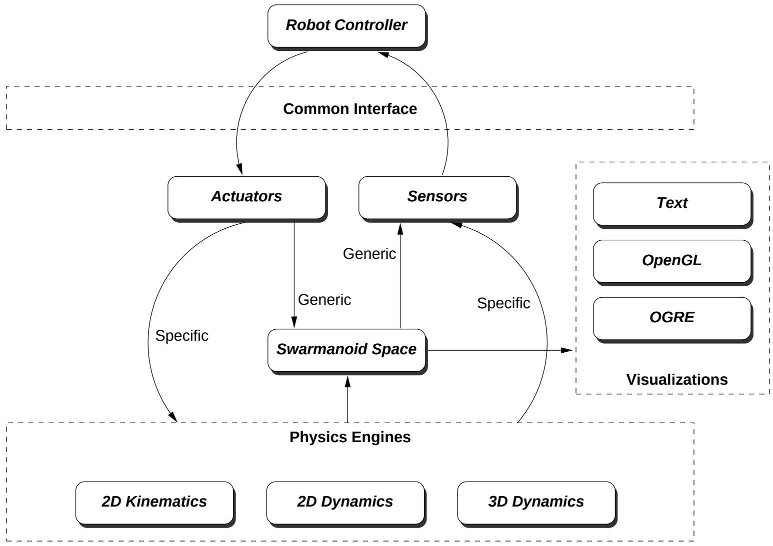

Figure 3.1: Overall architecture of the simulator.

of the real-world environment, makes sometimes hard the design of realistic simulation models to derive sound evaluations and predictions of the robotic system under study. In other words, the fact that a robot controller shows a given behavior in simulation does not mean that the same controller on the real robot will perform in the same way. This is due to the fact that a behavior arises from the interaction between the robot and its environment, and the simulated environment is different with respect to the real one. Adding noise to the simulations (e.g. to sensor readings and actuators outputs) helps bridging the gap between simulation and reality (Jacobi 1997).

We execute simulation-based experiments with a swarm of foot-bots using the ARGoS (Autonomous Robots Go Swarming) simulator (Pinciroli et al. 2011), an open-source[1], plug-in based, multi-physics engine simulator. The simulator was developed for the Swarmanoid project and is a custom software, written in C++ language, which implementation relies on free and open-source resources. An example of a swarm of simulated Foot-bots is given in Figure 3.2.

Despite the availability of several simulation software for robotics studies, the decision of writing a new simulator for the Swarmanoid project from scratch was taken. The main reason is the fact that Swarmanoid proposes a

[1] http://iridia.ulb.ac.be/argos/

novel set of robots, two of which (eye-bot and hand-bot) have peculiarities that exist only in the context of the project. Thus, in order to simulate the specific characteristics of the robots composing the Swarmanoid by using an existing simulator platform, we would have needed in any case to implement from scratch the majority of the modules. For instance, none of the currently available simulators include modules that could help to simulate the hand-bot climbing along the vertical dimension by shooting a rope that gets magnetically attached to the ceiling.

Therefore, in the case of choosing to adapt an existing simulator to our needs, we would have found ourselves in the position of implementing from scratch, and/or heavily adapting, most of the simulation modules. This choice would have vanished the benefits of using a preexisting simulator, and at the same time forced us to adapt to a general software structure selected by a third party.

The conceptual architecture of ARGoS is shown in Figure 3.1. The simulator architecture is organized around one single component, the *Swarmanoid Space*. This is a central reference system representing the state of the simulation at each simulation step. It contains information about the position and orientation of each of the simulated entities: robots and all other objects that are present in the simulated environment.

The other components of the simulator interact mainly with the Swarmanoid Space. Physics engines calculate physical movements and interactions based on the actions of the different simulated entities; they then update the Swarmanoid Space with the new state of the simulated system. Renderers allow the visualization of the content of the Swarmanoid Space at each simulation step. Sensors and actuators can interact either with the Swarmanoid Space or directly with the physics engines.

