# CONTROL OF A MOBILE ROBOT SWARM VIA INFORMED ROBOTS

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# ABSTRACT

CONTROL OF A MOBILE ROBOT SWARM VIA INFORMED ROBOTS

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In this thesis, we study how and to what extent a self-organized mobile robot flock can be guided by "informing" some of the robots within the flock about a preferred direction of motion. Specifically, we extend a flocking behavior that was shown to maneuver a swarm of mobile robots as a cohesive group in free space, avoiding obstacles. In its original form, this behavior does not have a preferred direction and the flock would wander aimlessly. In this study, we incorporate a preference for a goal direction in some of the robots. These "informed" robots do not signal that they are informed (a.k.a. unacknowledged leadership) and instead guide the swarm by their tendency to move in the desired direction. Through experimental results with physical and simulated robots we show that the self-organized flocking of a robot swarm can be effectively guided by an informed minority of the flock. We evaluate the system using a number of quantitative metrics: First, we propose to use the mutual information metric from Information Theory as a dynamical measure of the information exchange. Then, we discuss the accuracy metric from directional statistics and size of the largest cluster as the measures of system performance. Using these metrics, we perform analyses from two points of views: In the transient analyses, we demonstrate the information exchange between the robots as the time advances, and the increase in the accuracy of the flock when the conditions are suitable for an adequate amount of information

exchange. In the steady state analyses, we investigate the interdependent effects of the size of the flock in terms of the robots in it, the ratio of informed robots in the flock over the total flock size, the weight of the direction preference behavior, and the noise in the system.

Keywords: swarm robotics, flocking, control, informed robots, self-organization, unacknowledged leadership, decision making, multi-agent systems

# ÖZ

BIR GEZER ROBOT SÜRÜSÜNÜN BİLGİLENDİRİLMİŞ ROBOTLARLA KONTROL EDİLMESİ

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Bu tezde, kendi kendine örgütlenen bir gezer robot sürüsünün akın etmesi (*ing.* flocking) davranışının, sürüdeki bazı robotlara tercih edilen bir hareket yönü bilgisi verilerek nasıl ve ne dereceye kadar yönlendirilebileceği incelenmektedir. Bu amaçla, önceki çalışmalarımızda geliştirdiğimiz, bir gezer robot oğulunu engellerden kaçınan bütünleşik bir grup halinde gezdirebilen bir akın etme davranışı genişletilmektedir. Bu davranışın orijinal halinde bir hedef yön bulunmamaktadır ve sürü amaçsız bir şekilde hareket etmektedir. Bu çalışmada robotlardan bazılarına bir hedef yön bilgisi verilmektedir. Bilgilendirilmiş olan robotlar, bunu diğer robotlara iletmek yerine, sürüyü kendilerinin istenen yönde gitme eğilimleri ile yönlendirmektedirler. Fiziksel ve benzetimsel robotlarla yapılan deneylerle bir oğul robot sürüsünün kendi kendine akın etmesi davranışının, sürüdeki azınlık bir grubu bilgilendirerek etkin bir şekilde yönlendirilebileceği gösterilmektedir. Sistem bir dizi nesnel ölçütle değerlendirilmektedir: Bunlardan birincisi, bilgi alışverişinin dinamik bir ölçütü olarak kullanmayı önerdiğimiz, Bilgi Teorisinden karşılıklı bilgi ölçütüdür. Diğerleri ise sistemin başarımını öçmek için kullandığımız, yönlü istatistikten doğruluk ölçütü ve sistemdeki en büyük kümenin robot sayısıdır. Bu ölçütlerle iki tip analiz yapılmaktadır: Geçici rejim analizlerinde, zaman ilerledikçe robotlar arasında gerçekleşen bilgi aktarımı, ve şartlar yeterli

bilgi aktarımı için uygun olduğunda sistemin doğruluğundaki artış gösterilmektedir. Sürekli rejim analizlerde, birbirine bağlı etkiler olan, sürüdeki robot sayısının etkisi, bilgilendirilmiş robot sayısının sürü büyüklüğüne oranının etkisi, tercih edilen hareket yönüne verilen önemin etkisi, ve sistemdeki gürültünün etkisi incelenmektedir.

Anahtar Kelimeler: oğul robot bilimi, sürü halinde akın etme davranışı, kontrol, bilgilendirilmiş robotlar, kendi-kendine örgütlenme, duyurusuz liderlik, karar verme, çok erkinli sistemler

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# CHAPTER 1

# INTRODUCTION

There cannot be a human who has not once fancied themselves in a hammock by the sea in a quiet summer evening, the sun setting behind the waves, a soft breeze running through the leaves... A little bit of idleness is something that we all need every now and then, if it is not our ultimate dream. Yet there are things to take care of, dishes to clean, laundry to wash, dinner to cook... How can a man have a quiet time among all these? The man has found a feasible answer: Somebody else must take care of them.

Karel Čapek in his play R.U.R. (Rossum's Universal Robots) tells the story of such artificial humanoid creatures who are made to serve. The word "robot", originally following from Czech word "robota" meaning "work", has been borrowed from him, and used for various mechatronic creatures as the technology advanced. There are robots being used in factories for highly specialized work, which require much more precision than can be trusted to a human, but much less other kinds of decisions like when to run the drill: The drill will be run at every twentieth second, and the piece is guaranteed to be ready in front of the drill by then. Or there are robots which are made to resemble humans, like ASIMO, or even dogs, like AIBO. There are robots which take on space missions, like Phoenix, and there are robots which clean our houses, like Roomba. They have even gone a long way in the literature: Asimov wrote about robots that were built to comply with the Three Laws of Robotics, but who in the end find themselves guiding the construction of two Galactic Empires in succession, by adding a Zeroth Law to them.

As the mechatronics technology advances even further, it is enabling the mass production of cheaper and cheaper robots, even in micro or nano scale. What if we had thousands of robots, and it would not cause a financial breakdown if a hundred of them suddenly collapsed? Where could we use them? In area coverage tasks, for example, where a single robot would be a helpless officer in an area surveillance mission, but a thousand of robots spread all around could mean any attacks detected immediately. Risky tasks is another example, sending one robot to minesweeping means that all care must be taken that the robot is safe, sending a thousand robots means a hundred of them may survive the mission even if things go quite wrong. Yet another is tasks that can require a larger or smaller number of attendants at any time, such as when a leakage is detected in a station, many more robots becoming necessary at once to stop the leakage from spreading further. In all these areas, it seems not only beneficial, but also necessary that a group of robots must act together for a mission.

However, it is not very trivial to make a group of robots act together. First of all, how will they decide what to do? Will we need to guide them by sending a signal to each one? This does not seem very feasible, for there may be tasks where it is hard to send a signal to, such as a mission on Mars, or infeasible, such as the environmental monitoring of a lake continuing for years. If a human will not, then who will decide in the name of the group? A dedicated "leader" robot? What if this leader is "killed", or is somehow damaged? Will it suffice to add a few more leaders? Another issue is about scalability: If a robot needs to see the positions of all other robots via its camera in order to plan its move, how large an area can it see? Ten robots, or a hundred? And what if we have five hundred robots that goes beyond the field of view?

Swarm robotics approach has been proposed as an answer for these concerns. It is defined in [2] as "a novel approach to the coordination of large numbers of relatively simple robots which takes its inspiration from social insects", which "stand as fascinating examples of how a large number of simple individuals can interact to create collectively intelligent systems". These colonial beings demonstrate amazing capabilities when working together, greatly surpassing their individual abilities: Huge termite mounds, ants' foraging raids, massive preys carried by ants are all examples of this phenomenon. Together, they show many high level properties that we would wish for the multi-robot systems: Robustness, the ability to operate even if a part of the individuals become non-operational, or disturbances occur in the environment; flexibility, the ability to produce various solutions to various problems using the same basic behaviors; and scalability, the insensitivity to major increases or decreases in the number of the individuals. And what is most interesting is that they do not even know about these capabilities. These capabilities merely occur as a side effect of their local and simplistic interactions, or in other words, they are "emergent".

The appealing property of biological swarm systems, as well as many physical and chemical systems, is "self-organization", which is, quoting from Camazine et al. [3], "...is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of the system". Ant and termite colonies are completely self-organized. And so is the spontaneous magnetization of a substance, too. With this inspiration, swarm robotics also tries to achieve self-organization in a large groups of robots with no centralized control, while putting emphasis on flexibility, robustness and scalability. Therefore, most of the ongoing studies have focused on the "application" of self-organization approach. Many coordination problems studied try to exploit this property: Aggregation is the gathering of scattered robots in one large cluster, dispersion is the scattering of robots in order to cover the largest possible area without losing contact with each other, pattern formation is the formation of prespecified global patterns, flocking is the coherent movement of the robots in an environment as a super-organism which avoids obstacles on its way, and self-assembly is the gathering of robots in specific ways to physically form complex structures in order to solve certain problems. In all of these studies, these behaviors are strived to be obtained using only local interactions between the robots, that is, robots being only aware of their closest neighbors, and with no central control guiding the whole process.

Meanwhile, from an engineering point of view, the "controllability" of a self-organized robot swarm according to the objectives of a user is a subject that has been not yet been fully achieved, leaving the question of how useful the approach can be in real-world use, unanswered. If we have a swarm of unmanned air vehicles, we will need to control which way they go, otherwise they can be of no use. How can we tell this swarm to head to a specific goal direction, without disturbing their self-organization ability? We certainly would not want to control each and everyone of them separately, at the expense of all the autonomy advantages gained by the swarm robotics approach. Is it possible that we should give them a hint of what we want them to do, and that they just self-organize with this bias? In this study, we are interested in how, and to what extent we can control the behavior of a swarm robotic system. Specifically, we are interested in how behaviors that lead to self-organization in a robotic flock can be externally controlled via informing a (possibly quite small) subset of the robots about a preferred direction to follow.

The organization of the work is as follows: In the subsequent chapter, a survey of existing literature on swarm control, decision making in swarms and flocking is presented. In Chapter 3, we present the experimental framework utilized in this study, including the robotic platform and the corresponding simulation environment. In Chapter 4, we propose the flocking behavior and the control scheme built on this platform. Chapter 5 introduces some metrics for quantifying the performance, and Chapter 6 analyzes systematic experiments using these metrics. Chapter 7 concludes with stating the results and pointing future directions.

# CHAPTER 2

# RELATED WORK

In this section, a survey of the literature is presented as related to our work. The related studies can be divided into three groups: (1) studies which are related to the external control of swarm systems, (2) studies which are related to the control of swarm systems with a number of controlled individuals inside the swarm, and (3) studies which are related with the flocking behavior, and the implementations of the flocking behavior in robotics.

