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Collective Transport with Obstacle Avoidance through Socially-Mediated Negotiation

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Résumé

Dans cette thèse nous présentons une nouvelle méthode pour le transport collectif avec évitement d'obstacles. Le transport collectif est un comportement collectif très utile. Considérons, par exemple, le problème du déplacement d'une voiture en panne. Une seule personne n'est pas en mesure de la déplacer. Toutefois, si plusieurs personnes tentent de la déplacer, cette tâche devient possible. C'est l'idée du transport collectif en robotique collective : un objet lourd, plus lourd que le poids maximum qu'un seul robot peut déplacer, doit être transporté d'une zone de départ à une zone de destination par un groupe de robots.

L'utilisation de multiples robots pour s'attaquer à une tâche de transport a pour principal avantage d'accroître les capacités de charge du système. Toutefois, cet avantage a un coût : la coordination. La coordination d'un groupe de robots pour réaliser le transport collectif est une tâche complexe. L'un des problèmes de coordination principaux est la médiation entre les différentes directions désirées par les robots pour réaliser un mouvement sans heurt.

Les robots impliqués dans la tâche de transport collectif peuvent avoir différentes perceptions de l'environnement à des moments différents : un robot voit un obstacle et veut l'éviter, tandis qu'un autre robot voit l'objectif et souhaite l'atteindre. Dans cette thèse nous proposons une méthode pour effectuer le transport collectif qui permet à plusieurs robots de négocier entre les différentes directions souhaitées, c'est-à-dire, de combiner les directions d'évitement d'obstacles avec les directions vers l'objectif.

La méthode présentée dans cette thèse a été développée et utilisée au sein du projet swarmanoid, un projet européen qui avait comme objectif l'étude et le développement de stratégie de coordination pour de nouveaux essais de robots hétérogènes.

Abstract

In this dissertation we present a novel negotiation strategy that allows different robots to perform collective transport in the presence of obstacles. The coordination of the different robots involved can be difficult, as their sensor perceptions can be different or conflicting. For example, at a given moment, one robot perceives only the goal direction, another perceives an obstacle to avoid and a third does not perceive any information on the task to accomplish. To perform collective transport the robots have to negotiate a common direction that takes into account the different partial information available. The proposed collective transport strategy was tested with experiments in simulation and with real robots in the framework of the Swarmanoid project.

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Contents

Résumé	iii
Abstract	v
Acknowledgments	vii
Contents	ix
List of Figures	xi
1 Introduction	1
1.1 Swarm Robotics	2
1.2 Related Works	3
2 Context: the Swarmanoid Project	7
2.1 Overview of the Project	7
2.2 Hardware	10
2.2.1 Foot-bot hardware	10
2.2.2 Hand-bot hardware	11
2.2.3 Eye-bot hardware	12
2.2.4 Communication: the range and bearing communi- cation board	13
2.3 ARGoS: the Swarmanoid Simulator Framework	13
2.4 Integrated Scenario	16
3 Method	21
3.1 Task Definition	21
3.2 The Proposed Behavior	23
3.2.1 Social mediation	25

3.2.2	Collective transport and obstacle avoidance	26
4	Experiments and Results	31
4.1	Experiments in a simulated environment	31
4.2	Experiments with real robots	33
5	Conclusions and Future Work	39

List of Figures

2.1	The foot-bot	10
2.2	The hand-bot	11
2.3	The eye-bot	12
2.4	Overall architecture of the simulator.	14
2.5	Eye-bots search the empty room. Foot-bot chain follows.	17
2.6	The eye-bot swarm has found a shelf. The foot-bot chain did not have to enter the empty room, as eye-bot chain had already left. The eye-bots close to the nest freed by the foot-bot chain do continue exploration. Connectivity from nest to far end of eye-bot swarm maintained through heterogeneous chain (eye-bots and foot-bots). Communication passes through this heterogeneous chain back to the nest to indicate that a shelf has been found. This information triggers the assembly of a foot-hand-bot.	17
2.7	The eye-bots swarm has found a second shelf. Meanwhile the foot-bot chain has caught up to first shelf. The first assembled foot-hand-bot is following the foot-bot chain towards the second shelf. A second foot-hand-bot assembles in preparation to retrieve a book from the second shelf.	18

2.8	The foot-bot chain has followed the eye-bot swarm and now has topologically covered the arena, freeing up the eye-bots for use elsewhere. A foot-hand-bot has reached the first shelf, been informed of the location of the book to retrieve by the eye-bot stationed next to the shelf. The foot-hand-bot has disassembled and the constituent hand-bot is climbing to retrieve the book. The two constituent foot-bots mark the location on the shelf where the hand-bot is climbing to prevent other foot-hand-bots attempting to climb at the same place.	18
2.9	A foot-hand-bot has retrieved a book and is returning to the nest (foot-hand-bot with a book marked with a red asterisk). The foot-hand-bot performs mutual obstacle avoidance with another foot-hand-bot that is heading away from the nest towards the shelves.	19
2.10	The first book has been returned to the nest.	19
3.1	Three foot-bots attached to a hand-bot.	22
3.2	The decomposition of the collective transport behavior	24
3.3	The carried robot and the carrying robots. The circular arrows show the area of the distance scanner which is active for sensing, whereas dashed straight arrow show the line of sight communication relationships.	26
4.1	(a) The controlled obstacle's parameter in the first two sets of experiments and (b) an example of complex environment. S denotes the starting area, G the goal area.	33
4.2	Box plot of completion time for the experiment set with fixed m (a) and for fixed l (b).	34
4.3	A single robot can obtain the vector pointing towards the goal by considering the positions of two foot-bots in the chain as the beginning and the end of the goal vector.	36
4.4	The integrated scenario arena	36
4.5	A screen-shot of a video of the Swarmanoid project. In this screen-shot it is possible to see, lit in yellow, the two foot-bots transporting the hand-bot through the door. The two foot-bots lit in red are part of the chain that connects the nest to the shelf.	37

Chapter 1

Introduction

In this dissertation we present a novel method to perform collective transport with obstacle avoidance. Collective transport is a very useful collective behavior. Let us consider, for instance, the problem of moving a broken car. One person alone is not able to move it. However, if multiple persons attempt to move it, the task becomes feasible. This is the idea behind collective transport in collective robotics: a heavy object, heavier than the maximum weight a single robot can move, has to be carried from a start area to a destination area by a group of robots.

Using multiple robots to tackle a transport task has the main advantage of increasing the carrying capabilities of the system. However, this advantage comes at a cost: coordination. Coordinating a group of robots to achieve collective transport is a complex task. One of the main coordination problems is mediating the different desired directions of the robots to achieve a smooth movement.

The robots involved in the collective transport task might have different perceptions of the environment in different moments: one robot sees an obstacle and wants to avoid it while another robot sees the goal and wants to reach it. In this dissertation we propose a method to perform collective transport that allows multiple robots to mediate between different desired directions, that is, to combine obstacle avoidance directions with goal following directions.

The method presented in this dissertation has been developed and used in the Swarmanoid project, a European project that had as a goal the study and development of novel coordination strategies for heterogeneous swarm

of robots.

In Section 2 we introduce the context of this dissertation: the Swarmoid project. Section 3 and Section 4 present the methodology used and the experimental results obtained. We conclude in Section 5 proposing also possible future works.

1.1 Swarm Robotics

Swarm robotics has been defined as “*a novel approach to the coordination of large numbers of robots*” and as “*the study of how large numbers of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment.*” [10].

The relevant characteristics of a swarm robotics system are the following:

- Robots are *autonomous*.
- Robots are *situated* in the environment and can act to modify such environment.
- Robots are *relatively incapable* in performing the required task alone. This means they have to resort to cooperation to perform a given task.
- Robots are only equipped with *local sensing* and *local communication* capabilities.
- Robots have access *neither to centralized control nor to global knowledge*.

The main inspiration for swarm robotics comes from the observation of social animals. Ants, bees, birds, fish are some examples of how powerful simple individuals can become when they gather in groups. Swarm intelligence is the research field that studies the behavior of these social animals [5] in order to understand the principles that make them robust, scalable and flexible.

Robustness is the ability to cope with the loss of individuals and faulty behaviors. The redundancy given by having many individuals and the absence of a centralized controller promote robustness in social animals. **Scalability** is the ability to behave well with different group sizes. The introduction or removal of a few individuals does not have a major impact on the

performance of a swarm. The absence of a leader and the use of local communication and sensing promote scalability in social animals. **Flexibility** is the ability to cope with a broad spectrum of different environments and tasks. Camazine et al. [8] studied how self-organization promotes flexibility in social animals.

Swarm robotics applies the principles studied by swarm intelligence to the development of robotics systems.

1.2 Related Works

The ability of robots to move in a coordinated fashion is of central importance for the multi-robot research community. Research in coordinated motion can be divided in two categories. In the first category we find works in *multi-robot formation*, where no physical connection between robots is assumed. In the second category, we find works in *collective transport* and *coordinated motion* where there is a physical connection between the robots or between the robots and the object to be transported.