This architecture, with the *Swarmanoid Space* as central reference point, has been thought to give high modularity to the software: each of the sensors, actuators, renders and physics engines are implemented as plug-ins and can be easily changed, selected and tuned through an XML configuration file.

Another core feature of the simulator is the *Common Interface*. This is a collection of interfaces that defines the functions that are available to a robot controller for interacting with sensors and actuators. The common interface is the same on the real robots as it is in ARGoS. This has been done to allow having the same controller code working in ARGoSand on the real robots. The controller, in fact, ignores whether it is interacting with simulated sensors and actuators or real ones. This speeds up the development of the controllers as it is not necessary to port the code from the simulated version to the real robot version.

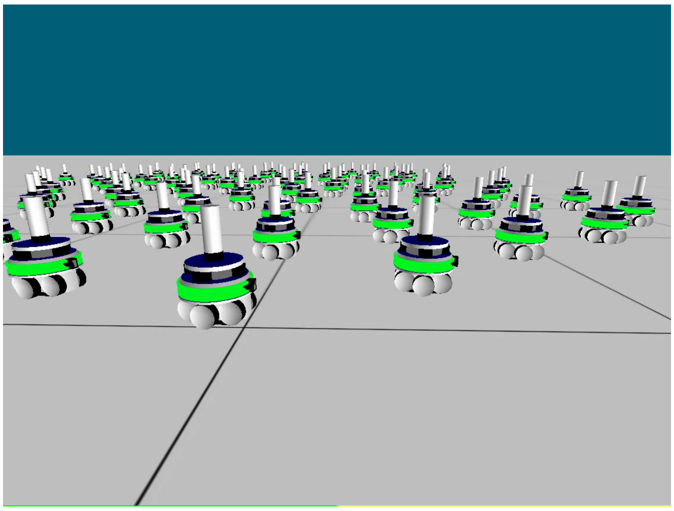

Figure 3.2: A swarm of simulated Foot-bots in ARGoS.

3.1.2 Experiment set-up

At the beginning of each experiment, N mobile robots are randomly placed (position and orientation-wise) with a proportion $\rho \in [0, 1]$ of aligning robots. The density of robots is kept fixed and equal to 6 robots per square meter on a square shaped area. A light source is placed at a fixed position in the environment, far away from the swarm, to provide the common reference frame.

In the experiments, noise is added to the orientation measurement and the angle of the proximal control vector. Noise is modeled as a uniformly distributed random variable within the range $[-\sigma\pi, \sigma\pi]$.

We conduct experiments considering the two different cases of motion control.

CMC-CMC In this case, all robots use CMC. Here, we study the effect of the ratio $\frac{\beta_1}{\alpha_1}$, and we do not change α_1 and β_1 independently, since CMC does not utilize the magnitude of $\mathbf{f}$, but only its angular component. As such, multiplying both α_1 and β_1 with the same constant

Variable	Description	Value(s) / Range
N	Number of robots	$\{25, 100\}$
ρ	Prop. of aligning robots	$\{0.4, 0.8\}$
β_1/α_1	Alig. robots parameters	$\{1, 2, 4, 6, 8, 10\}$
α_2	Non alig. robots parameter	$\{1, 2, 4, 6, 8, 10\}$
U	Maximum forward speed	1.5 cm/s
K	CMC angular gain	0.5 1/s
K_1	VMC linear gain	0.25 s/kg
K_2	VMC angular gain	0.1 s/(kg · m)
l	Inter-wheel distance	0.1 m
U_{max}	VMC max forward speed	20 cm/s
Ω_{max}	VMC max angular speed	$\pi/2$ rad/s
ϵ	Strength of pot. function	0.5
d_{des}	Inter-robot distance	0.6 m
σ	Amount of noise	0.1
T	Experiment duration	600 secs

Table 3.1: Experimental values or range of values for all constants and variables

value will produce no difference in the robot motion. For the same reason, α_2 does not effect the robot motion.