## 2.1 External Control of Swarm Systems

There have been a number of studies that investigated external control in natural swarms or in mixed robot-animal societies. One strategy is having an external shepherd outside the flock, which behaves in a certain way to act as a control input for the flock members. In a very interesting work, Vaughan et al. [4] used a robotic sheepdog to herd a duck flock to a predefined goal point. A simple model of flocking was assumed stating that the ducks would be attracted to and repelled from each other, while also being repelled from the walls and the robot. The robot, meanwhile, was attracted to and repelled from the ducks, and repelled from the goal point. The robot's momentary velocity vector was calculated using an overhead camera system which monitored its position and orientation, as well as the flock's center position and size. Real world experiments were conducted as well as simulations, which revealed a successful, although oscillatory, motion. In a second set of experiments, the oscillation was reduced by utilizing the flock's distance to the goal point as the control input for the attraction force between the robot and the ducks.

Lien et al. in [5] also discussed the "Shepherding Behaviors" using an external agent controlling the flock. They argued that the performance of flock control by an external shepherd depends on its approaching and steering strategies, for which they compared various methods. For the approaching strategy, they compared (1) approaching the flock on a straight line, (2) approaching the flock by leaving a safe zone, and (3) approaching the flock by using a dynamic roadmap. For the steering strategy, they compared (1) steering the flock from straight behind it, (2) steering the flock from sides, (3) initiating a turn by first stopping the flock by standing in front of it, and (4) initiating a turn by first standing in a position to shift the flock's heading towards the goal. Then they utilized these strategies for developing a variety of shepherding behaviors, namely herding (moving flock members towards a goal), covering (moving flock members towards unvisited areas in the environment), patrolling (guarding flock members off a prohibited area), and collecting (gathering scattered flock members together), and compared the performances. In another work, Lien et al. extended their work to the case of multiple shepherds with no explicit communication between them [6].

## 2.2 Control of Swarm Systems via Informed Individuals

A quite different point for view of controlling a swarm system is having a number of informed individuals in a swarm, which may be programmed agents that are somehow "integrated" as if normal flock members. These members are expected to affect the decisions of the whole swarm via their local interactions. The question is whether the informed individuals, who possess no explicit means of signalling their information or leadership to the others, can be perceived by the naive individuals to be acting in particular way so that the naive individuals also mimic their actions, leading to a global pattern.

Ward et al. [7] proposed that the decision making mechanisms in swarms may be dependent on quorum responses, with individuals responding only when a threshold number of other individuals are performing a behavior. They developed a probabilistic model, in which the probability of an individual preferring left or right direction increases with the number of individuals that have recently preferred the same direction. The model incorporates a parameter $k$ which indicates the steepness of the response. When $k = 1$, it indicates a weak linear response, where the probability of choosing a direction is linearly proportional to the number of individuals recently preferred the same direction. When $k > 1$, it indicates a quorum response, where the probability increases once a quorum is met. Three sets of experiments were then conducted with replica conspecifics to determine the underlying form of the response. In the first set, the response of fish to the replica conspesifics was tested. In these experiments, fish were observed to take the direction initiated by the majority of replica conspecifis. In the second set, the response of fish were tested in the presence of a replica predator. As the group size increased, more replica conspecifics were needed to deceive the fish to choose the direction of the predator. The results of both experiments were best fitted by a $k$ value greater than 3, indicating a quorum response. The results also suggested that quorum decision making decreased the likelihood that the effect of a wrong choice made by a small number of individuals (which is going in the direction of a predator) would be amplified by indiscriminative mimicry of others. In the final set of experiments, the effect of quorum decision making on accuracy was investigated by conducting simulations where the probability of an individual to detect a predator correctly was 1/3. The results showed that, as the group size increased, nonlinear quorum responses would become more accurate than independent decision making or weak linear responses.

Halloy et al. [8] manipulated the collective shelter selection process of a group of cockroaches with robots that were socially integrated into the group. In the test environment there were two shelters under which the cockroaches can aggregate to avoid light. A probabilistic model previously developed in [9] was employed, where the cockroaches encountered shelters randomly while exploring the environment. Each cockroach was assumed to have a probability of joining an encountered shelter which decreased linearly with the ratio between the number of individuals present in the shelter and the shelters carrying capacity (which stands for a crowding effect). Furthermore, a cockroach currently in a shelter had the probability of leaving it which was linearly affected from the quality of the shelter, i.e, its darkness, and exponentially affected from the number of individuals currently in the shelter. The exponent $n$ is a parameter which indicates a quorum response in time when greater than 1. This model was then run on robots which were coated with by a blend of hydrocarbons obtained from cockroaches. In one set of experiments, the robots were programmed to prefer darker shelters, just as the cockroaches do. Then, it was shown that, in an environment with two identically dark shelters, robots and cockroaches selected a common shelter, suggesting that a collective decision making took place in the mixed society, and that the group behaved as a whole. The second set of experiments were conducted in an environment with one darker and one lighter shelter, and the robots were programmed to prefer lighter shelters, in contrast with the cockroaches. Under these conditions, the robots were able to manipulate the group decision making process, and cause the whole group prefer the lighter shelter in most of the cases, although they were in the minority (4 robots vs. 12 cockroaches). Yet, the selection of the darker shelter was still possible, since the robots were also a part of the society, and responded to the choices of the cockroaches, instead of merely acting as a source of attraction.

A similar idea of swarm manipulation by informed individuals has recently been exploited for understanding directional decision making in flocking animals. The question now is whether a moving flock can be guided towards the right direction by a number of unacknowledged individuals who “know” which way to go. Reebs [10] studied the decision making mechanisms in the foraging movements of fish schools, and showed that relatively few individuals with a priori knowledge can guide the whole school. He trained 12 golden shiners in a tank to move to a brightly lit corner in a specific time of day to find food. Then, replacing 7, 9, and 11 of these trained individuals with untrained ones, he tested whether the minority of informed individuals could manage to move the whole flock in the trained direction. He showed that in all cases the flock could be guided, while the performance increased with the number of informed individuals. Moreover, the flock could manage to continue as an unfragmented group, and it was always led by the same fish, presumably the informed ones.

Couzin et al. [11] exploited the idea of a few number of informed individuals for modeling the dynamics of decision making of flocks. In their model, the naive individuals arranged their positions and alignments according to their neighbors, while the informed individuals also incorporated their preferred directions in their decisions. Numerical simulations showed that the accuracy of guiding increased as the size of flock increased while the ratio of informed individuals was kept fixed. The importance of the weight of the preferred direction was revealed to be less if the proportion of the informed individuals was too small or large. For intermediate proportions of informed individuals, increasing this weight increased the accuracy of the motion, however it also increased the fragmentation of the flock. The model furthermore predicted that if there were two informed groups with different preferences, the resulting behavior depended on the relative sizes of the groups. Although there were no mechanisms for the informed individuals to assess whether they were in a majority or minority, the flock moved collectively in the direction preferred by the majority of informed individuals, even when the majority was very small. On the other hand, if the two groups had the same number of informed individuals, the result depended on the difference between the two preferred directions. In case of small disagreements, the flock moved in the average of the two preferred directions, whereas in case of greater disagreements, one of the two preferred directions was randomly chosen. The authors mentioned that the capability of the group for averaging the preferences in case of small differences, but achieving a consensus in case great differences is an important ability. For achieving a similar and tunable capability in their model, they also incorporated an adaptiveness of the weight of the preferred direction, which increased when the informed individuals are moving in the same direction, and decreased otherwise.

In [12], Shi et al. investigated the effect of informing individuals in a flock with an external reference signal from a control point of view, using point mass dynamics. They introduced a number of control laws which depended of attraction/repulsion and alignment forces, as well as the external reference signal, called as a "virtual leader". They showed that the velocities of all agents asymptotically approached to the desired velocity, while collisions could be avoided, and a tight formation with minimized potential could be reached. They also considered cases in which velocity damping could not be ignored, and adding a velocity damping term into the control laws, they showed that the same stable motion could again be achieved. Furthermore, analyzing cases in which not all agents could receive the reference signal, they proved that stable motion was achievable even if there was a single informed individual, and increasing the number of informed individuals did not necessarily increase the convergence rate. However, it increased the robustness to noise, which was modeled as random forces acting on the agents, added to the control inputs.

## 2.3 Flocking

The pioneer to show that flocking behavior could emerge from completely decentralized, local interactions, was Reynolds [13], who was trying to obtain a realistic looking flocking behavior in computer animations. He proposed a set of simple rules for the individuals, which inspired the studies thereupon. Assuming the individuals could sense the bearing, range and orientation of their neighbors, if each individual tried to (1) avoid collisions with other individuals, (2) align its heading with nearby flockmates, and (3) move to the center of its nearby flockmates, then these local and individual based movements resulted in a totally decentralized flocking motion. Vicsek and Czirók [14] developed the self-driven particles (SDP) model to study the emergence of the self-aligned motion in biological systems. The SDP model incorporated a heading alignment rule for particles which move at a constant speed, in which the particles align themselves to the average of their neighbors. The model predicted that the group reached alignment as the noise is decreased, or the density of the particles is increased. Buhl et. al [15] analytically solved the SDP model in 1-dimension, and used it to model the flocking behavior of desert locusts with accurate predictions. Gregoire et al. [16] added an attraction/repulsion term for obtaining coherent flocking in open-space. Aldana and Huepe [17] proposed the vectorial network model (VNM), in which the particles are stationary, and studied the necessity of long-range interactions among particles for the settling of a common alignment (which can be considered as a phase transition from a disordered state to an ordered state). In accordance with the theorem of Mermin and Wagner [18], they showed that long-range interactions are crucial, either through even a small amount of long range sensing, or through the movements of individuals so as to change their local neighbors occasionally. Şamiloğlu et al. [19] extended the SDP model to be as realistic as possible, and with this aim they allowed for asynchronous sensing and actuation, as well as restrictions on the turning angle due to physical limitations. With these settings, they compared three different heading alignment strategies.

In the robotics side, Matarić [20] was one of the first to achieve flocking in a collective homing behavior, composed of safe-wandering, aggregation, dispersion and homing behaviors. The robots could localize themselves by stationary beacons and broadcast this information. Kelly and Keating [21] used robots that were able to sense the obstacles via ultrasound sensors, and the relative range and bearing of neighbors by a custom-made infrared (IR) system. A leader of the flock was elected by wireless communication, which wandered in the environment while others follow. Hayes and Tabatabaei [22] proposed a leaderless flocking algorithm, composed of collision avoidance and velocity matching flock centering behaviors. The robots were assumed to sense the range and bearing of their neighbors to compute the center-of-mass (CoM) of the group, and its heading towards a goal. The CoM was used for cohesion, and the change in CoM was used to align the robots. Although the algorithm was implemented on the Webots simulator, in the physical reality the sensors had to be emulated using an overhead camera system. Holland et al. [23] proposed a flocking scheme for unmanned air vehicles (UAVs) based on avoidance, flock centering and alignment behaviors. The range, bearing and velocity information were sent to the UAVs from a base station. Campo et al. [24] used a specifically designed colored LED system surrounding the body of s-bots, to have the s-bots negotiate their a priori estimations of the nest location. The s-bots then carried a heavy prey collectively to the collectively estimated nest location. Baldassarre [25] was the first to point out a link between the behavior of multi-robot systems and phase transitions, by proposing that self-organization in swarm systems could be considered as a phase transition from a disordered to an ordered phase. The degree of self-organization in a robot swarm was quantified by utilizing the Boltzmann Entropy metric, which measured the number of microstates a system can be in at a certain time. Then the time evolution of the Boltzmann Entropy was analyzed for viewing the phase transition from a disordered to an ordered phase, and drawing an analogy between physical systems and swarm systems. Nembrini et al. [26] developed a set of behaviors to achieve aggregation, collective obstacle avoidance, and collective taxis towards a beacon. The behaviors were developed on a swarm of 7 real robots that were equipped with a set of IR sensors for obstacle detection, an omni-directional IR system for robot detection and a wireless communication system. Although the simulations were successful, the experiments with physical robots suffered from the shortcomings of the hardware [27].