Works in multi-robot formation have been documented in some surveys [1, 25], where the authors compare centralized vs. decentralized approaches. The most studied decentralized method in this area are social potentials [2] and artificial physics [22]. These works are less interesting with respect to this work as they do not consider the problems related to conflicting goals and object transportation.

Several works on collective transport were developed using centralized approaches like leader-following behaviors. In these works [23, 17, 26], a group of robots is able to collectively push/pull an object. In order to coordinate their movements, the robots follow a leader that has the knowledge of the goal area or of the path.

Balch [3] was one of the first to study the impact of communication in multi-robot systems. Later, Donald et al. [11] and Yamada et al. [27], studied collective transport with limited communication. In the first work [11], robots had to transport an object without a goal location, whereas in the second work [27] robots had to carry an heavy object towards a common goal determined by a light emitter (photo-taxis).

Campo et al. [9] investigated the use of goal negotiation strategies for performing collective transport to a given goal location. The robots used by

the authors had only a noisy perception of the goal, or they were not able to perceive the goal at all. Furthermore, each of the robots used LEDs and an on-board camera to perceive the orientation of the other robots, and used this information to compute an average direction of motion.

Groß and Dorigo [14] used artificial evolution to synthesize a neural network and achieve collective transport. Their robots were able to cope with objects of different size and weight as well as with groups of different size (from 4 to 16). The authors were able to obtain three different transport strategies. In the first one, the robots directly connect to the object and pull it. In the second one, the robots connect to each other (self-assembly) and to the object in order to pull it. In the third strategy, the robots create a physical loop around the object. This last strategy involves a high number of robots and a small (but heavy) object.

Trianni et al. [24] studied a task similar to obstacle avoidance in collective transport. They call it *collective hole-avoidance*. In their task, robots are physically connected to each other, and they have to navigate in an environment with holes. The authors used artificial evolution for the synthesis of robots' neural network controllers, and studied different communication strategies among the robots: no direct communication, handcrafted signaling and communication induced by artificial evolution. Differently from the work described in this dissertation, in Trianni et al. [24] no object had to be transported. Furthermore, the robots did not have a specific goal direction on where to go but they were rather exploring the environment while avoiding holes.

Baldassarre et al. [4] studied a task similar to the one studied by in Trianni et al. [24]. In their study, physically connected robots collectively navigate in an environment with obstacles, furrows and holes and a light source to be found. The authors used artificial evolution to synthesize a behavior able to integrate these three sub-behaviors in a coherent fashion: collective motion, collective obstacle avoidance and collective light approaching. However, the synthesized behavior heavily exploited the traction sensor, a specialized sensor that is able to detect forces exerted by the connected robots and that might not be available on all robotics platforms.

In this dissertation, a group of three simulated robots have to transport an object from a start to a goal location in an environment with obstacles. Almost all tasks studied so far in the literature consider collective trans-

port in an obstacle-free environment where a goal location is given, with two notable exceptions. In Trianni et al. [24], the environment is cluttered but a goal direction is not given. In Baldassarre et al. [4], both elements can be present at the same time but the synthesized solution, rather than exploiting direct local communication, uses instead indirect communication via specialized hardware. In this paper, we propose a novel negotiation strategy for collective transport in presence of both obstacles and of a goal. The proposed negotiation strategy is based on local direct communication.

Chapter 2

Context: the Swarmanoid Project

The work presented in this dissertation has been developed under the Swarmanoid project. The Swarmanoid project is a Future and Emerging Technologies (FET-OPEN)¹ project funded by the European Commission. It started on October 2006 and finished on September 2010. Its goal was to study new ways to design and control a heterogeneous robotics swarm that can operate in an environment designed for humans.

An important part of the Swarmanoid project was to study new collective transport methods to carry a passive robot to the area of interest. The result of the work presented in this dissertation has been used in the final scenario of the Swarmanoid project.

In this chapter we present an overview of the project (Section 2.1), the hardware used (Section 2.2), the simulator framework (Section 2.3) and the integrated scenario (Section 2.4) which has been used to demonstrate the capabilities of the developed system.

2.1 Overview of the Project

The scientific goal of the Swarmanoid project was to propose a new way of designing robotic systems that can live along with humans in an environment designed for humans, performing general purpose tasks. The project goal was pursued through the design, implementation, and control of a novel

¹<http://cordis.europa.eu/ist/fet/home.html>

distributed robotic system. The system is composed of heterogeneous, dynamically connected, small autonomous robots. The collaboration between heterogeneous robots in a swarm, yields to a “super entity” called *Swarmanoid*, which gives the name to the project.

The Swarmanoid project, following and extending the *Swarm-bots* project (see [12, 20] for a review), involves five European partners: CNR-ITSC (Consiglio Nazionale delle Ricerche, Roma, Italy), EPFL-LIS (Laboratory of Intelligent Systems, École Polytechnique Fédérale de Lausanne, Switzerland), EPFL-LSRO (Institut de Production et Robotique - Laboratoire de systèmes robotiques, École Polytechnique Fédérale de Lausanne, Switzerland), IDSIA (Istituto Dalle Molle di Studi sull’Intelligenza Artificiale, Lugano, Switzerland), IRIDIA-CoDE (ULB, Bruxelles).

The Swarmanoid project is the first attempt at joining two separate fields: swarm robotics and humanoid robotics. On the one hand, swarm robotics studies how to coordinate large numbers of relatively incapable robots that have to cooperate to achieve a common goal. On the other hand, humanoid robotics studies how to design and control humanoid robots, that is, human-shaped robots that can operate in an environment designed for humans. In the Swarmanoid project we developed an heterogeneous robotics swarm that tries to achieve the best of both approaches. It aims at being scalable, robust and flexible, and able to operate in a complex environment.

The first goal of the project was to develop new hardware platforms. To operate on human-oriented tasks we can identify three main capabilities a robotic system must have: locomotion, manipulation, and vision. A robot that have these three capabilities is usually complex and expensive. Moreover, being complex, it can be subject to frequent hardware failures. In the Swarmanoid project, the used approach was to separate these three capabilities by developing three kinds of robots:

- the *foot-bot* – a ground based robot, able to assemble to other foot-bots and hand-bots. The foot-bot is in charge of locomotion, as it can transport hand-bots where they are needed.
- the *hand-bot* – a manipulator robot, able to attach to the ceiling and climb. The hand-bot is in charge of manipulation, as it can use its hands to climb and grasp objects.
- the *eye-bot* – a flying robot, able to explore indoor environments. The

eye-bot is in charge of vision, as it can explore and scan the environment thanks to its higher mobility and hi-res camera.

The hardware of these three robotics platforms is presented in detail in Section 2.2.

Besides the development of the hardware platforms, the Swarmanoid project aimed at studying new control methods for the three types of robots. The development of new control methods of an heterogeneous swarm of robots poses new challenges in comparison with the single robot approach or the homogeneous swarm robotics approach. Coordination and cooperation are the key aspects to consider when developing behaviors for an heterogeneous system. Also, each of the three kinds of robots composing the Swarmanoid have different capabilities, that is, different ways to sense and interact with the world. For these reasons, when developing the different behaviors for the Swarmanoid we developed them in parallel so that possible cooperative issues were tackled and solved in a smoother and more natural way. Another aspect tackled in the Swarmanoid project was the study of communication in an heterogeneous swarm of robots. For instance, the emergence of communication in a robotic system in which hardware differences plays a central role is a completely new question. For a comprehensive list of the research questions tackled during the Swarmanoid project go to the Swarmanoid website².

To ease the development of the different behaviors a simulator was used. The ARGoS simulator, developed for the Swarmanoid project, is a multi-robot simulator which has been used to develop and test the different behaviors composing the Swarmanoid project. The use of ARGoS has been particularly useful in the design phase of the robots, as through simulation it was possible to explore the capabilities of the hardware, have a first feedback in order to improve or fix eventual problems and parallelize the development of the hardware and the software behaviors. The ARGoS simulator is presented in Section 2.3

Finally, at the end of the project, a scenario showing the capabilities of the hardware and the developed behaviors was tackled. The integrated scenario had as a goal the exploration of an unknown environment and the retrieve of a book from a shelf. More details are presented in Section 2.4

²<http://www.swarmanoid.org>

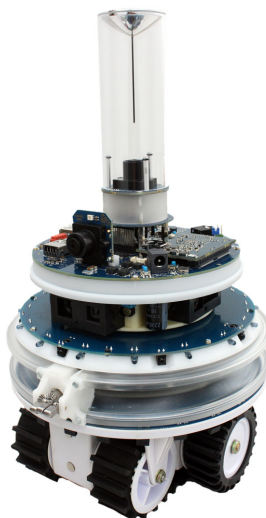


Figure 2.1: The foot-bot

2.2 Hardware

2.2.1 Foot-bot hardware

The foot-bots [6] (Fig. 2.1) are wheeled ground robots, whose design is based on the *s-bot*, the robotic platform of the *Swarm-bots* project. They can move on the ground through a powerful *treel* drive which is composed by wheels and tracks. Hot swappable, long-lasting, lithium polymer batteries allow the robots to run for long periods (around 2.5 hours of continuous use) and do not require to stop the robot and connect it to a recharging device. Moreover, a super capacitor keeps the robot alive while the battery is swapped, allowing for virtually limitless experiments.

