UNIVERSITAT POLITÈCNICA DE CATALUNYA

Doctoral Programme:

AUTOMATIC CONTROL , ROBOTICS AND COMPUTER VISION

Ph.D. Thesis

COOPERATIVE SOCIAL ROBOTS: ACCOMPANYING, GUIDING AND INTERACTING WITH PEOPLE

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November, 2013

Universitat Politècnica de Catalunya

Doctoral Programme:
Automatic Control, Robotics and Computer Vision

This thesis has been completed at:
Institut de Robòtica i Informàtica Industrial, CSIC-UPC

Advisor:
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To my dear parents, Toni and Lina,
my darling sister Eva,
and my beloved Xavi.

Acknowledgements

First, I would like to express sincere thanks to Professor Alberto Sanfeliu, who gave me the oportunity to work in the robotics field, and who became the advisor of the present dissertation. Thanks for your continuing encouragement, supervision and understanding help. To Professor Reid Simmons, for offering me an exciting project to work on during my visit at Carnigie Mellon University. Also to Dr. Francesc Moreno Noguer for his wise advices and comments at the times I needed more support.

I also would like to thank all my friends and colleagues from all over the world, you made this not just a career opportunity for me but a unique chance to make new friends with different backgrounds and interesting stories. Also, I am very grateful to all the volunteers who participate in my experiments.

En primer lugar, quisiera agradecer a todas las personas con las que he compartido los despachos 6 y 7, creasteis una gran atmósfera de trabajo. A mis compañeros del laboratorio de robótica, gracias por vuestra paciencia cuando trabajo con Tibi, sé que somos muy escandalosas. Una mención especial para Sergi Hernández y Fernando Herrero, muchas gracias chicos, no solo por enseñarme a trabajar en ROS y con Tibi, sino por vuestra predisposición a colaborar y ayudar, da gusto trabajar con personas como vosotros. A Gonzalo Ferrer, por hacer divertidas todas esas horas de desesperación en el Campus Nord con Dabo (estoy en home!).

También querría dar las gracias a Michael Villamizar por todos estos años de amistad y comprensión, empezamos como compañeros de trabajo, y te convertiste en un gran amigo, gracias por estar siempre a mi lado y confiar en mi. A Leonel Rozo, por sus consejos, por escucharme y por las terapias de grupo que nos daban esa fuerza necesaria para no abandonar y continuar hacia adelante, porque la llegada hacia la meta junto a ti ha sido mucho más fácil. Oscar y Diana, aunque no estemos juntos os tengo muy presentes, gracias a vosotros pasé grandes momentos en USA, Barcelona o Sils, os echo mucho de menos chicos. A Ernesto, por demostrarnos que la lucha constante y el esfuerzo hacia un objetivo conlleva una gran recompensa. To Farzad, you are a great person, colleague and coworker, I know you will achieve all you propose. A la doctora en química Saskia Speed, ara ja sé que és un fosfanato, o això crec, espero poder seguir compartint molts anys d'amistat amb tu.

Me gustaría recordar a todas aquellas personas que me acomapañaron durante mi estancia en Pittsburgh (los "Pittsburghers"), fue un placer compartir esos momentos con vosotros, y aprender de otros campos de la robótica. Durante esos meses fue muy afortunada ya que conocí a grandes personas que ahora son grandes amigos.

Per tots els amics d'abans, d'ara i de sempre, però molt especialment a la recient Doctora en Físiques, la meva gran amiga Laura, em sento molt afortunada de tenir-te a la meva vida, amb tu he descobert que hi ha universos locals. I a la també doctora (en matemàtiques) Mireia, m'encanta la teva visió i percepció del món.

Por último, estoy especialemente agradecida a mi querida familia. Al meu pare, qui m'ha ensenyat a no rendir-me mai, a ser exigent a mi mateixa i lluitar pels somnis, gràcies per confiar amb mi i ser un exemple de superació; a mi madre, la persona más bondadosa que conozco, por su gran apoyo y compresión eterna, todo el mundo te dice que eres una gran profesora, pero yo tengo la gran suerte de tenerte como madre; a la meva germana Eva, per valorar-me, protegir-me i fer-me tocar de peus a terra sempre, saps que el sentiment és comú, sé que conseguiràs tot el que et proposis, i vagis on vagis jo cuidaré dels teus felins; i al meu estimat Xavi, qui ha compartit aquest dur camí amb mi i ha estat el meu gran suport. Aquesta tesis és vostre, l'amor que m'heu demostrat dia a dia m'ha donat les forces necessàries per continuar endavant.

Quisiera terminar mis agradecimientos recordando a mi abuela, a Consuelo y "al padrí", allá donde estéis os dedico este trabajo, siempre os llevo en mi corazón.

Abstract

The development of social robots capable of interacting with humans is one of the principal challenges in the field of robotics. More and more, robots are appearing in dynamic environments, like pedestrian walkways, universities, and hospitals; for this reason, their interaction with people must be conducted in a natural, gradual, and cordial manner, given that their function could be aid, or assist people. Therefore, navigation and interaction among humans in these environments are key skills that future generations of robots will require to have. Additionally, robots must also be able to cooperate with each other, if necessary. This dissertation examines these various challenges and describes the development of a set of techniques that allow robots to interact naturally with people in their environments, as they guide or accompany humans in urban zones. In this sense, the robots' movements are inspired by the persons' actions and gestures, determination of appropriate personal space, and the rules of common social convention.

The first issue this thesis tackles is the development of an innovative robot-companion approach based on the newly founded Extended Social-Forces Model. We evaluate how people navigate and we formulate a set of virtual social forces to describe robot's behavior in terms of motion. Moreover, we introduce a robot companion analytical metric to effectively evaluate the system. This assessment is based on the notion of "proxemics" and ensures that the robot's navigation is socially acceptable by the person being accompanied, as well as to other pedestrians in the vicinity. Through a user study, we show that people interpret the robot's behavior according to human social norms.

In addition, a new framework for guiding people in urban areas with a set of cooperative mobile robots is presented. The proposed approach offers several significant advantages, as compared with those outlined in prior studies. Firstly, it allows a group of people to be guided within both open and closed areas; secondly, it uses several co-operative robots; and thirdly, it includes features that enable the robots to keep people from leaving the crowd group, by approaching them in a friendly and safe manner. At the core of our approach, we propose a "Discrete Time Motion" model, which works to represent human and robot motions, to predict people's movements, so as to plan a route and provide the robots with concrete motion instructions.

After, this thesis goes one step forward by developing the "Prediction and Anticipation Model".This model enables us to determine the optimal distribution of robots for preventing people from straying from the formation in specific areas of the map, and thus to facilitate the task of the robots. Furthermore, we locally optimize the work performed by robots and people alike, and thereby yielding a more human-friendly motion.

Finally, an autonomous mobile robot capable of interacting to acquire human-assisted learning is introduced. First, we present different robot behaviors to approach a person and successfully engage with him/her. On the basis of this insight, we furnish our robot with a simple visual module for detecting human faces in real-time. We observe that people ascribe different personalities to the robot depending on its different behaviors. Once contact is initiated, people are given the opportunity to assist the robot to improve its visual skills. After this assisted learning stage, the robot is able to detect people by using the enhanced visual methods. Both contributions are extensively and rigorously tested in real environments.

As a whole, this thesis demonstrates the need for robots that are able to operate acceptably around people; to behave in accordance with social norms while accompanying and guiding them. Furthermore, this work shows that cooperation amongst a group of robots optimizes the performance of the robots and people as well.

Resum

El desenvolupament de robots socials capaços d'interactuar amb els éssers humans és un dels principals reptes en el camp de la robòtica. Actualment, els robots comencen a aparèixer en entorns dinàmics, com zones de vianants, universitats o hospitals; per aquest motiu, aquesta interacció ha de realitzar-se de manera natural, progressiva i cordial, ja que la seva utilització pot ser col·laboració, assistència o ajuda a les persones. Per tant, la navegació i la interacció amb els humans, en aquests entorns, són habilitats importants que les futures generacions de robots han de posseir, a més a més, els robots han de ser aptes de cooperar entre ells si fos requerit. El present treball estudia aquests reptes plantejats. S'han desenvolupat un conjunt de tècniques que permeten als robots interectuar de manera natural amb les persones i el seu entorn, mentre que guien o acompanyen als humans en zones urbanes. En aquest sentit, el moviment dels robots s'inspira en la manera com es mouen els humans i en les convenvions socials, així com l'espai personal.

El primer punt que aquesta tesi comprèn és el desenvolupament d'un nou mètode per a "robots-acompanyants" basat en el nou model estès de forces socials. S'ha evaluat com es mouen les persones i s'han formulat un conjunt de forces socials virtuals que descriuren el comportament del robot en termes de moviments. Aquesta evaluació es basa en el concepte de "proxemics" i assegura que la navegació del robot està socialment acceptada per la persona que està sent acompanyada i per la gent que es troba a l'entorn. Per mitjà d'un estudi social, mostrem que els humans interpreten el comportament del robot d'acord amb les normes socials.

Així mateix, un nou sistema per a guiar a persones en zones urbanes amb un conjunt de robots mòbils que cooperen és presentat. El model proposat ofereix diferents avantatges comparat amb treballs anteriors. En primer lloc, es permet a un grup de

persones ser guiades en entorns oberts o amb alta densitat d'obstacles; segon, s'utilitzen diferents robots que cooperen; tercer, els robots són capaços de reincorporar a la formació les persones que s'han allunyat del grup anteriorment de manera segura. La base del nostre enfocament es basa en el nou model anomenat "Discrete Time Motion", el qual representa els movimients dels humans i els robots, prediu el comportament de les persones, i planeja i proporciona una ruta als robots.

Posteriorment, aquesta tesi va un pas més enllà amb el desenvolupament del model "Prediction and Anticipation Model". Aquest model ens permet determinar la distribució òptima de robots per a prevenir que les persones s'allunyin del grup en zones específiques del mapa, i per tant facilitar la tasca dels robots. A més, s'optimitza localment el treball realitzat pels robots i les persones, produint d'aquesta manera un moviment més amigable.

Finalment, s'introdueix un robot autònom mòbil capaç d'interactuar amb les persones per realitzar un aprenentatge assistit. Incialment, es presenten diferents comportaments del robot per apropar-se a una persona i crear un víncle amb ell/ella. Basant-nos en aquesta idea, un mòdul visual per a la detecció de cares humanes en temps real va ser proporcionat al robot. Hem observat que les persones atribueixen diferents personalitats al robot en funció dels seus diferents comportaments. Una vegada que el contacte va ser iniciat es va donar l'oportunitat als voluntaris d'ajudar al robot per a millorar les seves habilitats visuals. Després d'aquesta etapa d'aprenentatge assistit, el robot va ser capaç d'identificar a les persones mitjançant l'ús de mètodes visuals. Ambdues contribucions van ser extensa i rigurasament testejades en experimentació real.

En conjunt, aquesta tesi presenta i demostra la necessitat de robots que siguin capaços d'operar de forma acceptable amb la gent i que es comportin d'acord amb les normes socials mentres acompanyen o guien a persones. Per altra banda, aquest treball mostra que la coperació entre un grup de robots pot optimitzar el rendiment tant dels robots com dels éssers humans.

Resumen

El desarrollo de robots sociales capaces de interactuar con los seres humanos es uno de los principales retos en el campo de la robótica. Actualmente, los robots empiezan a aparecer en entornos dinámicos, como zonas peatonales, universidades u hospitales; por este motivo, dicha interacción debe realizarse de forma natural, progresiva y cordial, puesto que su utilización puede ser colaborar, asistir o ayudar a las personas. Por lo tanto, la navegación y la interacción con los humanos, en dichos entornos, son habilidades importantes que las futuras generaciones de robots deben poseer, además los robots deben ser capaces de cooperar entre ellos si fuese requerido. La presente disertación estudia los retos planteados. Se han desarrollado un conjunto de técnicas que permiten a los robots interactuar de manera natural con personas y sus ambientes, mientras que guían o acompañan a los humanos en zonas urbanas. En este sentido, el movimiento de los robots se inspira en la manera como se mueven las humanos y en las convenciones sociales, así como el espacio personal.

Un primer punto que esta tesis abarca es el desarrollo de un nuevo método para “robots-acompañantes” basado en el nuevo modelo extendido de fuerzas sociales. Se ha evaluado como se mueven las personas y se han formulado un conjunto de fuerzas sociales virtuales que describen el comportamiento del robot en términos de movimiento. Esta evalución se basa en el concepto de “proxemics” y asegura que la navegación del robot está socialmente aceptada por la persona que está siendo acompañada y por la gente que se encuentran en el entorno. Por medio de un estudio social, mostramos que los humanos interpretan el comportamiento del robot acorde con las normas sociales.

Asimismo, un nuevo sistema para guiar a personas en zonas urbanas con un conjunto de robots móviles que cooperan es presentado. El modelo propuesto ofrece varias ventajas comparado con trabajos anteriores. En primer lugar, se permite a un grupo

de personas ser guiadas en entornos abiertos o con alta densidad de obstáculos; segundo, se utilizan varios robots que cooperan; tercero, los robots son capaces de reincorporar a la formación las personas que se han alejado del grupo anteriormente de manera segura. La base de nuestro enfoque se basa en el nuevo modelo llamado "Discrete Time Motion", el cual representa los movimientos de los humanos y los robots, predice el comportamiento de las personas, y planea y proporciona una ruta a los robots.

Posteriormente, esta tesis va un paso más allá con el desarrollo del modelo "Prediction and Anticipation Model". Dicho modelo nos permite determinar la distribución óptima de robots para prevenir que las pesonas se alejen del grupo en específicas zonas del mapa, y por lo tanto facilitar la tarea de los robots. Además, se optimiza localmente el trabajo realizado por los robots y las personas, produciendo de este modo un movimiento más amigable.

Finalmente, se introduce un robot autónomo móvil capaz de interactuar con las personas para realizar un aprendizaje asistido. Incialmente, se presentan diferentes comportamientos del robot para acercarse a una persona y crear un vínculo con él/ella. Basándonos en esta idea, un módulo visual para la detección de caras humanas en tiempo real fue proporciado al robot. Observamos que las personas atribuyen diferentes personalidades al robot en función de sus diferentes comportamientos. Una vez que el contacto fue iniciado, se dio la oportunidad a las personas de ayudar al robot para mejorar sus habilidades visuales. Después de esta etapa de aprendizaje asistido, el robot fue capaz de detectar a las personas mediante el uso de métodos visuales. Ambas contribuciones fueron extensa y rigurosamente testeadas en experimentación real.

En conjunto, esta tesis presenta y demuestra la necesidad de robots que sean capaces de operar de forma aceptable con la gente y que se comporten de acuerdo con las normas sociales mientras acompañan o guían a personas. Por otra parte, este trabajo muestra que la cooperación entre un grupo de robots puede optimizar el rendimiento tanto de los robots como de los seres humanos.

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Nomenclature

Notation

A	interaction strength
a_{max}	maximum acceleration of the robot
B	parameter of repulsive interaction
d_{ij}	distance between p_i and p_j
$d_{\mathcal{L}i}$	distance between person p_i and robot $\mathcal{L}$
Δs_i	space traversed by the person p_i
Δs_{R_i}	space traversed by the robot R_i
i	intensity of a human perceived by the robot
K	number of groups in the F-distribution
l_i^d	desired separation between leader $\mathcal{L}$ and shepherd robot $\mathbb{S}_i$
m_{R_i}	mass of the R_i robot
N	overall sample size in the F-distribution
N_p	number of people who are being accompanied by robots
N_R	number of robots
p	p-value, if $p < 0.05$ the null hypothesis is rejected

p_i	a person in the environment
p_p	people perceived
R_i	i-th robot of the formation
s_0	an initial state, $s_0 \in \mathcal{H}$
V	valence
v	linear velocity
$v_{p_i}^0$	desired speed of a pedestrian p_i
$v_{p_i}^{max}$	maximal acceptable speed of a pedestrian p_i
z_l	specific intensity parameter for each level of engagement
α	scalar positive parameter controller of $\boldsymbol{f}_{R,dest}^{goal}$
β	scalar positive parameter controller of $\boldsymbol{f}_{R,i}^{goal}$
δ	scalar positive parameter controller of $\sum_{o \in O} \boldsymbol{f}_{R,o}^{int}$
γ	scalar positive parameter controller of $\sum_{j \in P} \boldsymbol{f}_{R,j}^{int}$
κ	scalar positive parameter of $\boldsymbol{F}_{att}$
λ	parameter defining the strength of the anisotropic factor
η^2	eta-squared, describes the ratio of variance explained in the dependent variable by a predictor while controlling for other predictors
o	obstacle in the environment
θ	orientation
ψ_i^d	desired bearing between leader $\mathcal{L}$ and shepherd robot $\mathcal{S}_i$
τ	the time of pedestrian stride
φ_{ij}	angle between the walking direction of the person p_i and the segment formed by person p_i and person p_j

ς	score representing the classifier confidence
ϱ_i^d	desired orientation between leader $\mathcal{L}$ and shepherd robot $\mathcal{S}_i$
ϑ	an interval in which the system is unable to know whether the detection is positive or negative
ω	angular velocity
$\boldsymbol{a}_{R_i}$	acceleration of the robot R_i
$\boldsymbol{c}$	robot's configuration
$\boldsymbol{c}^d$	desired robot's configuration
$\boldsymbol{e}_{p_i}(t)$	desired motion direction of a pedestrian p_i
$\boldsymbol{e}_{R_i}(t)$	direction motion of robot R_i
$\boldsymbol{g}_t$	position and velocity of the center of the group of people
$\boldsymbol{n}_{ij}$	unit vector pointing from pedestrian p_i to pedestrian p_j
$\boldsymbol{n}_{r_{R_i,tar}}$	unit vector pointing from the robot to target
$\boldsymbol{n}_{v_{R_i,tar}}$	unit vector denoting the relative velocity direction of the target with respect to the robot
$\boldsymbol{p}$	a point on the environment, $\boldsymbol{p} \in \mathbb{R}^2$
$\boldsymbol{r}_{\mathcal{L}}(t)$	position of robot $\mathcal{L}$ at time t
$\boldsymbol{r}_{p_i}^0$	destination that a person p_i wants to reach
$\boldsymbol{r}_{p_i}^k$	the subsequent edge of the polygon that will be reached by person p_i
$\boldsymbol{r}_{ij}(t)$	vector pointing from pedestrians p_i to p_j at time t
$\boldsymbol{r}_{p_i}(t)$	position of person p_i at time t
$\boldsymbol{r}_{R_i}(t)$	position of robot R_i at time t

$\boldsymbol{r}_{tar}(t)$	position of the target at time t
$\boldsymbol{u}_n$	process random noise
$\boldsymbol{v}_{g_t}$	mean velocity of the group of people
$\boldsymbol{v}^0_{p_i}(t)$	desired velocity of a pedestrian p_i
$\boldsymbol{v}_{p_i}(t)$	current velocity of a pedestrian p_i
$\boldsymbol{v}_n$	observation random noise
$\boldsymbol{v}_{R_i}(t)$	current velocity of a the robot R_i
$\boldsymbol{v}_{tar}(t)$	current velocity of the target
$\boldsymbol{w}_{p_i}(t)$	preferred velocity of a pedestrian p_i
$\boldsymbol{x}_n$	positions vector
$\boldsymbol{x}_{g_t}$	position of the center of the group of people
$\boldsymbol{x}_{0:n}$	positions up to time n
$\boldsymbol{y}_n$	observation vector
$\boldsymbol{y}_{0:n}$	observations up to time n
$\boldsymbol{\mu}$	mean
$\boldsymbol{z}^{obs}_k$	observation vector at time k
$\boldsymbol{z}^{sim}_k$	simulated position vector at time k
$\boldsymbol{\Theta}$	a vector formed by the parameters $\boldsymbol{\Theta} = \{\alpha, \beta, \gamma, \delta\}$
$\boldsymbol{\xi}$	parameter accounting for noise
$\boldsymbol{A}$	state transition matrix of PAM
$\boldsymbol{J}_{\boldsymbol{\Upsilon}}$	jacobian matrix of function $\boldsymbol{\Upsilon}$
$\boldsymbol{\Sigma}$	covariance matrix

$\boldsymbol{Q}$	matrix representing the acceleration capabilities of humans
$D_t(\cdot,\cdot)$	density of obstacles that a group of people finds at time t
$D_{t_{ext}}(\cdot,\cdot)$	density of obstacles and robots that a group of people finds at time t
F	F-statistic, it follows the F-distribution with $K-1$, $N-K$ degrees of freedom under the null hypothesis
$f(\cdot)$	process equation
G_i	relationship between leader $\mathcal{L}$ and shepherd robot $\mathcal{S}_i$
$h(\cdot)$	observation equation
$H(\cdot)$	the occupied space of the obstacles
$H_{ext}(\cdot,\cdot)$	the occupied space of the obstacles and robots
$N(T)$	difference between the number of times the person presses button '+' and button '-' at time T of the wii controller
$p(\boldsymbol{x}_n \mid \boldsymbol{y}_{0:n})$	posterior distribution
$T(\cdot,\cdot)$	repulsive force that a person/robot/obstacle generates in the environment
$U_{io}(\boldsymbol{r}_{io})$	repulsive and monotonic decreasing potential
$V_{ij}(b_{ij})$	monotonic decreasing function of b_{ij}
$\alpha(N(T))$	update function of the parameter α
$\beta(N(T))$	update function of the parameter β
$\gamma(N(T))$	update function of the parameter γ
$\pi(\cdot)$	sampling distribution

ρ	overall performance of the companion task accomplished by the robot
$\varkappa$	the state-transition function of the state machine
$\boldsymbol{f}_i^0$	deviation of the actual velocity from the desired velocity
$\boldsymbol{f}_{\mathcal{L}i}^{drag}$	dragging force
$\boldsymbol{f}_{ij}$	repulsive force between p_i and p_j
$\boldsymbol{f}_{io}$	attractive force between p_i and the point of interest o
$\boldsymbol{f}_{R_i}^{mot}$	robot force motion
$\boldsymbol{f}_{ij}^{push}$	pushing force
$\boldsymbol{f}_i^{goal}$	steering force of pedestrian p_i
$\boldsymbol{f}_{iR}^{int}$	repulsive force between the robot and the pedestrian p_i
$\boldsymbol{F}_i$	social force term of pedestrian p_i
$\boldsymbol{F}_R^{obs}$	addition of repulsive forces obstacles generates to the robot
$\boldsymbol{F}_R^{per}$	addition of repulsive forces each person generates to the robot
$\boldsymbol{F}_{att}$	virtual attractive force
$\boldsymbol{f}_{R,dest}^{goal}$	robot's force to the target's destination
$\boldsymbol{f}_{R,o}^{int}$	interaction force between robot and obstacles
$\boldsymbol{f}_{R,j}^{int}$	interaction between the pedestrian p_j and the robot R
$\boldsymbol{W}_{drag}$	dragging work
$\boldsymbol{W}_{R_i}$	cost function for robot R_i
$\boldsymbol{W}_{R_i}^{mot}$	robot work motion
$\boldsymbol{W}_{push}$	pushing work

$\boldsymbol{\Upsilon}(\boldsymbol{g}_{t-1}, \mathcal{O})$	description of the motion of the center of the group over time
$\mathcal{A}$	social distance area of pedestrian who is being accompanied
$\mathcal{B}$	human's field of view area of pedestrian who is being accompanied
$\mathcal{C}_i$	personal space of pedestrian p_i who is being accompanied
$\mathcal{C}_j$	personal space of pedestrian p_j
$\mathcal{F}$	set of final states
$\mathcal{G}_t$	space occupied by the intersection of the set of obstacles and group's position at time t
$\mathcal{H}$	a finite, non-empty set of states
$\mathcal{K}$	a finite, non-empty set of symbols
$\mathcal{L}$	leader robot
$\mathcal{O}$	set of obstacles in the map
$\mathcal{P}_i$	set of people in which one of the shepherd robots has invaded the person's personal space
$\mathcal{R}$	set of robots in the environment, $\mathcal{R} = \left\{\mathcal{L} \cup_{j=1}^{N_R-1} \mathcal{S}_j\right\}$
$\mathcal{S}$	shepherd robot

Acronyms

ANOVA	ANalysis Of VAriance
BRL	Barcelona Robot Lab
DTM	Discrete Time Motion Model
ESFM	Extended Social Force Model

FME	Facultat de Matemàtiques i Estadística
FSM	Finite State Machine
GPF	Gaussian Particle Filter
HRI	Human Robot Interaction
M	Medium
PAM	Prediction and Anticipation Model
PF	Particle Filter
SD	Standard Deviation
SFM	Social Force Model
UPC	Universitat Politècnica de Catalunya

Chapter 1

Introduction

There is a single light of science, and to brighten
it anywhere is to brighten it everywhere.

Isaac Asimov

Nowadays, human-robot interaction and robot navigation are two fields within robotics that have made great progress, thus, it is accepted and well known that in our future there will be mobile autonomous robots to help society in general, specially servicing robots to cooperate with humans in their everyday tasks. Concretely, robots are able to assist people in urban areas as a companion robot, a tour guide, or an information point.

Mobile robots will interact with people in everyday tasks and they must behave in such a way that humans perceive robots as human-like. Traditional motion methods for a mobile robot that navigates near and with people, may not be accepted by humans, because they might not follow human social norms. When robots do not behave as socially expected, human-robot interaction may fail.

To address these issues, we have developed a framework that allows robots to interact naturally with humans and their environment, while robots navigate, guide or accompany people in urban settings. In this sense, robots movements are inspired by people motion and human social conventions, such as personal space.