CMC-VMC In this case, aligning robots use CMC whereas non-aligning robots are using VMC. For the non-aligning robots, the magnitude of **f** plays a role in their motion. Thus, additionally to the effect of changing $\frac{\beta_1}{\alpha_1}$ of the aligning robots, we study the effect of changing α_2 of the non-aligning robots.

We show the results in heterogeneous self-organized flocking with medium ($N = 25$) and large ($N = 100$) swarm sizes and with low ($\rho = 0.4$) and high ($\rho = 0.8$) proportions of aligning robots. We study the effect of changing the ratio $\frac{\beta_1}{\alpha_1} \in \{1, 2, 4, 6, 8, 10\}$ and, for the heterogeneous case, we also study the effect of changing $\alpha_2 \in \{1, 2, 4, 6, 8, 10\}$, but we report here only the results obtained with the best case, that is, $\alpha_2 = 10$ (refer to Stranieri et al. (2011) for the complete set of results). In our supplementary page (Stranieri et al. 2011), we also report the flocking performance as a function of $\rho \in \{0.2, 0.4, 0.6, 0.8, 1.0\}$.

For each experimental setting, we execute R runs and report median and inter-quartile range of the results. The duration of one run is T simulated seconds.

We study how the heterogeneous flocking performance is influenced by: i) the way robots implement their motion (CMC-CMC motion versus CMC-VMC motion), ii) the parameters that affect the strength of the proximal control vector and of the alignment control vector, that is, $\frac{\beta_1}{\alpha_1}$ and α_2, and iii) the ratio of aligning robots ρ .

We also experiments in the VMC-VMC case, but we didn't obtain any positive results, even with $\rho = 1$.

3.1.3 Metrics

In this study, we are interested in having a swarm of robots that move cohesively as a single group. Furthermore, the swarm should be aligned towards the same direction and move towards it as fast as possible. We use three metrics to measure the degree of attainment of these objectives: order, group cohesion and rescaled group speed.

Order: The order metric ψ measures the angular order of the robots (Vicsek et al. 1995), $\psi \approx 1$ when the group shares a common heading and $\psi \ll 1$ when each robot is pointing in a different direction. The order is defined as:

$$\psi = \frac{1}{N} \| \sum_{i=1}^{N} e^{j\theta_i} \|.$$

Group cohesion: To measure group cohesion ξ, we determine the number of groups g present at the end of each experiment (Couzin et al. 2005). Group cohesion is computed as:

$$\xi = 2 - \min(2, g).$$

and therefore takes values in $\{0, 1\}$.

Rescaled Group speed: We calculate the average group speed as:

$$s = \| \frac{\mathbf{c}_T - \mathbf{c}_0}{T} \|,$$

where $\mathbf{c}_T$ and $\mathbf{c}_0$ are the position of the center of mass of the swarm at the end and at the beginning of the experiment, respectively. We