The foot-bot is equipped with a range of different sensors. It boasts two 2.0 mega-pixels cameras, with on-board image pre-processing. The first camera points towards a conical mirror, giving the footbot omnidirectional vision. The second camera can either point towards the ceiling, in order to see the eye-bots, or to the front, to have a non-deformed vision of a section of the environment. The foot-bot also has 24 short range (up to 10 cm) proximity sensors and a rotating long-range (up to 150 cm) infrared scanner. These sensors can be used to perform obstacle avoidance.

The foot-bot is able to connect to objects and robots thanks to its gripper. The connection capabilities of the foot-bot are particularly useful in

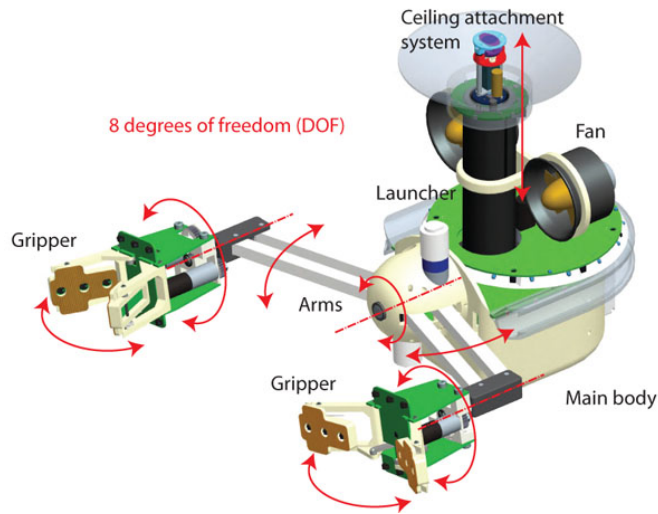


Figure 2.2: The hand-bot

the Swarmanoid project as they allow foot-bots to connect to hand-bots and transport them to the locations of interest. The connected robot formed by a hand-bot and two or three foot-bots connected is called foot-bot-hand-bot composite entity. In addition, foot-bots can connect to each other to form aggregates that allow them to perform tasks a single individual cannot: transporting heavy objects, crossing gaps, and climbing steps [for examples see 19].

2.2.2 Hand-bot hardware

The hand-bot [7], see Figure 2.2, is a unique robot that combines different characteristics. It is able to climb, and grasp and manipulate objects while being small and portable enough to be carried to the area of interest by the foot-bots. The hand-bot has several sensors and actuators: it has two grippers that are used for climbing and for grasping objects. The grippers are attached to the rotating head of the hand-bot through two arms. This mechanism allows the hand-bot to reach any position in a half sphere in front of the robot. In order to climb the hand-bot can shoot a magnet to the ceiling. The magnet is connected to the body of the robot with a rope which can then be used to climb. To stabilize the robot in the descending phase, the hand-bot has two fans that can be used to turn the robot. The hand-bot also has a 2.0 mega-pixels camera mounted on its head.

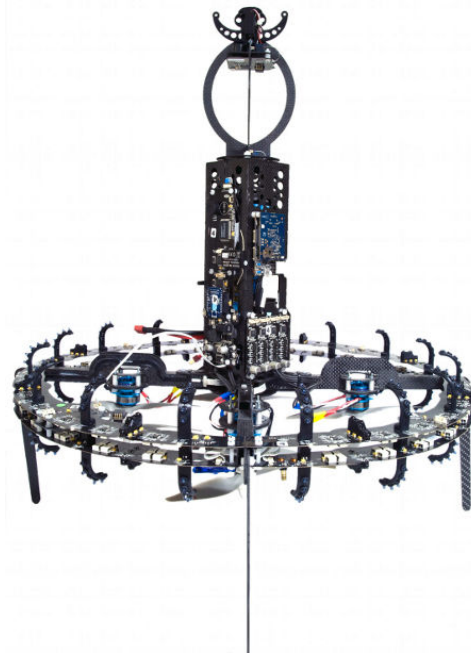


Figure 2.3: The eye-bot

Apart from its climbing system, the hand-bot does not have a locomotion system, that is, it cannot move in the horizontal plane. To overcome this limitation the hand-bot can be grasped by the foot-bots and carried to the desired area. Mechanically, this is possible thanks to a plastic connecting ring around the back of the hand-bot.

2.2.3 Eye-bot hardware

The eye-bot [21], see Figure 2.3 is a indoor flying robot with strong sensing capabilities. The eye-bot can explore an indoor environment with ease thanks to its 8 rotors that allow it to carry powerful sensors such as a hi-resolution pan and tilt camera. Several other sensors, like sonars and differential pressure sensors, are used to perform autonomous flight indoor.

The eye-bot has a battery life-time of around 20 minutes when flying, more than most of other similar sized flying robots. However, for performing experiments, 20 minutes is quite a limited amount of time. To increase its battery life-time, the eye-bot can attach to the ceiling thanks to a magnet positioned on its top. In this way the eye-bots can explore an environment, attach to the ceiling and communicate with the other robots while saving

battery power.

2.2.4 Communication: the range and bearing communication board

To ease cooperation, a common communication board has been developed and mounted on all the robots of the Swarmanoid project. This communication board, called range and bearing communication board [15], allows the robots to exchange up to 100 bytes/s of data. The range and bearing communication board is a situated communication device, that allows communication through infra-red and radio exchange. It is situated as the communication can happen only if there is line-of-sight between two robots. This allows the robots also to exchange their relative position: by measuring the angle and the power of the received signal, a robot can estimate the relative position of another robot.

The range and bearing communication board has proven a very important tool in the development of the Swarmanoid project. Thanks to this powerful communication device, the robots can coordinate themselves and exchange information about their status and the status of the environment.

2.3 ARGoS: the Swarmanoid Simulator Framework

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.

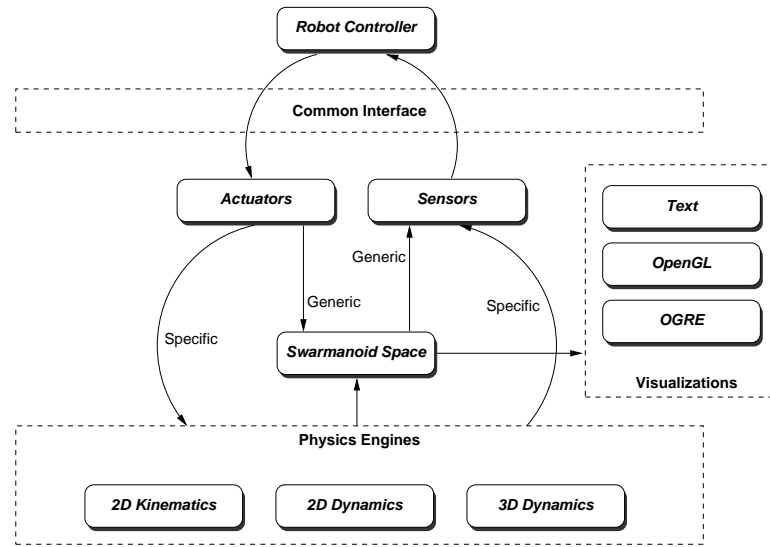


Figure 2.4: Overall architecture of the simulator.

On the downside, the intrinsic complexity of a (multi-)robot system and 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 [16].

The simulator developed for the Swarmanoid project is called ARGoS (Autonomous Robots Go Swarming). ARGoS³ is a custom software, written in C++ language, which implementation relies on free and open-source resources.

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

³<http://iridia.ulb.ac.be/argos/>

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 2.4. 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 ARGoS and 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.

2.4 Integrated Scenario

One of the goals of the Swarmanoid project was to show the capabilities of the developed hardware and collective behaviors through an integrated scenario. This integrated scenario demonstrates a subset of the full realizable behaviors of the Swarmanoid. Only a subset of the full realizable behaviors have been implemented due to the limited hardware, space (limited arena size), and workforce resources. In the following we present the integrated scenario of the Swarmanoid project.

All three robot types start in a “Nest” location. Eye-bots search the environment using a search behavior. To free up potentially scarce and valuable eye-bot resources, foot-bots form a chain following the eye-bot topology. Topological information is then stored in the foot-bot chain. Once a shelf of books to be retrieved is found, this knowledge is communicated back through the heterogeneous chain (eye-bot and foot-bot) back to the nest. At this point, the foot-bots connect to the hand-bot and follow the foot-bot chain to the shelf location.