Furthermore, robots must be able to cooperate between them if it is required, thus, one important application within the field of social and cooperative robots is that of using a set of autonomous robots for accompanying a group of people. This kind of application has already been used for guiding people in museums [19], however the robot navigation skills were limited to simple path planning functionalities with additional reactive behaviors to avoid collisions with humans. Besides, no particular actions were taken to avoid situations were the crowd did not follow the robot, which has been studied extensively in this dissertation.

Finally, regarding to the field of human-robot interaction research, it is important to give to the robots the ability to initiate interaction with humans. Generally, it is thought that social robots can engage in the same way people do, using human-like physical signals and gestures [122]. Recent studies show that robots are also able to encourage people to initiate interaction, expecting people to approach them instead of initiating it themselves [100]. The present work takes this a step further by looking at how robots can seek assistance from a person, after initiating a conversation and engaging meaningfully with him/her.

In the rest of this chapter, we briefly state the motivation, overview, main contributions and the derived publications, which had become the contents of the rest of monograph, set forth chapter by chapter.

1.1 Motivation

These days, robots are starting to emerge in human everyday environments, therefore, it becomes necessary to find methods, in which they can interact and engage seamlessly. Human environments, such as pedestrian streets, universities, hospitals or shopping centers, are places where robots are appearing.

In the last years, researchers developed autonomous mobile robots for outdoor and public environments. Studies performed on robots which serve to guide humans have been conducted in museums [20, 125], railway stations [72], as assistants [30, 141], and in shopping malls [152]; other studies have examined ways in which robots provide humans with the flexibility of deciding the way in which they want to be guided [132].

Thus, being able to accompany, guide and interact with people in these dynamic environments are important skills for future robot generations. So far, these tasks have been performed by humans, as observed in Fig. 1.1. The motivation of this research is

Figure 1.1: **Motivation of the thesis:** ***Left:*** A group of people being guided in Barcelona. ***Center:*** An information point in a public place. ***Right:*** Three men accompanying/escorting President Obama

to make the robots capable of carrying out these missions. Moreover, to be accepted, robots must be able to interact and move in a comfortable manner.

Imagine a service robot navigating in a University campus. Some goals the robot has to reach are the following ones:

- to move around people in the environment in a human-like way;
- to approach people who need assistance in an appropriate way;
- to interact with people to help with the needs of the person, using verbal and non-verbal communication;
- to accompany people to a certain interested location in a crowded environment in an acceptable social way;
- and, to guide a group of people and, if needed, to cooperate with other robots to achieve the task.

In this dissertation, we focus on designing robot behaviors to solve the above tasks. Moreover, to be accepted as cooperative partners, robots must not only have the ability to achieve these objectives efficiently, but they must also be accepted by people in the environment.

Doing so allows people to feel save with a robot, and therefore, humans will trust it and will follow its instructions. Specially, we believe that if such robots are able to behave according to human social norms –such as respecting personal space– and in a human-like motion, they will be better accepted by pedestrians around them. This will allow both the robots and people to accomplish their jobs more efficiently and easily.

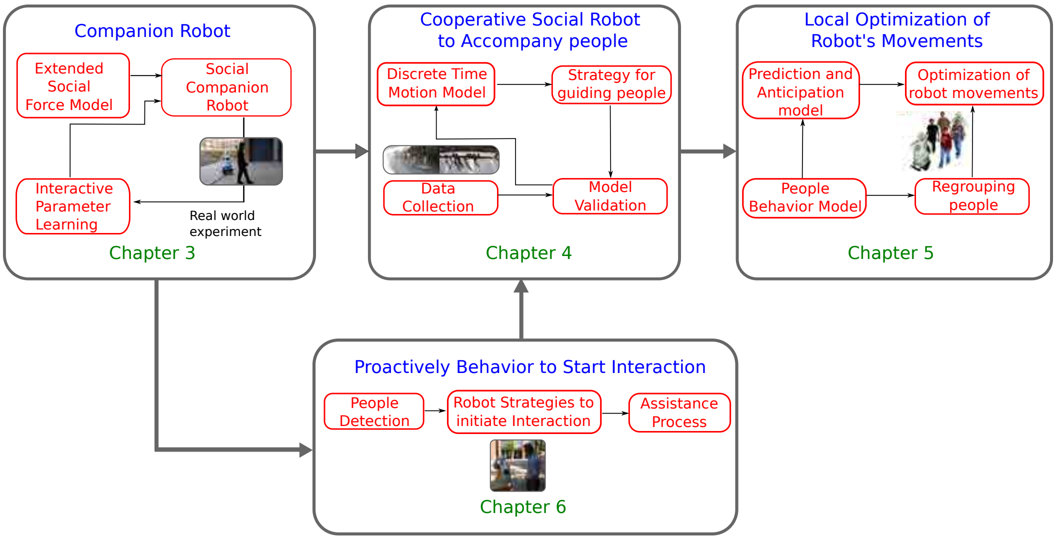

Figure 1.2: **Thesis outline.** Block diagram representing the different architectures proposed in this thesis.

Finally, we hope that this research will encourage development of more social robots able to escort and guide people in public places, and to cooperate with other robots in order to accomplish the tasks more efficiently.

1.2 Outlook at the Dissertation

This thesis is organized through seven chapters and two appendices. Next paragraphs outline the content of each chapter and appendix, and will serve to guide the reader througt the PhD dissertation.

- **Chapter 1** is the introduction. It summarizes the PhD dissertation, including the motivation, the outline of the thesis and the list of publications
- **Chapter 2** reviews the state of the art on robot navigation in urban environments, cooperative robotics, robot companion and human-robot interaction.
- **Chapter 3** defines a novel robot companion framework based on the so-called Social Force Model to guide or accompany people in dense urban areas. Additionally, we present a new metric to evaluate the robot companion performance

based on vital spaces and comfortableness criteria. Also, a multimodal human feedback is proposed to enhance the behavior of the system.

- **Chapter 4** describes a new model for people guidance in urban settings using several mobile robots. The novelty of this approach resides in how the environment and human and robot motions are modeled. In particular, we present a "Discrete-Time-Motion" model, which from one side represents the environment by means of a potential field, that makes it appropriate to deal with open areas, and on the other hand, the motion models for people and robots respond to realistic situations.

- **Chapter 5** investigates the circumstances in which people might stray from the formation when following different robots' instructions. We introduce a novel approach to locally optimize the work performed by robots and people using the minimum robots' work criterion and determining human-friendly types of movements. The guidance missions were carried out in urban areas that included multiple conflict areas and obstacles.

- **Chapter 6** proposes the results of several experiments conducted at the Barcelona Robot Lab, in which we studied various aspects of the interaction between a mobile robot and untrained human volunteers. Different pro-active robots behaviors to use when approaching a person and engaging with him/her are presented. Furthermore, we developed additional communication skills to allow people to assist the robot and help it to enhance its facial recognition system.

- **Chapter 7** concludes the work highlighting the original contributions of this thesis. Furthermore, this chapter points out future research lines identified as key trends in the near future for single/multiple mobile robot cooperation to accompany/guide/interact with people in urban pedestrian scenarios.

- **Appendix A** shows the two robots used in most of the experimental sections of this dissertation, listing the on board sensors and devices.

- **Appendix B** details the method used in Chapters 3 and 6 to evaluate people perception of robots behaviors. A single factor analysis of variance (ANOVA) has been computed, according to [13].

Fig. 1.2 shows the blocks diagrams representing the different architectures proposed in this thesis, and it also outlines the structure of this document.

1.3 Main Contributions

This dissertation provides four main contributions. First and foremost is our social companion robot framework. We provide results, both in simulation and in user studies with a physical robot. In addition, we introduce the "Discrete-Time Motion Model", which allows a set of cooperative robots to guide and escort a group of people in a human-safe manner. Furthermore, we provide an extension to the mentioned model, it is called "Prediction and Anticipation model". It enables to determine the particular distribution of robots that can be used to best prevent people from straying from the formation in specific areas of a map. By using this model, we were able to prevent people from straying from the guided group and, thus facilitate the task of the robots. Furthermore, we could locally optimize the work performed by robots and people alike, and therefore obtain a human-friendly motion. Finally, we present different robot's pro-active behaviors that can be used when approaching a person and engaging with him/her designed for social human-robot interaction.

1.3.1 Social Companion Robots (Chapter 3)

In Chapter 3, we describe a new model that has been designed to accompany people using the Extended Social Force Model. The social force model presented in [75] takes into account both destinations and interactions by defining a summation of existing forces determining people trajectories. The social companion robot framework is the main contribution of this chapter. The proposed model is validated throughout simulations and a set of real-life experiment.

Furthermore, an interactive approach tests the model forces and learns which is the desired robots behavior by humans. The purpose of the provided feedback is to learn a general approaching rule that defines a better robot behavior. The proposed interactive learning helps to enlighten the nature of the model, and to generate controlled interaction forces that otherwise would be extremely complicated to generate.

Moreover, to evaluate the performance of the companion task accomplished by the robot, a quantitative metric is defined. This assessment is based on "proxemics", proposed by Hall [70]. Finally, we conducted a user study to determine whether the robot's behavior was perceived as socially appropriate by the experiment participants.

1.3.2 Discrete Time Motion Model (Chapter 4)

Chapter 4 presents the architecture we developed to guide and escort a group of people using several robots behaving in a cooperative and human-safe manner. The main contributions of this chapter are twofold: on the one hand, we represent the environment by means of a potential field which allows to deal with either open or closed areas, and with or without obstacles. On the other hand, the motion models for both people and robots are grounded on social human behaviors learned from training databases of groups of pedestrians moving in real-world scenarios. All these pieces are integrated within a common "Discrete-Time Motion Model" that allows to estimate the motion of people and robots and to compute the robot's trajectory for guiding people to a specific goal.

In addition, the guiding capabilities of our approach are initially validated through synthetic data. Moreover, we also use real data. For the collection of the real data, we used the camera network available in the Barcelona Robot Lab, which integrates 21 cameras. Using this camera network, we captured a set of video sequences of groups of people while following a leader. For the validation process, we compared the estimations obtained by the Discrete Time Motion model and the results obtained from the real data.

1.3.3 Prediction and Anticipation Model (Chapter 5)

One of the main challenges when robots try to perform the task of guiding a group of people is the possibility that one or more people will move away from the group, either out of boredom or due to his/her interest in something which lies away from the group's path. In this chapter, we investigate the circumstances in which people might stray from the formation when following different robots' instructions. For this reason, we introduce a "prediction and anticipation model" that predicts the position of the group using a Particle Filter, while determining the optimal robot behavior to help people stay in the group in areas where they may become distracted.

Furthermore, it is crucial to understand the environment in which the group moves. As a result, we need to know the set of robots and people that would be situated in the hallways, open spaces, intersections and other settings. We also describe a mathematical function which determines the density of obstacles that surround the group during their movement along the path. In the areas with open spaces and a low density of obstacles, the probability that a person will move away is high and, thus, these areas were treated as conflict areas in our investigation.

Finally, we present a cost function which computes the optimal configuration of robots (defined as the behavior of all the members of the group). That configuration should not only minimize the work performed by the robots, but also make the interaction between robots and people as "comfortable" as possible, in terms of motion.

1.3.4 Robot's Proactive Behavior to Create Engagements with Humans (Chapter 6)

The final contribution of this thesis is to enable robots to interact naturally with people when carrying out the accompanying task. In this chapter, we present the results of several conducted experiments, in which we studied various aspects of the interaction between a mobile robot and untrained human volunteers.

First, we identify the optimal robot behavior for initiating interaction with a human. To do so, we analyzed three variations on this behavior, looking at scenarios in which: (1) The robot uses only verbal cues to communicate with the participant; (2) The robot uses both verbal and non-verbal cues (e.g., gestures and eye gazes); and (3) The robot uses verbal and non-verbal cues and actually approaches humans. Moreover, to synthesize Tibi's emotions of happiness, sadness and anger, we used the emotion model of the three dimensions of emotion [146]. This model characterizes emotions in terms of *stance*, *valence* and *arousal*.

Secondly, once the robot has engaged with a human, we proposed an approach in which the robot was able to enhance its visual skills using the human's help. Following each interaction, we were able to prove that the robot's skills were visibly improved.

Finally, we conducted a user study to determine whether the robot's behavior was perceived as socially appropriate by the experiment participants.

1.4 Derived Publications

The derived publications during the PhD are listed below. They correspond to articles submitted to relevant international and national journals and conferences.

1. G. Ferrer*, **A. Garrell***, F. Herrero and A. Sanfeliu. Robot Social-Awareness Navigation Framework to Accompany People. IEEE Transactions on Robotics, [Second revision], [41]. (* indicates equal contribution)

2. G. Ferrer, **A. Garrell** and A. Sanfeliu. Social-Aware Robot Navigation in Urban Environments. In 6th European Conference on Mobile Robots, September 2013, [43].

3. **A. Garrell**, M. Villamizar, F. Moreno-Noguer, A. Sanfeliu. Proactive Behavior of an Autonomous Mobile Robot for Human-Assisted Learning. In 22nd IEEE International Symposium on Robot and Human Interactive Communication, pages 107-113, August 2013, [59].

4. G. Ferrer*, **A. Garrell*** and A. Sanfeliu. Robot Companion: A Social-Force based approach with Human Awareness-Navigation in Crowded Environments. In IEEE/RSJ International Conference on Intelligent Robots and Systems, November 2013, [42]. (* indicates equal contribution)

5. G. Ferrer, **A. Garrell**, M. Villamizar, I. Huerta and A. Sanfeliu. Robot Interactive Learning through Human Assistance. In Multimodal Interaction in Image and Video Applications, pages 185-203, Springer Berlin Heidelberg, 2013 [44].

6. **A. Garrell** and A. Sanfeliu. Cooperative social robots to accompany groups of people. The International Journal of Robotics Research , 31(13): 1675-1701, 2012, [57].

7. M. Villamizar, **A. Garrell** A. Sanfeliu and F. Moreno-Noguer. Online human-assisted learning using random ferns. In 21st IEEE International Conference on Pattern Recognition, pages 2821-2824, Tsukuba, Japan, November 2012, [171].

8. **A. Garrell**, A. Corominas Murtra and A. Sanfeliu. Robots companions for guiding people in urban areas. In Workshop de Robótica Experimental, pages 419-426, Seville, 2011 [49].

9. **A. Garrell**, O. Sandoval and A. Sanfeliu. Adaptive multi agent system for guiding groups of people in urban areas. In Highlights in Practical Applications of Agents and Multiagent Systems, Springer Berlin Heidelberg, pages 175-184, 2011, [51].

10. **A. Garrell** and A. Sanfeliu. Cooperative robots in people guidance mission: DTM model validation and local optimization motion. In IEEE/RSJ IROS Workshop on Network Robot Systems, Taipei, October 2010, [52].

11. **A. Garrell** and A. Sanfeliu. Model validation: robot behavior in people guidance mission using DTM model and estimation of human motion behavior. In IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 5836-5841, Taipei, October 2010, [56].

12. **A. Garrell** and A. Sanfeliu. Local optimization of cooperative robot movements for guiding and regrouping people in a guiding mission. In IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 3294-3299, Taipei, October 2010, [55].

13. **A. Garrell**, O. Sandoval, J. M. Mirats Tur and A. Sanfeliu. Guiding and regrouping people missions in urban areas using cooperative multi-robot task allocation. In 15th IEEE International Conference on Emerging Technologies and Factory Automation, pages 2682-2690, Bilbao, September 2010 [50].

14. **A. Garrell** and A. Sanfeliu. Cooperative robot movements for guiding and regrouping people using cost function evaluation. In RSS Workshop on Learning for Human-Robot Interaction Modeling, pages 14-15, Zaragoza, June 2010, [53].

15. **A. Garrell** and A. Sanfeliu. La influencia del efecto *uncanny valley* en el diseño de un robot social. In 1st International Congress of Design and Innovation of Catalonia, FUNDIT, pages 84-95, Sabadell, March 2010, [54].

16. **A. Garrell**, A. Sanfeliu and F. Moreno-Noguer. Discrete time motion model for guiding people in urban areas using multiple robots. In IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 486-491, Saint Louis, October 2009, [58]. *Nominated to best paper Award*

Chapter 2

State of the Art

Do not have to start always with the first notion of things that are studied, but for that which can facilitate learning.

Aristotle

The overall goal of this research is to develop robots that work cooperatively while accompanying people in socially acceptable ways. As such, this thesis draws on work from diverse fields, including robot navigation in urban environments, cooperative robotics, robot companion and human-robot interaction. This chapter introduces the data yielded by some of the most relevant research on this subject.

2.1 Social Navigation in Urban Environment

In the last several decades, major technological achievements have been accomplished with respect to the development of autonomous mobile robots for outdoor and public environments. Robust and reliable systems for navigation [104, 112], environmental perception [68], obstacle avoidance [34], and localization [27] have been successfully integrated into several kinds of robotic platforms [1, 142, 144]. At the same time, advances in the field of human-robot interaction aimed at making interfaces more natural [122] and effective [15, 16, 86] have brought robots and human beings closer than ever before.

Because a mobile robot must be able to avoid obstacles in the environment where it is working, many different algorithms for obstacle avoidance have been developed.

Often, dynamic obstacles are handled only in a locally reactive manner, as static (non-moving). Some works that do account for vehicle dynamic include the Curvature Velocity Method [156]; the Dynamic Window Approach [48]; or randomized kinodynamic planning using rapidly-exploring Random Trees [98]. Other algorithms consider obstacles moving over time [93, 116]. Finally, several approaches consider both vehicle dynamics and dynamic obstacles [46, 131]. While all of these algorithms may be used to generate varying degrees of safe and effective obstacle avoidance, none of them explicitly accounts for the pre-established social conventions that people use when moving around each other.

On top of this, urban pedestrian areas present additional challenges to the robotics community, such as narrow passages, ramps, holes, steps and staircases, as well as the ubiquitous presence of pedestrians, bicycles and other unmapped dynamic obstacles. This leads to new challenges in perception, estimation and control [10, 102], calling for additional research in robot navigation technologies.

A number of methods have been developed to allow robots to navigate around people in specific, typically non-generalizable, tasks. Some of these tasks include standing in line [123]; tending toward the right side of a hallway, particularly when passing people [129]; and approaching people to join conversational groups [3]. Museum tour guide robots are often given the capability to detect and attempt to handle people who are blocking their paths [20, 125, 163]. In [135], a robotic wheelchair that can follow a person was presented, but this method does not account for the social cues that the human might use in a certain situation, nor does it allow for any spontaneous social interaction. Some researchers have begun researching how a robot might adapt its speed when traveling besides a person, but they have obtained mixed results, even in controlled laboratory settings [160].

Furthermore, several groups have begun to address issues on how to plan complete paths around people, rather than relying on solely reactive behaviors. One method for how a robot might alter its velocity around people is discussed in [151]. While this method begins to address ideas of planning around people, it does not directly consider the issue of prevailing social conventions. In contrast, the Human-Aware Motion Planner, introduced in [159], considers the safety and reliability of the robot's movement as well as "human comfort", by attempting to keep the robot in front of people and visible at all times. However, the paths that the planner generates may be very unnatural, as a direct result of its attempts to stay visible to the people it leads.

Safety and reliability are key to the successful introduction of robots into human environments. In most studies, safety is assured by preventing humans from approaching the robots. But said methods are rendered ineffective whenever the robot is designated to directly assist a human individual. In [2], the notion of safety is studied in detail with respect to all relevant aspects of Human-Robot Interaction.

Two different notion of human safety are treated in [178]: "physical" safety and "mental" safety. According to the posits of this work, the notion of safety includes both physical aspects and psychological effects of the robot's motions on humans. Physical safety is necessary for the human-robot interaction. Physical safety is usually assured by avoiding collisions with humans and by minimizing the intensity of the impact in case of a collision.

Introducing the science of "proxemics", Hall demonstrates how man's use of space can affect personal business relations, cross-cultural exchanges, city planning, and urban renewal [70]. A robot should comply with the same conventions [47]. In human-robot interaction, the spatial formation around a robot has been studied in relation to initiating interaction [118]. A classification of people's motion toward a robot was treated in [12]. In [162], a robot that chooses a target person based on distance was developed.

Another approach that deals not only with safety but also implicitly with comfort issues is the work on velocity along a planned trajectory [113]. In this research, the robot adapts its trajectory and its speed in order to guarantee that no collision will occur in a dynamic environment. Although the human is not addressed explicitly, this method guarantees a motion without collision by taking into account the natural dynamics of the given environment.

This work, in contrast, introduces an innovative notion, whereby the robots are aware of other robots, the people that are accompanying them, and the bystanders naturally in the environment. Furthermore, the present study focuses on behaviors that are not only aware of people but also socially acceptable to the general population. Moreover, we are interested in developing robots that cooperate effectively while accompanying humans in an acceptable social way. In the next section, we present some relevant prior studies in robot cooperation.

2.2 Multi-Robot Systems

The majority of research on multiple mobile robot cooperation can be categorized into a set of key areas of study. Several topics that this field includes are architecture [84], communication [92], swarm robots [36], and task allocation [61]. The advantages of multi-robot systems over single-robot systems are the fact that in multi-robot systems robots are able to take on a higher task complexity.

The first publications on multiple mobile systems where introduced in 1980, since then the number of publications in the field has grown exponentially. At the most general level, approaches to multiple mobile robot systems fall into one of two broad categories: collective swarm systems and intentionally cooperative systems [133]. Collective swarm systems are those in which robots execute their own tasks with only minimal need for awareness of other robot team members. It is designed for a large number of homogeneous mobile robots that execute their own tasks with only minimal need for knowledge about other robot team members [119].

On the other hand, robots in intentionally cooperative systems have awareness of the presence of other robots in the environment, and act in unision based on the state, actions, or capabilities of their teammates in order to accomplish common goal. Intentionally cooperative systems can be divided into Strongly cooperative systems or Weakly cooperative systems, in function of the dependence on the other robots in taking decisions [18]. Whereas Strongly cooperative solutions require that robots act in concert to achieve the common goal [9], Weakly cooperative solutions allow robots to have periods of operational independence, subsequent to coordinating their selection of tasks or roles [40]. Intentionally cooperative multi-robot systems can deal with heterogeneity amongst the various robot involved, whereby team members vary in their sensor and effector capabilities.

Farinelli et al. provides a sound classification of works on multi-robot systems [38]. The proposed taxonomy is characterized by two kinds of dimensions: coordination

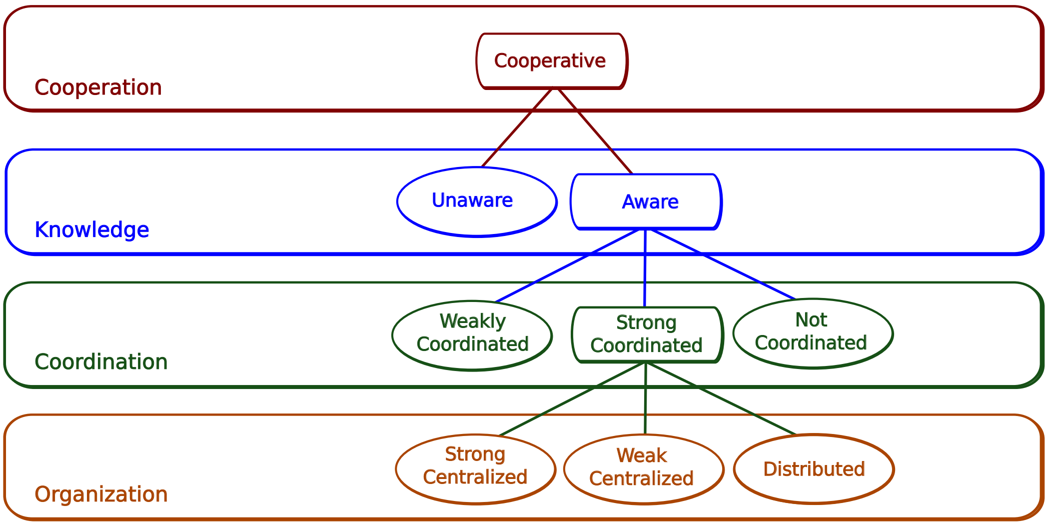

Figure 2.1: **Multi Robot classification.** Taxonomy introduced in [38].

dimensions and system dimensions. Here, the term "dimension" refers to specific features that are grouped together in the classification. More specifically, a hierarchical structure is given in Fig. 2.1. The classification dimensions are described below.

Cooperation Level: The first level of the hierarchical structure involved the system's ability to cooperate in order to accomplish a specific task. At the cooperation level, cooperative systems are distinguished from uncooperative ones. A cooperative system is comprised of "robots that operate together to perform some global task" [124]. In this manuscript, we are interested only in cooperative multi-robot systems.

Knowledge Level: The second level of the hierarchical structure refers to the awareness that each robot in the team has of its team mates. Aware robots have some degree of knowledge of their team mates, while unaware robots act without any knowledge of the other robots in the system. It has to be mentioned that the notion of knowledge in this instance is not equivalent to communication: in fact, using a communication mechanism does not imply awareness and on the contrary, a multi-robot system can be aware even when there is no direct communication among the robots.

Coordination Level: The third level refers to the mechanisms used for cooperation. Coordination is considered as cooperation in which the actions performed by each robotic agent consider the actions executed by the other robots. However, a robot may take the actions of the other team members into account in various ways. The coordinated multi-robot system is based on the type of coordination protocol, defined as a set of rules that the robots must follow while interacting with one other in the environment. Said classification is as follows: strong coordination refers to a form of coordination that relies on a coordination protocol, whereas in weak coordination [8, 147] the cooperation does not rely on a given coordination protocol.