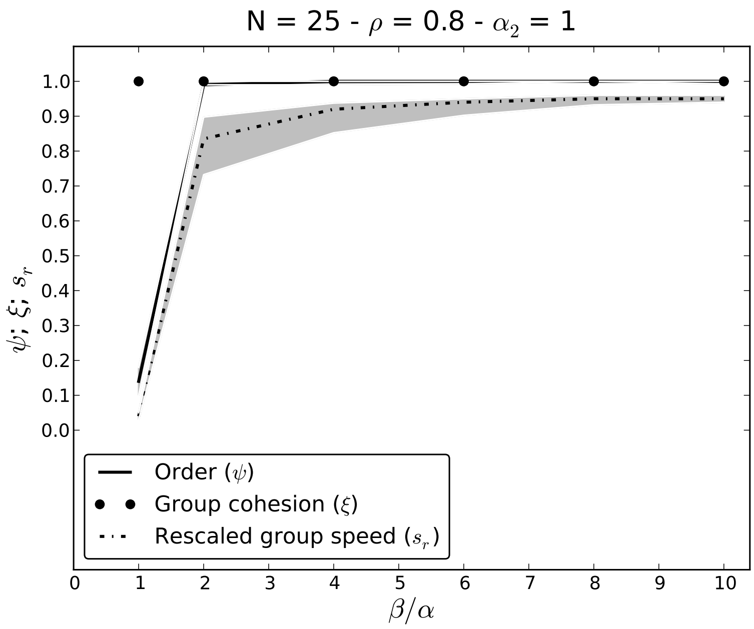

Figure 3.3: CMC-CMC case experiments for $N = 25$ and ratio of aligning robots $\rho = 0.8$. Thick lines show the median values, whereas the gray areas show the 25% and the 75% inter-quartile range of the data. For group cohesion, filled circles correspond to median values and empty circles to the 25% percentile score of the data.

then rescale the average group speed:

$$s_r = \frac{s}{U},$$

where U is the maximum forward speed of CMC.

3.2 Results

In this section we describes the results obtained in our study. This sections is sub-divided in two further parts, according to the two different motion control combination considered.

3.2.1 CMC-CMC case

We first focus on the $\rho = 0.8$ case, for both $N = 25$ (Figure 3.3) and $N = 100$ (Figure 3.4). Results show that the swarm is cohesive in most runs. However, order and speed are high only when $\frac{\beta_1}{\alpha_1} \geq 2$. Furthermore,

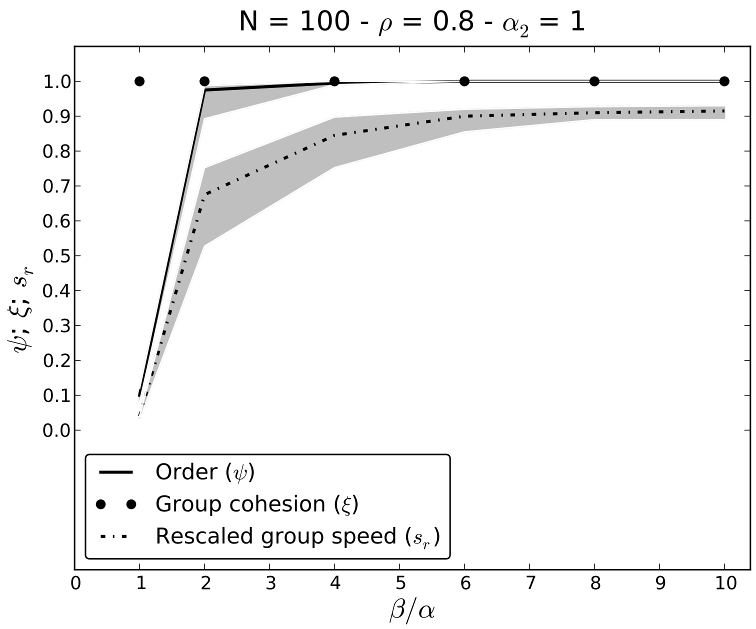

Figure 3.4: CMC-CMC case experiments for $N = 100$ and ratio of aligning robots $\rho = 0.8$.

while order is high at different values of the ratio $\frac{\beta_1}{\alpha_1}$, speed increases with increasing values of $\frac{\beta_1}{\alpha_1}$, until it saturates at around $\frac{\beta_1}{\alpha_1} = 6$. This shows that, when the alignment control vector is higher, robots tend to move faster. This is explained by the fact that the alignment control vector is more stable, over time, than the proximal control vector. Thus, the higher the weight of the alignment control vector, the more the robots tends to move forward rather than to turn. This allows the swarm to move faster, until speed saturates at the maximum forward speed U.