When the robots arrives at a shelf location, the information about the 3 dimensional location of the book to be retrieved is communicated from the eye-bot to the foot-hand-bot. The hand-bot thus knows from where it should climb, and how high it must climb, in order to retrieve the book. The foot-bots disconnect from the hand-bot and retreat, allowing the hand-bot to climb. These foot-bots also act as markers to subsequent foot-bots letting them know not to approach the shelf at that location, as it is already occupied.

The hand-bot retrieves the book, and descends from the shelf, using it’s fans to control its lateral rotation. The foot-bots then re-assemble and follow the foot-bot chain back to the Nest. The foot-bots will perform obstacle avoidance to avoid any other robots following the foot-bot chain in the other direction towards the same (or other) shelves.

The above sequence of events is shown diagrammatically in figures 2.5 through 2.10.

Since they are not the topic of this dissertation, the details of each behavior of the final scenario will not be analyzed. In the remaining part of

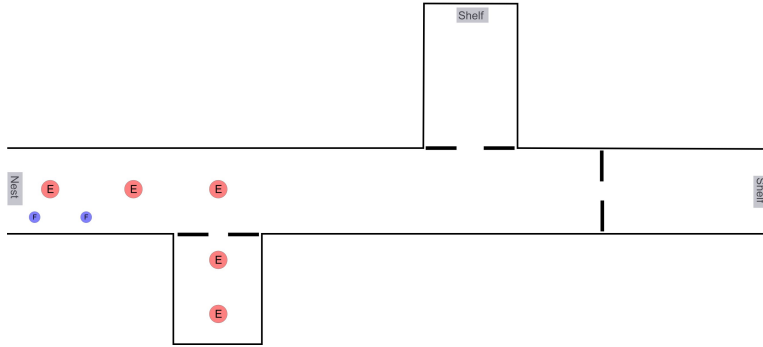


Figure 2.5: Eye-bots search the empty room. Foot-bot chain follows.

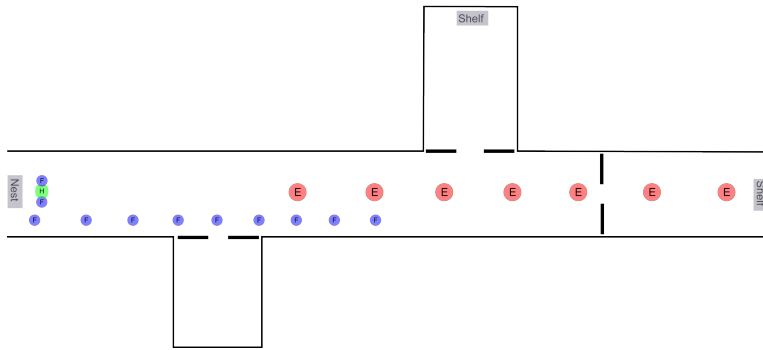


Figure 2.6: The eye-bot swarm has found a shelf. The foot-bot chain did not have to enter the empty room, as eye-bot chain had already left. The eye-bots close to the nest freed by the foot-bot chain do continue exploration. Connectivity from nest to far end of eye-bot swarm maintained through heterogeneous chain (eye-bots and foot-bots). Communication passes through this heterogeneous chain back to the nest to indicate that a shelf has been found. This information triggers the assembly of a foot-hand-bot.

this section we present in details the collective transport part of the Swarmoid project. The methodology presented in this dissertation has been developed mainly to tackle this problem.

The goal of the collective transport behavior is to let two foot-bots carry the hand-bot from the nest area to the shelf area. While doing this the foot-bots have to avoid obstacles, such as static objects or other robots, and go through narrow passages. The collective transport behavior starts with the two foot-bots connected to the hand-bot either in the nest area (at the beginning of the experiment) or in the shelf (after retrieving the book). A chain of foot-bots, developed with the foot-botchain creation behavior, will

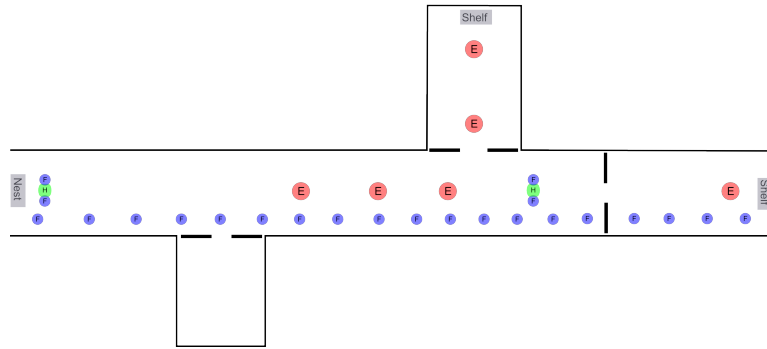


Figure 2.7: The eye-bots swarm has found a second shelf. Meanwhile the foot-bot chain has caught up to first shelf. The first assembled foot-hand-bot is following the foot-bot chain towards the second shelf. A second foot-hand-bot assembles in preparation to retrieve a book from the second shelf.

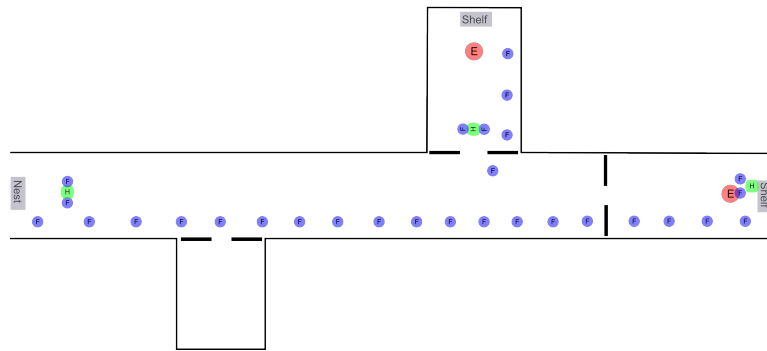


Figure 2.8: The foot-bot chain has followed the eye-bot swarm and now has topologically covered the arena, freeing up the eye-bots for use elsewhere. A foot-hand-bot has reached the first shelf, been informed of the location of the book to retrieve by the eye-bot stationed next to the shelf. The foot-hand-bot has disassembled and the constituent hand-bot is climbing to retrieve the book. The two constituent foot-bots mark the location on the shelf where the hand-bot is climbing to prevent other foot-hand-bots attempting to climb at the same place.

be deployed to guide the navigation of the other foot-bots. Each foot-bot attached to a hand-bot computes a directional vector using the position of two members of the foot-bot chain obtained via the range and bearing communication board. In this way it has a directional information about the path to follow. The foot-bots in the chain broadcast the distance with respect to the goal and the nest, allowing the foot-bots to discriminate between the two possible directions: towards the shelf area or towards the nest area.

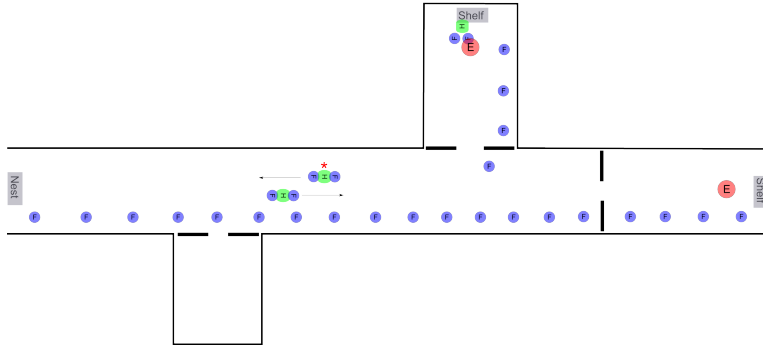


Figure 2.9: A foot-hand-bot has retrieved a book and is returning to the nest (foot-hand-bot with a book marked with a red asterisk). The foot-hand-bot performs mutual obstacle avoidance with another foot-hand-bot that is heading away from the nest towards the shelves.

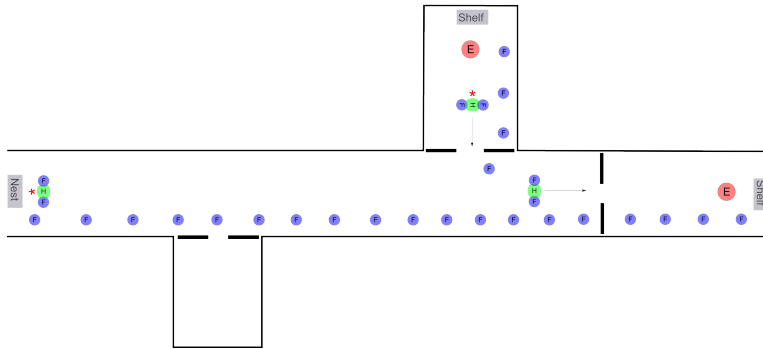


Figure 2.10: The first book has been returned to the nest.