Organization Level: The final level of the proposed taxonomy is concerned with the way the decision system is performed within the multi-robot system. The organization level introduces a distinction in the forms of coordination, by distinguishing centralized approaches [157] from distributed ones [22]. The classification of centralized systems can be further refined, depending on the way the leadership of the group is encated. Specifically, strong centralization is used to characterize a system in which decisions are made by the same predefined leader agent for the entire duration of the mission [170], while in a weakly centralized system, more than one agent is permitted to take on the role of the leader as the task is being carried out [138].

The kind of coordination that the robots engage in within the confines of this research is “strong coordination”, seeing as the robots are aware of the position of their team members, and are dependent on a certain coordination protocol. In addition, the organization level is centralized, because there is always a leader, though not a pre-determined one, and other robots may change roles in order to assume the leadership position at various intervals.

Because this work is predominantly interested in the ways multi-robot systems can accompany individuals, it is important to review relevant prior research on robot formation, seeing as the robots themselves must comply with a certain formation as they perform their task. Conversely, we also discuss the works that uses the concept of “flocking”, since we have used this concept in our research.

2.2.1 Robot Formation

In recent years, researchers have been interested in the problem of navigation in order so that multiple robots may achieve a certain desired formation. The basic motivation arises from the fact that multi-robot navigation cannot achieve a given task without a certain necessary information. It has been written in the area of formation control for multi-robot systems [33, 105, 128]. Occasionally, formation control has been linked to motion planning, obstacle avoidance, and navigation.

There are primarily two ways to address the problem of motion planning for a team of mobile robots: centralized and decentralized. On the one hand, the problem has been addressed in the past with centralized navigation scheme by a number of groups [32].

In the centralized architecture, robots are monitored and controlled by a central processor. In [37], a formation function is used in order to encode the formation objectives and constraints. A centralized system has an agent (leader) that is in charge of organizing the performance of the other agents; the leader is involved in the decision process for the whole team, while the other members can act only according to the directions of the leader. Other works apply physical analogies to the motion controller. Concretely, potential fields have been widely used to model the influences over robots and to define the control laws for the maintenance of their formation. In [67, 111] these methods are used to mantain the formation shape.

However, the centralized approach involves computational complexity, and it is based on the assumption that robot information can be transmitted extremely rapidly. Loizou et al. discusses a multi-robot navigation function that considers all the robots movement restrictions simultaneously [107]. Nevertheless, this centralization imposes a limitation on the number of robots in the formation, and can also be a problem when applied to realistic scenarios.

On the other hand, decentralized solutions are alternatively sought in order to allow the control architecture to scale nicely with the size of the group. A decentralized system is composed of agents which are completely autonomous in the decision-making process with respect to one other. These systems typically involve obstacle avoidance in a moving formation using potential field base [35, 110]; reactive or optimal control approaches [126]; or agent-based local potential fields [60, 101]. In [140], robot navigation using artificial potential functions is introduced. It is also important for the formation movement that the controller provides a smooth trajectory for all members of the group. Furthermore, robot kinematics and dynamics impose constraints that can provoke abrupt and sudden movements, if they are not properly taken into account.

Some published papers use spring-damper systems as links to adapt the formation topology to the shape and constraints of the surrounding environment. Several navigation methods for formations navigating in scenarios with obstacles have been proposed. A well-known solution is to modify the interconnections between robots to adapt the shape of the formation [85]. But the problem of deciding the best robot interconnection graph is not easy to solve, generally speaking. A novel approach was proposed in [126], wherein the authors computed a configuration space for the whole formation, treating the team of robots as one entity. This solution presents a lack of flexibility in the shape of the group.

A navigation system for robot formations with obstacle avoidance and path-planning capabilities that takes into consideration kinematic and dynamic movement restrictions was proposed in [126]. However, the provided obstacle avoidance technique presents some problems, as it does not define the influence of the environment on the formation, which may lead to unpredictable behaviors. A solution to these problems is presented in [167].

In this work, robots must follow a certain formation as they accompany a group of people. However, the above mentioned formation is not purely determined by environmental factors, but rather by the behavior exhibited by the people in the group. Therefore, the robots must be able to adapt their movements to not only their surroundings, but also to the unpredictable aspects of human behavior. As previously mentioned, the robots must prevent the group of people from straying, hence our interest in the concept of "flocking". Below some of the most relevant studies in this field are discussed.

2.2.2 Flocking by a set Autonomous Mobile Robots

As mentioned above, coordinating the movements of robots with respects to one other has been a topic of great interest in multiple mobile robot systems since the inception of the field. In particular, a great deal of attention has been paid to flocking and formation control problems. The flocking problem could be seen as a particular case of the formation control problem, as it requires robots to move collectively along a certain path, but with only minimal requirements for paths taken by specific robots.

Flocking is a kind of collective behavior amongst a large number of interacting agents who share a common objective [127]. For many years, scientists from diverse disciplines including animal behavior, social sciences, and computer science have been

Figure 2.2: **Flock of animals.** A group of wild geese/sheep/birds together, staying close to each other and maintaining a certain desired formation while in motion.

interested in the emergence of flocking/guiding/schooling in groups of agents. Examples of these agents include birds, fish, sheep, insects, and crowds (see Fig. 2.2). Specifically, robot flocking refers to the ability of a group of robots to move in formation and to maintain the above mentioned formation in motion. Specifically, simple robots are allowed to move, with only basic rules governing their behavior. This field of research has many applications, for instance, transporting large objects, exploring hazardous areas, and withstanding surveillance.

Vaughan introduced a complete robot system that controlled the behavior of another intelligent system with the presence of variability, uncertainty, and noise [169]. The robots used in the Sheepdog Project demonstrated the ability to gather a flock of ducks and carry out maneuvers to safely deliver them to a predetermined point. The use of ducks in the place of sheep made it possible to conduct the experiment in a controlled environment. More importantly, the behavior of flocks of ducks is considered by shepherds to be similar to that of sheep; in fact, ducks are sometimes used to train sheepdogs, due to their relatively slow movements. A generalized model of group behavior was designed in order to identify animal-robot interaction. The hypothesis pointed that if the model accurately captures the basis of behavior, then the system controlling the model should be able to control behavior in the real world.

Later in the study, it was suggested that it would be possible to describe this behavior according to a model of the force of attraction between animals, with the magnitude of attraction varying with the inverse square of the mutual distance between the animals [71]. It was suggested that the mentioned relationship represents a linear response in sensorial information, which also varies with the inverse square of the distance. Other models have yielded similar results with flocks of birds [168].

These concepts have been adapted to robotics, where these techniques are used in potential fields for navigation [114]. This type of algorithm uses the analogy of forces which act on particles, such that the robot moves in a similar way as an individual physical particle, attracted or repelled alternatively by the characteristics of its surroundings. A robot is usually attracted to objects and repelled by obstacles.

Most researchers so far have taken a leader-followers approach [127]. In these works, a robot leader is designated in the system to lead the other robots, called followers. This leader is identified and recognized by the other robots in the system. In other words, the followers just need to follow the leader wherever it goes, and to maintain the given formation while they are in motion.

A robot formation control strategy based on a visually perceptible follow-the-leader scenario was proposed in [139], with a strong emphasis on its reliability. Perception is enhanced by a pan&tilt camera, which enlarges the robot field of vision, and enhanced leader detection. In [161], the authors showed that a group of autonomous mobile agents, in which each agent is steered using local state information from its nearest neighbors, can asymptotically exhibit stable flocking behavior. This paper introduced a set of control laws that guarantees flocking asymptotically, under the assumption that the graph representing agent interconnections remains connected at all times.

A leader distributed flocking algorithm was presented in [73]. The combined problem of obstacle avoidance, navigation towards a goal point, and flocking has been introduced, which is a very difficult problem.

Some areas for further research in order to improve robot flocking, as identified by researchers based on flocking algorithm problems [174], are discussed below.

Collision avoidance: There exist two different kinds of collisions that must be considered: collision between robots and collision between robots and environmental obstacles [176].

Maintaining robot formation: Robots need to keep the neighboring graph connected during the entire execution of the algorithm. Some applications need to generate a particular desired formation during flocking. Furthermore, all robots need to maintain the above mentioned formation to complete the specific tasks at hand.

Finding the failure detector: The goal of the implementation of failure detection schemes is to detect the other robots status (alive or crash). Some failures that can occur during the task performance are: *(i)* Initially dead robot: A robot is referred to as initially dead if it does not execute a single step of its local algorithm; *(ii)* Crash permanent: a robot is said to crash if it executes its local algorithm correctly up to a certain point, and does not execute any step thereafter. *(iii)* Transient failure (crash recovery): in this case, a robot executes its local algorithm correctly, a transient moment temporarily interrupts it from performing its task, after which it fully recovers. *(iv)* Byzantine failure: a robot is said to be Byzantine, if it acts arbitrarily and possibly maliciously [136].

Investigating the communication failures: The communication between robots may cause delays, and so communication is not always reliable, due to limited bandwidth, range, and interferences, especially in harsh environments. The design of an efficient flocking algorithm under these conditions represented an important challenge.

Flocking with other failure detectors: To design a fault-tolerant algorithm, one important (core) question concerns how to ably detect and distinguish the crashed processes from the correct ones [175]. In [174], a perfect failure detector was used by strictly managing the robots' motion.

The present work also adopts a leader-followers structure, in which a certain leader is designated to guide the rest of the robots, or followers. However, during the realization of the task, the robots' roles can vary, if necessary, such that the leader designation is not fixed.

A new iteration of the flocking element involves guiding people. Interest in companion robots has grown significantly in recent years. Some of the major studies conducted in this field are discussed below.

2.3 Companion Robots

Although human-robot interaction is currently a very active field of research, there is an extensive research on motion planning in the presence of humans that has to be studied. Certain methods have been developed to allow robots to navigate around people while performing specific tasks. The above mentioned tasks include tending toward the right

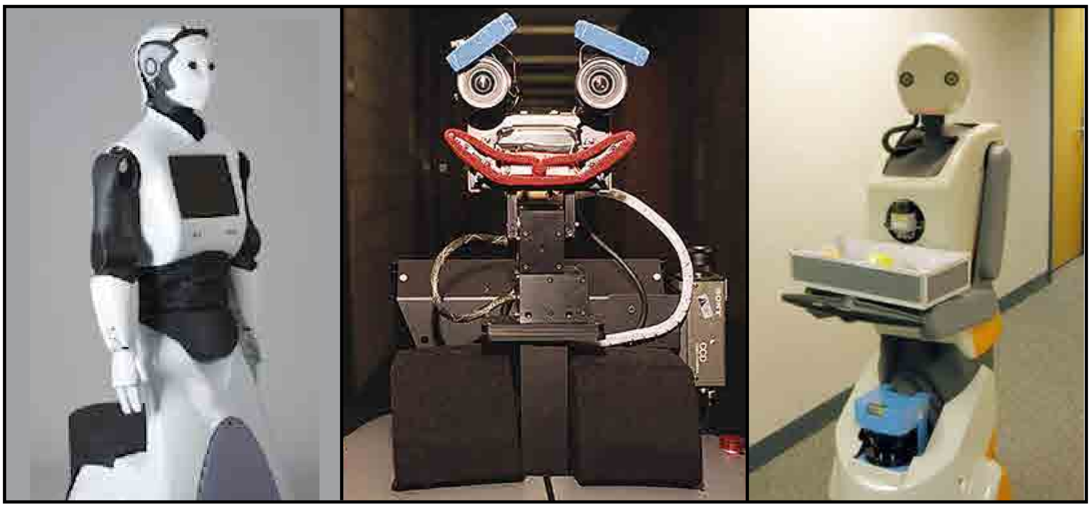

Figure 2.3: **Examples of Companion Robots.** ***Left:*** The REEM service robot developed at PAL-Robotics. ***Center:*** Minerva, a museum tour-guide robot [163]. ***Right:*** Snackbot, a mobile autonomous robot intended for delivering snacks to students, faculty, and office workers at Carnegie Mellon University [99].

side of a hallway [129] and standing in line [123]. Museum tour guide robots are often given the capacity to detect and attempt to deal with people who are blocking their paths on a case-by-case basis, [20].

Research in the field of companion robots is still relatively new in comparison to traditional service robotics, such as robots serving food in hospitals or providing specific security-related services. Therefore, prior research in this particular field is relatively minimal [30, 173]. The current research predominantly treats robots that act as companion in the context of social-human interactions [82]. Fig. 2.3 illustrates some examples of companion robots.

Researchers are currently working on developing this type of companion robot [80]. Many studies have investigated people's attitudes towards robots and their perception of robots. For example, robotic dogs such as AIBO, developed by Sony [87], are autonomous robots created for entertainment purposes; they are made for home use and are capable of provoking emotions, showing instinct, learning and developing their skills, as well as interacting with children. The design for AIBO was based on a dog's appearance and behavior [117] and various studies have shown that AIBO is capable of forming psychological relationships with adults and children alike [97].

Furthermore, researchers are making efforts towards facilitating more natural instances of human-robot interaction. A robot companion should detect the human operator and carry out his/her commands [69]. In [29], researchers showed that a seated person prefers to be approached by a robot in a fetch-and-carry task from the front left or right direction rather than frontally or from behind. Further research showed that there are other important factors which can affect this preference, such as a person's prior experience with robots [94], gender [29] or in which part of the room she was standing or sitting [172]. Satake et al. [145] proposed an approach model for robots that could initiate interaction in a shopping mall.

In [134], a new perspective on the different uses and identities of a companion robot has been introduced, while additionally describing the advantages and disadvantages of this type of companion. The "Robotic Butler/Maid" was able to perform domestic tasks, but also caused difficulties in relationships at home by being too efficient and making people feel redundant. In [30], a human-centered approach was adopted in order to look into people's perceptions and their desires for a companion robot. If social robots are going to be used in office and domestic environments, where they will have to interact with different individuals, they will have to survive and perform tasks in dynamic, unpredictable environments, and they must act safely and efficiently. The presence of human beings creates new problems for motion planning and control, as their security and comfort must be taken into account. The principal goal of the motion planner is to consider human movements carefully in order to ensure their safety. This requires the development of routes that are both safe and socially acceptable.

Robots accompanying humans is one of the core capacities every service robot deployed in urban settings should have. Most published works in this field use a single robot, and only relatively recently researchers have begun to study inter-robot coordination wherever they must work in unison to achieve a common goal.

2.3.1 Single Robot

A museum-guide robot called Rhino was developed to guide and interact with museum visitors [20]. The challenge was to guide museum visitors in crowded environments, achieving localization and motion planning with obstacle avoidance for navigation. An improved version of the museum robot was later called Minerva [163], and was used to interact in a larger museum.

The evolution of robotics and the creation of robots with a greater capacity to interact with human beings, have together led to the development of cognitive robots equipped to assist people by acting as assistants and companions. However, robots need communicative capabilities similar to those of humans in order to truly be accepted as companions. An autonomous companion robot should be seen as a special type of service robot, specifically designed for personal home use. Companion robots are expected to be able to communicate with non-expert users in a natural and intuitive way.

More recently, researchers performed studies to evaluate different navigation strategies for a robot moving along with a single person [63]. Their study concludes that people prefer a robot that shows human-like navigation behavior. Mueller et al. [121] developed a technique that efficeintly navigates trough crowed spaces by following people. Their approach continuously tracks people in the robot's vicinity and chooses to follow people moving in the direction of the goal. While this technique might result in more efficient navigation, it relies on manually tuned heuristics and has no explicit criterion for generating human-like behavior.

However, various new projects in which robots accompany humans have recently demonstrated that robots are capable of determining safe paths, and also of planning out socially acceptable routes for humans [158]. Robots operating around people should move coherently and in easily-understood ways. As a result, they might show themselves to be capable of acquiring spatial social skills [72].

2.3.2 Multiple Robots

Within the field of companion robots, a small number of studies describe the behavior of robots when guiding a person or group of people.

Since the initial development of biologically-inspired robots, researchers have been interested in how humans react in their presence, and have been fascinated by the possibilities of interaction between robots and their surroundings, and ways in which they interact amongst themselves. These groups of social robots are designed to maximize benefits (for example, performing tasks) through collective actions. Until now, researchers have used the principles of self-organization and social behavior based on interactions within groups of hymenopterous insects, anonymous, homogeneous groups wherein unique elements are insignificant. This type of social behavior has proved to be an attractive model for robotics, especially since it allows groups of relatively simple robots to perform difficult tasks.

The development of a robot as a "social individual" requires the use of different models and techniques based on "social groups" for robots working collectively. Here, important factors include learning and social imitation, gestures and natural language for communication, as well as emotion and recognition of interaction by all the participants. Furthermore, most research in this field has focused on the application of social behaviors and, as a result, social robots are generally understood as assistants, companions or pets.

Some researchers have developed projects that introduce group attention control, a system that allows robots to interact with a group of people [154]. The work presented in [153] looks into human interaction variations when a robot moves forward or backward as people move around.

The above mentioned methods consider either single robots or multiple robots moving independently. To our knowledge, only a small number of studies discuss multiple robots behaving in cooperative manners. For instance, [115] performed a qualitative analysis of the movements of different entities, humans or animals, and built a multi-robot system architecture of three robots to guide them. However, they failed to consider realistic situations, which often involve obstacles, or people straying from the group. A certain study carried out by Casper and Murphy discusses several types of robot formations and different strategies for drawing the robots to people [23]. However, these issues and the general movements of the robots, are governed by a large number of heuristics, which makes the system impractical.

2.4 Main Contributions of the Thesis within the State of the Art

In this chapter, many research works relevant to cooperative social robots that accompany people have been described. Below, the main contributions of the dissertation within the state of the art are presented.

Looking at the Section 2.1, it is interesting to notice that the research on social robot navigation have been successfully integrated into several kinds of robotic platforms. However, in Chapter 3 we introduce an innovative notion, whereby the robots are aware of other robots and pedestrians, while they accompany a person in a crowded environment in an acceptable social way.

The main contributions of the thesis within the robot formation and flocking by a set of autonomous robots -Section 2.2- are proposed in Chapters 4 and 5. In this dissertation a leader-followers structure is considered, in which a certain leader is designated to guide the rest of the robots, or followers. A new iteration of the flocking element involves guiding people. In Chapter 4, a model capable of performing guidance tasks within an open and unbounded area with obstacles is defined. This model is also able to estimate the position, orientation and velocity of the robots and people, as well as the position of the obstacles at a certain point in time. In addition, Chapter 5 proposes the a model which offers a new framework for tackling more realistic situations, without needing to use such a large number of heuristics, by allowing robots to prevent people from straying from the formation, which is undeniably among the most challenging aspects of this topic.

Finally, in Section 2.3, works in the field of robot companion have been presented. On the one hand, this methods consider either single robots or multiple robots moving independently, this issue has been studied in Chapters 4 and 5. On the other hand, in Chapter 6, we introduce the ultimate goal of our research, we enable robots to interact naturally with people when carrying out the accompanying task.

Chapter 3

Social Companion Robots

Don't walk behind me; I may not lead. Don't walk in front of me;
I may not follow. Just walk beside me and be my friend.

Albert Camus

In this chapter we present a novel robot companion framework based on the Social Force Model (SFM) for guiding or accompanying people in dense urban areas, with high numbers of moving people and obstacles. This framework uses people tracking, social companion robot, and interactive learning to enhance the robot's behavior. We have designed new methods for the aforementioned components. First, we have extended the SFM to include interactions between robot and human, and among obstacles, people and the robot; we refer to this model as "Extended Social-Force Model" (ESFM). Second, we developed a model to allow robots accompany people which relies on the ESFM. Third, we designed an interactive learning method using multimodal human feedback to compute the parameters of the model. Finally, we used a quantitative metric, based on people's personal space and comfortability criteria in order to evaluate the robots's performance in completing the accompanying task. The model was validated throughout an extensive set of simulations and real-life experiments. In addition, a volunteer survey was given to measure the social acceptability of the robot companion's behavior. The work in this chapter has been presented in [41, 44, 49].

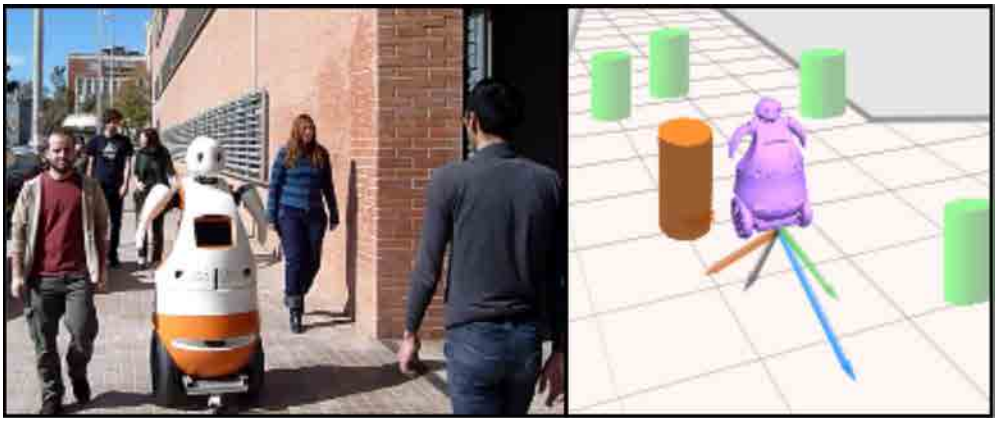

Figure 3.1: **Tibi accompanies a person.** ***Left:*** Person being accompanied by Tibi in an urban area. ***Right:*** The same scene using the system interface.

3.1 Introduction

Nowadays, urban robots require some specialized skills to be useful and to successfully serve people. The robot companion is a basic tool that an urban robot should have, as it enhances the robot's ability to accompany people in a safety and natural way; see Figs. 3.1-3.2.

Robot companion is a multidisciplinary field of robotics that involves a diverse set of subjects, such as perception, robot navigation, and human-robot interaction. Because of the heterogeneity of the treated subjects, the robot companion issue must be addressed in a holistic way, which is not an easy endeavor.

On the one hand, we expand upon the Social Force Model (SFM) introduced by Helbing [75] to model the social interactions in the robot companion task, and we obtain the robot-person interaction force parameters specifically suited for Tibi robot [143] to perform this task. On the other hand, we present a powerful scheme to define robot's behavior in terms of motion based on the social-forces concept to accompany a pedestrian. To this end, additional considerations are required to make the system work properly, such as a learning stage for the parameters used.

Moreover, we introduce a new metric to evaluate the robot companion's performance, based on vital spaces and comfortability criteria. Since the verification of man-in-the-loop systems is usually subjective, we require an objective analytical metric that

Figure 3.2: **Tibi accompanies different people.** Several experiments where Tibi is interacting with volunteers.

serves to validate the behavior of our robot companion approach.

Finally, we propose an interactive learning scheme to learn the model's parameters, using the human feedback response in the companion system. The parameters are learned through an extensive analysis of the robot companion task in diverse situations, where the human feedback response enhances the accuracy of the robot's companion performance, yielding improved companion behaviors.

The model was validated through a large set of simulations and real-life experiments, as well as a questionnaire administered to each individual who participated in the experiments.

3.2 Chapter's Overview

As stated earlier, this chapter describes a new model that has been designed to accompany people.The contributions and topics described in this chapter are presented below; see Fig. 3.3.

- *ESFM-based Robot Companion*: A robot model capable of approaching a person and accompanying him/her to a known destination is presented. The social force model described in [75] takes into account both destinations and interactions by defining a summation of existing forces that detemine people's trajectories. The term "social force model" does not refer to a social robot's behavior, but rather to the existence of a non-physical force that robots can exert to move or drag people. More specifically, this work proposes a robot's reactive motion, based on an extension of the social force model which results from the internal motivations of the

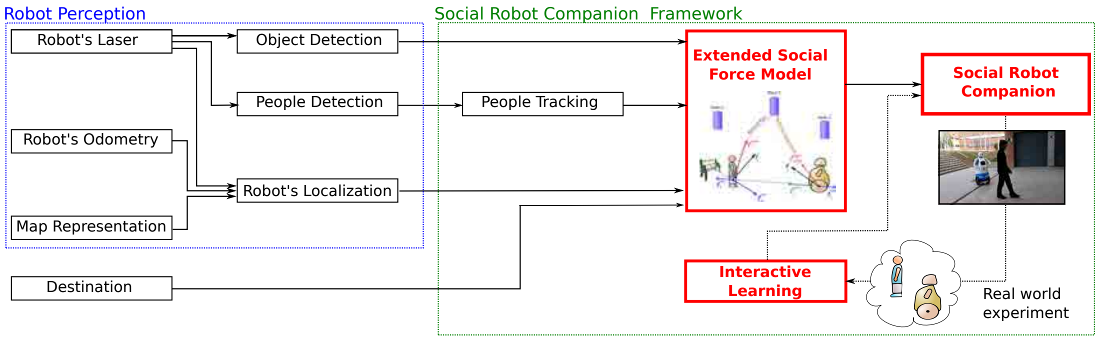

Figure 3.3: **Overview of the presented work.** A general diagram of the robot companion framework is depicted, as well as its requirements. Our contributions to advance the topics discussed later in the present work are highlighted in red.

individuals performing certain movements [177]. A robot accompanying humans is one of the core capacities every service robot deployed in urban settings should have [57]. The proposed model is validated through a series of simulations and a set of real-life experiments. We also demonstrate that the interactive learning enhances the overall performance of the robot companion.