Without resorting to use the emulated sensors, a priori knowledge of the goal direction, or a leader to guide the flock, Turgut et al. [28] presented the first truly self-organized, leaderless, decentralized flocking in a robot swarm. In [29], the sensitivity of the system to the behavioral parameters and communication characteristics were investigated, and in [30] its transition from aligned to unaligned state was analyzed by extending the vectorial network model in the stiff-vectorial network model (S-VNM) to capture the robot dynamics.

The step that awaits to be taken now is towards controlling the direction of this self-organized flocking motion, which is our aim in this work. Inspired by the findings of [10], [11] and [12] on the decision making mechanisms in swarms, we extend the flocking behavior in a way to include a preference for a goal direction in some of the robots, which we call the "informed" robots. These "informed" robots do not signal that they are informed, and instead guide the rest of the swarm by their tendency to move in the desired direction. We present experimental results on both physical and simulated robots, and show that the self-organized flocking of a swarm of robots can be effectively guided by a minority of informed robots within the flock. Proposing a set of quantitative metrics, we analyze the system's performance under various conditions. To the best of our knowledge, this is the first study in which the direction of motion of a robotic flock is controlled via informing a subset of robots.

# CHAPTER 3

# EXPERIMENTAL FRAMEWORK

In this chapter, we present the details of the experimental framework used in this study, namely the Kobot, a robotic platform designed specifically for swarm robotics research, and Controllable-Swarm Simulator, a physics based simulator which is modeled according to the specifications of the Kobot platform.

## 3.1 Kobot Robotic Platform

As the experimental platform in this study, we use the Kobot, a CD-sized (12 cm diameter) robotic platform which has been developed specifically for swarm robotic studies (Figure 3.2) [29]. The Kobot hosts two differentially driven motors. There are eight infrared (IR) sensors placed evenly at 45° intervals around its base, through which it can measure the proximities of nearby artifacts in approximately 20 cm range, and which has a novel design for distinguishing other kin robots from unknown obstacles. It hosts a digital compass for measuring its own heading with respect to the magnetic field of the Earth. An IEEE 802.15.4/ZigBee compliant wireless communication module with a range of approximately 20 m indoors is used for communication between Kobots. The main controller on Kobot is a 20 MHz PIC18F4620A microcontroller, which can be programmed through the wireless communication channel. Kobot is specifically designed with the aim of low power consumption, and it can operate for 10 hours with a 2000 mAh lithium-polymer battery.

### 3.1.1 Infrared Short-Range Sensing System

The infrared short-range sensing system (IRSS) is responsible for measuring the proximities of nearby beings. It is specifically designed for distinguishing other kin robots

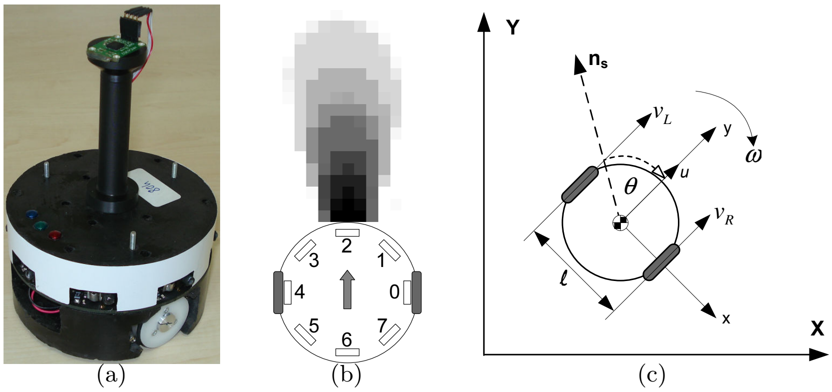



Figure 3.1: (a) The Kobot. (b) The scaled sketch of Kobot. The rectangles indicate the IR sensors located around the base. (c) The body-fixed reference frame of Kobot. It is concentric with the base of the robot, and the $x$-axis coincides with the rotation axis of the wheels. The forward velocity ($u$) is the velocity of the robot along its $y$-axis. $\omega$ is the angular velocity. $v_R$ and $v_L$ are the velocities of the right and left motors. The measured heading of the robot is $\theta$, which is the angle of the $y$-axis with the *sensed North* direction ($n_s$). $l$ is the distance between the wheels. Figures courtesy of [1].

from ordinary obstacles. It is composed of 8 IR sensors placed at 45° intervals around the base (Figure3.1(b)). The sensors can sense artifacts within a range of approximately 20 cm at seven discrete levels at 18 Hz. The output of the $k^{th}$ sensor is a 2-tuple ($o_k$, $r_k$). $o_k \in \{0, 1, \cdots, 7\}$ denotes the detection level to the object being sensed ($o_k = 1$ and $o_k = 7$ indicate respectively a far and nearby object. $o_k = 0$ indicates no object is detected by the sensor), and $r_k \in \{0, 1\}$ indicates whether the sensed object is another kin robot ($r_k = 1$) or an ordinary obstacle ($r_k = 0$). The utilization of modulated IR signals provides minimum environmental interference from the Sun and other light sources.

### 3.1.2 Virtual Heading Sensor

The virtual heading sensor (VHS) is composed of a digital compass, which measures the robot's heading ($\theta$) in clockwise direction with respect to the *sensed North* (Figure 3.1(c)), and a wireless communication module, which broadcasts this information at every control step, as well as collecting the information broadcasted by other robots. In effect, the VHS virtually *senses* the relative orientations of the neighboring robots.


(a) (b)

Figure 3.2: (a) A photo of 7 Kobots. (b) A snapshot from the CoSS environment. Figures courtesy of [1].

### 3.2 The Simulation Environment

A physics-based simulator, called Controllable-Swarm Simulator (CoSS) as shown in Figure 3.2 has been developed for conducting experiments with more robots than physically available, and for longer durations than possible on the current experimental setups [29]. CoSS is developed on the ODE (Open Dynamics Engine) physics engine which provides a physically realistic environment, by modeling forces, collisions between physical bodies, friction and slippages. The DC motors are simulated using virtual motorized hinge joints and the virtual weights of the components are adjusted to obtain a similar movement pattern with similar motor torques.

The IRSS is modeled in the simulator according to systematic experiments [29]. Meanwhile, the VHS is modeled using three parameters, the range of the communication, the number of robots whose broadcasted heading values can be received at one control step (referred to as the VHS neighbors), and the noise in the VHS. The range is determined by the range of the wireless module, which is 20 m. The number of VHS neighbors is set as 20 according to radio simulations [29]. The noise is added to the self-heading measurements of each robot, since the noise in the VHS is mostly due to the noise in the measurements of the digital compass, and the broadcasting process of the wireless module is virtually noiseless. Although the inherent noise of the compass is about $\pm 0.5°$ in ideal operating conditions, the indoor environments typically contain a large amount of ferrous metals, so the measurement noise is usually much higher than the provided range. We model the noise on the VHS with the vectorial noise model [16]. A random noise vector is added with a vector sum to the heading measurements performed by each robot. The robots then broadcast this noisy measurement, therefore, the heading values sensed by the VHS neighbors are likewise noisy. The noise vectors are characterized by a random direction and a constant magnitude. The direction ($\xi_o$) is chosen from a Gaussian distribution, whose mean is the noiseless heading value, and standard deviation is $\pi/2$. The magnitude ($\eta$) is a free variable which determines the effect of noise.

# CHAPTER 4

# THE FLOCKING BEHAVIOR

In [29], a self-organized, fully distributed flocking algorithm for a swarm of robots is proposed, which emerges from two simpler behaviors: (1) the heading alignment behavior, which serves to obtain a common direction of motion for the whole flock, and (2) the proximal control behavior, which prevents collisions and separations in the flock. In the original form of the emergent flocking behavior, the flock does not have a preferred direction of motion, and wanders aimlessly in the environment. In this work, we aim to control the direction of motion of the flock, by including a predefined direction as a bias. The resulting behavior can be expressed as a weighted vector sum of these three terms:

$$\vec{a} = \frac{\vec{h} + \beta \ \vec{p} + \gamma \ \vec{d}}{\|\vec{h} + \beta \ \vec{p} + \gamma \ \vec{d}\|}$$

where $\vec{h}$ is the heading alignment vector, $\vec{p}$ is the proximal control vector and $\vec{d}$ is the preferred direction vector. $\vec{a}$ is the resultant desired heading vector, according to which a robot calculates its own direction of motion. The relative importance of the terms are controlled by $\beta \in [0, \infty)$, which is the weight of the proximal control vector, and $\gamma \in [0, \infty)$, which is the weight of the direction preference vector. Each robot in the flock calculates its own desired heading vector at each control step and updates its forward and angular velocities accordingly.

It must be noted that not all robots need to have a direction of preference. Indeed, this direction of preference may be known to only a *subset* of the robots. Therefore, the direction preference term is meaningful for only these robots. We will call such robots as the *informed robots*, and set their $\gamma$ to a nonzero constant. The rest of the robots are unaware that a directional preference exists, and they merely apply the heading alignment and proximal control terms. They are called as the *naive robots* and their $\gamma$ is set to 0, effectively discarding the third term.

An important aspect of the proposed behavior is that the informed robots cannot signal that they are "informed" to the naive robots. Thus, our expectation is that they will guide the swarm by their tendency to move in the desired direction, acting as unacknowledged, distributed, and possibly redundant leaders of the flock.

The details of the three terms which constitute the overall behavior are discussed in the following sections.

## 4.1 Heading Alignment Behavior

The aim of the heading alignment term is to align the robot with the average heading of its neighbors. The heading values of the neighbors are obtained by the VHS which collects the broadcasted heading values. We calculate the heading alignment vector $\vec{h}$ as:

$$\vec{h} = \frac{\sum_{j \in \mathcal{N}} e^{i\theta_j}}{\| \sum_{j \in \mathcal{N}} e^{i\theta_j} \|}$$

where $\mathcal{N}$ denotes the set of VHS neighbors, $\theta_j$ is the heading of the $j^{th}$ neighbor converted to the body-fixed reference frame and $\| \cdot \|$ calculates the Euclidean norm.