When the proportion of aligning robots is $\rho = 0.4$, performance gets sensibly worse (Figures 3.5 and 3.6). In both cases ($N = 25$ and $N = 100$), we observe two possible outcomes: for small values of the ratio $\frac{\beta_1}{\alpha_1}$, the swarm remains cohesive, but does not move. This happens because the relative contribution of the alignment control vector is not enough for the aligning robots to pull the entire swarm towards the agreed goal direction. For larger values of the ratio $\frac{\beta_1}{\alpha_1}$, group speed and order get higher. However, in at least 25% of the runs, the swarm splits. This happens because, in those runs, clusters of non-aligning robots are present. Since the motion of these robots is governed only by the proximal control vector, they are not able

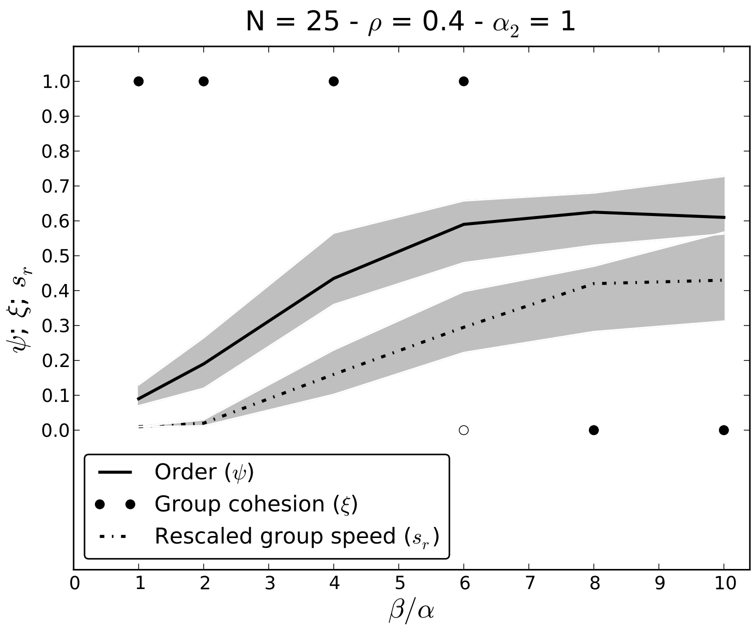

Figure 3.5: CMC-CMC case experiments for $N = 25$ and ratio of aligning robots $\rho = 0.4$.

to match the higher speed of the aligning robots since they tend to turn more rather than to move forward, thus they remain disconnected from the group, as exemplified in Figure 3.7.

In Stranieri et al. (2011), we also report the performance as function of ρ. We consider the case $\frac{\beta_1}{\alpha_1} = 10$, as it generally provides the best overall results. As shown in Stranieri et al. (2011), the flocking performance is acceptable in terms of the metrics used for $\rho \geq 0.6$ in both cases $N = 25$ and $N = 100$.

3.2.2 CMC-VMC case

In the CMC-VMC case, results with $\rho = 0.8$ (Figures 3.8 and 3.9), are similar to the results obtained, with the same ratio, in the CMC-CMC case. The results with $\rho = 0.4$ are much better in the CMC-VMC case (Figures 3.10 and 3.11) with respect to the CMC-CMC case (Figures 3.5 and 3.6). With both swarm sizes we have that, when $\frac{\beta_1}{\alpha_1} > 2$, the swarm is able to effectively flock together at the cost of a reduced speed.

InStranieri et al. (2011), we also report the flocking performance as a function of ρ for $\frac{\beta_1}{\alpha_1} = 10$ and $\alpha_2 = 10$. Differently from the CMC-CMC