- *Interactive Robot Companion Parameters Learning*: An interactive approach evaluates the learned forces model. At the same time, it learns which robot's behavior is preferred by humans. Although the feedback provided here is a subjective metric, its purpose is to learn a general approaching rule that defines a better robot behavior. The proposed interactive learning scheme enhances the nature of the model, in addition it generates controlled interaction forces that otherwise would be extremely complicated to produce. The online feedback is provided by the target person whom the robot attempted to approach.

- *Robot Companion Performance Metric*: A quantitative metric is used to evaluate the performance of the task accomplished by the robot. This assessment is based on "proxemics", as proposed by Hall [70].

- *User study of robot's behavior*: We conducted a user study to determine whether the robot's behavior was perceived as socially appropriate by the experiment participants. We also looked at various key aspects of the interaction between a mobile robot and untrained human volunteers.

3.3 Social Force Model

Pedestrian behavior was first modeled in the late 1950s. These models were primarily focused on the dynamics of macroscopic quantities (densities and fluxes), and pedestrian dynamics was initially treated in a way similar to that of gases or fluids [77]. As the discipline progressed, researchers' attention shifted to a more microscopic description, in which the motion of each pedestrian is described individually. These models can be roughly divided into Cellular Automata models, which use a discrete-space description [21], and models that use a continuous-space description.

The social-force model (SFM) described in [75] simulates pedestrian dynamics by using forces of interaction. It introduces a rather general framework, in which the details of human motion behavior can be expressed through a function depending on the pedestrians' relative and absolute positions and velocities.

This model considers both destinations and interactions by defining a summation of existing forces which determine people's trajectories. Moreover, [177] proposes a deviation from the social force model by taking into account the time of collision. However, the cited works do not consider the interaction between a person and a robot, nor the interaction between the obstacles which substantiated the coinage of the Extended Social-Force model (ESFM).

In our development of a model capable of representing the interactions between a pedestrian and a robot, we were inspired by the works of Helbing [75] and Zanlungo [177]. The main contribution of their research is the concept that changes in behavior can be explained in terms of social fields or forces.

Formally, this approach treats each pedestrian p_i with mass m_{p_i} as a particle abiding the laws of Newtonian mechanics:

$$\begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix}_{t+1} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix}_{t} + \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix} \begin{bmatrix} a_x \\ a_y \end{bmatrix} \tag{3.1}$$

where (x, y) is person's position, (v_x, v_y) is his/her velocity and (a_x, y_x) is the acceleration.

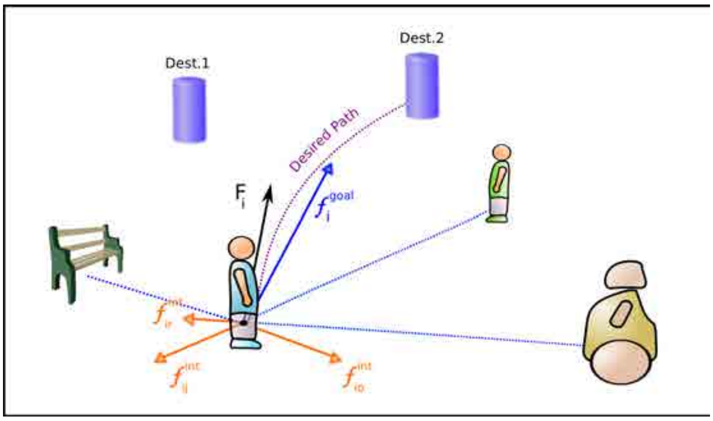

Figure 3.4: **Social Force Model.** Diagram of the social forces corresponding to the person p_i. The blue arrow represents the force aiming at a destination and the orange arrows represent each of the different kinds of interaction forces: person-person, object-person, and robot-person. The summation of all three forces is represented by the black arrow F_i.

Formally, the social forces model assumes that a pedestrian p_i with mass m_{p_i} tries to move at a certain *desired speed* $v^0_{p_i}$ in a *desired direction* $\boldsymbol{e}_{p_i}$, i.e., with *desired velocity* $\boldsymbol{v}^0_{p_i} = v^0_{p_i} \cdot \ \boldsymbol{e}_{p_i}$. The desired velocity's direction is given by a vector pointing from the present position of the person $\boldsymbol{r}_{p_i}$ to the next subgoal $\boldsymbol{g}_{p_i}$, where the speed is the one at which the human feels more comfortable to walk.

Hence, the basic equation of motion for a pedestrian is given by a social force term:

$$\frac{d\boldsymbol{v}_{p_i}(t)}{dt} m_{p_i} = \boldsymbol{F}_i(t) \tag{3.2}$$

which describes the movements of the pedestrian p_i over time.

A person wants to keep his/her desired velocity through the steering force, $\boldsymbol{f}_i^{goal}$, but is also influenced by others pedestrians p_j, $\boldsymbol{f}_{i,j}^{int}$, by obstacles, $\boldsymbol{f}_{i,o}^{int}$ and, in the present study we model the robot interaction $\boldsymbol{f}_{i,R_j}^{int}$. The resulting force $\boldsymbol{F}_i$ governs the trajectory described by the target p_i.

$$\boldsymbol{F}_i = \ \boldsymbol{f}_i^{goal} + \ \boldsymbol{F}_i^{int} \tag{3.3}$$

Assuming that pedestrian tries to adapt his or her velocity within a *relaxation time* k_i^{-1}, $\boldsymbol{f}_i^{goal}$ is given by:

$$\boldsymbol{f}_i^{goal} = k_i(\ \boldsymbol{v}_i^0 - \ \boldsymbol{v}_i) \tag{3.4}$$

The relaxation time is the interval of time needed to reach the desired velocity and the desired direction.

Furthermore, repulsive effects from the influences of other people, obstacles and robot in the environment are described by an interaction force F_i^{int}. This force prevents humans from walking along their intended direction, moreover, it is modeled as a summation of forces either introduced by people p_j, by static obstacles in the environment o or the robot R. A diagram of the social forces corresponding to the person p_i is plotted in Fig. 3.4.

$$\boldsymbol{F}_i^{\ int} = \sum_{p_j \in \mathcal{P}} \boldsymbol{f}_{ij}^{int} + \sum_{o \in \mathcal{O}} \boldsymbol{f}_{io}^{int} + \boldsymbol{f}_{iR_j}^{int} \tag{3.5}$$

Where, $\mathcal{P}$ is the set of people moving in the environment where the human interacts and $\mathcal{O}$ is the set of obstacles. The description of each force is described below.

The motion of a pedestrian p_i is influenced by other pedestrians p_j: $\boldsymbol{f}_{ij}^{int}$

A pedestrian keeps a certain distance from other people in the environment. Humans normally feel increasingly uncomfortable the closer he/she gets to a strange person, who may react in an aggressive way. Below, we introduce different ways in which such force can be described.

Circular specification:

Circular specification assumes forces to depend only on the distance $\|\boldsymbol{r}_{ij}\| = d_{ij}$ between pedestrians p_i, p_j. This assumption works well under high-density conditions. The interaction force is

$$\boldsymbol{f}_{ij}^{\ int} = Ae^{(d-d_{ij})/B} \frac{\boldsymbol{r}_{i,j}(t)}{d_{i,j}(t)} \tag{3.6}$$

where A denote the strength, B the range on interaction force, d is the sum of radii of the two pedestrians and $\ \boldsymbol{r}_{i,j} = \boldsymbol{r}_{p_i} - \boldsymbol{r}_{p_j}$.

Elliptical specification I:

This specification was introduced in [75], here, the force between two pedestrians is defined as:

$$\boldsymbol{f}_{ij}^{int} = -\nabla_{\boldsymbol{r}_{ij}} V_{ij}(b_{ij}) \tag{3.7}$$

A repulsive potential V_{ij} is introduced:

$$V_{ij}(b_{ij}) = ABe^{b_{ij}/B} \tag{3.8}$$

$V_{ij}(b_{ij})$ is a monotonic decreasing function of b_{ij} with equipotential lines having the form of an ellipse, which is directed into the direction of motion. b_{ij} denotes the semi-minor axis of the ellipse and is given by

$$b_{ij} = \frac{\sqrt{(\|\boldsymbol{r}_{ij}\| + \|\boldsymbol{r}_{ij} - v_{p_j}\tau\|)^2 - \|v_{p_j}\tau\|^2}}{2} \tag{3.9}$$

τ is the time of pedestrian stride, $\tau = k^{-1}$.

By derivation, the obtained force is

$$\boldsymbol{f}_{ij}(\boldsymbol{r}_{ij}) = Ae^{-b_{ij}/B}\frac{\|\boldsymbol{r}_{ij}\| + \|\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}\|}{4b_{ij}} \times \left(\frac{\boldsymbol{r}_{ij}}{\|\boldsymbol{r}_{ij}\|} + \frac{\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}}{\|\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}\|}\right) \tag{3.10}$$

where,

$$\boldsymbol{y}_{ij} = \boldsymbol{r}_{ij} - \boldsymbol{v}_{p_j}\tau \tag{3.11}$$

This specification takes into account the relative distance and the movements of the other pedestrians.

Elliptical specification II:

A second elliptical specification was presented in [83]. This work takes into account the relative positions and velocities of pedestrians. Here, b_{ij} is defined by,

$$b_{ij} = \frac{\sqrt{(\|\boldsymbol{r}_{ij}\| + \|\boldsymbol{r}_{ij} - (v_{p_j} - v_{p_i})\tau\|)^2 - \|(v_{p_j} - v_{p_i})\tau\|^2}}{2} \tag{3.12}$$

that is, $\boldsymbol{v}_{p_j}$ is substituted by $\boldsymbol{v}_{ij} = v_{p_j} - v_{p_i}$. Then, the force is the same as Eq. 3.10, but with $\boldsymbol{y}_{ij}$ as follows:

$$\boldsymbol{y}_{ij} = \boldsymbol{r}_{ij} - (\boldsymbol{v}_{p_j} - \boldsymbol{v}_{p_i})\tau \tag{3.13}$$

Given the limited field of view of humans, forces' influences might not be isotropic. This is formally expressed by scaling the interaction forces with an anisotropic factor, which is described below.

Anisotropy:

The anisotropy factor depends on φ_{ij} between $\boldsymbol{v}_{p_i}$ and $\boldsymbol{r}_{i,j}$, it can be written as:

$$\begin{aligned} w(\varphi_{ij}) &= \left(\lambda + (1-\lambda)\frac{1 + cos(\varphi_{ij})}{2}\right) \\ 0 \leq \quad & \lambda \quad \leq 1 \end{aligned} \tag{3.14}$$

where λ defines the strength of the anisotropic factor,

$$cos(\varphi_{ij}) = -\boldsymbol{n}_{ij} \cdot \boldsymbol{e}_{p_i} \tag{3.15}$$

The term $\boldsymbol{n}_{ij}$ is the normalized vector pointing from p_j to p_i, and it describes the direction of the force. Fig. 3.5 presents the value of the presented forces and the anisotropic factor.

The motion of a pedestrian p_i is influenced by obstacles: $\boldsymbol{f}_{io}^{int}$

Moreover, a pedestrian keeps a certain distance from buildings, walls and obstacles. People feel more uncomfortable the closer to an obstacle he/she walks. Therefore, an obstacle o provokes a *repulsive effect* that can be expressed as

$$\boldsymbol{f}_{io}^{int} = -\nabla_{r_{io}} U_{io}(\|\boldsymbol{r}_{io}\|) \tag{3.16}$$

$$U_{io}(\|\boldsymbol{r}_{io}\|) = U_{io}^0 e^{-\|r_{io}\|/C} \tag{3.17}$$

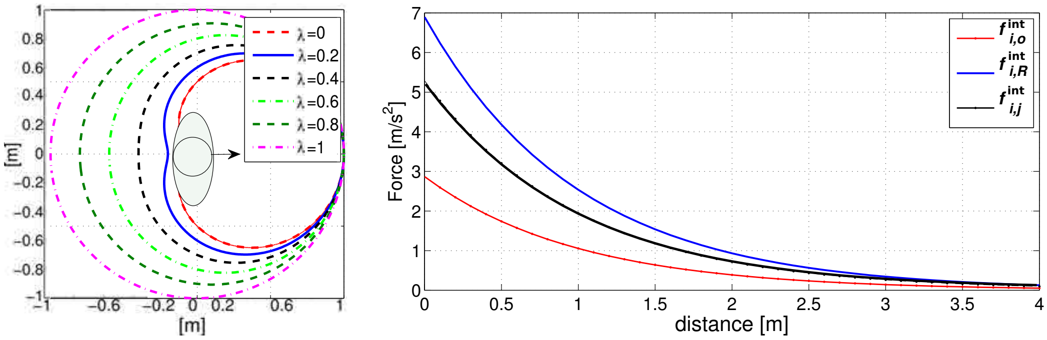

Figure 3.5: **Forces graph.** ***Left:*** Representation of Eq. 3.15, defined as the given limited field of view of human. ***Right:*** Forces magnitudes, the x-axis shows the distance from person p_i to an object, a person p_j or the robot R. The radius of p_i is $0.2m$ and the sum of the radii of p_i and p_j is 0.4m. The radius assumed fot the robot is $1m$.

$U_{io}(\|\boldsymbol{r}_{io}\|)$ is a repulsive and monotonic decreasing potential. The vector $\boldsymbol{r}_{io}$ is computed as $\boldsymbol{r}_{io} = \boldsymbol{r}_{p_i} - \boldsymbol{r}_o^i$, where $\boldsymbol{r}_o^i$ denotes the location of the piece of the obstacle o that is nearest to pedestrian p_i.

The motion of a pedestrian p_i is influenced by robots: $\boldsymbol{f}_{iR}^{int}$

Finally, the repulsive force between the robot and the pedestrian p_i must be defined. As this thesis considers robots accompanying people, we introduce this repulsive force. People keeps a certain distance from robots. If the robot is too close to a person, he/she may feel uncomfortable. Thus, the robot R provokes a *repulsive effect* if the distance to the human is lower than a threshold. This effect can be expressed as

$$\boldsymbol{f}_{iR}^{int} = A_{iR} e^{(d_R - d_{iR})/B_{iR}} \frac{\boldsymbol{r}_{iR}(t)}{d_{iR}(t)} \left(\lambda_{iR} + (1 - \lambda_{iR}) \frac{1 + cos(\varphi_{iR})}{2} \right) \tag{3.18}$$

Fig. 3.5 presents the value of the presented forces and the anisotropic factor.

3.3.1 Parameters Learning: $\{k, A_{iR}, B_{iR}, \lambda_{iR}, d_R\}$.

We have already mentioned the three kinds of interaction forces: person-person $\boldsymbol{f}_{ij}^{int}$, person-obstacle $\boldsymbol{f}_{io}^{int}$, and person-robot $\boldsymbol{f}_{iR}^{int}$. The first two interactions have been studied in previous works, such as [75, 109, 177]. However, as person-robot interaction parameters had not been directly obtained in any previous work, therefore we use this section to present a learning method to obtain the parameters $\{k, A_{iR}, B_{iR}, \lambda_{iR}, d_R\}$.

We decouple the training in two steps: firstly, we optimize the intrinsic parameters of the model forces $\{k\}$ describing the expected human trajectories under no external constrains. Secondly, we optimize the extrinsic parameters of the force interaction model $\{A, B, \lambda, d\}$ under the presence of a moving robot, making sure it is the only external force altering the outcome of the described trajectory. All optimizations used to learn the model forces parameters are carried out using genetic optimization algorithms [65] minimizing the following error function throughout all N training trajectories:

$$\{A, B, \lambda, d\} = argmin_{\{A,B,\lambda,d\}} \left\{ \sum_{N} \sum_{time} \|\mathbf{x_o}(\mathbf{t}) - \mathbf{x_e}(\mathbf{t})\| \right\} \tag{3.19}$$

where $\mathbf{x_o}$ is the person's observed position and $\mathbf{x_e}$ is the value expected according to Eq. 3.1.

3.4 Perception System

Before presenting the robot's behavior using the Extended Social Force Model to accompany people, we will introduce the perception requirements, which are needed for the system's real-world implementation, though they remain outside of the scope of this chapter.

3.4.1 Robot Localization

Dead reckoning navigation proved to be insufficient to make the system work properly. Because of this, robot localization became indispensible to the system's implementation.

We use a state-of-the-art localization implementation, known as *AMCL*. The *AMCL* is a probabilistic localization system for a robot moving in 2D. It implements the adaptive (or KLD-sampling) Monte Carlo localization approach (as described in [164]), which uses a Particle Filter to track the position of a robot along a known map.

3.4.2 People Detection and Tracking

People's perception is essential for achieving autonomous navigation in urban environments. Thus, it is crucial to know where the human beings are located, and where they intend to go. Sensors, such as lasers and cameras, are able to give us all these data.

Our implementation of the laser detector is fundamentally based on [6], which uses a boosting method to determine if a set of laser points is a human being. This tool is built by combining a set of weak classifiers that determine if the laser points correspond to a leg and consequently to a human being.

The people tracking implementation follows a similar approach to that presented in [109]. This multi-hypotheses tracker uses linear propagation that can handle occlusions, crossings, and loss of targets, at a relative low error. However, rather than using a Kalman filter, we used a particle filter in order to accomodate humans' unpredictable changes in motion.

3.5 Robot Behavioral using Social Force Model

Previous sections describe a general social interaction model based on social-forces (Section 3.3) and a perception system to detect pedestrians (Section 3.4). These independent areas are aggregated to build a robot companion framework, using the following idea: the robot is considered as a social agent, moving naturally in human environments according to the Extended Social-Force Model, headed towards a certain destination, and responding suitably to obstacles and people in its path. Furthermore, we believe that a more humanized navigation, in the sense that the robot responds to the ESFM, will greatly increase the acceptance among pedestrians, do primarily to the similarities between the robot's behavior and the expected movements of other pedestrians.

To this end, we describe the robot companion behavior in terms of motion, understood as an instantaneous reaction to sensory information, driven by the social-forces centered at the robot, as in the research condunted in [90], but focussing more on the social nature of the approach. In addition, we make use of the ESFM framework to successfully accompany a person while safely navigating in crowded environments and avoiding both static and dynamic objects.

Therefore, in this section, we aim to formulate all the social-forces intervening in the social robot companion, based on Section 3.3. The following equations are straightforward derivations of the Eqs. 3.3-3.15.

The force to the target's destination is inferred by considering that the robot is aware of person's destination.

$$\boldsymbol{f}_{R,dest}^{goal} = k_R(\ \boldsymbol{v}_R^0 - \ \boldsymbol{v}_R) \tag{3.20}$$

The forces of interaction due to other pedestrians are the repulsive forces every person generates to the robot, as follows:

$$\boldsymbol{F}_R^{per} = \sum_{p_j \in \mathcal{P}} \ \boldsymbol{f}_{R,j}^{int} \tag{3.21}$$

where the forces $\boldsymbol{f}_{R,j}^{int}$ represent the interaction between the pedestrian p_j and the robot R:

$$\boldsymbol{f}_{R,j}^{int} = A_{Rp} e^{(d_{Rp} - d_{R,j})/B_{Rp}} w(\varphi_{R,j}, \lambda_{Rp}) \tag{3.22}$$

which is the formulation of the spherical force (Eq. 3.6) using the parameters $\{A_{pR}, B_{pR}, \lambda_{pR}, d_{pR}\}$. These parameters correspond to the person-to-robot interaction, and in general are dependent of the robotic platform used.

Correspondingly, the interaction between robot and obstacles is modeled as:

$$\boldsymbol{F}_R^{obs} = \sum_{o \in \mathcal{O}} \boldsymbol{f}_{R,o}^{int} \tag{3.23}$$

where $\boldsymbol{f}_{R,o}^{int}$ is obtained following

$$\boldsymbol{f}_{R,o}^{int} = A_{Ro} e^{(d_{Ro} - d_{R,o})/B_{Ro}} w(\varphi_{R,o}, \lambda_{Ro}) \tag{3.24}$$

using the specific parameters $\{A_{Ro}, B_{Ro}, \lambda_{Ro}, d_{Ro}\}$ corresponding to the interaction person-obstacle.

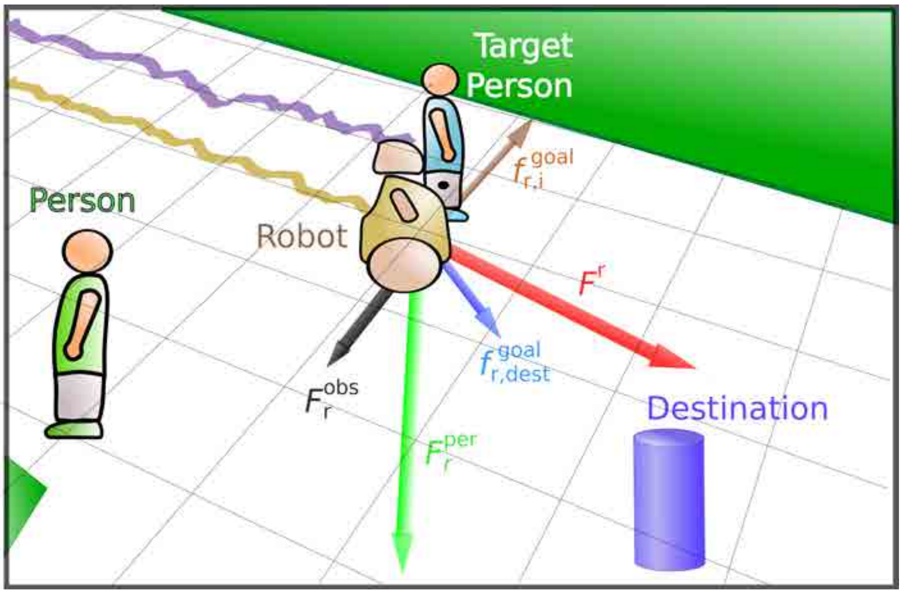

Figure 3.6: **Robot's Social Forces:** Forces applied to the robot while accompanies a person.

As shown in Fig. 3.6, we have defined an additional destination to the robot approach. The robot aims to the target person in order to accompany him/her, following the Eq. 3.20.

As described in Section 3.3, repulsive effects from the influences of other people and obstacles in the environment are described by an interaction force, which is a sum of forces introduced either by people or by static obstacles in the environment.

In contrast to the social-force model, this scheme yields two discrete goals. Firstly, a force goal makes the robot drive towards the destination $\boldsymbol{f}_{R,dest}^{goal}$. Furthermore, the robot must approach the person who it accompanies, and hence a second goal compels the robot to move closer to the person p_i, $\boldsymbol{f}_{R,i}^{goal}$. The trade off of these forces, in addition to the interacting forces, describes the resultant force governing the robot movement:

$$\boldsymbol{F}^R = \alpha\ \boldsymbol{f}_{R,dest}^{goal} + \beta\ \boldsymbol{f}_{R,i}^{goal} + \gamma\ \boldsymbol{F}_R^{per} + \delta\ \boldsymbol{F}_R^{obs} \tag{3.25}$$

Once the reactive force action is obtained, the system responds duly to these stimuli, and linearly propagates its position and velocity according to this force value.

Additional constraints are also taken into account. All those robot propagations which result in a collision with obstacle are discounted. Current robot maximum velocity is also a constraint, and it depends on the robot navigation state, which is a function of the proximity of persons:

$$v_R = \begin{cases} v_{safety} & \text{if } \frac{d_{R,i}}{w(\varphi_{R,i})} \leq \mu_{safety} \\ v_{cruise} & \text{if } \mu_{safety} < \frac{d_{R,i}}{w(\varphi_{R,i})} \leq \mu_{social} \\ v_{free} & \text{otherwise} \end{cases} \tag{3.26}$$

The v_{safety} is the maximum velocity the robot can achieve when at least one person is inside its inner safety zone. We have proposed a *social distance* to define this region as $d_{R,i}w(\varphi_{r,p})$, similarly as described in Section 3.3, as a metric of the relative distance between the robot and a pedestrian and an asymmetric factor deforming the distance measure $w(\varphi_{R,i})$. This condition also corresponds to the *inner robot navigation* state. On the other hand, v_{cruise} is the cruise velocity when someone is inside its social safety zone and v_{free} is the maximum robot velocity when there are no people inside its safety zone. The navigation states associated to this configurations are the *social robot navigation* and the *free robot navigation*, correspondingly.

The most interesting part of the system so far, resides in the fact that the proposed approach does not require static targets, the robot is able to move near to persons. Moreover, it can accompany those people who aim to the same destination. The following section discusses the procedure to obtain the value of the parameters $\{\alpha, \beta, \gamma, \delta\}$ and how they are updated.

3.5.1 Quantitative Metrics

A quantitative metric is defined in order to evaluate the the robot's performance while accomplishing the task. This assessment is based on "proxemics" [1], proposed by Hall [70]. This work considers the following taxonomy of distances between people:

- Intimate distance: the presence of another person is unmistakable; appropriate for close friends or lovers (0-45cm).

[1]Proxemics is the study of the cultural, behavioral, and sociological aspects of spatial distances between individuals.