The heading values received by the VHS are converted from global reference frame to the robot's body-fixed reference frame. The conversion is performed by $\theta_j = \frac{\pi}{2} - (\theta_j^{global} - \theta))$, where $\theta$ is the robot's own heading measurement. The $\frac{\pi}{2}$ term stands for aligning the opposite positive directions of the global and body-fixed reference frames (Figure 3.1(c)).

## 4.2 Proximal Control Behavior

The aim of the proximal control term is to keep the robots fixed at some desired distance to each other so that collisions and separations are prevented. Obstacle avoidance is also achieved through this term, by setting the desired distance from an obstacle as infinity. For calculating the proximal control vector, infrared sensor readings from the IRSS are utilized. When an obstacle or a robot is detected by an IR sensor, a virtual force proportional to the square of the deviation of the current detection level ($o_k$) from the desired detection level ($o_{des}$) is applied to the robot. The

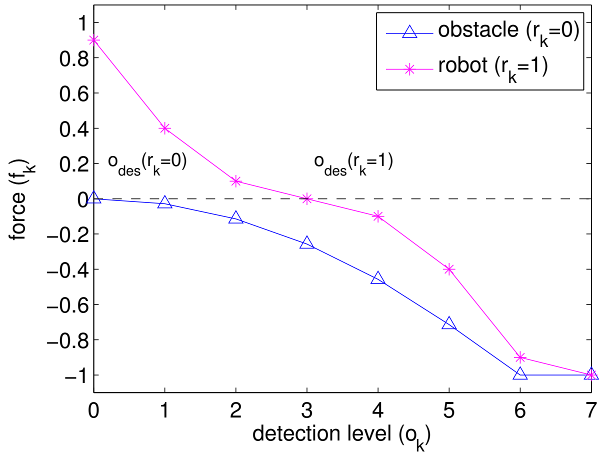



Figure 4.1: The virtual force ($f_k$) versus detection level $o_k$. Higher values of $o_k$ indicate closer distances. The virtual force value is saturated in range $[-1, 1]$. Figure courtesy of [1].

virtual force on sensor $k$, denoted by $f_k$, is defined as:

$$f_k = \begin{cases} -\frac{(o_k - o_{des})^2}{C} & \text{if } o_k \geq o_{des} \\ \frac{(o_k - o_{des})^2}{C} & \text{otherwise} \end{cases} \tag{4.1}$$

where $C$ is a scaling constant. $o_{des}$ is taken as a finite value for kin-robots, and 0 for obstacles (remember that $o_k$ indicates the detection level, $o_k = 1$ and $o_k = 7$ denote respectively a far and a very close obstacle/robot, and $o_k = 0$ indicates no detection). This setting keeps the flock together as a coherent body which avoids obstacles on its way. The $f_k$ values for robots ($r_k = 1$, $o_{des} = 3$) and obstacles ($r_k = 0$, $o_{des} = 0$) are plotted in Figure 4.1.

The normalized proximal control vector, $\vec{p}$, is the vector sum of the forces acting through the eight IR sensors:

$$\vec{p} = \frac{1}{8} \sum_k f_k e^{i\phi_k} \tag{4.2}$$

where $k \in \{0, 1, \cdots, 7\}$ is the index of the sensor which is located at $\phi_k = \frac{\pi}{4}k$ with the $x$-axis of the body-fixed reference frame (Figure 3.1(b)).

## 4.3 Direction Preference Behavior

The direction preference behavior is meaningful for only the informed robots, and it acts as a bias favoring the externally dictated direction. We expect this term to asymptotically determine the steady-state direction of motion of the flock. The direction preference vector $\vec{d}$ is calculated as:

$$\vec{d} = \vec{d_p} - \vec{a}_c$$

where $\vec{a}_c$ is the current heading vector of the robot coincident with the $y$-axis of the body-fixed reference frame (see Figure 3.1(c)), and $\vec{d_p}$ stands for the preferred direction.

## 4.4 Motion Control

At each control step, a robot updates its forward ($u$) and angular ($\omega$) velocities using the instantaneous desired heading vector, $\vec{a}$. The forward speed is calculated as:

$$u = \begin{cases} (\vec{a} \cdot \vec{a}_c)\, u_{max} & \text{if } \vec{a} \cdot \vec{a}_c \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

where $\vec{a}_c$ is the current heading vector of the robot coincident with the $y$-axis of the body-fixed reference frame (Figure 3.1(c)).

The robot's instantaneous "urge" to turn determines the instantaneous forward velocity of the robot. The forward velocity takes a value between 0 and a "maximum" forward velocity ($u_{max}$) regarding the amount of this urge. The urge is calculated by the dot product of the desired ($\vec{a}$) and current heading ($\vec{a}_c$) vectors. If the two vectors are in the same direction, i.e, the robot is already moving in the desired direction, the urge to turn is small, and the dot product is approximately 1. In this case, the forward velocity is at maximum. On the other hand, when the two vectors are near to orthogonal to each other, the dot product diminishes to 0. In this case, the forward velocity also diminishes, and the robot mostly rotates around its center. This capability of the robot to turn in place in times of urgency provides it with increased agility when avoiding collisions and aligning itself in case of sharp turns, such as when the flock turning collectively away from a wall. When the angle between the two vectors is greater than 90°, $u$ is not allowed to be negative, but it is bounded at 0. The robot again rotates only around its center. Therefore a backward movement of the robots does not occur, which would complicate the analysis of the behavior.

The angular velocity ($\omega$) of the robot is controlled by a proportional controller using the deviation of the desired heading from the current heading of the robot:

$$\omega = (\angle\vec{a}_c - \angle\vec{a})K_p \tag{4.4}$$

where $K_p$ is the proportionality constant of the controller.

The rotational speeds of the right and left motors (Figure 3.1(c)) are eventually calculated as follows:

$$N_R = \left(u - \frac{\omega}{2}l\right)\frac{60}{2\pi r}$$

$$N_L = \left(u + \frac{\omega}{2}l\right)\frac{60}{2\pi r}$$

where $N_R$ and $N_L$ are the rotational speeds (rotations per minute) of the right and left motors respectively, $l$ is the distance between the wheels of the robot (meters), $u$ is the forward velocity (meters per second) and $\omega$ is the angular velocity (radians per second).

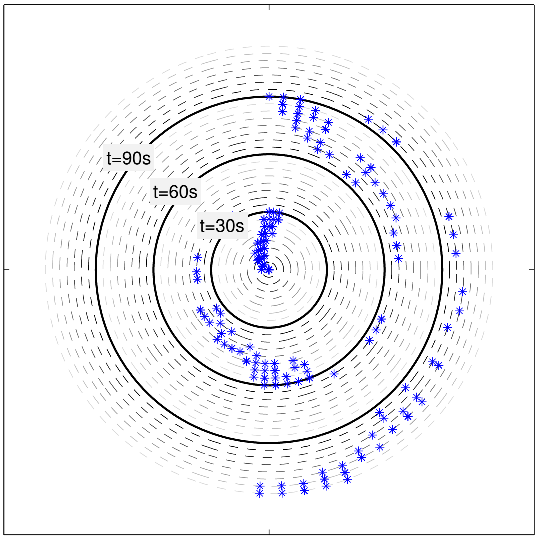
## 4.5 Controlling Flocking: A Sample Case Analysis

In this section, we present three sample runs with Kobots in order to demonstrate the controlling of the flock via a number of informed robots. In these runs, the behavioral parameters are set as $\beta = 4$, $\gamma = 1$, $u_{max} = 7$ cm/s and $K_p = 0.5$. The preferred direction of the informed Kobots are changed in every 30 seconds, being 90° direction in $t = 0 - 30$ s, 270° direction in $t = 31 - 60$ s, 90° direction in $t = 61 - 90$ s and 270° direction in $t = 91 - 120$ s, in order to demonstrate the transient performance of the flock in complying with the extreme changes in the preferred direction.

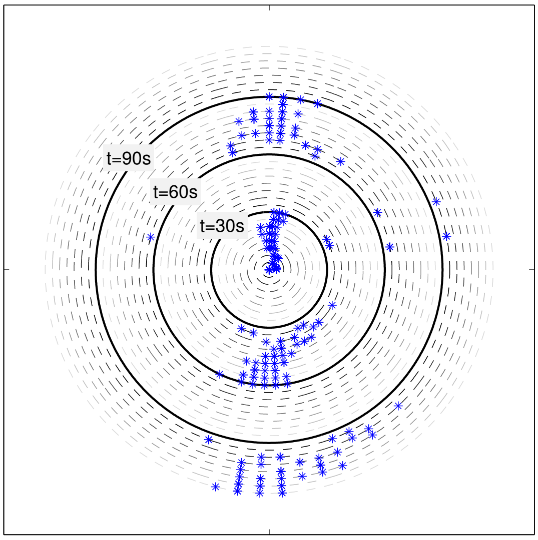
Figure 4.2 presents the time evolutions of the headings of the robots in these runs, where there are 2, 4, and 7 informed Kobots respectively. The time axis is shown with radially growing circles, with $t = 0$ being denoted by the innermost circle, and $t = t_f$ by outermost circle. In all the cases, the flock is able to comply with the sudden and extreme changes in the preferred direction, although the time needed for this adjustment varies. It takes approximately 30 seconds of the flock to turn in the desired direction in the 2 informed robots case, whereas this transient time is reduced to 15 seconds in the 4 informed robots case and to 5 seconds in the 7 informed robots case.

These experiments demonstrates that, even when there is a small number of informed robots, such as 2, the flock can change its direction in response to the changes in the preferred direction, whereas this adjustment is much more rapid in the presence of more informed robots. Obviously, there must be a great deal more factors affecting this performance, such as the relative weights of the behaviors, the size of the flock, and the amount of noise inherent in the system. In the following section, we will introduce the metrics to quantify the time evolution and performance of this control scheme, and in the subsequent section we will present systematic experiments to analyze it by using these metrics.

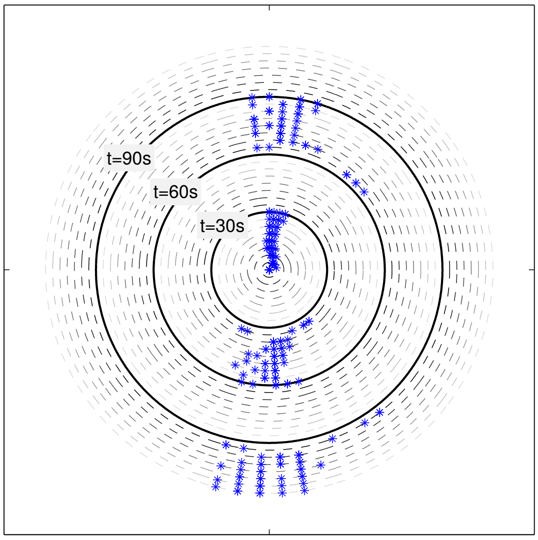
Another sample case is shown in Figures 4.3 and 4.4 which present two sample runs with 100 robots in CoSS, with 10 and 50 informed robots respectively. They are commanded to go in $90°$ direction in $t = 0 - 120$ s, $0°$ direction in $t = 121 - 240$ s, $270°$ direction in $t = 241 - 360$ s and $180°$ direction in $t = 361 - 480$ s. It is seen that in both cases the flock can be guided accordingly, although the ratio of informed robots is as low as $1/10$ in the former case. The response to the changes in the preferred direction is much more rapid in the 50 informed individuals case, as can be expected.