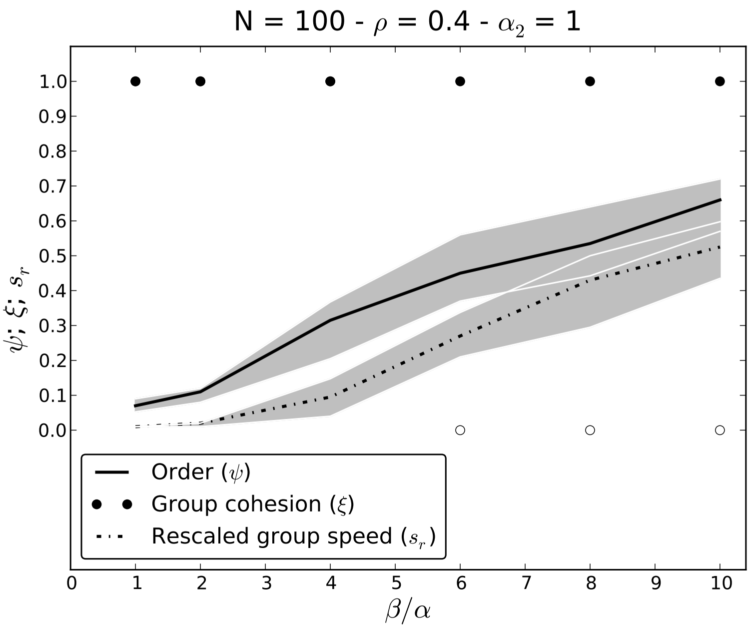

Figure 3.6: CMC-CMC case experiments for $N = 100$ and ratio of aligning robots $\rho = 0.4$.

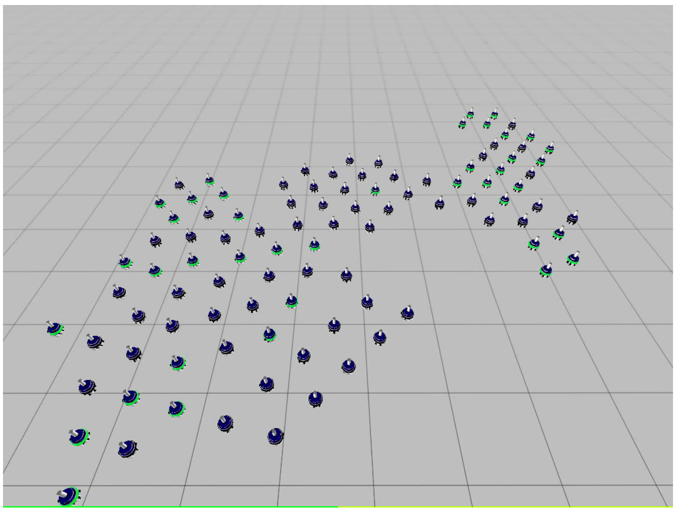

Figure 3.7: A condition of unsuccessful flocking behavior. The swarm after while splits in different groups. The aligning robots are able effectively flock, whereas the non-aligning ones are unable to keep the pace.

case, in the CMC-VMC case the performance of flocking degrades more gracefully as the proportion of non-aligning robots decreases.