Moreover, the foot-bot uses the distance scanner sensor to perceive if there are obstacles in its path, at which angle and their distance. Since different information may be available to the two foot-bots transporting the hand-bot a way of obtaining a common heading direction has to be implemented. According to which information is available to the foot-bot, different situation can arise. If the foot-bot perceives at least two members of the foot-bot chain and/or perceives an obstacle, it enters in a state defined as stubborn state. When in stubborn state the individual broadcast via the range and bearing communication board its desired direction. This direction can be the target or nest direction computed using the foot-botchain, the direction opposite to the closest obstacle or a weighted average of the two, based on the distance of the obstacle. In the stubborn state the received direction, is averaged with the own desired direction. This averaged value is then used

for navigation. If, instead, the robot does not have any information, i.e., it is not able to perceive at least two members of the foot-botchain and no obstacle is in range, it goes into a social state. In this state the robot receives the direction from the other robot and uses it for navigation. It then re-sends the received message to the other foot-bot. Through this mechanism the two foot-bots are able to follow a common direction even with varying information achieving collective transport with obstacle avoidance.

The collective transport behavior assumes two foot-bots connected to a hand-bot. One foot-bot has to be connected on the left side and the other on the right side of the hand-bot. Each foot-bot must know its position relatively to the hand-bot in order to filter out the readings of its distance scanner in the area occupied by the hand-bot. This is done in order to avoid perceiving the hand-bot as an external obstacle. A chain of foot-bots connecting the nest area with the shelf area is necessary for navigation. In addition, in order to properly filter and use the range and bearing communication board messages, each of the robots forming the assembly must know the range and bearing communication board ids of the other robot and the desired direction of motion, i.e., towards the nest or towards the shelf.

The transport of the hand-bot has been initially developed using three foot-bots. For this reason all the simulated experiments are presented with three robots. During the development of the real hand-bot a lighter version has been developed, allowing transport with only two foot-bots. This allows for better coordination and fewer mechanical problems.

More details on how the collective transport behavior is implemented will be given in Section 3.

Chapter 3

Method

In this chapter we first introduce the main idea behind the proposed method. Subsequently, we present the *collective transport* behavior, which we decompose into three sub-behaviors: *go to goal*, *obstacle avoidance* and *social mediation*.

3.1 Task Definition

A group of two or three identical simulated foot-bots (see Section 2.2.1) attach to a simulated hand-bot (see Section 2.2.2). The task is to collectively transport the hand-bot from an initial to a goal location. Picture 3.1 shows the assembled entity composed by two foot-bots and a hand-bot.

The environment is an arena where a number of cuboid-shaped obstacles are present, each with an arbitrary position and orientation. Each of the three simulated mobile robots is equipped with a number of sensors and actuators. We considered and used only the following sensors and actuators: i) a light sensor, that is able to perceive the intensity of the light coming from different directions around the robot; ii) a distance scanner, that is used to obtain distance and angular values from the robot to other objects in the environment [18]; iii) a range and bearing communication system, with which a robot can send a message to other nearby robots in line of sight [15]; iv) a gripper, that is used to physically connect to the transported robot considered in the experiment; v) a turret actuator which, when set to active mode, can be used to rotate the gripper installed on a rotating ring or, when set to passive mode, can freely rotate in accordance with the speed

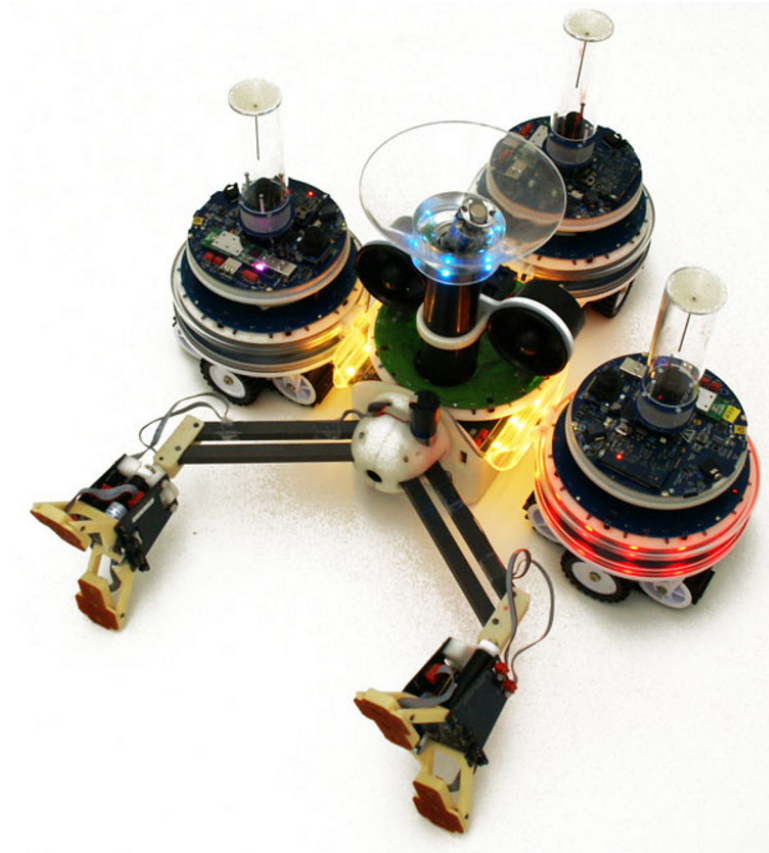


Figure 3.1: Three foot-bots attached to a hand-bot.

of the wheels when the gripper is gripping an heavy object; vi) a wheels actuator, that is used to control independently the speed of the left and right wheels of the robot. The range and bearing communication device can perceive messages coming from up to 4 meters away, more than enough to guarantee communication between the robots when connected. The distance scanner has a range of 1.5 meters.

In the experiments, we also place a light source in a fixed position in the environment behind the goal area. The light source has a high intensity such that it can be perceived by all the robots. The aim of the light source is to act as a common environmental cue, which is used as an implicit and shared reference frame by the robots.

For the sake of simplicity, the robots use the direction of the light source as the goal direction, that is, they perform photo-taxis. Since the proposed method is not restricted to this case, in Section 3.2 we consider the goal

direction and the environmental cue (or light) direction as two separated concepts. In the case where the goal direction is different from the light direction, the robot might need to be equipped with a separate sensor to detect the goal direction.

The presence of obstacles and the need to move to a given goal location create the need of handling conflicting individual decisions, which can be produced due to the non uniform perception of the environment.

For each individual robot, information of the following nature can be available at a given time:

No information: The goal is not perceived, for example because occluded by obstacles, and no obstacles are perceived as well.

Goal only: Only the goal is perceived, hence the robot moves towards it.

Obstacle only: The robot does not perceive the goal. However, it perceives an obstacle, hence it has to avoid it. At the same time, it has to inform other robots about the obstacle avoidance direction.

Goal and obstacle: The robot perceives both the goal and an obstacle. The direction of movement, considered by the robot and communicated to the other robots, has to take into account both these elements.

We now have all the elements to introduce our approach for tackling this task.

3.2 The Proposed Behavior

In this section we first introduce the main idea behind the proposed method. Subsequently, we present the *collective transport* behavior, which we decomposed into three sub-behaviors: *go to goal*, *obstacle avoidance* and *social mediation*.

In the following, we will use a certain notation to denote directional information used in the behaviors. This is explained and summarized in Table 3.1.

The low level behaviors *go to goal* and *obstacle avoidance* are used as follows. The go to goal behavior is used to query sensors and to obtain a goal direction, denoted as θ_G ; the obstacle avoidance behavior is used to

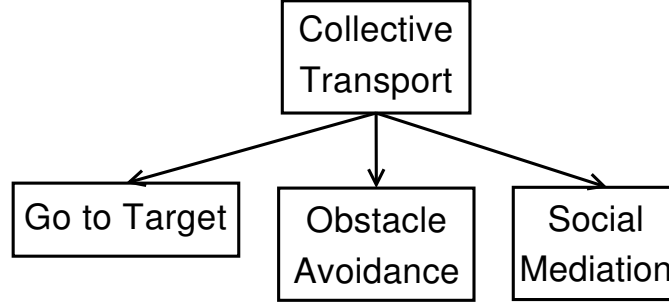


Figure 3.2: The decomposition of the collective transport behavior

Notation	Meaning	Behavior
θ_P	Preferred direction when in $S_{stubborn}$ state	Social mediation
θ_S	Socially mediated angle $\theta_S \leftarrow \angle \sum_{i=0}^k e^{j\theta_i}$	Social mediation, collective transport
θ_0	Direction sent by social mediation behavior: θ_S in S_{social} state or θ_P in $S_{stubborn}$ state	Social mediation
$\theta_1 \dots \theta_k$	Direction received from the k neighbors	Social mediation
θ_G	Goal direction	Collective transport
θ_{CO}	Obstacle direction	Collective transport
θ_{OA}	Obstacle avoidance direction. It has to take into account also θ_G if the goal is perceived.	Collective transport
θ_F	Direction of the shared environmental cue. All other directions are always relative to this	Collective transport
$\bar{\theta}_S$	Weighted time average of θ_S	Collective transport

Table 3.1: Explanation of the notation used to describe the two behaviors.

detect the presence of obstacles and the angle θ_{CO} of the closest one. The *social mediation* and *collective transport* behaviors are the core focus of the proposed method.