(a)




(b)




(c)

Figure 4.2: Sample runs with 7 Kobots among which (a) 2, (b) 4, (c) 7 of them are informed. Time evolutions of the heading values of the robots are shown. The time axis is shown with radially growing circles, with $t = 0$ being denoted by the innermost circle, and $t = t_f$ by outermost circle. The informed robots are commanded to go in 90° direction in $t = 0-30$ s, 270° direction in $t = 31-60$ s, 90° direction in $t = 61-90$ s and 270° direction in $t = 91-120$ s. The time steps at which the preferred direction has been changed are indicated with bold continuous lines.

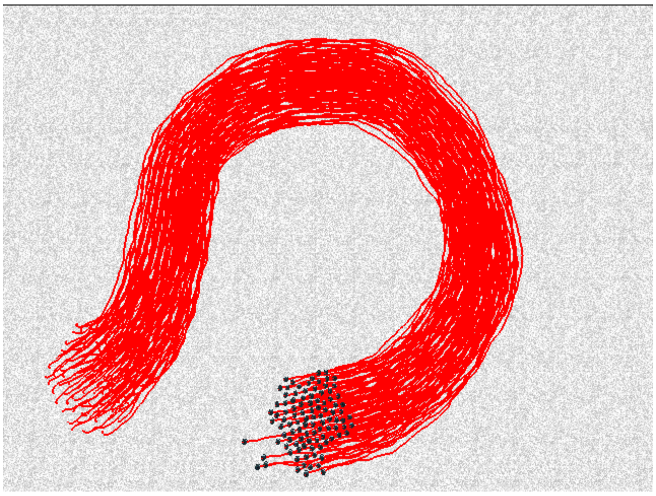


Figure 4.3: The trajectories of 100 robots from a sample run in CoSS, where 10 of the robots are informed. The informed robots are commanded to go in 90° direction in $t = 0 - 120$ s, 0° direction in $t = 121 - 240$ s, 270° direction in $t = 241 - 360$ s and 180° direction in $t = 361 - 480$ s.

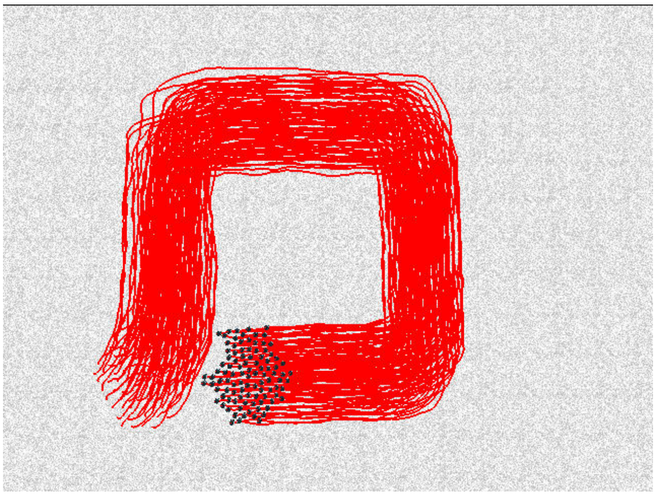


Figure 4.4: The trajectories of 100 robots from a sample run in CoSS, where 50 of the robots are informed. The informed robots are commanded to go in 90° direction in $t = 0 - 120$ s, 0° direction in $t = 121 - 240$ s, 270° direction in $t = 241 - 360$ s and 180° direction in $t = 361 - 480$ s.

# CHAPTER 5

# METRICS

In this section, we present two kinds of metrics to quantify the properties of the proposed scheme: The first is the mutual information metric, used for analyzing the time evolution of information sharing between the informed and the naive robots. The second is the measures of performance, which are the accuracy and size of largest cluster metrics, for evaluating the extent of our control on the flock.

## 5.1 Mutual Information

With two subgroups of informed and naive robots in the flock, we expect that some kind of information transfer, no matter how implicit and unacknowledged, must take place between these two subgroups if the informed robots are to guide the whole flock. We utilize the tools of Information Theory, introduced by Shannon [31], to quantify this information transfer, namely the *information entropy* and *mutual information* concepts.

### 5.1.1 Formal Definition and Applications

Quoting from Feldman [32], mutual information gives "the reduction in uncertainty of one variable due to knowledge of another. If knowledge of Y reduces our uncertainty of X, then we say Y carries information about X". Thus, it can be utilized as a measure of the information transferred from an informed robot to a naive one during the motion.

The mutual information is defined in terms of information entropy. Adopting the notation of Feldman[32], and indicating a discrete random variable with the capital letter $X$, which can take values $x \in \mathcal{X}$, the information entropy is defined as:

$$H[X] = -\sum_{x\in\mathcal{X}} p(X=x).\log_2 p(X=x)$$

where $p(X=x)$ is the probability that $X$ will take the value of $x$. $H[X]$ is also called the *marginal* entropy of $X$, since it depends on only the marginal probability of one random variable.

The marginal entropy of the random variable $X$ is zero if X always assumes the same value with $p(X=x')=1$, and maximum if $X$ assumes all possible states with equal probability.

Having defined the marginal entropy of a single random variable, this definition is easily extended to the joint entropy of two random variables:

$$H[XY] = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(X=x,Y=y).\log_2 p(X=x,Y=y)$$

as well as the conditional entropy of these two random variables:

$$H[X|Y] = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(X=x,Y=y).\log_2 p(X=x|Y=y)$$

where $p(X=x,Y=y)$ is the joint probability that $X$ will take the value of $x$ and $Y$ will take the value of $y$, and $p(X=x|Y=y)$ is the conditional probability that $X$ will take the value of $x$ given that $Y$ takes the value of $y$. Thus, the conditional entropy is the entropy of $X$, given that $Y$ is known.

Then, the mutual information $MI[X,Y]$ is defined as:

$$MI[X,Y] = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(X=x,Y=y).\log_2 \frac{p(X=x).p(Y=y)}{p(X=x,Y=y)}$$

or equivalently,

$$\begin{aligned} MI[X,Y] &= H[X]+H[Y]-H[XY] \\ &= H[X]-H[X|Y] \\ &= H[Y]-H[Y|X] \end{aligned}$$

The mutual information has a number of favorable properties that renders its utilization appropriate. It is obvious that $MI[X,Y]$ is zero when there is no statistical dependence between the two variables, in which case $H[XY]=H[X]+H[Y]$, and which corresponds to the case of no information transfer. Moreover, it is also zero when the marginal entropies of the two variables $H[X]$ and $H[Y]$ are zero, when there is already no uncertainty about either of the variables. It is nonnegative and bounded by some finite maximum value. It is a symmetric metric ($MI[X,Y] = MI[Y,X]$), agreeing with our intuition that the more information transfer occurs between $X$ and $Y$, the more information they should convey about each other. It has the capability of capturing the nonlinear statistical dependencies, unlike other widely utilized metrics such as Euclidean distance, Pearson coefficient, or covariance [33, 34]. For instance, quoting from Steuer et al. [33], "a vanishing mutual information does imply that two variables are independent, while for the Pearson correlation this does *not* hold". Finally, it can be calculated as a function of time, so it can be used to demonstrate the time evolution of information transfer in a dynamical system.

The mutual information concept has been widely utilized for various purposes. Parunak et al. [35] suggested the use of mutual information as a measure of *correlation* in multi-agent systems, through which the concepts of *coherent*, *collaborative*, *cooperative*, *competitive* and *coordinated* can then be defined. Sperati et al. [34] employed the mutual information between robots as a fitness function to evolve coordinated behavior in a robot swarm. They showed that maximizing the mutual information in task-independent manner as the fitness function results in the emergence of coordination among the robots. Sporns and Lugarella [36] used information theoretic metrics, including mutual information, complexity and integration (the latter two metrics due to [37]) for evolving coordinated behavior in a simulated sensorimotor creature. In all these works, mutual information has been revealed to be a very effective, task-independent metric of shared information.

### 5.1.2 Methodology

The application of the mutual information concept has some aspects that require certain design choices. First of all is the question of whose mutual information to be measured. In this study, we will measure the mutual information between a (randomly chosen) informed and a (randomly chosen) naive robot, with the expectation of seeing that the information shared between an informed and a naive robot increases in time, i.e, a naive robot mimics the motion of an informed robot with increasingly more accuracy. We will also analyze the necessary conditions for this information transfer.

We will calculate the shared "information" in terms of the two robots ability to move in the same direction. If the heading of one robot can be deduced from the knowledge of the heading of another, than we can say that this is because some transfer of heading information has occurred between these two robots, so that they have aligned to a more or less common orientation. We expect this information transfer to occur through the heading alignment behavior, whereas the direction preference behavior is expected to keep the informed robot in the preferred direction meanwhile. If the necessary conditions are provided, a sufficient amount of information transfer occurs between the informed and the naive robots, and the naive robots also start to move in the preferred direction in due time.

Since the mutual information is calculated as the degree of agreement in the direction of motions of the robots, the random variables X and Y correspond to the heading values of the informed robot and the naive robot, respectively. Then, the state space of X and Y are the set of possible heading values they can assume. Since this state space is infinite, it must be discretized. Parunak and Brueckner [38] point out to the importance of not dividing an infinite state space into too many states, in which case the possibility of observing two random variables in the same state would be "vanishingly small". Another issue is the concern of statistical significance when trying to obtain the probability distribution of a random variable from a finite number of observations. Sperati et al. [34] notes as a general heuristic that three times more samples than the possible states of a variable must be observed for a faithful estimation of the probability distribution of the variable. Regarding these concerns, we divide the unit circle into 8 discrete intervals of $\pi/4$ radians, so the number of states that a robot can be in at any time is 8, and the number of states that an informed-naive robot pair can be in is $8 \times 8$. We conduct $200 > 3 \times 8 \times 8$ experiments for estimating the probability distributions, which provides us with a safe range for estimating the joint probability distribution.

Another concern is the need to capture the dynamical aspects of the information transfer. Therefore, we calculate the mutual information as a function of time. For each time step, we calculate the probability distributions $p(X)$, $p(Y)$ and $p(X,Y)$ separately. Our expectation is that $X$ and $Y$ will be independent of each other at the initial phases of the experiments, and will become correlated as time advances, provided that the necessary conditions are supplied.

### 5.1.3 Finite Size Effects

A final issue about the calculation of the mutual information is the bias introduced due to the observation of a finite number of samples. It has been discussed by Grassberger [39], Herzel et al. [40] and Roulston [41] that when the entropy of a random variable is estimated from the observation of a finite number of samples, the estimation is "systematically biased downwards". Moreover, the nature of this bias is "independent of the underlying probability distribution" of the random variable [33].