The improved capability of the swarm to stay together is due to the

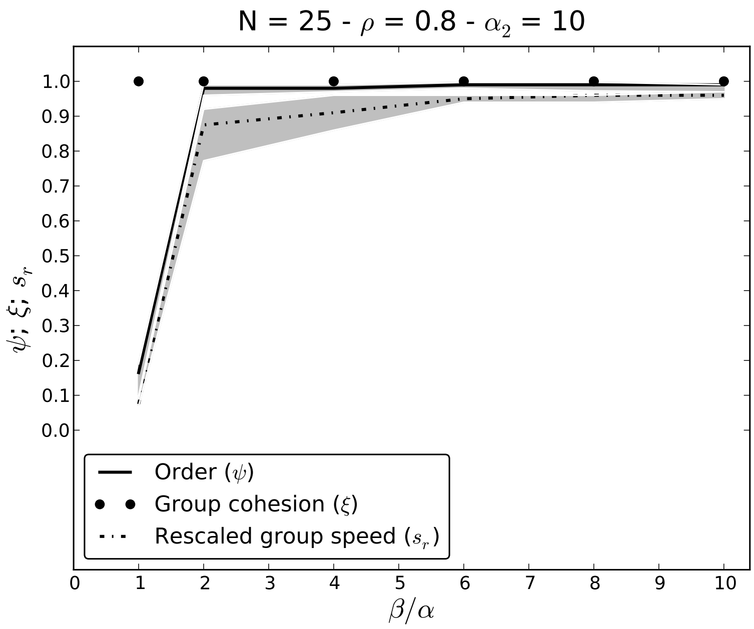

Figure 3.8: CMC-VMC case experiments for $N = 25$ and ratio of aligning robots $\rho = 0.8$.

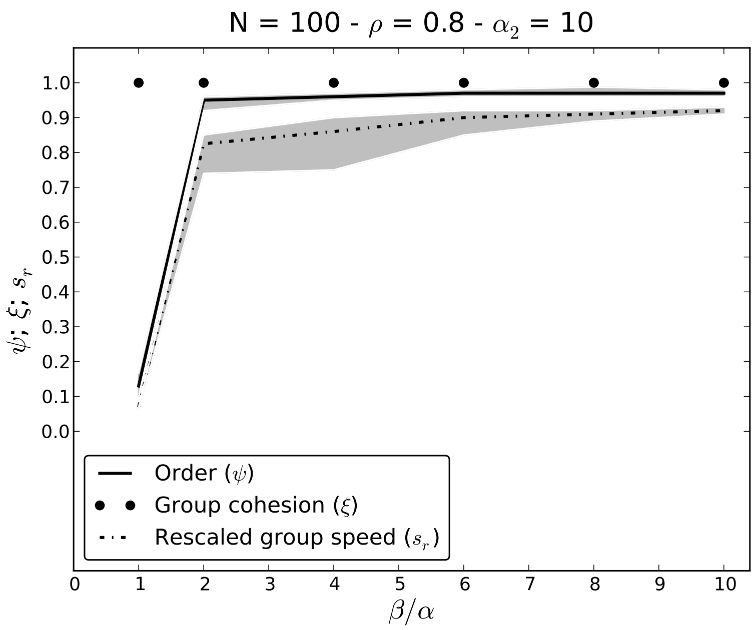

Figure 3.9: CMC-VMC case experiments for $N = 100$ and ratio of aligning robots $\rho = 0.8$.

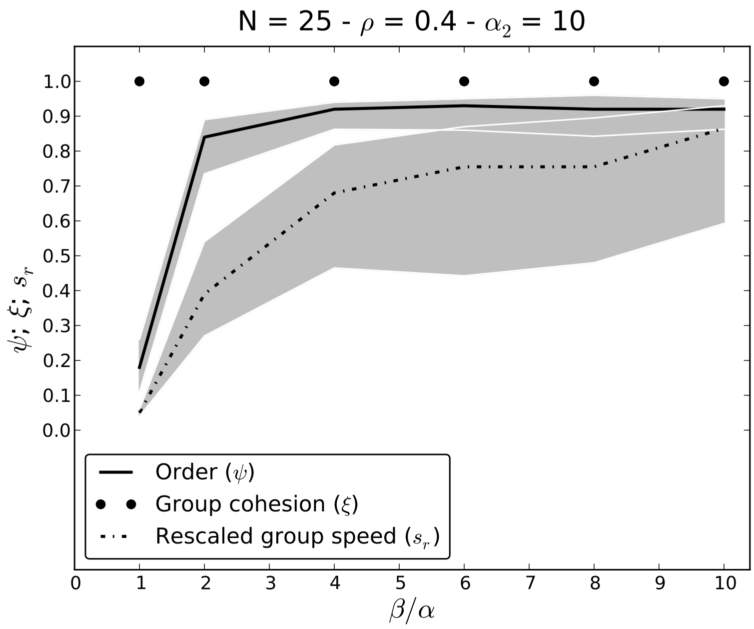

Figure 3.10: CMC-VMC case experiments for $N = 25$ and ratio of aligning robots $\rho = 0.4$.