The social mediation behavior, explained in Section 3.2.1, is used to negotiate the direction to be followed in collective transport. This is needed since, as explained in Section 3.1, different robots in the group can have access to conflicting information, for example one might perceive the goal as well as an obstacle while the others might perceive just the goal. Furthermore, when two or more robots perceive an obstacle, they can perceive it from different angles.

Once a collective decision has been made on the direction to be followed, this is used by the *collective transport* behavior, explained more in details in Section 3.2.2.

3.2.1 Social mediation

The social mediation behavior is responsible for the negotiation of the direction of motion. The behavior uses the directional information given by θ_S and θ_P : θ_S represents a socially mediated heading direction and θ_P the robot desired heading direction. The main idea behind the algorithm is the following. When a robot in the group has no information (i.e., it does not have any information on the goal or on the obstacles), it has an internal *state* set to S_{social} . In this state, the robot acts as a repeater, that is, it computes θ_S , the average of the direction information available to its neighbors, and it sends this value around. However, when information (such as on the obstacle) is available to the robot, its internal *state* is set to $S_{stubborn}$. In this state, it will relay its own preferred direction θ_P (for example the obstacle avoidance direction) instead of θ_S . When all other robots are still sending θ_S , the opinion of the stubborn robot will soon diffuse in the entire group, that is θ_S through the group will converge to θ_P . The internal state of this behavior can be changed only by the overall collective transport behavior, as explained in Section 3.2.2. Algorithm 1 depicts the steps executed at every control step.

Algorithm 1 Social mediation control loop

```

1: Receive( $\theta_1, \theta_2, \dots, \theta_k$ )
2:  $\theta_S \leftarrow \angle \sum_{i=0}^k e^{j\theta_i}$ 
3: if state =  $S_{social}$  then
4:    $\theta_0 = \theta_S$ 
5: else
6:    $\theta_0 = \theta_P$ 
7: end if
8: Send( $\theta_0$ )

```

At the beginning of the control loop, the robot receives the heading direction information $\theta_1, \theta_2, \dots, \theta_k$ of its neighbors, where k is the number of neighbors. Communication is restricted to all neighboring robots in line of sight [15], as we are using the range and bearing communication mechanism. Due to this restriction, the robot attached at the center has $k = 2$ neighbors, whereas the other two have $k = 1$ neighbor (see Figure 3.3). The socially mediated heading θ_S is computed by averaging the directional information (\angle means “the angle of”) received by the neighbors (line 2), with the robot’s

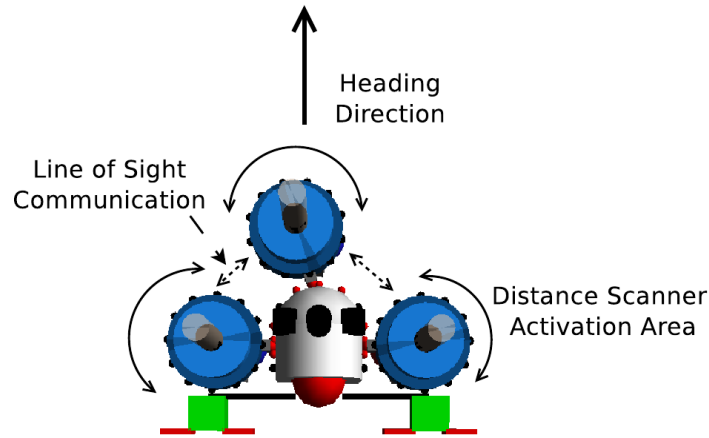


Figure 3.3: The carried robot and the carrying robots. The circular arrows show the area of the distance scanner which is active for sensing, whereas dashed straight arrow show the line of sight communication relationships.

own information θ_0 .

By using the mechanism depicted above, we are solving the issue of how to diffuse a heading direction information, perceived only by one robot, through the entire group, without the need of special signaling. This allows all robots in a group to be aware of the direction to follow to avoid the obstacle, even if only one member of the group can perceive the obstacle.

In the following section, we describe how this mechanism is used to achieve effective collective transport with obstacle avoidance.

3.2.2 Collective transport and obstacle avoidance

In this section we present the behavior responsible for collective transport with obstacle avoidance. This behavior uses the directional information computed in the social mediation behavior. In this behavior, θ_O denotes the direction of the obstacle (if perceived), θ_G denotes the goal direction (if the goal is perceived) and θ_{OA} denotes the obstacle avoidance direction (see table 3.1 for a summary). This directional information is always considered as relative to the direction of the shared environmental cue, denoted with θ_F and represented in our case by the light source.

At the beginning of Algorithm 2, sensors are queried to detect whether

Algorithm 2 Collective transport control loop

```

1:  $[\theta_G, goalPerceived] \leftarrow PerceiveGoal()$ 
2:  $[\theta_{CO}, d, obstaclePerceived] \leftarrow PerceiveObstacle()$ 
3: if  $goalPerceived$  or  $obstaclePerceived$  then
4:    $SocialMediation :: state \leftarrow S_{stubborn}$ 
5: else
6:    $SocialMediation :: state \leftarrow S_{social}$ 
7: end if
8: if  $goalPerceived$  then
9:    $SocialMediation :: \theta_P \leftarrow \theta_G$ 
10: end if
11: if  $obstaclePerceived$  then
12:   if  $goalPerceived$  then
13:      $w \leftarrow -\frac{d}{\min(d, d_{max})} + 1$ 
14:   else
15:      $w \leftarrow 1$ 
16:   end if
17:    $\theta_{OA} \leftarrow \angle w \cdot e^{j\theta_O + \pi} + (1 - w) \cdot e^{j\theta_G}$ 
18:    $SocialMediation :: \theta_P \leftarrow \theta_{OA}$ 
19: end if
20:  $SocialMediation :: ControlStep()$ 
21:  $\bar{\theta}_S \leftarrow \angle (1 - \alpha) \cdot e^{j\bar{\theta}_S} + \alpha \cdot e^{j\theta_S}$ 
22:  $MotionControl(\bar{\theta}_S)$ 

```

the goal and/or obstacles are perceived (lines 1-2). Directions θ_G , that is, the goal direction, and θ_{CO} , that is, the closest obstacle, are also queried.

According to the information available to the robot (see Section 3.1) the internal state of the social mediation behavior is set (lines 3-7). If the robot perceives an obstacle with its distance scanner its state is set to $S_{stubborn}$. The same happens when the robot perceives the goal. In all other cases, that is when both the goal and the obstacles are not perceived, the state is set to S_{social} .

If the goal is perceived, the robot simply informs the others about the goal by setting its desired direction θ_P to the goal direction θ_G (line 9).

In case an obstacle is perceived two things can happen. If no goal direction θ_G is available, the robot simply tries to avoid the obstacle using the angle $\theta_{OA} = \theta_{CO} + \pi$ and by setting $w = 1$ (line 15). If, however, both the obstacle and the goal are perceived, the robot needs to compute the desired direction according to this two pieces of information: θ_O and

θ_G are thus averaged using a weighted average and the result is assigned to θ_{OA} (lines 17). The weighted average uses a weight $w \in [0, 1]$ dependent on the distance between the robot and the obstacle (line 13) which represents how urgent it is to avoid obstacles: it is 1 when the obstacle is very close ($d = 0$) and 0 when it is far away ($d = d_{max}$, the maximal perception range of the obstacle avoidance behavior). We set $d_{max} = 0.75$ meters, half of the maximal range of the distance scanner, and we use the min operator to avoid negative values for w . The angle θ_{OA} is then assigned to the desired direction θ_P of the social mediation behavior (line 18).

Once θ_P is computed, the control step of the social mediation behavior is executed (line 20). As a result, the angle θ_S is computed by the social mediation behavior. This angle is then filtered by computing a time average (line 21) to filter out the effect of noise.