Thus, following Steuer et al. [33] and Sperati et al. [34], we remove this systematic bias from the estimated entropies as follows:

$$H[X] = \tilde{H}[X] + \frac{a-1}{2.b}$$

where $\tilde{H}[X]$ is the estimated entropy, $a$ is the number of discretized states of the random variable X, $b$ is the number of observed samples, and $H[X]$ is the true entropy. In our calculations, $a$ is 8 for the marginal entropies and $8 \times 8$ for the joint entropy (the unit circle is divided into 8 intervals of $\pi/4$ radians), and $b$ is 200.

## 5.2 Accuracy

The mutual information metric discussed above is not a metric of performance, for it can only measure the degree of alignment between the informed and naive robots. Since it has no notion of the desired direction, it cannot distinguish whether a commonly converged direction is also aligned with the desired direction. Therefore, another measure must be utilized to evaluate the success of the informed robots in directing the flock's motion. For this purpose, we utilize the *accuracy* metric adopted from Couzin et al. [11], which measures the flock's degree of alignment with the desired direction.

### 5.2.1 Formal Definition and Applications

The accuracy metric depends on the angular deviation of the direction of the flock from the desired direction. The angular deviation is analogous to the standard deviation from linear statistics for inherently directional data. It is calculated as follows, as discussed in [42]:

Let $\theta_1 \ldots \theta_n$ denote a set of unit vectors whose angular deviation is to be calculated. Then, their (normalized) mean vector is the vector from $(0,0)$ to $(\bar{C}, \bar{S})$, where

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} \cos\theta_i$$

$$\bar{S} = \frac{1}{n}\sum_{i=1}^{n} \sin\theta_i$$

Let $\bar{R} = \sqrt{\bar{S}^2 + \bar{C}^2}$ be the length of this normalized mean vector and $\bar{x}_0$ be its angle with the $x$-axis such that:

$$\bar{C} = \bar{R}\cos\bar{x}_0$$

$$\bar{S} = \bar{R}\sin\bar{x}_0$$

Then, the angular deviation of these vectors *around their normalized mean vector* is given by:

$$S_0 = 1 - \bar{R}$$

This intuitively means that, the more aligned the vectors are, i.e, the less the angular deviation is, the longer is the mean vector. On the other hand, if they are scattered around the unit circle in a random manner, then their vector sum results in a shorter mean vector, denoting a greater angular deviation from the mean.

The angular deviation *around a specific direction* can be calculated as an extension of this formulation:

Let $\alpha$ denote the angle of the desired direction with the $x$-axis. Then

$$\bar{C}' = \bar{R}\cos(\bar{x}_0 - \alpha)$$

and

$$\bar{S}' = \bar{R}\sin(\bar{x}_0 - \alpha)$$

give the components of the mean vector in the desired direction, and

$$S_0' = 1 - \bar{C}'$$

gives the angular deviation around this direction.

In this study, we utilize the extended formulation for calculating the angular deviation around the desired direction of the flock.

The angular deviation metric is successfully utilized in many biological studies for evaluating the variability in the routes followed by animal flocks, such as [43] and [44]. In this study, we follow Couzin to define the accuracy metric, which measures how small the angular deviation is:

$$Accuracy = 1 - S_0'/2$$

Accuracy is 1 when the angular deviation is minimum, and 0 when the angular deviation is maximum. We expect it to be as high as possible in a desired scenario.

### 5.2.2 Methodology

The angular deviation is calculated by measuring the direction of motion of the flock in all experiments. In the steady state analyses, the direction of motion is defined as the direction vector between $\text{CoM}_t$ and $\text{CoM}_{t_f}$. In the simulations, this direction vector is calculated between the positions of the center of mass at $t$=875 s, and $t_f$=1000 s. Therefore, we do not consider the transient dynamics of the system, and only consider the converged direction of motion. In the experiments with Kobots, since we cannot accurately determine the flock center positions, we collect the heading values of Kobots between $t$=20 s and $t_f$=60 s, and calculate their ensemble average, which gives an accurate approximation of the direction of motion of the flock.

On the other hand, in the transient analyses, we calculate the instantaneous average heading of the robots at all instants, which gives the instantaneous direction of motion of the flock with respect to time.

Once the direction of motion is calculated for all experiments associated with one parameter set, we then calculate the angular deviation over these samples, each of which corresponds to the direction of motion in one experiment. In the steady state analyses, we then calculate a single accuracy value which measures the overall performance in all the experiments, whereas in the transient analyses, we plot the time evolution of the accuracy associated with these experiments. Since the accuracy metric is already a measure of variance, we do not explicitly show error bars in the plots.

## 5.3 Size of Largest Cluster

The maintenance of the swarm cohesion is an important issue, due to the limited range of the infrared sensors. Although the VHS has a range of 20 m, which is quite large, the infrared sensors that are employed in positional adjustments have a range of approximately 20 cm (Chapter 3). Therefore it is an interesting case when a robot gets out of the infrared range of the swarm, but still remains in the VHS range, which is a quite common issue if the swarm cohesion is not properly handled. In such a case, the robot can still communicate with the other robots via VHS, which allows it to align itself with the flock, and affect the flock's heading by broadcasting its own heading. However, it has no means of finding the flock's location again, so it cannot reunite with the flock except due to chance. Since losing more and more of the robots in the periphery in this manner can be a major problem as time advances, one of the main concerns is minimizing the number of robots that ever get out of the infrared range of their neighbors.

Therefore, we need an extra metric together with the accuracy to evaluate the performance. We employ the size of largest cluster as a measure of cohesiveness, which indicates how large a swarm can continue together under a certain parameter set. When clustering the flock, we take into account the infrared range of the sensors. Although the clustering of robots according to the VHS range is also an interesting subject, this is a situation that occurs only under extremely inconvenient conditions due to the VHS range being comparatively quite large.

### 5.3.1 Formal Definition

There is a quite wide literature on extracting the connected components from a disconnected graph, many of which can be easily applied for finding the clusters in a swarm. There exists breadth-first search or depth-first search graph algorithms, as well as algebraic methods [45] which depends on the algebraic connectivity concept proposed by Fiedler [46]. We have utilized the simple algorithm in Algorithm 1 since our case does not require computational cost related enhancements or further algebraic analyses. The algorithm is taken from [47], assuming that each robot is a vertex, and an edge exists between two robots if they are within the infrared range of each other.

**Algorithm 1** Clustering Algorithm

**for** each vertex $v$ **in** V(G) **do**
    MAKE_SET($v$)
**end for**
**for** each edge ($u$, $v$) **in** E(G) **do**
    **if** FIND_SET($u$) $\neq$ FIND_SET($v$) **then**
        UNION(FIND_SET($u$), FIND_SET($v$))
    **end if**
**end for**

In the algorithm, G denotes the graph representing the swarm, V(G) is the set of vertices in the graph, E(G) is the set of edges in the graph, MAKE_SET(x) creates a set whose only element is x, FIND_SET(x) finds the set containing x, and UNION(x, y) combines the sets x and y in one set.

### 5.3.2 Methodology

In this study, we calculate the size of the largest cluster at time $t = t_f$, that is, at the end of the experiments. The robots are clustered in terms of infrared range. Two robots are taken to be in the same cluster if they are in the infrared range of each other. Clustering is made in terms of metric distance range rather than whether actual instantaneous infrared sensing takes place at the final time step, because it is computationally not feasible to check whether infrared sensing takes places, as well as it being an over-restrictive condition. Rather, we assume that if two robots are in the infrared sensing range of each other, sooner or later infrared sensing will occur, although at a certain time step it may not, due to the noise effects or an inconvenient relative bearing of the robots.

# CHAPTER 6

# EXPERIMENTAL RESULTS

In this chapter, we present the experimental results with physical and simulated robots. We conduct analyses from two points of views: In the transient analyses, we demonstrate the time evolution of the system under various conditions. We investigate the dynamical characteristics of information sharing between the informed and the naive robots, and the effect of this information sharing on the accuracy of the system in following the desired direction.

In the second part of this chapter, we proceed to analyze the steady state characteristics of the system, in which we are no longer interested in the dynamics, but only in the final performance. We investigate the interdependent effects of the size of the flock in terms of the robots in it, the ratio of informed robots in the flock over the total flock size, the weight of the direction preference behavior, and the noise in the VHS mechanism. We demonstrate that, though significant these effects are, their mutual effects are so dependent on each other, that the system has quite complex dynamics, and reacts a varying parameter in a quite context-dependent manner.

## 6.1 Transient Response

In this section, we analyze the dynamics of the system as a time evolution. We present an analysis over four interesting cases: In the first case, the flock is composed of 100 robots, 10 of which are informed of the desired direction. The informed robots have a direction preference weight ($\gamma$) of 0.5. The second case has also the same conditions, except that the informed robots have $\gamma = 1$. In the third and fourth cases, only 1 robot out of 100 robots is informed. In the third case $\gamma = 1$, and in the fourth case $\gamma = 10$. The experiments in this section are conducted on the simulator since the transient dynamics are much more visible with a greater number of robots than physically available, and as well as longer simulations (1000 s) being possible.

These four cases represent four major conditions of information exchange and flock guidance. First, we analyze the dynamics of the system in an explicit manner by presenting the time evolutions of the headings in four sample experiments, then we discuss statistical results about the information exchange as the time advances, and finally we present the resulting accuracy evolutions.

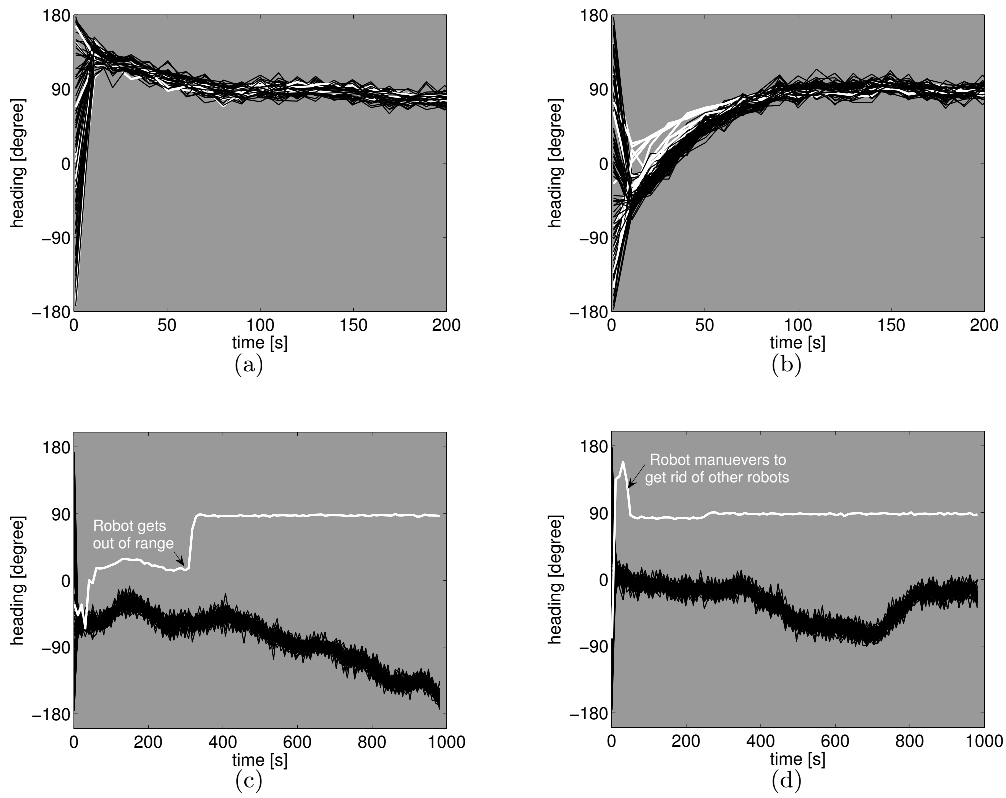



Figure 6.1: The time evolutions of headings in four sample experiments. (a) [10 informed robots, $\gamma = 0.5$] Initial 200 seconds of the experiment are presented. (b) [10 informed robots, $\gamma = 1$] Initial 200 seconds of the experiment are presented. (c) [1 informed robot, $\gamma = 1$] The whole course of the experiment is presented. (d) [1 informed robot, $\gamma = 10$] The whole course of the experiment is presented. The headings of the informed robots are plotted with white and the headings of the naive robots are plotted with black.