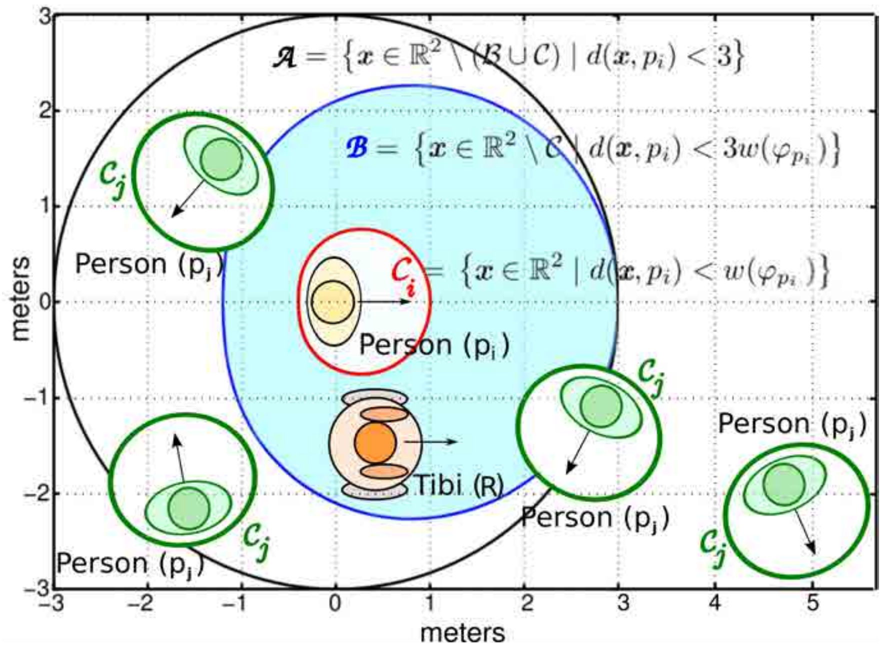

Figure 3.7: **Quantitative Metrics:** Diagram of the areas used in the evaluation of the robot's performance.

- Personal distance: comfortable spacing; appropriate for friends (45cm-1.22m).
- Social distance: limited involvement; appropriate for interaction with non-friends (1.22m-3m).
- Public distance: outside circle of involvement; appropriate for public speaking (> 3m).

To define the metric used in the present work, four different areas must be defined: *(i)* The pedestrian's personal space p_i $\mathcal{C}_i$, the robot's navigation must be socially acceptable to the person being accompanied; and the robot must not invade the human's personal space, eq. 3.27. *(ii)* Social distance area $\mathcal{A}$; robots must be placed at an acceptable social distance. *(iii)* The robot should be in the human's field of vision while they interact $\mathcal{B}$. *(iv)* Finally, if there are other pedestrians in the environment p_j, the robot is not allowed to invade those pedestrians' personal space $\bigcup_{p_j} \mathcal{C}_j$. These different areas are formalized as follows:

$$
\begin{aligned}
\mathcal{A} &= \left\{ \boldsymbol{x} \in \mathbb{R}^2 \setminus (\mathcal{B} \cup \mathcal{C}) \mid d(\boldsymbol{x}, p_i) < 3 \right\} \\
\mathcal{B} &= \left\{ \boldsymbol{x} \in \mathbb{R}^2 \setminus \mathcal{C} \mid d(\boldsymbol{x}, p_i) < 3w(\varphi_{p_i,R}) \right\} \\
\mathcal{C} &= \left\{ \boldsymbol{x} \in \mathbb{R}^2 \mid d(\boldsymbol{x}, p_i) < w(\varphi_{p_i,R}) \right\}
\end{aligned} \tag{3.27}
$$

where $w(\varphi_{p_i,R})$ is defined in Eq. 3.15.

Moreover, the robot can be represented as a circle of 1 meter of diameter, with center robot's position R, $\mathcal{R} = \{\boldsymbol{x} \in \mathbb{R}^2 \mid d(\boldsymbol{x}, R) < 0.5\}$, whose area is $|\mathcal{R}| = \frac{\pi}{4}$.

Thus, we can now define the performance of the task accomplished by the robot, depending on human's position p_i and robot's position R.

$$
\rho(R, p_i) = \int_{(\mathcal{B} \setminus \bigcup\limits_{p_j} \mathcal{C}_j) \cap \mathcal{R}} \frac{d\boldsymbol{x}}{|\mathcal{R}|} + \int_{(\mathcal{A} \setminus \bigcup\limits_{p_j} \mathcal{C}_j) \cap \mathcal{R}} \frac{d\boldsymbol{x}}{2|\mathcal{R}|} \in [0, 1] \tag{3.28}
$$

Where $\boldsymbol{x} \in \mathbb{R}^2$. The introduced function has the maximum performance in the area described by $\mathcal{B}$, since it is the area of the human's field of vision, and where the interaction between the robot and the human is greatest. Additionally, the area $\mathcal{A}$, is a partial success, since this area is less tolerated by humans. Finally, in the area described further than three meters there is no interaction, and therefore its performance is zero.

3.5.2 Parameter Learning: $\boldsymbol{\Theta} = \{\alpha, \beta, \gamma, \delta\}$

In order to learn the values of the introduced parameters $\boldsymbol{\Theta} = \{\alpha, \beta, \gamma, \delta\}$, we used a two-step learning approach. First, we required an initial estimation to learn the magnitude of $\boldsymbol{\Theta}$.

We aimed to obtain a social robot model capable of dealing with navigation issues in a more human-oriented manner. Consequently, it would be wise to define the overall performance of the task accomplished by the robot $\bar{\rho}(\boldsymbol{\Theta})$,

$$
\bar{\rho}(\boldsymbol{\Theta}) = \frac{1}{T} \sum_{t=0}^{T} \rho(R, p_i) \tag{3.29}
$$

where p_i is the human's position and r robot's position, $\rho(R, p_i)$ is the metric function introduced in Section 3.5.1.

Although the initial conditions could be copied identically throughout all simulations, given the interactive nature of the approach, the parameters $\mathbf{\Theta}$ alter the outcome $\bar{\rho}(\mathbf{\Theta})$ for each experiment –random variable. This is the main reason for considering stochastic optimization as an appropriate method for estimating the navigation parameters. Monte Carlo methods [4] are especially useful for simulating phenomena with significant uncertainty in inputs and systems with a large number of coupled degrees of freedom. More concretely, we have implemented a Markov Chain Monte Carlo Metropolis-Hastings (MCMC-MH) algorithm to find the best set of $\mathbf{\Theta}$.

Using this method, we obtain the best $\hat{\mathbf{\Theta}}$ parameters as follows:

$$\hat{\mathbf{\Theta}} = argmax_{\mathbf{\Theta}} \left\{ E_{P(\mathbf{\Theta})}\{\sum_t \bar{\rho}(t, \mathbf{\Theta})\} \right\} \tag{3.30}$$

Note that the outcome of the simulations is averaged using the expectation $E_{P(\mathbf{\Theta})}\{\}$ over the probability function of $\mathbf{\Theta}$.

3.5.3 Interactive Parameter Learning

The second step of the learning approach consists of an Interactive Learning technique [88]. Our approach is based on robots interacting with people, and therefore, it requires a people's feedback in order to refine the parameters values $\{\alpha, \beta, \gamma\}$, in the form of each person's response to the stimuli generated by the robot. This method enhances the nature of the model, while also generating controlled interaction forces that would otherwise be extremely difficult to generate.

The on-line feedback was provided by the target person whom the robot attempted to accompany. The interaction was generated by a human agent using a wii remote control. Here, we expected to receive feedback to measure the subjective comfortability of the target being approached.

Although feedback is inherently a subjective measure, we have modeled a system weighting the contribution of all active forces. Volunteers used a wii remote control. They were told to press the button '+' if they wanted the robot to move closer to them. However, if they preferred the robot to move directly towards the destination, they were instructed to push button '-'. Below, we present the parameters' variations depending on people's feedback.

Firstly, we can define the function N(T) as follows:

$$N(T) = \sum_{t=0}^{T} \epsilon(t) \tag{3.31}$$

where $\epsilon(t)$ is expressed as:

$$\epsilon(t) = \begin{cases} 0 & \text{if human does not pres any button at time } t \\ +1 & \text{if human presses button '+' at time } t \\ -1 & \text{if human presses button '-' at time } t \end{cases} \tag{3.32}$$

$N(T)$ is the difference between the number of times the person presses button '+' and button '-' at time T. Then, $N(T) \geq 0$, if $N(T) < 0$ we impose $N(T) = 0$.

Secondly, the forces that appear during the accompanying process vary according to the distance between the robot and the person. Then, the variation of the parameters will change, in function of such distance.

Formally, if $h(N(T))$ denotes the function corresponding to human's response, it can be expressed as:

$$h(N(T)) = \begin{cases} \alpha(N(T)), \beta(N(T)) & \text{if } d_{R,i} \geq w(\varphi_{R,i}) \\ \gamma(N(T)) & \text{if } d_{R,i} < w(\varphi_{R,i}) \end{cases} \tag{3.33}$$

Where, $\{\alpha(N(T)), \beta(N(T)), \gamma(N(T))\}$ is the set of weighting functions for the parameters $\{\alpha, \beta, \gamma\}$, $d_{R,i}$ is the distance between the robot and the person, and, $w(\varphi_{R,i})$ represents the personal space of a person, see Eq. 3.15.

Below, the definitions of the weighting functions are presented.

Force to the target destination α: As it has been described above, a parameter α controls the magnitude of the force $\boldsymbol{f}_{R,dest}^{goal}$. The value of this parameter is computed as follows:

$$\alpha(N(T)) = log(1 + N(T)/\sigma_\alpha) \tag{3.34}$$

Force to the person being accompanied $\boldsymbol{\beta}$: An attractive force towards the accompanied person has been described. Either the current target position as well the expected motion prediction are known. The parameter β controls the magnitude of the force $\boldsymbol{f}_{R,i}^{goal}$. The value of this parameter is computed as follows:

$$\beta(N(T)) = 1 - \alpha(N(T)) \tag{3.35}$$

Force of interaction with people $\boldsymbol{\gamma}$: A repulsive force due to the relative position and velocity between the robot and people must be considered, $\sum_{j \in P} \boldsymbol{f}_{R,j}^{int}$, this force is controlled by the parameter γ. The value of γ is defined as:

$$\gamma(N(T)) = log(1 + N(T)/\sigma_\gamma) \tag{3.36}$$

Force of interaction with obstacles $\boldsymbol{\delta}$: Finally, a repulsive force due to the relative position and velocity between the robot and obstacles has to be considered, $\sum_{o \in O} \boldsymbol{f}_{R,o}^{int}$, this force is controlled by the parameter δ. This parameter is not refined with human feedback since it only involves robot and obstacles.

The combination of these four forces determines the behavior of the robot while it physically approaches a person. Although a general approaching rule must be obtained, it varies greatly from person to person, in addition to the highly noisy environment in which we are working. While iteratively repeating the robot's physical approach, the feedback provided refines the weights of the force parameters, allowing us to infer an interactive behavior wherein the person feels comfortable under the presence of the robot.

3.6 Results

In previous sections, we presented the theoretical aspects of a wide variety of topics, including the extended social force model (ESFM) and a reactive navigation. Additionally, we discussed how these independent topics could be used jointly in a single robot companion framework. In this section, we focus specifically on experiments and tests conducted among robot companion, both real or simulated. Due to the complexity

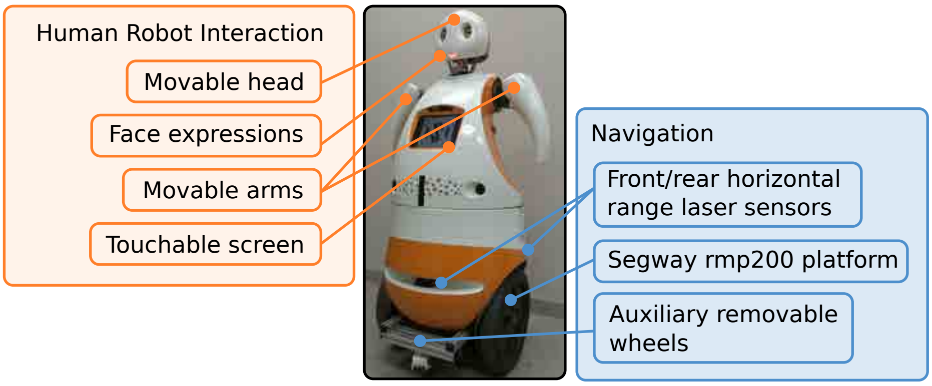

Figure 3.8: **Tibi Robot.** Mobile robot platform used in the experiments.

of the present work, which involves many different topics, such as human perception, robot movement, and human behavior, we will address each area independently.

3.6.1 Robotic Platform and Testing Environment

To conduct all the experiments and to test the approach presented, we used two twin mobile service robots developed for the URUS project [166], called Tibi and Dabo, each designed to work in urban pedestrian areas and to interact with people.

They are based on a two-wheeled Segway RMP200 platform, which works as an inverted pendulum in constant balancing. They can rotate on the spot (nonholonomic), and have wheel encoders providing odometry, and inclinometers providing pitch and roll data. To perceive the surrounding environment, they are equipped with two Hokuyo UTM-30LX 2D laser range sensors, which help them to detect obstacles and people, giving scans over a local horizontal plane at 40 cm above ground, facing both forward and backward. A stereo Bumblebee camera is used for computer visualization purposes.

As social robots, Tibi and Dabo are designed to interact with people. They are equipped with several interaction devices to enable them to engage with friendly interactions, such as a touchable screen, speaker, movable arms and head, and LED illuminated facial expressions. Power is supplied by two sets of batteries, one for the segway platform and one for the computers and sensors, giving about a 5 hours' worth of full working autonomy. Two onboard computers (Intel Core 2 Quad CPU @ 2.66 and 3.00 GHz) manage all the running processes and sensory signals, and a laptop is

Figure 3.9: **BRL and FME.** ***Left:*** Barcelona Robot Lab, North campus of the UPC. ***Right:*** FME Lab, South Campus of the UPC.

used for external monitoring. The systems run Ubuntu-Linux, and use a middleware called ROS [137], a software developmental environment for robot system integration that provides a wide and useful set of libraries and tools. Fig. 3.8 shows one of the robots and some of its components.

The experiments were conducted at the BRL (Barcelona Robot Lab) and the FME (Facultat de Matemàtiques i Estadística) lab, outdoor urban environments located at the North and South Campus of the Universitat Politècnica de Catalunya (UPC), respectively.

The BRL (Fig. 3.9-*Left*) is a large area of the campus that was outfitted as an experimental area, covering over 10.000 m^2, comprising six buildings and a central square, with multiple ramps, staircases, and typical obstacles such as bulletin boards, bicycle stands, trashcans and flower pots. The FME lab (Fig. 3.9-*right*) consists of a green space and a paved area, separated by stairs.

3.6.2 ESFM parameters

The first step required for the robot companion is the study of the ESFM, which governs human motion in general. We take into account three kinds of interaction forces: person-person, person-obstacle, and person-robot. The first and second interactions have been studied in previous papers such as [75, 109, 177]. However, as the person-robot interaction parameters had not been directly obtained in any previous work, in this section we present the results obtained for the parameters $\{A_{Rp}, B_{Rp}, \lambda_{Rp}, d_{Rp}\}$.

ESFM parameters					
Interaction	k $[s^{-1}]$	A $[m/s^{-1}]$	B $[m]$	d $[m]$	λ
Per-Per [108]	2	1.25	0.1	0.2	0.5
Per-Per [177]	4.9	10	0.34	0.16	1
Robot-Per (our approach)	2.3 (± 0.37)	2.66 (± 4.51)	0.79 (± 0.21)	0.4 (± 0.25)	0.59 (± 0.36)

Table 3.1: **Model forces parameters:** Parameter values of $\{A_{Rp}, B_{Rp}, \lambda_{Rp}, d_{Rp}\}$.

As discussed in Section 3.3.1, we have recorded two different databases in a real scenario. During the first part, we optimized the intrinsic parameter of the ESFM $\{k\}$, by describing the expected human trajectories under no external constraints.

The second part of the ESFM parameter learning was carried out under the influence of the Tibi robot. We optimized the extrinsic parameters of the force interaction model $\{A_{Rp}, B_{Rp}, \lambda_{Rp}, d_{Rp}\}$, under the presence of a moving robot, making sure it was the only external force affecting the outcome of the trajectory described by the person.

Table 3.1 shows the parameters learned after applying the minimization process (see Section 3.3.1), using genetic algorithms, to all database trajectories. Each parameter includes a standard deviation, obtained after estimating each trajectory independently. Table 3.1 also demonstrate the parameters proposed by Luber [108] and Zanlungo [177], works that referred to the person-person ESFM. However, in contrast to these studies, the presented work implements the ESFM to learn the parameters for a human-robot interaction. Furthermore, the standard deviation of some parameters is quite high, because people behave differently when they interact with robots.

3.6.3 Simulations: parameter learning and validation

In order to obtain a good initial estimation of the $\mathbf{\Theta} = \{\alpha, \beta, \gamma, \delta\}$ parameters, and to mathematically evaluate the accuracy of the social robot companion model, we constructed a simulated social environment. This simulated environment serves two purposes: firstly, it allows for an initial estimate of the system parameters $\mathbf{\Theta}$; and secondly, it permits us to validate the performance of the approach, using the function defined in Section 3.5.1, in different environments with different density of pedestrians.

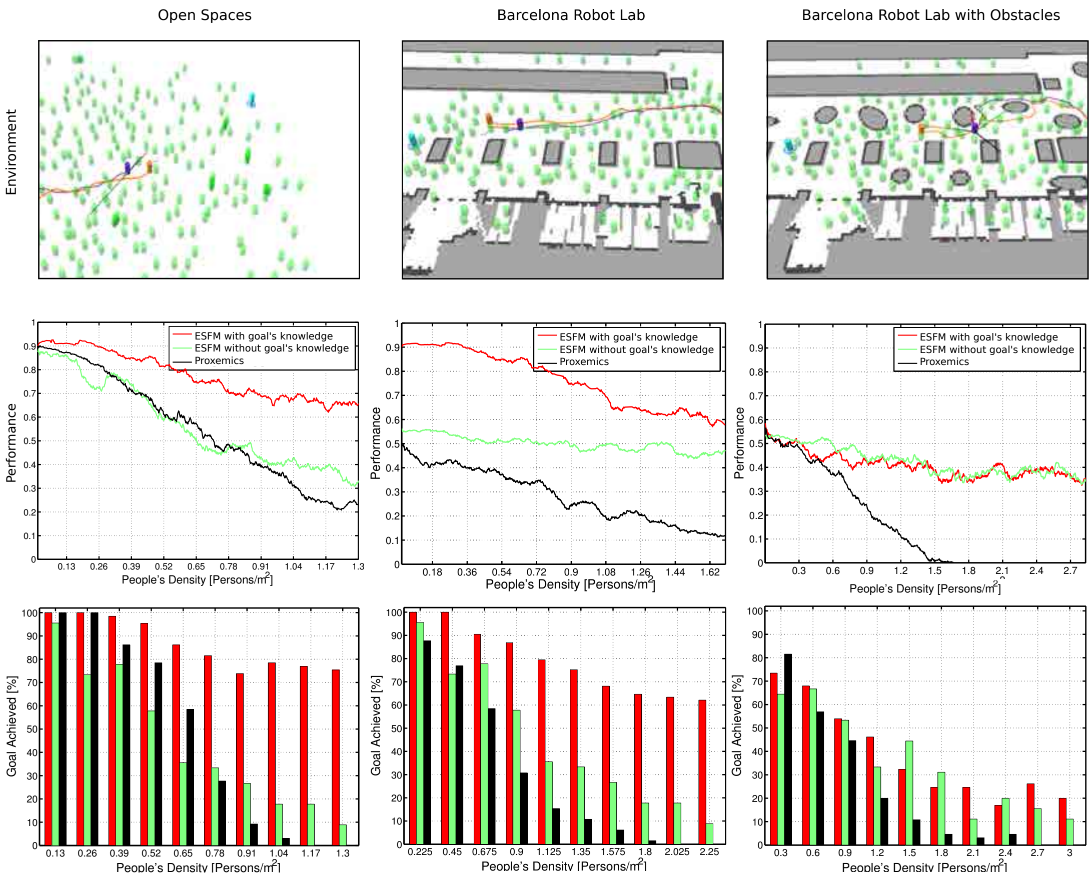

Figure 3.10: **Simulations comparative.** ***Left column:*** unconstrained area with four destinations. ***Central column:*** urban settings, corresponding to the Barcelona Robot Lab. ***Right column:*** variation of the BRL with extra obstacles. ***Top row:*** different scenarios of the simulations. ***Second row:*** simulations performance; black indicates the proxemics approach, green shows ESFM companion and red highlights the ESFM with the human's destination data. All results are a function of the pedestrian density in the environment. ***Third row:*** rate of successful robot arrivals in bar diagrams.

To this end, we have implemented a complete social environment, as depicted in the top row of Fig. 3.10. This considers pedestrians, obstacles, and robots, in an interactive way, and treating each element in relation to its surroundings, according to the ESFM. This method allowed us to obtain a dynamic environment, in which each action of the robot affected the behavior of nearby pedestrians, and vice versa.

We have set the accompanying position at 1.5 m from the target and 60° from the target's heading. Our approach for the robot companion task is evaluated in a simulated environment. This simulated environment consists of an urban setting –inspired by the BRL– in which obstacles, and a fixed number of pedestrians are both presented.

To obtain a good initial estimation of the system parameters, we developed a set of simulations. The results of the MCMC-MH optimization, as discussed in Section 3.5.2, were obtained after two thousand simulations. The outcome of each experiment is dependent on the parameters $\mathbf{\Theta}$, since the system reacts to the behavior of the robot navigation, and vice versa. After applying the optimization method described in Section 3.5.2, we obtained an initial guess of the magnitude of $\mathbf{\Theta}$ roughly rounded to the values $\{\alpha = 0.1, \beta = 0.6, \gamma = 5.0, \delta = 0.50\}$. Note that these parameters were obtained after random initializations and within a virtual environment. However, this initial guess is a good estimation of $\mathbf{\Theta}$ and their corresponding standard deviations, which will be the initial values of the system parameters that we will use for the interactive learning.

The second objective of the simulations was to validate the parameters obtained earlier, in a challenging environment. Our method makes use of the ESFM of surrounding persons and obstacles while approaching the target. It also assumes that the robot knows the person's destination so as to enhance its performance – as shown in red in Fig. 3.10. We have also implemented two additional methods to compare with our approach. A second configuration takes into account only the ESFM model –shown in green in Fig. 3.10–, wherein the robot did not have any previous knowledge of human's intended destination. For this reason, the avoidance of moving targets and obstacles is executed dynamically using the interaction forces. Our method is also compared with a robot companion based on proxemics, where the robot follows the target person, ignoring the force of interactions with other people. When a person enters the robot's inner safety zone, the robot halts until the path is clear – as shown in black lines in Fig. 3.10.

The experiment's settings were tested in three different scenarios, as observed in the top row of Fig. 3.10. The first setting is an unconstrained area, free of obstacles, where four destinations are defined. The second is a urban setting, littered with obstacles, as well as pedestrians. The third is a variation of the previous setting, with a higher density of obstacles.

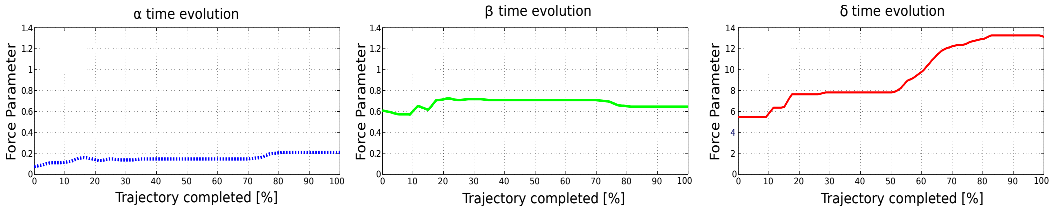

Figure 3.11: **Force parameters** α, β, γ**.** Evolution in time from start to end of each experiment of the force parameters α, β, γ. These variables were averaged using results chosen for each participant within the course of the experiment.

For each environment, the algorithms have been tested depending on the density of persons in the unoccupied area. To lend our results greater statistical consistency, we conducted over 50.000 experiments, changing only the initial conditions of each pedestrian in the scene and their intended destination. This conditions are calculated randomly and the robot has to accompany a person under this uncertain environment. It is important to note that the environment has a high density of persons and each individual is headed towards a random destination. This rapidly generates a chaotic and challenging environment for the robot companion testing.

We consider our robot companion approach as a type of potential navigation system. Despite their already well-known limitations [96], in which local minima problems may arise, we did not experience such problems, since either the destination, or the person being accompanied, consistently described affordable configurations of navigation.

The second row of Fig. 3.10 shows the overall performance of the different methods, with respect to the density of pedestrians in the scene (Section. 3.5.1), taking into account penalities due to nearby persons. As expected, using social interaction forces –red and green lines– highly increases the robot's performance. Prior knowledge of the human's destination clearly enhances the performance of the task, as observed in the first and second columns. When there is a low density of obstacles, this information is highly useful. Nevertheless, when there is a high number of obstacles in the scene, and the robot knows the destination in advance, the strategy is equally successful. This is due to the fact that such knowledge leads the robot to decide on an alternative paths, rather than just following the target. This is particularly true in the third scenario, where we observed movement towards a column to the right when the target moves to the left; the destination would be more accessible by taking this route. Although this

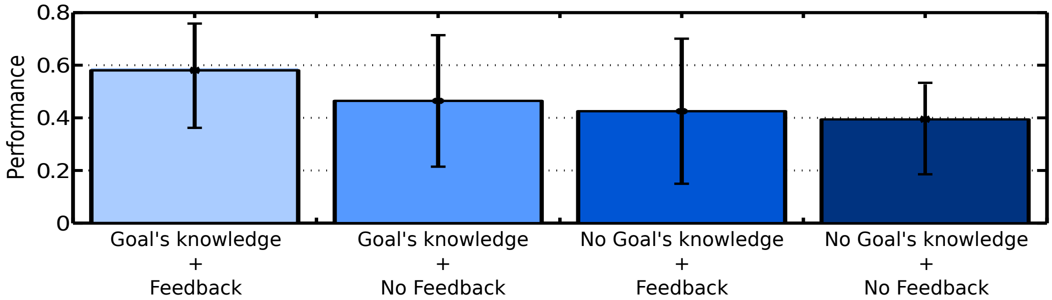

Figure 3.12: **Experiment results:** An average of the performance and its standard deviation for the experiments, combination using the target's knowledge and feedback.

behavior denotes some intelligence, its performance is not rewarded in our metric, as shown in Fig, 3.10. However, the companion's general performance was better overall when it knew the human's destination.