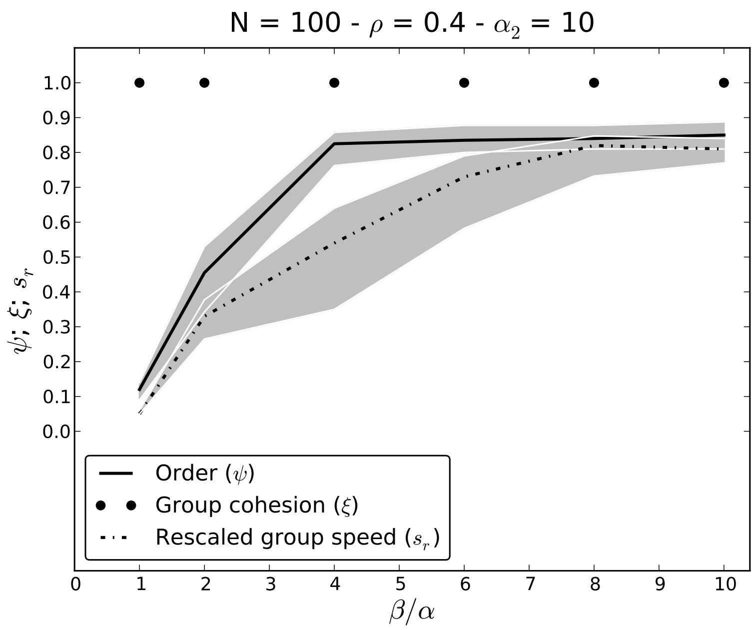

Figure 3.11: CMC-VMC case experiments for $N = 100$ and ratio of aligning robots $\rho = 0.4$.

advantage of using VMC in the non-aligning robots. In fact, non-aligning robots are able to respond to the high variations in the proximal control vector much more when they can also change their forward speed. As such, they are also able to stay together with the aligning robots, both when they are alone and when they are in small or big clusters. Finally, the reduced speed and the high variation of speed among runs is due to the following fact. In presence of a low proportion of aligning robots, we observed that the group heading direction is stable over short periods of time but changes over long periods of time due to the disturbances caused by the non-aligning robots. This results in a non-linear trajectory executed by the entire swarm, which is different for each run. Since the rescaled group speed is computed assuming a linear trajectory, this measurement has large variation in the total displacement changes from run to run.

Chapter 4

Conclusions and Future Work

In this work, we studied self-organized flocking in a swarm composed of behaviorally heterogeneous mobile robots. The swarm is composed of aligning robots, which are able to agree on a common heading direction, and non-aligning robots which lack this capability. We furthermore propose a new model for achieving motion in self-organized flocking. According to this model, aligning robots only change their angular speed, whereas non-aligning robots change both their forward and their angular speed.

We study the performance in terms of group alignment order, cohesiveness and speed. Results show that self-organized flocking is also possible when some individuals in the swarm lack the capability to agree on a common direction. More in particular, we showed that: i) a higher proportion of aligning robots always corresponds a to better performance; ii) performance is affected by the relative contribution of alignment and proximal control, and iii) for smaller proportions of aligning robots, flocking is possible only when the non-aligning robots also change their forward speeds .

Possible directions for future work are the following: First, we plan to study energy efficiency within the same framework of study. In particular, the use of a heterogeneous group of aligning and non-aligning robots poses a trade-off between efficiency of the motion and energy utilized. In fact, we observed that, in order for the swarm to hold cohesiveness, the non-aligning robots spend a lot of energy to vary their speed more reactively. Second, we would like to study the correlation between spatial aspects of the swarm composition. In particular, we would like to study whether particular configurations (i.e., topology, connectivity, ...) have different effects on the flocking performance. Third, we plan to perform experiments involving two different types of real robots.

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