Finally, the motion control logic uses the filtered socially mediated direction $\bar{\theta}_S$ as a reference direction to be followed. The robot first converts the socially mediated direction to its local frame of reference using the common environmental cue direction θ_F . All robots then compute the left and right wheels speed in the following way:

$$N_L = u + \omega b, N_R = u - \omega b, \omega = K_p \bar{\theta}_S,$$

where N_L, N_R are the wheels rotation speed of the left/right wheel speed respectively, b is the distance between the center of the robot and each of the wheels, u and ω are the forward and angular velocities respectively. The forward velocity u is kept constant, whereas we vary the angular velocity ω proportionally to the socially mediated direction $\bar{\theta}_S$ to be followed, where K_p is a proportional factor (we assume a clockwise convention for the angles). Furthermore, the motion control rule considers the robot attached to the left as the left wheel of the compound system and the robot attached to the right as the right wheel. This assumes that the two robots have always the direction of the wheels axis parallel to each other and it is ensured by the fact that we set the turret to active mode, that is, the position of the turret with respect to the body is kept fixed. Hence, the robot attached to the left of the compound will set both wheels speed to N_L , whereas the robot to the right will set them to N_R . The robot at the center can instead independently control its own left and right wheels depending on value computed by the

motion control logic. The turret of the central robot, which is set to passive mode, freely rotates passively and follows the dynamics of the compound and the one imposed by the wheels.

To summarize the idea, the collective transport behavior interacts with the social mediation behavior to obtain a socially mediated direction $\bar{\theta}_S$ which is consistent in the group and allows a coherent motion. The social mediation behavior needs to be set in the appropriate state ($S_{stubborn}$ or S_{social}), according to which information is available to the robot. It also needs the direction θ_P to be sent to the neighbors in case it is in $S_{stubborn}$ state. θ_P can be the direction to the goal, the obstacle avoidance direction or the direction which takes into account both the goal and the obstacles. The behavior achieves coherent collective motion even in case of conflicting opinions, since the motion control logic uses the socially mediated direction, that is the direction negotiated through the entire group, as the target direction to be followed.

Chapter 4

Experiments and Results

The experimental section of this dissertation is divided in two sections: simulated experiments and real robots experiments.

The simulated experiments had the goal of testing the collective transport with obstacle avoidance behavior. The goal of the real robots experiments was to provide a reliable behavior component for a more complex scenario. Several runs have been run demonstrating the reliability of the collective transport behavior.

4.1 Experiments in a simulated environment

In this section experiments in a simulated environment are presented. These experiments have been performed using the ARGoS simulator (see Section 2.3). All the sensors used, that is, the light sensor, the distance scanner and the range and bearing communication device, are used adding a certain amount of noise, in order to test the behavior in a realistic context.

We performed three sets of experiments. The first two sets consider a simple environment, where we position an obstacle at the center of the arena with varying angle α (see Figure 4.1a). For each setting, we executed 100 runs. Our prior expectation is that the more α tends to 0, the longer it takes to avoid the obstacle in collective transport. We also expect that the proposed behavior is robust enough to always accomplish the task (move from an initial to a goal location, see Figure 4.1b) in this simplified setting. We hence report the completion times as a function of α . The difference between the first and the second set of experiments is that in the first set we

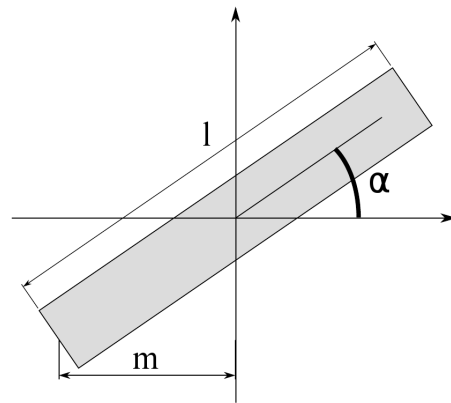
just analyze the impact of the angle α by keeping the projected size of the obstacle m fixed (Figure 4.1a), whereas in the second set we also analyze the impact of the varying projected size, keeping l fixed. Execution times are reported in time-steps. Each simulated second corresponds to 10 time-steps.

In the third and last set of experiments, we generate at random some more complex environments, of the type depicted in Figure 4.1b. We report the success rate of the behavior. We executed a total of 1000 runs, where in each run the angle and an offset of the position of each obstacle is generated at random.

Figure 4.2 shows the results for the first two sets of experiments performed in the simple environments. As we can see, the initial hypothesis can be accepted, as the execution times solely depends on α and not on the projected length m of the obstacle. In fact, execution times increase with increasing values for α . The more the obstacle is perpendicular to the direction of motion, the longer it takes for the robots to perform obstacle avoidance.

The case $\alpha = 0$ is particularly problematic. Average times are much higher, and many more outliers are present (not fully shown due to scale differences). This is explained by the fact that, when the obstacle is perpendicular to the direction of motion, i.e. $\alpha = 0$, the avoidance direction θ_{OA} takes some time to converge to one of the two possible obstacle avoidance sides. All the runs were successful and no collision was registered.

In the third set of experiments, results showed a success rate of 96%. In the remaining 4% of the cases, robots hit an obstacle and hence the corresponding run was terminated. After analyzing failures cases separately, we found out that they were all due to slow turning rate achieved by the compound robot structure in the goal direction after avoiding an obstacle. This slow turning rate made the robot hit the next obstacle with the blind side of the carried structure, corresponding to the region of the object where the robots cannot attach and which is blind with respect to the distance scanner. A video showing one typical run for this set of experiments can be found in a supplementary page [13].



(a)



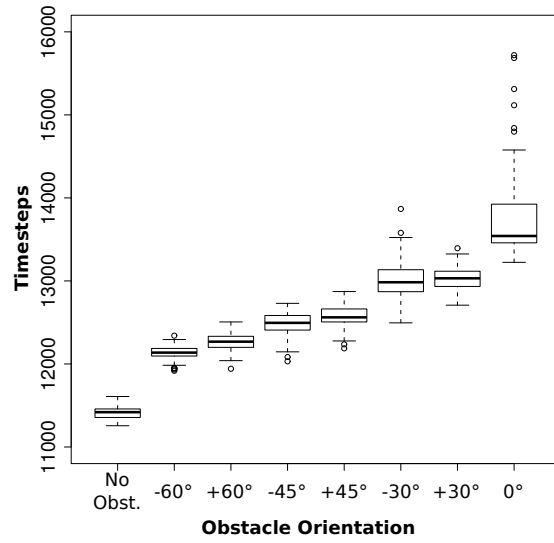
(b)

Figure 4.1: (a) The controlled obstacle's parameter in the first two sets of experiments and (b) an example of complex environment. S denotes the starting area, G the goal area.

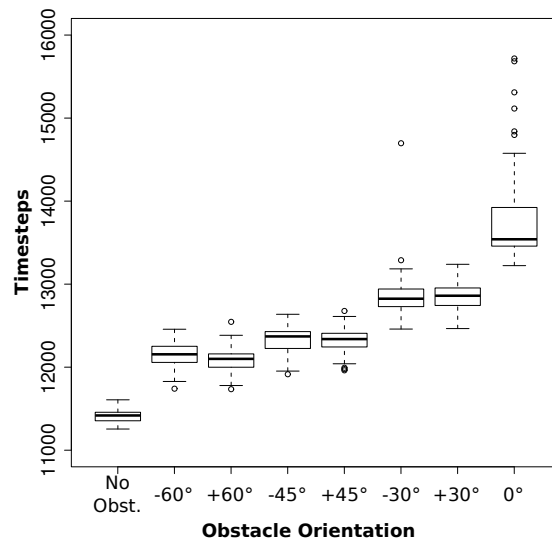
4.2 Experiments with real robots

To fully validate the collective transport algorithm we also performed experiments with real robots. These experiments were performed and used in Swarmanoid project (see Chapter 2).

In the real robots case, the experimental setting was slightly different, as some of the assumptions adopted for the simulated case proved difficult



(a)



(b)

Figure 4.2: Box plot of completion time for the experiment set with fixed m (a) and for fixed l (b).

or impossible to maintain.

The first difference is that the experiments were conducted using only two active robots. This solution has been adopted mainly for simplicity rea-

sons. When we developed the original algorithm the hand-bot was supposed to be quite heavy. Thus we thought that three foot-bots were necessary to transport it. However, the final hand-bot had a smaller weight, thus allowing transport with only two foot-bots. Using two foot-bots instead of three is a simpler solution, as less coordination and communication is necessary. Moreover, the risks of hardware problems due to mechanical stress are reduced and other foot-bots can be used for other sections of the integrated scenario.

Another difference is in the removal of the global environmental clue, that is, the common light that was used as a goal direction. The Swarmanoid project is assumed to take place in an unexplored environment, that is, no clues are assumed to be present before the start of the experiment. Moreover, different groups of robots are supposed to reach different areas, e.g. multiple shelves. To deal with this problem the foot-bots do not have a light as a goal, as in the simulated case, but use a chain of foot-bots to navigate. This chain, built in another behavioral component of the integrated scenario (see Section 2), is composed of several foot-bots linking the nest area with the destination area. Each robot in the chain is continuously broadcasting two distances: its distance with respect to the nest and its distance with respect to the goal. The foot-bots transporting the hand-bot can then receive information from two, or more, robots in the chain, understand which one is closer to the target destination and computed a vector using the range and bearing positional information. This means that the two robots are used as start and end of a virtual vector pointing towards the target, see Picture 4.3. By following the robots composing the chain, the foot-bots can reach the desired destination.