The third row of Fig. 3.10 shows the average percentage of successful arrivals at the given destinations, reflecting instances in which the robot was within the companion zone –Section 3.5.1– at the moment the target arrived at his/her destination. Although this metric is highly correlated, we observed that using the human's destination increases the arrival rate with respect to the ESFM only and proxemic approaches. That is, this kind of information increases the likehood of the robot arriving at the destination simultaneously with the target.

3.6.4 Real experiments: interactive learning and real performance

The proposed robot companion approach was tested in the FME and the Barcelona Robot Lab, Fig. 3.9. The experiment setting considers a robot within a real scenario, as follows: we instruct each volunteer to walk naturally towards a chosen destination, among two options represented as red pylons. While approaching the desired destination, the robot accompanies the volunteers and they should behave naturally.

As part of the interactive multimodal learning, the system learns the desired robot behavior, as explained in Section 3.5.3. While the feedback provided by the target is a subjective metric, its purpose is to lead to a general approaching rule for a better robot behavior. It is provided directly by the target, using a remote control; in this way, the system automatically weights the contributions of the active forces (Section 3.5.3). An initial estimation of the θ parameters is calculated in simulations, and this information is useful, although a readjustment is provided by the human feedback.

We prepared a set of four experiments, that combine the knowledge of the destination and feedback provided, in order to evaluate the overall performance within each combination:

- Without knowledge of the goal and no feedback.
- Knowning the goal but not having feedback.
- Without knowledge of the goal but having feedback.
- Knowning the goal and having feedback.

Fig. 3.11 shows the $\{\alpha, \beta, \gamma\}$ obtained from the user feedback that determines the robot behavior. It has been averaged using 20 different experiments and is depicted as a function of time, normalized from the start of the experiment to the end $t \in [0, 1]$. The δ parameter is not drawn in the figure, since not many obstacles were present in the scene. However, the δ parameter remains mandatory when navigating within the presence of multiple obstacles.

The robot was able to achieve its goal in all experiments conducted. The volunteers were told to walk naturally and the robot accompanied the target using the social robot companion framework described in Section 3.5.3. During the validation of the model in real experiments, we set unexpected obstacles and pedestrians in the targets' path, which the robot was able to avoid successfully.

A summary of the overall performance for each setting is depicted in Fig. 3.12. Clearly, the goal's knowledge consistently enhanced the robot companion's approach. When we address the human poll results, we get a very similar conclusion.

During the real world experiments, we observed unexpected difficulties that did not come up during the simulations. We found severe limitations to the perception system, the laser people detector, and the people tracker. People were not always properly detected, and the data association was at times wrong. However, a comprehensive review of the perception system falls outside the scope of the present dissertation, and

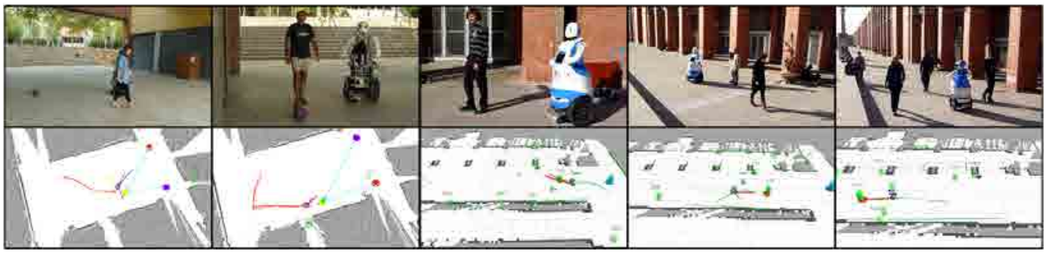

Figure 3.13: **Real-life experiments:** Some examples of the conducted real experiments. ***Top:*** Dabo accompanying a person to a desired destination. ***Bottom:*** The same scene using the system interface.

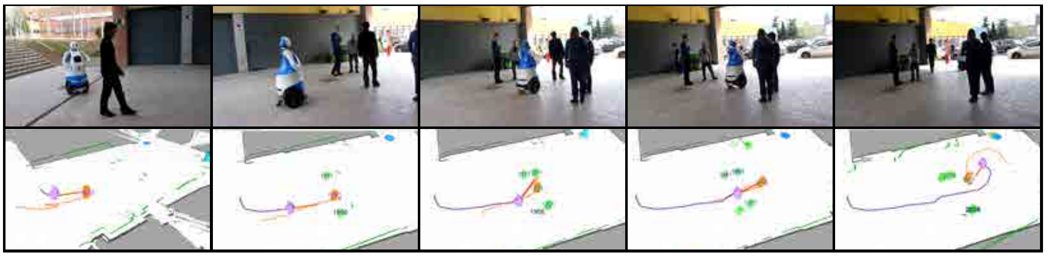

Figure 3.14: **Real-life experiments 2:** A single robot companion experiment. ***Top:*** Dabo accompanying a person to a desired destination. ***Bottom:*** The same scene using the system interface.

it is important to note that any other system –vision detection, RF, etc..– would also be subject to limitations under realistic conditions.

We carried out 80 experiments, 41 of which were used to measure the performance of the robot companion under different settings as described above. Later, we will discuss the effect of the feedback, enlighten by the results of the volunteer survey.

This new set of experiments was performed mostly in the BRL, with the interaction of multiple pedestrians and obstacles. Fig. 3.13 depicts examples of different experiments performed with volunteers in different urban environments. Moreover, it shows several case scenarios where multiple objects and people are in the scene. In Fig. 3.14, an example of a single sequence is depicted, wherein a robot accompanies a person, within the presence of a group of people.

Survey's Questions	
Robot's Intelligence Scale	Cronbach's alpha = 0.702
How intelligent did the robot behave?	
How well could the robot anticipate to your movements?	
Human-Like Motion Scale	Cronbach's alpha = 0.742
How social was the robot's behavior?	
How natural was the robot's behavior?	
How human-like did the robot behave?	
Level of Confidence Scale	Cronbach's alpha = 0.704
How comfortable did you feel near the robot?	
How safe did you feel around the robot?	
How well did the robot's movements adhere to human social norms?	

Table 3.2: **Questionnaire.** Survey questions asked of each participant. All questions were asked on a 7-point scale from "Not at all" to "Very much".

3.7 User study

The results presented above demonstrate that the robot is able to successfully accompany a person. A user study was also conducted to determine whether the different strategies presented above were perceived by people as socially appropriate.

3.7.1 Results

As mentioned previously, 45 real-life experiments with different volunteers were carried out. Upon their conclusion, each participant was asked to fill out a questionnaire. The measurement was a simple rating on a Likert scale between 1 to 7. For the evaluation score, repeated ANOVA measurements were conducted. In this section, we provide two different results. On the one hand, we sought to find out if the robot truly needed to know in advance pedestrian's desired destination. And, on the other hand, we hoped to determine if the use of the remote control enhanced or did not the quality of the human-robot interaction.

Social Scales

Participants were asked to answer eight questions, as shown in Table 3.2, following their encounter with the robot in each mode of behavior. To analyze their responses, we grouped the survey questions into three scales: the first measured the robot's intelli-

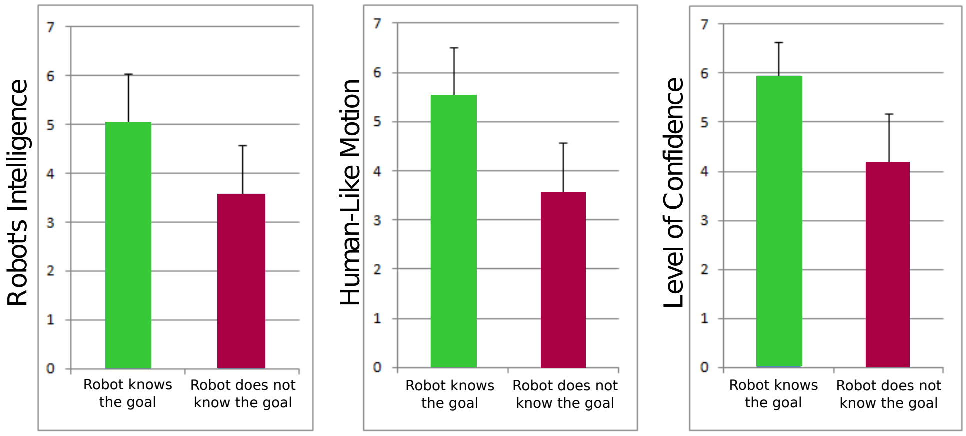

Figure 3.15: **Knowledge of the destination.** People's perception of the robot's knowledge of the intended destination. ***Left*** : Robot's Intelligence. ***Center:*** Robot's Human-like motion. ***Right:*** Level of confidence.

gence, the second evaluated more specific questions on the robot's movements, and, the third measured the level of confidence. This scales surpassed the commonly-used 0.7 level of reliability (Cronbach's alpha)[2]. Each scale response was computed by averaging the results of the survey questions comprising the scale. ANOVAs were run on each scale to highlight differences between the robot behaviors.

Firstly, in order to know if it is necessary that the robot knows the pedestrian's destination, human perception has been studied. To analyze the source of the difference, three different scores were examined: "Robot's Intelligence", "Human-Like Motion" and "Level of confidence", plotted in Fig. 3.15. For robot's intelligence a repeated-measures analysis of variance revealed a significant main effect, $F(1, 44) = 14.82$, $p < 0.001$. For robot's Human-like motion the ANOVA test revealed a great effect, $F(1, 44) = 36.28$ $p < 0.001$. And, finally, the analysis of variance revealed a remarkable difference in the level of confidence $F(1, 44) = 61.79$ $p < 0.001$.

Secondly, in order to analyze if the use of the remote control enhances the interaction between the robot and a person, three different scores were examined: "Robot's Intelligence", "Level of interaction" and "Level of confidence", plotted in Fig. 3.16. For

[2]Cronbach's alpha is a measure used to determine how reliably a set of questions measures a single dimension. Values less than 0.7 imply that the scale is measuring more than one thing; higher levels indicate that the questions are essentially asking about the same thing, so the items can be combined for analysis.

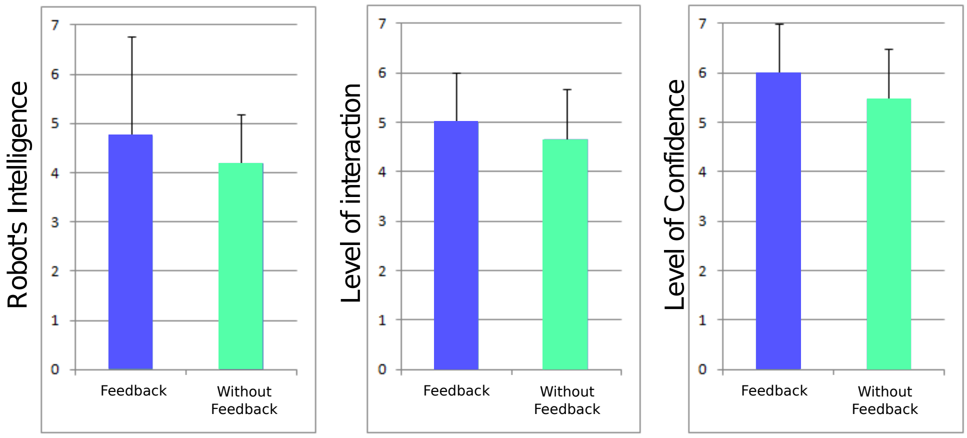

Figure 3.16: **Remote control.** People's perception of the use of the remote control. ***Left*** : Robot's Intelligence. ***Center:*** Level of interaction. ***Right:*** Level of confidence.

robot's intelligence a repeated-measures analysis of variance revealed that no significance was found, $F(1,44) = 1.88$, $p = 0.18$. For the level of interaction the ANOVA test do not revealed a significant main effect, $F(1,44) = 0.48$ $p = 0.18$. And, finally, the analysis of variance showed that there is not a remarkable difference in the level of confidence $F(1,44) = 3.57$ $p = 0.07$.

In summary, after analyzing these two components, we may conclude that when the robot has the ability to know the human's intended destination, it yields a greater degree of human acceptance. People perceived the robot to be more intelligent, as it could detect and approach them, and they felt that it had a better social skills. Moreover, we found that the use of the remote control did not enhance the interaction between the robot and the accompanied person.

Participants Comments

Each questionnaire included several blank lines underneath the social scales, where participants could record additional thoughts on the experiments. While we did not explicitly codify and analyze these comments, they do provide further insight into the effect of the three robot behaviors.

Comments when the robot knew the destination : Many of the comments we received reflect that volunteers felt that the robot ably accompanied them and interacted with them. Participants noted:

"I liked that the robot accompanied me to the destination, I felt comfortable along the way."

"I feel that the robot is very sociable because it walks close to me and respects my personal space."

"She knew that there were people around us and could navigate with me while avoiding other people, it is very funny!"

Note that the comments on this behavior generally indicate that participants felt that the robot accompanied them and respected social conventions.

Comments when the robot did not know the destination: Many of the comments reflect that participants did not notice that the robot walked with them, and that if the robot did not know the destination, it navigated behind the person; therefore, these participant did not feel that the robot was really interacting with them:

"I didn't think the robot was walking with me because it was behind me the whole time."

"It seems that the robot is just following me instead of accompanying me."

"I find the experiment very interesting, however I did not notice that Tibi was walking with me."

Note that the comments on this behavior generally indicate that although participants felt that the robot tried to walk with them, Tibi was not able to accompany them, and thusm did not achieve its task.

Comments when the volunteer used the Wii remote control: Many of these comments indicated that participants did not notice a difference between using the remote control or not.

"I don't think we need to use the remote control, I did'nt notice any difference between using it or not using it."

"I expected that the remote control would enhance the interaction between Tibi and me."

"I felt that Tibi obeyed social conventions, but the remote control was a hindrance, it is useless."

"The remote control is useless, I didn't notice any relationship between using the remote and a change on robot's behavior."

3.8 Summary

In this chapter a novel robot companion approach based on the so called Social-Forces Model has been presented. The major contributions of this chapter are threefold. First, we obtained the force parameters of robot-person interactions, specifically suited for Tibi. We went one step further into the development of the SFM for robot interactions, by presenting a powerful scheme for social companion robots based on the social-forces concept.

Second, we introduced a novel robot companion metric was presented. Since the verification of any system in which humans intervene is hard to objectively evaluate, we used an analytical metric that justifies the behavior of our robot companion approach.

Finally, we developed a model of human feedback that successfully yielded a set of weighting parameters for the robot companion's behavior. We believe that human feedback for parameter learning is a key point for the development of robots whose purpose is to interact with people.

We validated the model through an extensive set of simulations and real-life experiments in an urban area. In contrast to other existing approaches, our method can handle realistic situations, such as dealing with large environments littered with obstacles and dense crowds. For that reason, this work can be applied to various specific real-life robot applications; for instance, guiding tourists. The overall validation of the approach in real scenarios was achieved by using feedback information obtained directly from the volunteers.

Moreover, we can conclude that when the robot knows the human's destination, it greatly increases the overall human-perceived performance of the system, according to the user surveys. Nevertheless, the multimodal feedback in the form of a wii remote control did not improved the subjective performance, according to the poll. Moreover, the force parameters did not really changed so drastically enought to justify the use of an additional input channel.

Chapter 4

Multi-Cooperative Robots to Guide and to Escort people using Discrete Time Motion Model

The nice thing about teamwork is that you always have others on your side.

Margaret Carty

In this chapter, we present a new model for guiding people in urban areas using several cooperative robots that overcomes the limitations of existing approaches, which are either tailored to tightly bounded environments, or based on unrealistic human behaviors. The main contributions of our approach are twofold: from one side, we represent the environment by means of a potential field which allows to cope with open or closed areas, and with obstacles. On the other side, the motion models for both people and robots are grounded on social human behaviors learned from training databases of groups of pedestrians moving in real-world scenarios. All these pieces are integrated into a common "Discrete-Time Motion Model" that allows to estimate the motion of people and robots and to compute the robot's trajectory for guiding people to a specific location goal. Several experiments on real and synthetic data demonstrate the validity of the proposed model. The work in this chapter has been presented in [56, 58].

4.1 Introduction

The interest on developing social and cooperative robots has significantly increased throughout the recent years. The applications of this field are very diverse, from developing automatic exploration sites [165], to building robot formations for transporting and evacuating people during emergency situations [33].

One important application within this field is that of using one or several robots for accompanying a group of people. This kind of application has already been used for guiding people in museums [19, 31], although the robot navigation skills were limited to simple path planning functionalities with additional reactive behaviors to avoid collisions with humans. No particular actions were taken to avoid situations were the crowd did not follow the robot. These shepherding capabilities were developed in [169] for guiding flocks of animals. Yet, this approach was constrained to closed areas with no obstacles and only considered one single robot.

The approach we propose in the present chapter offers several advantages with respect to the existing works just mentioned: (1) It allows guiding a group of people within open or closed areas that potentially may contain obstacles; (2) The approach uses multiple cooperative robots and (3) it has functionalities to avoid people leaving the crowd in a friendly and safe manner. We use a design in which one of the robots is the *leader*, as a human tour-guide. It is placed at the front of the group and its role is to estimate the trajectory of people and the rest of robots. The other robots, called *shepherd*, are responsible for guiding the people, preventing any person to leave the group, and following the path given by the leader. A diagram representing this proposed approach is shown in Fig. 4.1.

At the core of our approach we propose a "Discrete Time Motion" (DTM) model which is used to represent people's and robot's motions. The DTM predicts people's movements in order to perform path planning and provide the motion instructions to the robots. This is done by means of a Particle Filter formulation [7], in which the dynamical models are based on realistic human motions. On the other hand, the interaction with the obstacles of the environment is considered through a potential field, where both the positions of people and robots are represented by continuous and

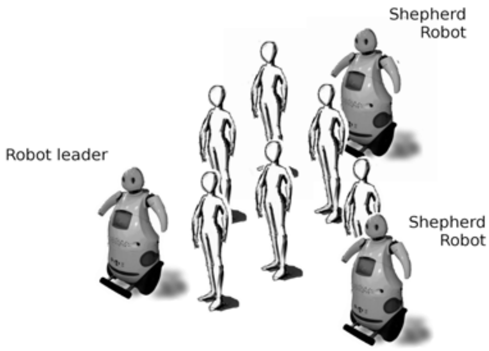

Figure 4.1: **Guiding people using a group of cooperative robots**. In our approach, one of the robots is the *leader* and is responsible for estimating the trajectory of the people and the rest of robots. The *shepherd* robots follow the instructions of the leader for guiding the people and avoiding any person to leave the group.

derivable functions. Using these parameterizations each point in the space will have an associated potential value, which will be used to control the motion of all the robots.

Finally, another important virtue of our model is the realism we achieve in the dynamic models for both robots and persons. We validate these models on several video sequences of groups of persons performing different types of movements. We show through this experimental validation that the proposed models are good approximations to real situations.

4.2 Chapter's Overview

In the next sections we will describe the architecture we developed to accompany a group of people using several robots behaving in a cooperative and human-safe manner. This is achieved by means of a framework that enables considering realistic motion models, as describing environments that include an arbitrary number of obstacles. More specifically, the main ingredients of our approach (see Fig. 4.2) are the following:

- *Realistic people motion model*: To represent people's motion we use realistic models that describe the dynamics of pedestrian crowds from the "social" point of view. These models were already introduced in early works [75, 76], and describe

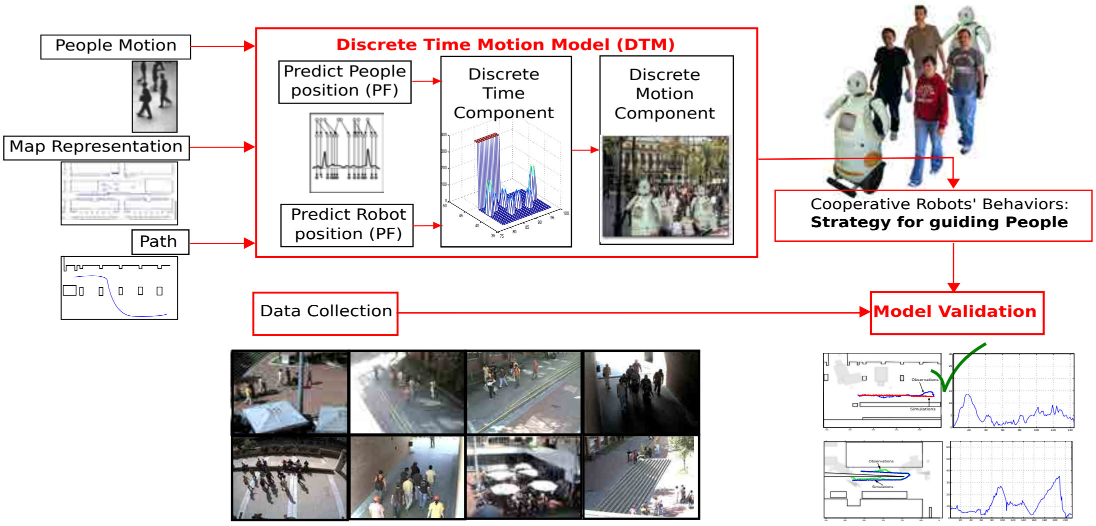

Figure 4.2: **Overview of our approach for guiding people.** Given a map representation, a desired target position and a motion model for people, we compute the robots movements in order to guide the group of people along the desired path. The mathematical framework to compute the motion commands sent to the robots is called Discrete Time Motion Model, which includes sub-modules to predict people and robot position, and to represent the whole environment including persons, robots and obstacles. We validate our approach both on synthetic data and real video sequences of a urban setting.

the motion of pedestrians based on social forces which are the result of the internal motivations of the individuals to perform certain motions.

- *Prediction of people and robots' positions*: In order to model the motion space, it is necessary to estimate people positions and velocities. We use Particle Filtering for this purpose.

- *Environment representation*: Before providing the motion commands to robots to achieve their goals, we need a unified representation of the obstacles, robots and people. This is done by means of a potential field. Each person and robot are represented as a Gaussian distribution centered in its position. Obstacles are represented by a mixture of Gaussians distributed along the obstacle's boundary. Then, the overall potential field is computed by the intersection of all the Gaussian functions with their associated covariances.

- *Strategy for Guiding People*: Once the working environment of the robots is defined by a potential field, robot's trajectories and motion commands are computed by minimizing the energy of the potential field. We call the component of our architecture that performs this minimization the *Discrete Time Motion Model*.

- *Data Collection*: The guiding capabilities of our approach are initially validated through synthetic data. In addition, we also use real data. For collecting real data, we use the camera network available in the Barcelona Robot Lab, that integrates 21 cameras, partially and sequentially overlapped. Using this camera network we captured a set of video sequences of groups of people while following a leader.

- *Validation Process*: For validating the model with real data, we initially extract the ground truth trajectories of each person and the group. These ground truth trajectories are the compared with the estimations obtained by the Discrete Time Motion model. Moreover, we perform a set of simple real-life experiments where our robots Tibi and Dabo carried out the task of leader or shepherd.

4.3 Modeling People's Motion

In order to model people's motion we use the formalism introduced by the works of Helbing et al. [75, 76], that study the dynamics of pedestrian crowds from the "social" point of view [103]. Fig. 4.3 shows a schematic representation of processes leading to behavioral changes. A behavioral reaction has been caused by a sensory stimulus, this reaction depends on personal intentions and it is chosen from a set of behavioral alternatives.

More specifically, they describe the motion of pedestrians based on social forces which are the result of the internal motivations of the individuals to perform certain motions. These forces, for some simple situations, can be described through probabilistic models. The three considered basic concepts that rule the movement of people are:

1. The pedestrian wants to reach a certain destination as comfortable as possible.

2. The motion of a pedestrian is influenced by other pedestrians.

3. Pedestrians are sometimes attracted by other humans or objects.

For the first situation, people usually take the shortest path, which may be formally represented as the shape of a polygon with edges $\boldsymbol{r}_{p_i}^1, \ldots, \boldsymbol{r}_{p_i}^n := \boldsymbol{r}_{p_i}^0$, where p_i refers to a given person and $\boldsymbol{r}_{p_i}^0$ the destination that he/she wants to arrive.

The desired motion direction $\boldsymbol{e}_{p_i}(t)$ of a pedestrian p_i will then be:

$$\boldsymbol{e}_{p_i}(t) := \frac{\boldsymbol{r}_{p_i}^k - \boldsymbol{r}_{p_i}(t)}{\left\|\boldsymbol{r}_{p_i}^k - \boldsymbol{r}_{p_i}(t)\right\|} \tag{4.1}$$

where $\boldsymbol{r}_{p_i}$ is the *current position* and $\boldsymbol{r}_{p_i}^k$ is the subsequent edge of the polygon that will be reached. Since we assume the group of persons is moving together and following the leader robot, the previous equation becomes:

$$\boldsymbol{e}_{p_i}(t) = \boldsymbol{e}_R(t) + \boldsymbol{\xi} \tag{4.2}$$

where $\boldsymbol{e}_R(t)$ is the robot's direction motion and $\boldsymbol{\xi}$ is a parameter accounting for noise.