Figure 6.1 presents the time evolutions of the headings of the robots in one sample experiment from each of the four cases. The headings of the informed robots are shown with white plots, while the headings of the naive robots are shown with black plots. From the time evolutions of the headings, it is possible to visualize the fundamental differences between the four cases. Figures 6.1(a) and 6.1(b) present the first 200 seconds of the experiments, because the interesting dynamics are visible until a common alignment is reached. In Figures 6.1(c) and 6.1(d) however, the whole course of the experiments are shown, which last for 1000 seconds.

In Figure 6.1(a), the time evolution of the [10 informed robots, $\gamma = 0.5$] case is presented. The informed robots are commanded to go in the 90° direction. It is seen that 10 robots are enough to guide a flock of 100 robots to the desired direction. Yet, since the weight of the direction preference behavior is half of the heading alignment behavior, they first align themselves with the rest of the flock (at around $t = 15$ s), and then slowly converge to the desired direction together with the rest of the flock (at around $t = 75$ s). The flock is able to converge to the desired heading in a safe manner and is stable in this direction thereafter.

In Figure 6.1(b), the time evolution of the [10 informed robots, $\gamma = 1$] case is presented. The informed robots are again commanded to go in the 90° direction. In this case however, the weight of the direction preference behavior is equal to that of the heading alignment behavior, so it is seen that the informed robots try to turn to the desired direction more hastily, and it is left to the naive robots to strive for a common alignment. Until the alignment is finally reached by the naive robots, the flock continues in an unaligned manner for a while.

In Figure 6.1(c), the time evolution of the [1 informed robot, $\gamma = 1$] case is presented. In this case, it is seen that the information in only 1 robot is not enough for driving a 100-robot flock in the 90° direction. However, since the weight of the preferred direction is not overwhelmingly higher than the weight of the heading alignment behavior, it can be seen that the robot spends a short time of alignment with the flock. Then in time, it turns towards the preferred direction, yet it is unable to manipulate the common alignment direction of the flock. It continues in its own direction in this manner for a while, paying equal attention to the heading alignment and direction preference behaviors (which have an equal weight), thus following a direction that is *the average* of the desired direction and the flock's common alignment direction. However, since it is moving in a direction that is different from the flock's direction of motion, it goes out of the VHS communication range of the flock at about $t = 350$ s. From this point on, it cannot get information about the flock's direction of motion, so it rapidly turns to its own desired direction, and continues in this direction until the end of the experiment.

In Figure 6.1(d), the time evolution of the [1 informed robot, $\gamma = 10$] case is presented. Once more, the information in only 1 robot is not enough for driving the flock in the 90° direction. Yet, now the weight of the preferred direction is ten times the weight of the heading alignment behavior, so it is seen that the robot quickly turns to its own preferred direction (even having occasional collisions with the robots that get into its way). It is seen that until it can get rid of the other robots by getting out of the flock, its heading varies due to encounters with other robots in its way. However, as soon as it gets out of the flock, it instantaneously turns into the desired direction, and continues in this direction until the end of the experiment. Since the weight of the preferred direction is significantly more than the weight of the heading alignment behavior, its direction is not affected significantly by the common alignment of the flock even when it is in the VHS range, unlike the previous case.

### 6.1.1 Transfer of Information

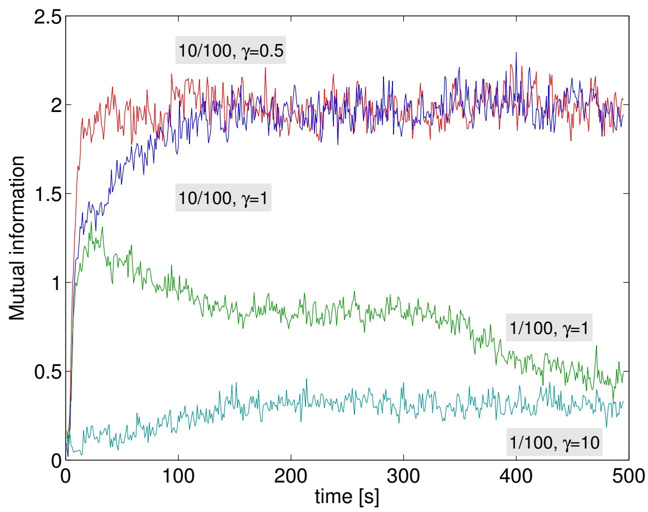



Figure 6.2: Time evolution of mutual information for [10 informed robots, $\gamma = 0.5$], [10 informed robots, $\gamma = 1$], [1 informed robot, $\gamma = 1$] and [1 informed robot, $\gamma = 10$] cases in 200 experiments.

In this section, we present the time evolutions of mutual information in the four cases. The statistics are obtained from 200 experiments, which provides statistical significance (See Section 5.1).

Figure 6.2 presents the mutual information change with respect to time. The dynamics during the first 500 seconds are presented, since the dynamics do not show much variance from the point until the end of the experiments. It is seen that, in the [10 informed robots, $\gamma = 0.5$] case, the mutual information increases rapidly due to the quickly established common alignment between the informed and the naive robots. In the [10 informed robots, $\gamma = 1$] case, however, since the informed robots are more persistent in following their desired direction, the mutual information increases only when the naive robots can converge to the same alignment, which needs more time. In the [1 informed robot, $\gamma = 1$] case, it is possible to observe the initial but short period of the informed robot trying to comply with the common alignment, but as the time advances it turns into its own direction, and the mutual information decreases again. In the [1 informed robot, $\gamma = 10$] case, the mutual information never increases, since the informed and naive robots never agree on a common direction of motion.

### 6.1.2 Accuracy of Direction of Motion

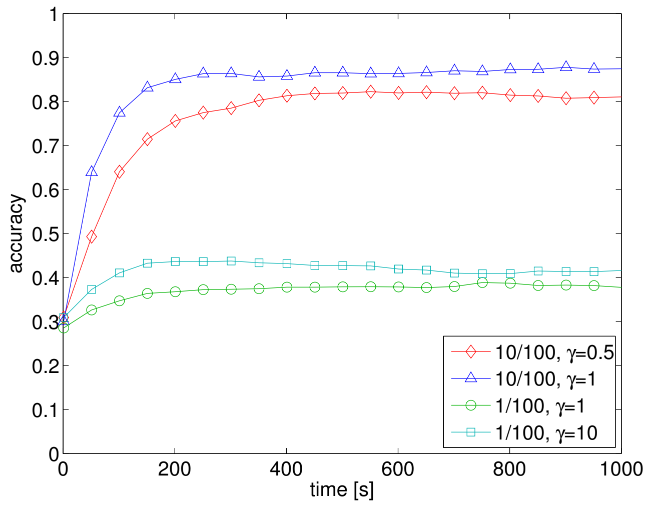



Figure 6.3: Time evolution of accuracies for [10 informed robots, $\gamma = 0.5$], [10 informed robots, $\gamma = 1$], [1 informed robot, $\gamma = 1$] and [1 informed robot, $\gamma = 10$] cases in 200 experiments.

In this section, we present the time evolutions of accuracy in the four cases. The accuracy values are obtained from the angular deviation of the instantaneous average direction of the flock in 200 experiments (See Section 5.2).

Figure 6.3 presents the accuracy results with respect to time. It is seen that, in the 10 informed robots cases, the accuracy increases with time, meaning that an informed robot ratio of 10/100 is enough for guiding the flock, and in the 1 informed robot cases the accuracy stays low, meaning that an informed robot ratio of 1/100 is not enough. As expected, the accuracy increases quicker when $\gamma$ is higher.

## 6.2 Steady-State Response

In this section, we analyze the steady state characteristics of the system. We investigate the interdependent effects of the size of the flock in terms of the robots in it, the ratio of informed robots in the flock over the total flock size ($\rho$), the weight of the direction preference behavior ($\gamma$), and the noise in the VHS mechanism ($\eta$).

The experiments are conducted with both physical and simulated robots. 7 Kobots are used in the physical robot experiments, and 10, 20 and 100 robots are employed in the simulations. The weight of the proximal control behavior ($\beta$) is set to 4, while $o_{des}$ is set to 3 for kin robots and 0 for obstacles, $u_{max} = 7$ cm/s and $K_p = 0.5$. The experiments are repeated 5 times for physical robots, and 300 or 500 times for the simulations. The experiments are conducted for 60 s for physical robots, and 1000 s in the simulations. In the experiments, the robots are initialized with random orientations, and the informed robots are assigned randomly. The magnitude of the VHS noise is set as $\eta = 1$ unless otherwise stated.

### 6.2.1 Effect of Flock Size

In this set of experiments, we investigate the effect of the size of flock on the accuracy of motion. We vary the size of the flock ($10, 20$ and 100 in simulations and 7 for physical robots) and measure accuracy for different ratios of informed robots ($\rho$). In the experiments, $\gamma$ is set to 0.1 and the results are plotted in Figure 6.4.