About a hundred experiments were performed in a human-built environment. The robots were starting already assembled to the hand-bot at the end of a corridor and the foot-bot chain was already in place. The goal was at the end of a room connected with a corridor with a standard door, see Picture 4.4. The entity composed by the two foot-bots and the hand-bot has to go through this door without hitting the sides in order to reach the goal. The door is approximately 50 centimeters larger than the composite robot. A very precise control and obstacle avoidance was thus necessary to be able to avoid the door sides.

In all the experiments, when there were no mechanical damages to the

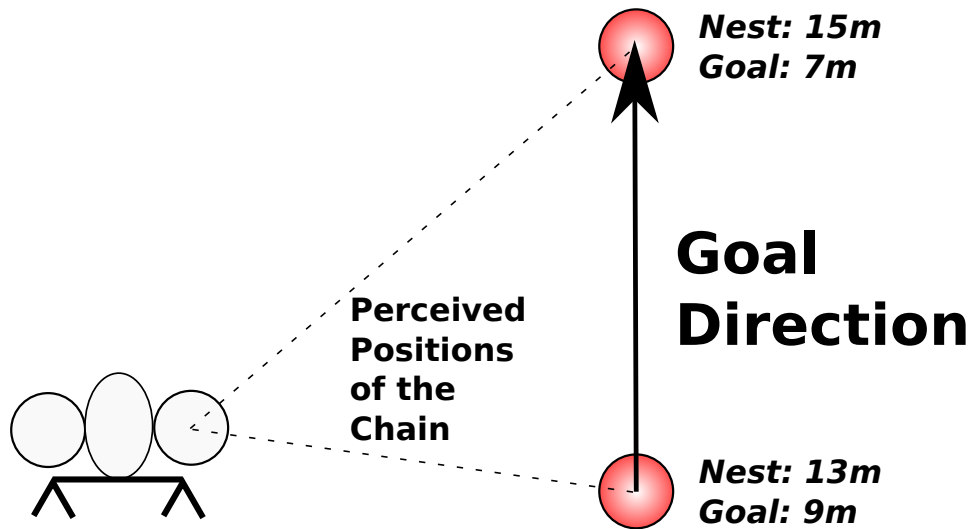


Figure 4.3: A single robot can obtain the vector pointing towards the goal by considering the positions of two foot-bots in the chain as the beginning and the end of the goal vector.

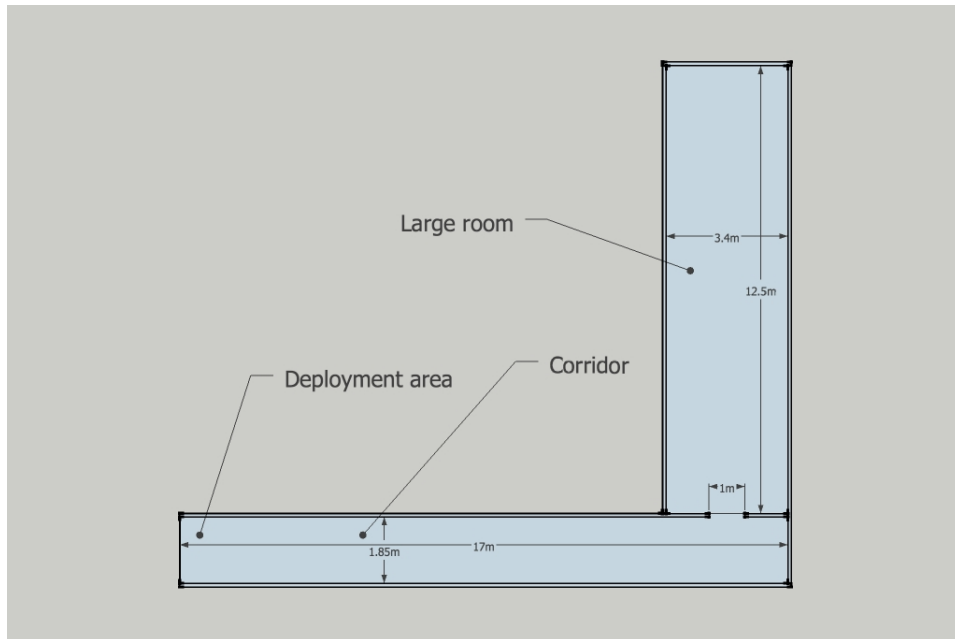


Figure 4.4: The integrated scenario arena

robots, the robots were able to successfully reach the goal and come back. Moreover a mechanism to avoid other connected was implemented with success. A video of the Swarmanoid experiment showing the collective trans-

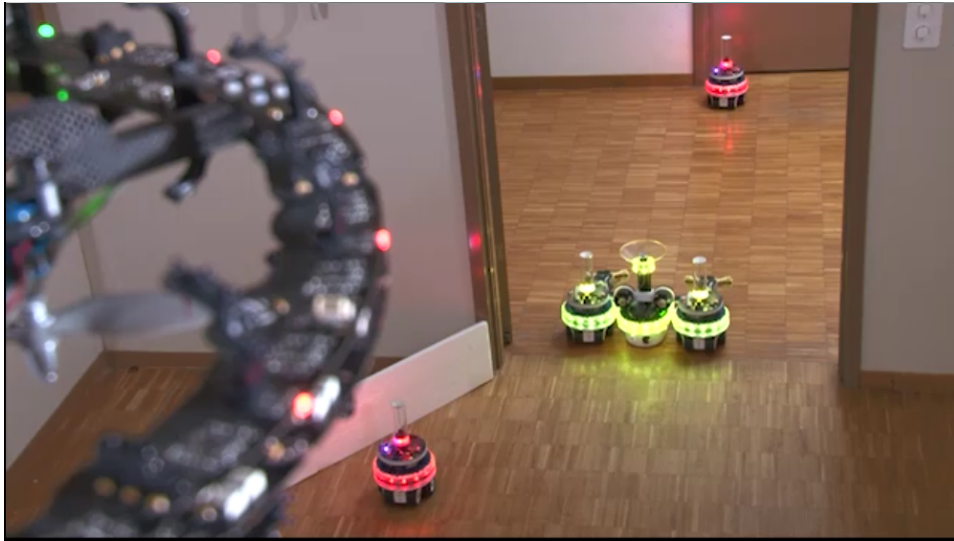


Figure 4.5: A screen-shot of a video of the Swarmanoid project. In this screen-shot it is possible to see, lit in yellow, the two foot-bots transporting the hand-bot through the door. The two foot-bots lit in red are part of the chain that connects the nest to the shelf.

port with obstacle avoidance behavior will be published on the Swarmanoid website in the future. See Picture 4.5 for a frame of the video.

Chapter 5

Conclusions and Future Work

In this dissertation, we presented an original method to tackle a task that has received limited attention in the literature: obstacle avoidance in collective transport. The task involves collective transport of an object by a group of three robots. In this task, robots assemble to the object and have to navigate to a given goal location while avoiding obstacles.

The proposed method consists of two interacting behaviors. The first behavior is called social mediation and is used to perform negotiation of an heading direction which takes into account possibly conflicting perceptions of the members of the group. The second behavior achieves collective transport, using this mediated heading direction.

Two sets of experiments were performed: simulated experiments and real robot experiments. Simulated experiments were performed in a simple arena with one obstacle placed at different angles and in a more complex arena with several obstacles. Results in the simple arena show that the efficiency (inversely linked to execution times) of the behavior solely depends on the angle at which obstacles are placed, and that the more the obstacle is placed perpendicularly to the direction of motion the more time it takes to avoid it. In a more complex environment, we measured the success rate of the proposed approach, obtaining 96% of success.

Experiment with real robots were performed. The goal was to perform collective transport with obstacle avoidance in a human-made environment. Two foot-bots had to carry the hand-bot in a corridor, cross a door, reach the

end of the room and come back to the beginning. Several tens of experiments were performed showing the reliability of the presented behavior.

This work can be extended in a number of directions. As a first step, some of the assumptions made in this work could be relaxed. For example, it can be interesting to investigate how to solve the task by assuming that the irregular shape of the object is not known in advance. In this case, we speculate that the motion control logic will need to be extended. Secondly and more ambitiously, a long term goal would be to understand how to control a group of an arbitrary number of robots, connected between each other and/or to an irregular object at different positions. In this case, we speculate that the social mediation methodology can be extended to tackle dynamic negotiation of heading direction with an arbitrary number of robots. Finally, a theoretical model of the system can be developed and used to prove some properties of the algorithm, such as that no cyclic situations (i.e. no “deadlocks”) can arise.

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