We also consider that a deviation of the actual velocity $\boldsymbol{v}_{p_i}(t)$ from the desired velocity, $\boldsymbol{v}_{p_i}^0(t) := v_{p_i}^0 \boldsymbol{e}_{p_i}(t)$, may also exist due to deceleration or obstacle avoidance processes. This can be written as:

$$\boldsymbol{f}_i^0(\boldsymbol{v}_{p_i}, v_{p_i}^0 \boldsymbol{e}_{p_i}) = \frac{1}{\tau_{p_i}}(v_{p_i}^0 \boldsymbol{e}_{p_i} - \boldsymbol{v}_{p_i}) \tag{4.3}$$

where $v_{p_i}^0$ is the current speed and τ_{p_i} is a relaxation term of pedestrian stride. In practice, we set the term τ to 0.5 for all the pedestrians.

Let us now consider the second situation in which the pedestrian motion is influenced by other pedestrians from the group. This situation responds to the fact that each individual tries to maintain an empty security volume surrounding him/her which is called the *vital space*. This is in fact a repulsive effect that we model as:

$$\boldsymbol{f}_{ij}(\boldsymbol{r}_{ij}) = Ae^{-b_{ij}/B} \frac{\|\boldsymbol{r}_{ij}\| + \|\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}\|}{4b_{ij}} \times \left(\frac{\boldsymbol{r}_{ij}}{\|\boldsymbol{r}_{ij}\|} + \frac{\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}}{\|\boldsymbol{r}_{ij} - \boldsymbol{y}_{ij}\|} \right) \tag{4.4}$$

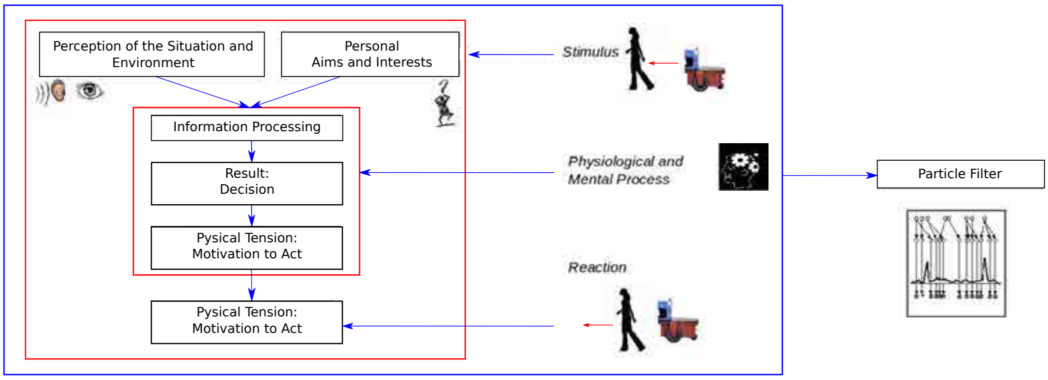

Figure 4.3: **Processes leading to behavioral changes.** A sensory stimulus causes a behavioral reaction which depends on personal aims and is chosen from a set of behavioral alternatives with the objective of utility maximization.

where $\boldsymbol{f}_{ij}(\boldsymbol{r}_{ij})$ is a repulsive potential which is assumed to be a monotonic decreasing function of b_{ij} with equipotential lines having an elliptical shape, $\boldsymbol{r}_{ij} = \boldsymbol{r}_{p_i} - \boldsymbol{r}_{p_j}$. The parameter b_{ij} denotes the semi-minor axis of the ellipse and is given by:

$$b_{ij} = \frac{\sqrt{(\|\boldsymbol{r}_{ij}\| + \|\boldsymbol{r}_{ij} - v_{p_j}\tau\|)^2 - \|v_{p_j}\tau\|^2}}{2} \tag{4.5}$$

where,

$$\boldsymbol{y}_{ij} = \boldsymbol{r}_{ij} - \boldsymbol{v}_{p_j}\tau \tag{4.6}$$

and $v_{p_j}\tau$ is an approximation to the step size of a pedestrian p_j, see Fig. 4.4 for details.

Moreover, we consider the repulsive effect produced by the distance that people try to keep from the obstacles of the environment. The nature of this force is the same we just described between individuals, with the difference that we assume static obstacles.

Furthermore, pedestrians are sometimes attracted by other persons or objects in the environment, such as friends, street artists or windows displays. These attractive effects $\boldsymbol{f}_{io}$ has the the same form as the inter-agent repulsive forces. The main difference is that the attractiveness decreases with time t since the interest is declining, $\boldsymbol{f}_{io}(\|\boldsymbol{r}_{io}\|, t)$, $\boldsymbol{r}_{io} = \boldsymbol{r}_{p_i} - \boldsymbol{r}_o$.

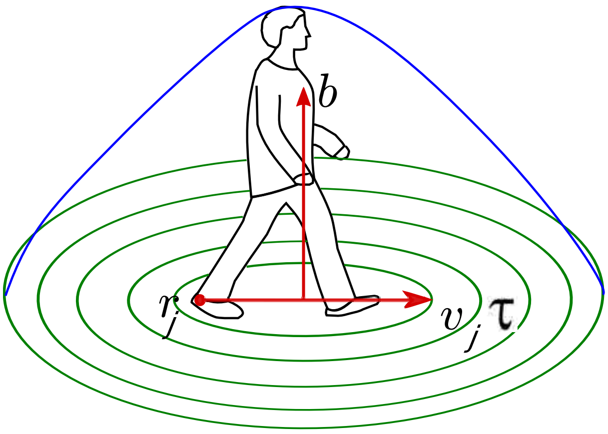

Figure 4.4: **Person's vital space.** Diagram of the elliptical specification of pedestrian interaction forces.

Finally, to complete the model of human motion a relation between the actual velocity $\boldsymbol{v}_{p_i}(t)$ and the preferred velocity $\boldsymbol{w}_{p_i}(t)$ has to be described. The actual speed is limited by a pedestrian's *maximal acceptable speed* $v_{p_i}^{max}$, thus, we assume that the realized motion is given by

$$\boldsymbol{v}_{p_i}(t) = \boldsymbol{w}_{p_i}(t) g \left(\frac{v_{p_i}^{max}}{\|\boldsymbol{w}_{p_i}\|} \right) \tag{4.7}$$

with

$$g \left(\frac{\boldsymbol{v}_{p_i}^{max}}{\|\boldsymbol{w}_{p_i}\|} \right) = \begin{cases} 1 & \text{if} \quad \|\boldsymbol{w}_{p_i}\| \leq v_{p_i}^{max} \\ v_{p_i}^{max} / \|\boldsymbol{w}_{p_i}\| & \text{otherwise} \end{cases} \tag{4.8}$$

In the present chapter, the described Social Force Model is used to simulate people motion, and thus, to obtain humans' movements similar to the behaviors found in reality.

4.4 Computing Robots Motion Commands

In this section, we will describe the model we use to represent the whole environment, made of an open and not bounded area with obstacles, and how the elements of this environment are related with the group of robots and persons. The key element to represent these relations is the *Discrete Time Motion* (DTM) model previously introduced, whose ultimate goal is to determine how the robots must operate to guide the group of persons towards a certain place.

For this purpose, we split the DTM into a static and a dynamic components. The former (called Discrete Time Component) estimates position, orientation and velocity of the robots and persons, and the position of the obstacles at a specific time instance. These estimations are then used to predict the intersection and collision points of the people with the obstacles and to detect if someone is leaving the group. All this information is jointly represented using potential maps. The dynamic (or Discrete Motion) component estimates the change of position, orientation and velocity of people and robots between two consecutive time instances. In conjunction with the potential map previously computed, it is then used to compute the robots' motion commands necessary to reach the goal while preventing people leaving the group. Fig. 4.5 shows a schematic representation of the modules used to build the DTM. We next describe in detail each of these components.

4.4.1 The Discrete Time Component

The first task of the Discrete Time component is to estimate position, orientation and velocity of the robots and people. This is done using a particle filter formulation, for which we postpone the details until Section 4.5.

Then, the Discrete Time component represents the areas where the robots will be allowed to move, by means of potential fields. To this end, we define a set of functions that describe the tension produced by the obstacles, people and robots over the working area. These tensions are computed based on the area defined by a security region surrounding each one of the persons, robots and obstacles.

Particularly, we first define the position and dimension of the *working area* as a circle large enough to include all the robots and persons, and placed in such a way that its perimeter intersects the position of the *leader* robot. Fig. 4.6 depicts this working area along with the obstacles within its bounds at a specific instant of time. Note that the size of this area changes over time, and consequently the whole dimension of the environment is not strictly limited.

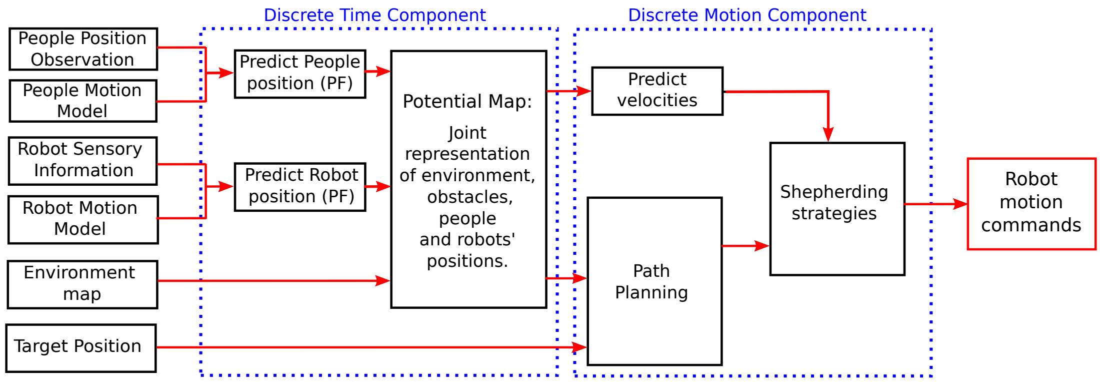

Figure 4.5: **Diagram of the Discrete Time Motion model.** To compute the motion commands sent to the robots for guiding people we propose a two-stage process. First, we estimate people and robots positions, and merge all this information into a potential map which also contains obstacles position. We call this initial step *Discrete Time Component*. We then use this information to plan the robot trajectories to reach the goal while preventing people to leave the group. This second stage is called *Discrete Motion Component*, which output are the motion commands given to the robots.

In order to decide the trajectories the robots follow we will use a similar approach to [81] and define a potential field over the working area, that includes all of the information of the environment and the position of the robots, persons and obstacles. To this end, we define a set of attractive and repulsive forces. In particular, the target position the robots try to reach will generate an attractive force pulling the robots towards it. On the other hand, the obstacles will generate a repulsive potential pushing a given robot away. The rest of robots and persons will generate similar repulsive forces, although with less intensity than the obstacle's forces.

We parameterized all these attractive and repulsive forces by Gaussian functions. For instance, the repulsive force that a person generates is written as:

$$T_{p_i}(\boldsymbol{\mu}_{p_i}, \boldsymbol{\Sigma}_{p_i})(\boldsymbol{p}) = \frac{1}{|\boldsymbol{\Sigma}_{p_i}|^{1/2}\,(2\pi)^{n/2}} e^{-\frac{1}{2}(\boldsymbol{p}-\boldsymbol{\mu}_{p_i})^T \boldsymbol{\Sigma}_{p_i}^{-1}(\boldsymbol{p}-\boldsymbol{\mu}_{p_i})} \tag{4.9}$$

where $\boldsymbol{\mu}_{p_i} = (\mu_{p_{i_x}}, \mu_{p_{i_y}})$ is the center of gravity of the person, and $\boldsymbol{\Sigma}_{p_i}$ is a covariance matrix whose principal axes $(\sigma_{p_{i_x}}, \sigma_{p_{i_y}})$ represent the size of an ellipse surrounding the person which is used as a security area. A similar expression defines the potential map associated to each robot.

These repulsive forces may be interpreted as continuous probability functions over

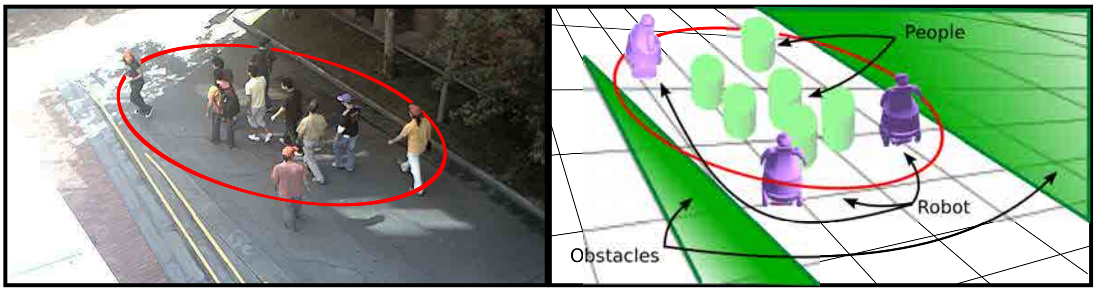

Figure 4.6: **Working area at a specific time instance**. The dimension and position of the working area changes over time. ***Left:*** Group of people being accompanied by three individuals. ***Right:*** The same scene using the system interface.

the entire space. Once they are defined, the tensions at each point of the space may be computed as the intersection of these Gaussians.

We can then define people and robots location by the set $\{(\mu_x, \mu_y), (\sigma_x, \sigma_y), v, \theta, T\}$, where v and θ are the velocity and orientation estimated by the particle filter and T is the associated tension. As said above, the variances (σ_x, σ_y) represent the security area around each individual. This could be set to a constant value. However, for practical issues one may need larger security areas when the robots or persons move faster. As a consequence, we changed appropriately the values of the variances σ_x and σ_y depending on the velocity parameter v.

In the case of the obstacles, we define their tension as a set of Gaussian functions collocated at regular intervals along their boundaries. Let us denote by $\boldsymbol{X} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$ the set of points uniformly distributed along the boundary. This boundary will be then represented by a set of positions and their associated potentials: $\{(x_i, y_i), (\sigma_{x_i}, \sigma_{y_i}), T_i\}$ for $i = 1, \ldots, n$, where T_i follows Eq. 4.9.

After having defined the tensions for each of the components of the environment –i.e. robots, persons and obstacles– the complete potential field is easily computed as the intersection of all the Gaussian functions. We can then compute the trajectories of the robots, based on the position of the persons and the desired goal, and following the paths with minimum energy in the potential field. The details of this computation are explained in the following section.

Algorithm 1 General strategy for guiding people

```
Establish the initial and goal positions.
Compute the trajectory using path planning.
Search the shortest path of the trajectory.
Set every internal node of the shortest path as a new subgoal.
for Every subgoal do
    Choose a motion strategy depending on the situation (open path, narrow passages...) while ensuring the priorities (prevent people leaving the group) are satisfied.
    Move to the next subgoal.
end for
```

4.4.2 Discrete Motion Component

The Discrete Motion Component computes the motion strategies to be achieved by the robots in order to achieve their goals, which are following a path to reach a specific target position while preventing people from leaving the group. Therefore, we consider two different motion strategies: (i) path planning till the goal, and (ii) shepherding strategies for avoiding people leaving the group.

In the first case the robot motion is computed using a simple path planning algorithm by reasoning directly on the potential field [79]. We first compute all the possible paths to reach the goal. The whole set of paths is known as the *trajectory*. Among all these paths, we then choose the shortest one, and each node of this path will be considered as a subgoal to reach. The robots will then move between consecutive subgoals while ensuring that people does not leave the group. This path planning is only performed by the *leader* ($\mathcal{L}$) robot who transmits the computed path to the rest of the robots called *shepherd* ($\mathcal{S}_i$).

The group non-holonomic mobile robots move along a desired trajectory. During the motion, the robots are required to maintain a formation. With the leader-follower formation strategy, the group's leader $\mathcal{L}$, whose configuration is defined as $c_{\mathcal{L}}$, leads the group motion, and the other robots, labeled as $\mathcal{S}_i$ ($i = 1, \ldots, N_R - 1$, where N_R is the total number of robots in the group) are the followers that maintain the respective relationships with the group's leader $\mathcal{L}$.

A number of leader-follower pairs are introduced with pre-defined relationships of $G_1, \ldots, G_{N_R-1}$, where $G_i = LF(\mathcal{S}_i \leftarrow \mathcal{L})$. In order to design the relationship G_i, two physically close robots are determined as two neighbors. All robots in the group are linked, either directly or indirectly, as a network in the group movement. The robots are labeled in advance based on their relative positions in the group at the beginning. Without loss of generality, we assume that the desired formation configurations are designed in a feasible way such that the robots can form the required formations without conflicts with each other.

A group of N_R non-holonomic mobile robots are controlled to move along a desired trajectory, led by the group's leader $\mathcal{L}$, whose configuration determines the motion of the shepherd robots which have to follow the leader with the required leader-follower relationships $G_1 - G_{N_R-1}$, through controlling separation, guiding and orientation deviation of the followers with respect to the leader.

Consider that the robots are differential mobile robots with non-holonomic constraints. The robot configuration, denoted by $\boldsymbol{c}_i = [x_i \quad y_i \quad \theta_i]^T$, is described by a unicycle model as the follows,

$$\dot{\boldsymbol{c}}_i = \begin{bmatrix} \dot{x}_i \\ \dot{y}_i \\ \dot{\theta}_i \end{bmatrix} = \begin{bmatrix} cos\theta_i \\ sin\theta_i \\ 0 \end{bmatrix} v_i + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega_i \tag{4.10}$$

where x_i and y_i are robot coordinates, θ_i is the orientation of the robot, and v_i and ω_i are the linear and angular velocities of the robot, respectively.

To ensure the shepherd robots maintain the desired separation and the orientation deviation with respect to the leader, we used the work presented in [24], where control schemes to derive the desired postures of the followers were proposed.

A two-robot formation with the desired leader-shepherd relationship $G_i = LF(\mathcal{S}_i \leftarrow \mathcal{L})$. With this scheme $\mathcal{S}_i$ follows $\mathcal{L}$ with desired separation l_i^d, bearing ψ_i^d and orientation ϱ_i^d. The desired configuration $\boldsymbol{c}_i^d = [x_i^d \quad y_i^d \quad \theta_i^d]^T$ of the shepherd $\mathcal{S}$ is given by:

$$\boldsymbol{c}_i^d = \begin{bmatrix} x_i^d \\ y_i^d \\ \theta_i^d \end{bmatrix} = \begin{bmatrix} x_{\mathcal{L}} & + & l_i^d cos\psi_i^d \\ y_{\mathcal{L}} & + & l_i^d sin\psi_i^d \\ \theta_{\mathcal{L}} & + & \varrho_i^d \end{bmatrix} \tag{4.11}$$

The second case is the study of shepherding algorithms [17, 169], which are inspired in the shepherd dogs. The shepherding task is performed by all the robots except the *leader*, that only carries out the function of a guide. The rest of robots follow the strategy depicted in Algorithm 1. Note that this algorithm does not explicitly consider safety conditions for the persons; i.e., when the robots are working it is necessary to satisfy a set of priorities for the safety of the people, such as avoiding collisions. However this was already taken into account when we defined the security areas in the Gaussian functions parameterizing the tensions.

Algorithm 1 just presents the general shepherding strategy. However, we may find several particular situations which should be considered, such as guiding in open roads with no obstacles, guiding in narrow corridors, moving closer the group of persons or rescuing a group member that left the group. In these particular situations one may have to design specific algorithms.

One important situation we must carefully consider is the case when people move away from the group. We are not aware of any approach tackling this problem. The solution we take for this situation is to choose one of the robots –the one closer to the person who left– and bring him/her back to the formation.

For computing the trajectory that will be considered for intercepting the person that left the group, we first used a Particle Filter to estimate the position and velocity of the person and compute the interception point.

Furthermore, the navigation of the robot is tackled with an attractive potential field. Conventionally, the attractive potential is defined as a function of the relative distance between the robot and the target only where the target is a fixed point in space. In this thesis, we believe that it is beneficial to have the velocities of the robot and the target considered in the construction of the potential field. When the target is moving, the conventional pure position based potential function is not directly applicable and has to be modified. Here, the potential field functions are presented as follows:

$$U_{att}(\boldsymbol{r}, \boldsymbol{v}) = \kappa_r \|\boldsymbol{r}_{tar}(t) - \boldsymbol{r}_{R_i}\|^2 - \kappa_v \|\boldsymbol{v}_{tar}(t) - \boldsymbol{v}_{R_i}\|^2 \tag{4.12}$$

where $\boldsymbol{r}_{R_i}(t)$ and $\boldsymbol{r}_{tar}(t)$ denote the positions of the robot and the target, $\boldsymbol{v}_{R_i}(t)$ and $\boldsymbol{v}_{ta}r(t)$ denote the velocities of the robot and the target, respectively; $\|\boldsymbol{r}_{R_i}(t)$ - $\boldsymbol{r}_{tar}(t)\|$ is the Euclidean distance between the robot and the target at time t; $\|\boldsymbol{v}_{R_i}(t)$

- $\boldsymbol{v}_{tar}(t)\|$ is the magnitude of the relative velocity between the target and the robot at time t, κ_r and κ_v are scalar positive parameters.

From Eq. 4.12, the attractive potential $U_{att}(\boldsymbol{r},\ \boldsymbol{v})$ approaches its minimum zero if and only if the relative distance and velocity between the robot and the target are zero. The attractive potential $U_{att}(\boldsymbol{r},\ \boldsymbol{v})$ increases as the relative distance or velocity between the robot and the target increases. If $\kappa_v = 0$, Eq. 4.12 degenerates to a conventional quadratic form, and it does not contain velocity information:

$$U_{att}(\boldsymbol{r},\boldsymbol{v}) = U_{att}(\boldsymbol{r}) = \kappa_r\|\boldsymbol{r}_{tar}(t) - \boldsymbol{r}_{R_i}\|^2 \tag{4.13}$$

The corresponding virtual attractive force is defined as a the negative gradient of the attractive potential in terms of position,

$$\boldsymbol{F}_{att}(\boldsymbol{r}) = -\nabla U_{att}(\boldsymbol{r}) = \frac{\partial U_{att}(\boldsymbol{r})}{\partial \boldsymbol{r}} \tag{4.14}$$

In this dissertation, the attractive potential function $U_{att}(\boldsymbol{r},\boldsymbol{v})$ depends on both position $\boldsymbol{r}$ and velocity $\boldsymbol{v}$ of the robot. Therefore, it is necessary to define the attractive force with respect to position and velocity:

$$\boldsymbol{F}_{att}(\boldsymbol{r},\boldsymbol{v}) = -\nabla U_{att}(\boldsymbol{r},\boldsymbol{v}) = -\nabla_{\boldsymbol{r}} U_{att}(\boldsymbol{r},\boldsymbol{v}) - \nabla_{\boldsymbol{v}} U_{att}(\boldsymbol{r},\boldsymbol{v}) \tag{4.15}$$

where,

$$\nabla_{\boldsymbol{r}} U_{att}(\boldsymbol{r},\boldsymbol{v}) = \frac{\partial U_{att}(\boldsymbol{r},\boldsymbol{v})}{\partial \boldsymbol{r}} \tag{4.16}$$

$$\nabla_{\boldsymbol{v}} U_{att}(\boldsymbol{r},\boldsymbol{v}) = \frac{\partial U_{att}(\boldsymbol{r},\boldsymbol{v})}{\partial \boldsymbol{v}} \tag{4.17}$$

Substituting Eq. 4.12 into Eq. 4.14, we obtain:

$$\boldsymbol{F}_{att}(\boldsymbol{r},\boldsymbol{v}) = \boldsymbol{F}_{att_r}(\boldsymbol{r}) + \boldsymbol{F}_{att_v}(\boldsymbol{v}) \tag{4.18}$$

$$\boldsymbol{F}_{att_r}(\boldsymbol{r}) = 2\kappa_r\|\boldsymbol{r}_{tar}(t) - \boldsymbol{r}_{R_i}\|\boldsymbol{n}_{r_{R_i,tar}} \tag{4.19}$$

$$\boldsymbol{F}_{att_v}(\boldsymbol{v}) = 2\kappa_v\|\boldsymbol{v}_{tar}(t) - \boldsymbol{v}_{R_i}\|\boldsymbol{n}_{v_{R_i,tar}} \tag{4.20}$$

Here, $\boldsymbol{n}_{r_{R_i,tar}}$ is the unit vector pointing from the robot to target; $\boldsymbol{n}_{v_{R_i,tar}}$ is the unit vector denoting the relative velocity direction of the target with respect to the robot. As it can be seen, attractive force $\boldsymbol{F}_{att}$ consists of two different components: the first component, $\boldsymbol{F}_{att_r}(\boldsymbol{r})$, pulls the robot to the target while the distance between them reduces; the second component, $\boldsymbol{F}_{att_v}(\boldsymbol{v})$, attempts the robot to move at the same velocity than the target.