It is observed in Figure 6.4 that for a fixed ratio of informed robots, the size of the flock does not have a significant effect on the performance. A flock of 100 is as accurate as a flock of 10. It is also observed in the figure that for a fixed system size, increasing the ratio of informed robots increases the accuracy of motion of the system asymptotically which settles to approximately 0.9. The results of the Kobot experiments are less accurate due to the limited test area used for the experiments. Since the Kobots reach the walls in about 60 seconds, the experiments are much shorter than the simulations (1000 seconds). Especially in low ratio experiments the

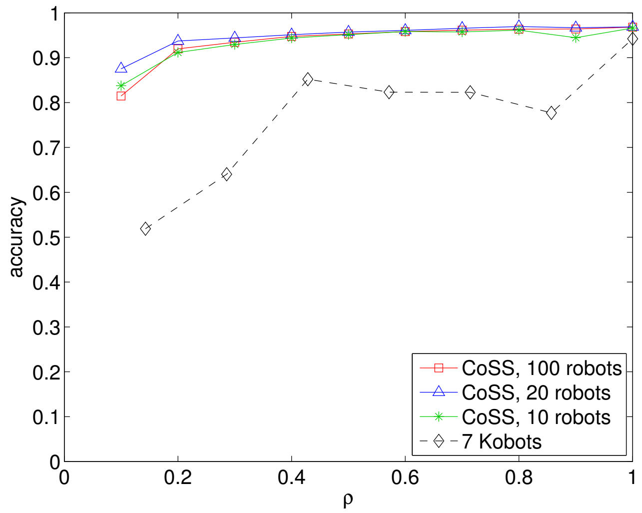



Figure 6.4: The effect of flock size for varying ratios of informed robots on accuracy. 300 simulations are conducted with 100 robots and 5 experiments are conducted with 7 Kobots.

steady state phase usually cannot be reached within 60 seconds. However, the trends are the same.

### 6.2.2 Effect of the Weight of Direction Preference Behavior

In this set of experiments, we investigate the effect of the weight of direction preference behavior ($\gamma$) on the accuracy of flocking motion. We vary $\gamma$ and measure accuracy for different ratios of informed robots ($\rho$). We also measure the size of the largest cluster for various $\gamma$ and $\rho$. The size of the flock is 100 and 7 for simulations and Kobot experiments, respectively. The results are plotted in Figures 6.5 and 6.6.

It is observed in Figure 6.5 that $\gamma$ has a significant effect on the accuracy of motion for moderately low ratios ($\rho = 0.1$). It has an optimum value, until which the accuracy increases due to the increasing persistence of the informed robots in following the desired direction. After this point the accuracy decreases a little due to increasing number of failing experiments in which all or most of the informed robots get out of VHS range. This is a situation which occurs more frequently especially before the transient phase is over, when their weight of the direction preference behavior is high, and the initial conditions are convenient, such as when all the informed robots are initially located together towards the preferred direction with respect to the flock center. For the high ratios, the accuracy stays flat at approximately 1 irrespective of $\gamma$.

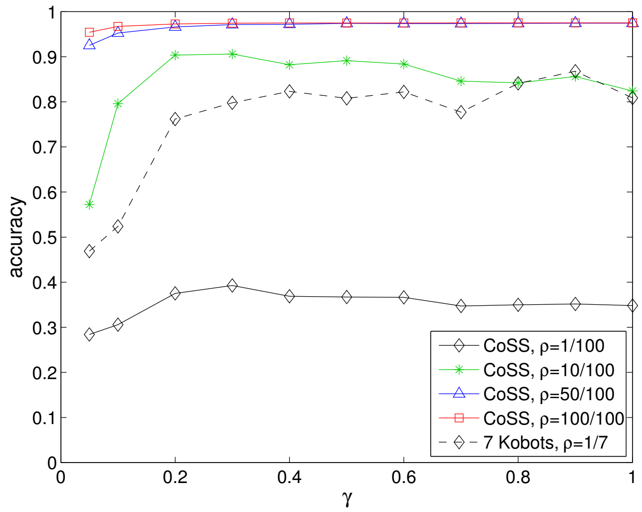



Figure 6.5: Accuracy for varying $\gamma$ for different informed robot ratios. 500 simulations are conducted with 100 robots and 5 experiments are conducted with 7 Kobots.

Likewise, for very low ratios, the accuracy does not increase with $\gamma$. The experiments with 1 informed Kobot out of 7 Kobots are again slightly less accurate than 100 robot simulations with 10 informed robots, especially for moderately low values of $\gamma$, due to the limited test area. However, the trends are the same. The final decreasing effect is not observed in the Kobot experiments, since the informed robot cannot get out of the range in 60 seconds.

Figure 6.6 shows that for the intermediate ratios of informed robots ($\rho = 0.1$ and $\rho = 0.5$), increase in $\gamma$ decreases the size of the largest cluster and results in fragmentation of the flock which is not observed in low or high ratios ($\rho = 0.01$ and $\rho = 0.8$).

The reason of this phenomenon is that the more "stubborn" the informed robots are to move in their preference, the more probable it is that they will be separated from the flock. This effect is naturally less visible when $\rho = 0.01$, since the loss of a single robot does not alter the size of the largest cluster much. On the other hand, when the ratio is high enough ($\rho = 0.8$), they are faster in changing the direction of the whole flock, which reduces the length of the transition phase, and decreases separations.

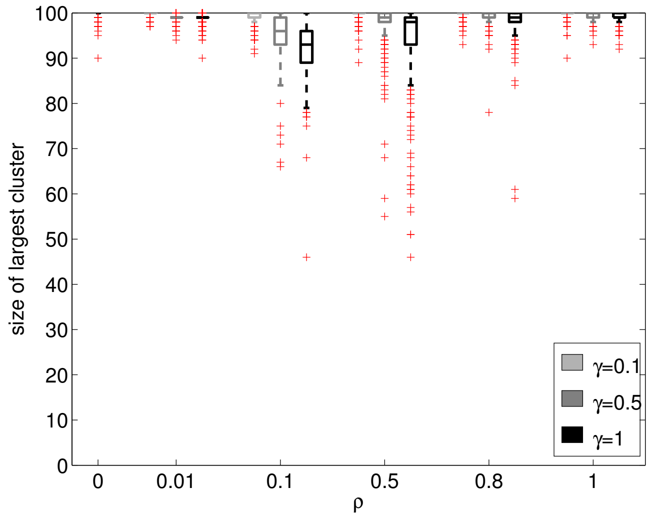



Figure 6.6: Size of the largest cluster at $t = t_f$ for varying $\gamma$ for different ratios of informed robots. 500 simulations are conducted with 100 robots. 0 informed robots case is included as a reference. The ends of the boxes and the horizontal line in between correspond to the first and third quartiles and the median values, respectively. The top and bottom whiskers indicate the largest and smallest non-outlier data, respectively. The data in between the first and third quartiles lie within the 50% confidence interval, while the data in between the whiskers lie within the 99.3% confidence interval.

### 6.2.3 Effect of Noise

In this set of experiments, we investigate the effect of the noise in the VHS for varying $\gamma$ values. The experiments are conducted in CoSS with 10 informed robots in a flock of 100 robots. We vary the magnitude of noise ($\eta$) and plot the results in Figure 6.7.

It is seen that the system is quite robust to moderate amounts of noise, since its response to the $\eta = 1$ setting is not significantly worse than the $\eta = 0$ setting. When the noise is increased to extreme amounts, by setting $\eta = 10$ and $\eta = 100$, it is observed that the accuracy significantly decreases for especially low values of $\gamma$, while as $\gamma$ increases, the accuracy also increases and for $\gamma >= 0.7$, it reaches the performance of the low noise cases. The final decreasing effect with increasing $\gamma$ is not observed in the high noise cases, because the intermediate values of $\gamma$ cannot produce as accurate results as in the low noise cases.

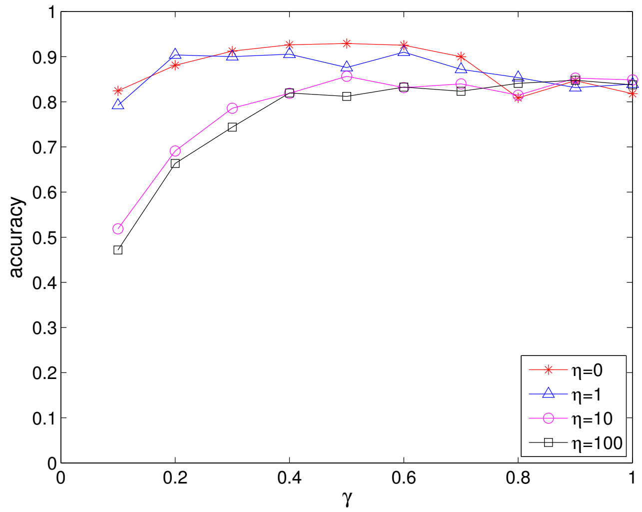



Figure 6.7: Varying $\gamma$ for different levels of noise. 500 simulations are conducted with 100 robots.

# CHAPTER 7

# CONCLUSION

In this study, we investigated the idea of controlling the direction of motion of a mobile robot swarm by informing some robots within the flock. We proposed an extension for a self-organized flocking behavior by including a preference for a specific direction without disturbing the essential self-organization property. Then, for a quantitative analysis of the system, we suggested using two kinds of metrics:

- The mutual information metric, from the Information Theory, which serves as a dynamical measure of the information exchange between the informed and the naive robots
- The accuracy metric, from directional statistics, and the size of the largest cluster, as metrics of performance of the guidance

Using these metrics, we conduct systematic experiments on physical and simulated robots, and demonstrate that:

- The self-organized flocking motion of a robot swarm can be guided effectively by informing a minority of the robots about a preferred direction to go.
- Provided that there exists a certain proportion of informed robots, than a rapid information exchange can be conducted through the heading alignment behavior, which results in the whole flock turning to the preferred direction.
- This information exchange cannot occur if the number of informed robots is negligible.
- The success of the system is independent of the flock size, that is, the proposed behavior is scalable.

- When the weight of the preferred direction is kept fixed, the accuracy of the system is positively effected by an increasing ratio of informed individuals.

- For intermediate ratios of informed individuals, increasing the weight of the preferred direction up to an optimum point has a significant positive effect on the accuracy. After this point, the performance shows a slightly decreasing trend due to increased clustering in the system.

- For very low (high) ratios of informed individuals, the accuracy is stable at a low (high) value, and increasing the weight of the preferred direction does not have a significant effect.

- The clustering effect is mostly visible for moderately low ratios of informed individuals and high values of the weight of the preferred direction. At very low or high ratios of informed individuals, or low values of the weight of the preferred direction, the clustering effect is negligible.

- The system is quite robust to moderate amounts of noise in the VHS, whereas the performance degrades in case of extreme noise in the system.

Work that awaits to be done includes the extension of the S-VNM model proposed in [30], an analytically solvable model for the original form of the flocking behavior, which captures the physical robot dynamics such as inertia. The model will be extended to include the direction preference behavior, and will be analyzed for further predictions.

Further algebraic analyses on the connectivity of the flock may also be conducted for discriminating the nearly-disconnected parts of the flock prior to fragmentation. Since the fragmentations are mostly due to the informed robots, an adaptive behavior may be introduced for them to reduce fragmentations. Furthermore, an analysis of the importance of spatial location of the informed robots might also be conducted, to reveal the advantages of choosing the informed individuals wisely with respect to their positions.

Finally, the behavior of the system when there is more than one subgroups with different preferred directions must also be investigated. For instance, this may be the case when not all the informed robots can "hear" the information signal correctly, and thus there exists some individuals who are "misinformed", yet as stubborn as the correctly informed ones. Therefore, robustness of the system under such circumstances needs to be investigated.

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