If the robot approaches the target, that is, $\|\boldsymbol{r}_{tar}(t) - \boldsymbol{r}_{R_i}\|$ approaches zero, $\boldsymbol{F}_{att_r}$ decreases until zero, and when the velocity of the robot approaches target's velocity, $\boldsymbol{F}_{att_v}$ decreases to zero as well. Therefore, if both the position and velocity of the robot approach those of the target, the attractive force $\boldsymbol{F}_{att}$ approaches zero. Thus, when the robot catches the target they travel at the same velocity, and the robot maintains the velocity and moves with the target.

In this work, robot motion is subjected to its physical limitation and the magnitude of its acceleration is upper bounded. The maximum acceleration of the robot is denoted as a_{max}. According to Newton's law, the acceleration applied to the robot is given by

$$\boldsymbol{a}(t) = \begin{cases} \frac{\boldsymbol{F}_{att}}{m_{R_i}} & \text{if } \frac{\|\boldsymbol{F}_{att}\|}{m_{R_i}} \leq a_{max} \\ a_{max}\frac{\boldsymbol{F}_{att}}{\|\boldsymbol{F}_{att}\|} & \text{otherwise} \end{cases} \tag{4.21}$$

In the next subsection, we present the Particle Filter to estimate the position and velocity of the person.

4.5 Estimating People and Robots Motions

As we previously mentioned, in order to model the space where the robots are allowed to move, we need to predict both people and robot positions. At a specific time instance, this is done using a Particle Filter formulation, which is explicitly designed to take into account the information of the potential field used to represent the environment in previous time instances.

The problem of predicting the persons and robots positions may be seen as that of estimating the dynamic state of a nonlinear stochastic system based on a set of noisy observations. These noisy observations come either from the odometry, in the case of the robots, or from data such as laser scans or images, for the case of the persons. In any event, the estimation process can be written in terms of a process equation and an observation equation:

$$\begin{aligned} \boldsymbol{x}_n &= f(\boldsymbol{x}_{n-1}, \boldsymbol{u}_n) \quad \text{(process equation)} \\ \boldsymbol{y}_n &= h(\boldsymbol{x}_n, \boldsymbol{v}_n) \quad \text{(observation equation)} \end{aligned} \tag{4.22}$$

where $f(\cdot)$ and $h(\cdot)$ are known nonlinear functions, $\boldsymbol{x}_n$ is the state vector with either the robots or persons positions, $\boldsymbol{y}_n$ the observation, and $\boldsymbol{u}_n$ and $\boldsymbol{v}_n$ are random noise components.

Let us denote by $\boldsymbol{x}_{0:n}$ and $\boldsymbol{y}_{0:n}$ the positions and observations up to time n, i.e., $\boldsymbol{x}_{0:n} := \{\boldsymbol{x}_0, \ldots, \boldsymbol{x}_n\}$ and $\boldsymbol{y}_{0:n} := \{\boldsymbol{y}_0, \ldots, \boldsymbol{y}_n\}$. The problem can be then formulated in terms of a Bayes filter in which the posterior distribution $p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n})$ is recursively updated according to

$$p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n}) \propto C_n p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n-1}) p(\boldsymbol{y}_n|\boldsymbol{x}_n) \tag{4.23}$$

$$C_n^{-1} = \int p\left(\boldsymbol{x}_n|\boldsymbol{y}_{0:n-1}\right) p\left(\boldsymbol{y}_n|\boldsymbol{x}_n\right) dx_n$$

$$p(\boldsymbol{x}_{n+1}|\boldsymbol{y}_{0:n}) = \int p(\boldsymbol{x}_{n+1}|\boldsymbol{x}_n) p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n}) d\boldsymbol{x}_n \tag{4.24}$$

where $p(\boldsymbol{y}_n|\boldsymbol{x}_n)$ is the *observation (or measurement model)*, and $p(\boldsymbol{x}_{n+1}|\boldsymbol{y}_{0:n})$ corresponds to the *updating process*.

Since we seek to handle situations in which the observations may potentially have non-Gaussian and multimodal distributions, we use Particle Filtering to approximate Eqs. 4.23 and 4.24 by a set of weighted particles. The approximation of measurement and update processes in terms of particle filters is summarized in Algorithms 2 and 3. Initially, a set of M particles $\boldsymbol{X} = \{\boldsymbol{x}_n^{(1)}, \ldots, \boldsymbol{x}_n^{(M)}\}$ from a so-called importance sampling distribution $\pi(\boldsymbol{x}_n)$ are generated. A weight $w^{(j)} = p(\boldsymbol{x}_n^{(j)})/\pi(\boldsymbol{x}_n^{(j)})$ is then assigned to each one of the particles. If we write $\boldsymbol{W} = \{w^{(1)}, \ldots, w^{(M)}\}$, the set $\{\boldsymbol{X}, \boldsymbol{W}\}$ will approximate the posterior distribution $p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n})$.

We set the sampling function $\pi(\cdot)$ to a normal distribution,

$$p(\boldsymbol{x}_n|\boldsymbol{y}_{0:n-1}) = \mathcal{N}\left(\boldsymbol{x}_n, \bar{\boldsymbol{\mu}}_n, \bar{\boldsymbol{\Sigma}}_n\right) \tag{4.25}$$

Algorithm 2 Approximation of the measurement model

1: Draw samples from $\pi(\boldsymbol{x}_n|\boldsymbol{y}_{0:n}) \rightarrow \left\{\boldsymbol{x}_n^{(j)}\right\}_{j=1}^{M}$

2: Compute the associated weights by:

$$\bar{w_n}^{(j)} = \frac{p(\boldsymbol{y}_n|\boldsymbol{x}_n^{(j)})\mathcal{N}(\boldsymbol{x}_n = \boldsymbol{x}_n^{(j)}, \bar{\boldsymbol{\mu}}_n, \bar{\boldsymbol{\Sigma}}_n)}{\pi(\mathbf{x_n}^{(j)}|\boldsymbol{y}_{0:n})} g(\boldsymbol{x}_n^{(j)}) \tag{4.26}$$

$$g(\boldsymbol{x}_n^{(j)}) = \begin{cases} \zeta \text{ if } T(g(\boldsymbol{x}_n^{(j)})) = 0, \ \zeta >> 1 \\ \\ \frac{1}{T(g(\boldsymbol{x}_n^{(j)}))} \text{ otherwise} \end{cases} \tag{4.27}$$

3: Normalize the weights

$$w_n^{(j)} = \frac{w_n^{(j)}}{\sum_{j=1}^{M} \bar{w}_n^{(j)}} \tag{4.28}$$

4: Estimate the mean and covariance:

$$\begin{aligned} \boldsymbol{\mu}_n &= \sum_{j=1}^{M} w_n^{(j)} \boldsymbol{x}_n^{(j)} \\ \boldsymbol{\Sigma}_n &= \sum_{j=1}^{M} w_n^{(j)} (\boldsymbol{\mu}_n - \boldsymbol{x}_n^{(j)})(\boldsymbol{\mu}_n - \boldsymbol{x}_n^{(j)})^T \end{aligned} \tag{4.29}$$

What is novel from our particle filter implementation is the way we compute the weights. More specifically, each particle is assigned a weight based on the magnitude of the potential field in the previous iteration, at the current particle location. This is formally written in Eq. 4.27 as a new function $g(\boldsymbol{x}_n^{(j)})$, which re-adjusts the weights of all particles $\boldsymbol{X} = \{\boldsymbol{x}_n^{(1)}, \ldots, \boldsymbol{x}_n^{(M)}\}$.

4.6 Experimental Results

The current work was carried out as a part of the European Project URUS [143], and the scenario where the experiments were performed corresponds to an urban area of about 10.000 m^2 within the Campus of the Technical University of Catalonia (UPC). The area contains different obstacles, such as buildings, benches and trash cans. An aerial view and a schematic representation of this experimental site is depicted in Fig. 4.7.

In order to evaluate the proposed approach, we did both synthetic and real exper-

Algorithm 3 Approximation of the update process

Draw samples from $\mathcal{N}(\boldsymbol{x}_n, \boldsymbol{\mu}_n, \boldsymbol{\Sigma}_n) \rightarrow \left\{\boldsymbol{x}_n^{(j)}\right\}_{j=1}^{M}$
for j=1,...,M **do**
  sample from $p(\boldsymbol{x}_{n+1}|\boldsymbol{x}_n = \boldsymbol{x}_n^{(j)})$ to obtain $\left\{\boldsymbol{x}_{n+1}^{(j)}\right\}_{j=1}^{M}$
end for
Compute the mean $\bar{\boldsymbol{\mu}}_{n+1}$ and covariance $\bar{\boldsymbol{\Sigma}}_{n+1}$:

$$\begin{aligned} \bar{\boldsymbol{\mu}}_{n+1} &= \frac{1}{M}\sum_{j=1}^{M} \boldsymbol{x}_{n+1}^{(j)} \\ \bar{\boldsymbol{\Sigma}}_{n+1} &= \frac{1}{M}\sum_{j=1}^{M} (\bar{\boldsymbol{\mu}}_{n+1} - \boldsymbol{x}_{n+1}^{(j)})(\bar{\boldsymbol{\mu}}_{n+1} - \boldsymbol{x}_{n}^{(j)})^T \end{aligned} \tag{4.30}$$

Figure 4.7: **Barcelona Robot Lab.** ***Left:*** An aerial view of our experimental site, the Barcelona Robot Lab, and the distribution of cameras in the network. The solid line depicts a sample path followed by the group of persons and guides. ***Right:*** A few images of the group of people, seen from different cameras.

iments. For the synthetic experiments we simulated robot and people trajectories in open areas, areas with obstacles and in situations were people was leaving the group. For the real experiments we built a database of people and robot trajectories extracted from a set of real image sequences. This database was then used to validate the simulated experiments. Moreover, we perform a set of simple real-life experiments where our robots Tibi and Dabo carried out the task of leader or shepherd.

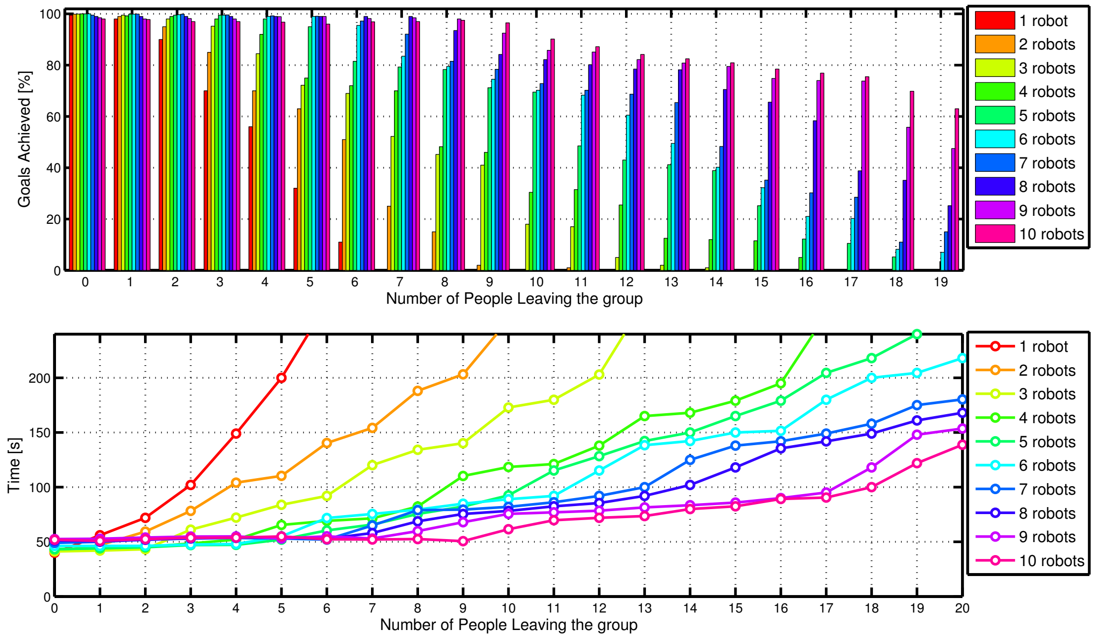

Figure 4.8: **Synthetic Experiments.** ***Top:*** Rate of successful group arrivals in bar diagrams. ***Bottom:*** Time execution of the simulated experiments .

4.6.1 Synthetic Results

In order to evaluate the correctness of the Discrete Time Motion model, we performed more than 2.000 simulations. In these experiments, we increased the number of people thay moves away from the group, and the number the robots that perform the guidance task. We used a computer Intel Core 2 Quad CPU @ 2.66 and 3.00 GHz, which managed all the running processes.

Firstly, we evaluated the average percentage of successful arrivals to the destinations, that is, if the group of people and robots arrive to the goal destination, see Fig. 4.8-*Top*. On the one hand, we observed that as the number of people who leave the group increases, the task of guiding becomes more difficult. On the other hand, as more robots carry out the task, the number of successful arrivals to the destinations increases. It has to be mentioned, if a large number of robots are used, the system is overcrowded, therefore, the task is not performed efficiently, for that reason, in Chapter 5, a function that evaluates the cost of carrying the task is presented.

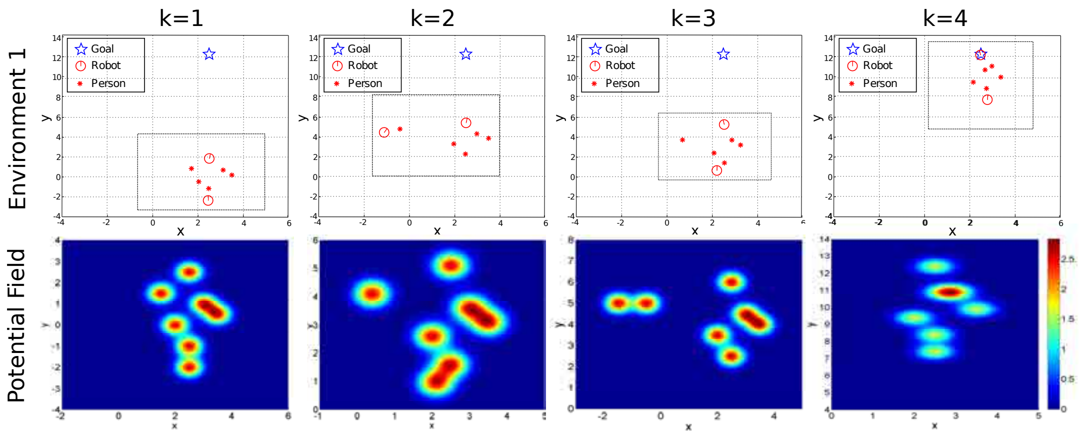

Figure 4.9: **Synthetic Experiment #1:** Guiding people in an open area with no obstacles.

It can be seen, when the group of robots is small (1-3 robots), the time required to perform the task increases rapidly, meanwhile, for large groups of robots the time is much lower. However, as mentioned above, it is necessary to compute the work performed by robots and people, which is presented in the next Chapter 5.

As an example, we present several synthetic experiments in which two robots guided a group of persons. The robots were supposed to reach a specific target position and react to unexpected situations in which some of the individuals left the group. Both the trajectories of the robots and persons were updated according to the motion models described in Sections 4.3 and 4.4. To simulate the observations of people and robots positions, Gaussian noise was added to the true values.

In order to make the problem tractable when computing the potential field, we approximated the working space by a rectangular mesh, with a resolution and size proportional to the density of people in its interior. Typical sizes are 15×15 meshes with an internode distance of 25 cm. This mesh corresponds to only a local discretization, that is swept along the whole environment of 10.000 m^2. The tension values and potential field are uniquely computed at the nodes of the mesh.

We analyzed three different situations. In the first experiment two robots guided a group of 5 people in an open area without obstacles. Fig. 4.9 shows different time instances of the simulation process. The top images represent a top view of the envi-

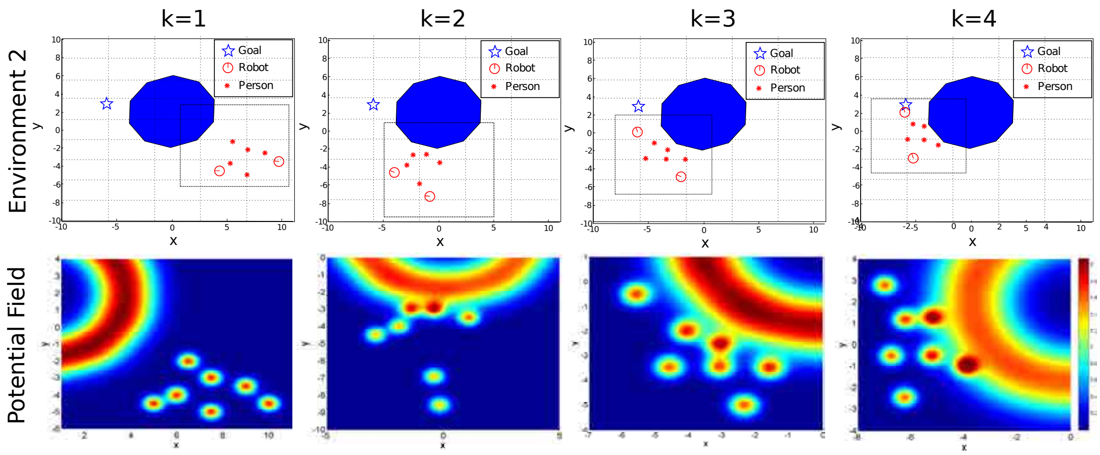

Figure 4.10: **Synthetic Experiment #2:** Guiding people in an area with one obstacle.

ronment map, in this case without obstacles. The position of the two robots is plotted with circles and the five persons are represented by red asterisks. The blue asterisk represents the target position the robots want to reach. The images at the bottom row depict the corresponding potential field. The graphs at time $k = 1$ show the initial configuration with the robots at the front and back of the group of persons. At time $k = 2$ one of the individuals just left group, and immediately after, at $k = 3$, one of the robots followed him/her. In the last column we plot the final configuration, where all the persons reached the goal.

Fig. 4.12-*Top*, shows the trajectories followed by all the robots and persons and the covariance of the group distribution. This is an indication of the density of people and is used to update the size of the working area. Observe that when one of the persons leaves the group, it is approached by the shepherd robot and returned back to the group.

In the second experiment we introduced one obstacle between the starting position of the group and the goal. Fig. 4.10 shows different time instances, again assuming that one robot is required to intercept one of the individuals who left the group. Note in the potential field graphs that persons, robots and obstacles are jointly represented. Yet, since this representation is only local, the decisions of where the robots need to move can be computed very efficiently. The paths followed by all robots and persons

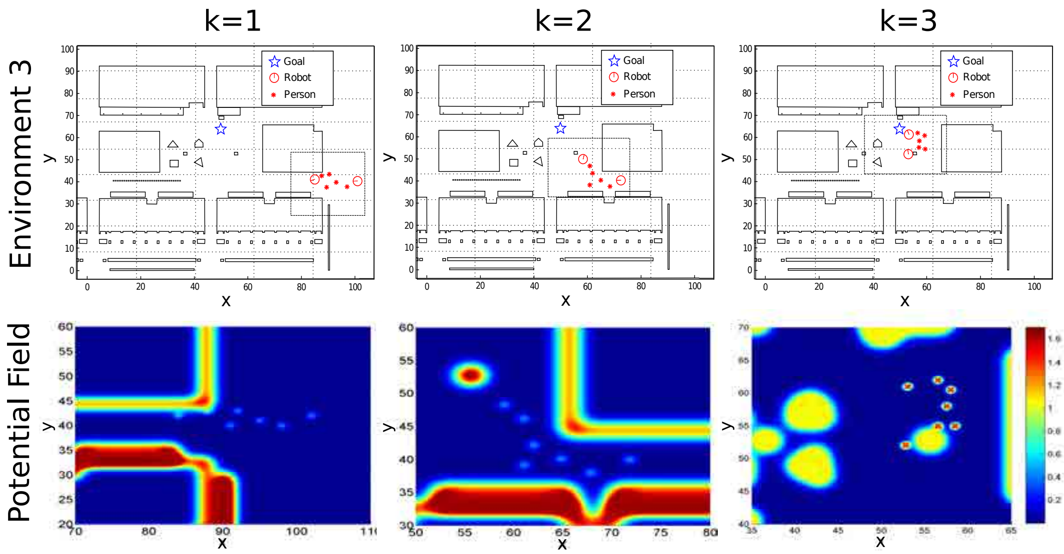

Figure 4.11: **Synthetic Experiment #3:** Guiding people in the Barcelona Robot Lab.

are depicted in Fig. 4.12-*Bottom*.

Finally, in the third experiment we show the performance of our algorithm when the group of 5 people moves across the Campus area (Figs. 4.11 and 4.12-*Bottom*). In this case the task of the robots is made easier because the large number of obstacles –buildings, walls, stairs– highly constrain the movement of the persons.

4.6.2 Validation with Real Data

We also evaluated our approach on real data. For this purpose we captured a large collection of video sequences of a group of people which was led by three tourist guides towards a target location. We studied specific situations in which one of the pedestrians left the group, and one the tourists guides approached him/her and requested returning back to the group. The behaviors and paths of both the robot and person were then compared to those simulated with our models. We will next detail these experiments. First we will focus on the data collection process, and then we will validate our models in these real situations.

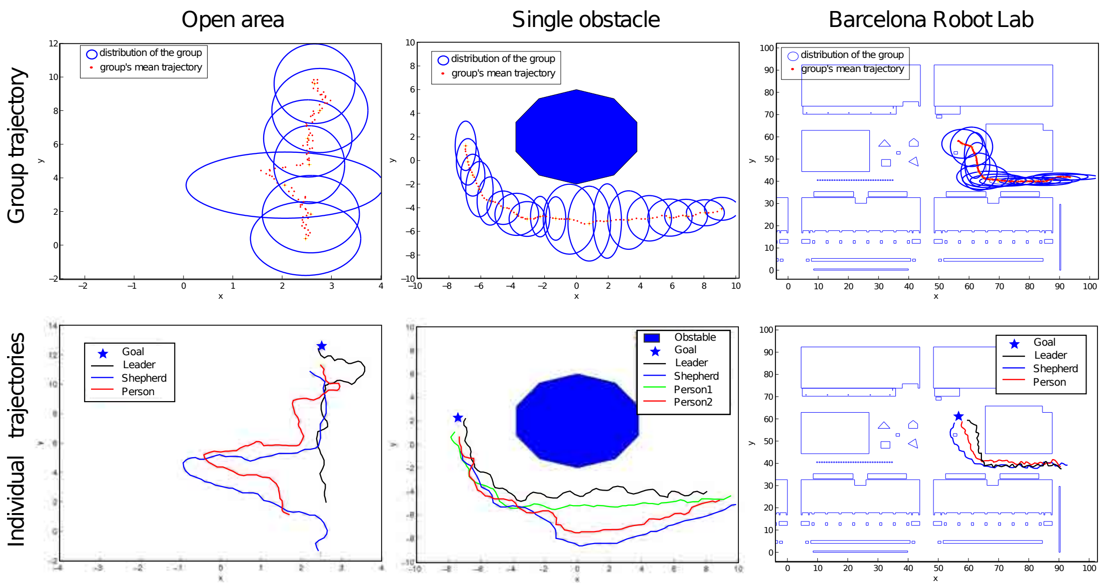

Figure 4.12: **Summary of the synthetic experiments.** People and robots paths for the three synthetic experiments. ***Top:*** Trajectory of the whole group, shown as a mean path and a covariance. The increase of the covariance size is produced when a person leaves the group. ***Bottom:*** Sample trajectories of a few persons.

Figure 4.13: **Images of the BRL.** Different situations considered for the validation with real data: walking in open areas; going back and forth; and walking through narrow corridors.

4.6.2.1 Data Collection

For collecting the data we used the distributed camera network of the Barcelona Robot Lab, which is composed of 21 interconnected cameras (see Fig. 4.7). We acquired several video sequences of a group of seven people being guided by three other people playing the role of the guide robots. The path followed by the group, shown as thick lines in Fig. 4.7, was repeated 9 times. For each repetition a different behavior was analyzed. For instance, some examples of the situations we considered are the following:

- The group follows the guides.
- A person leaves the group and one of the guides has to approach and bring him back.
- Several people move away from the formation simultaneously and in opposite directions.
- The whole group stops and moves again.
- The guides are placed at specific locations to create a robot barrier and prevent people from escaping.

A few sample images of these situations are shown in Fig. 4.13.

The complete database contemplating these situations contains more than 10,000 images, acquired from several synchronized and fully calibrated cameras. The calibration of the whole camera network was done using [130]. We then manually annotated the 2D position (on the ground level) of all the persons and guides in all the images. After computing the homography between the ground plane in the image and that in the 3D model we could easily map the 2D image positions to the corresponding 3D camera coordinate system. In addition, since we knew the rigid transformation of each camera with respect to a global coordinate system, we could finally merge the 3D positions observed from the different cameras and obtain the complete trajectories (except, of course, for those areas of the map which were not visible).

4.6.2.2 Validation of the Discrete Time Motion Model

The real trajectories of all the persons of the group and the guides was then used to validate the accuracy of the motion models we proposed for the persons and robots (both leaders and shepherds). To simulate the robot paths, we injected the real observations of the people trajectories and the location of the obstacles into the motion models described in Section 4.4. A similar operation was done to evaluate the accuracy of the motion models we defined for the pedestrians. If $\boldsymbol{z}_k^{obs}$ is the observed 2D position of the robot or the person at time k, and $\boldsymbol{z}_k^{sim}$ is the corresponding simulated position we then computed the error at time k as:

$$error(k) = \sqrt{\left(z_k^{obs} - z_k^{sim}\right)\left(z_k^{obs} - z_k^{sim}\right)^T}\,. \tag{4.31}$$

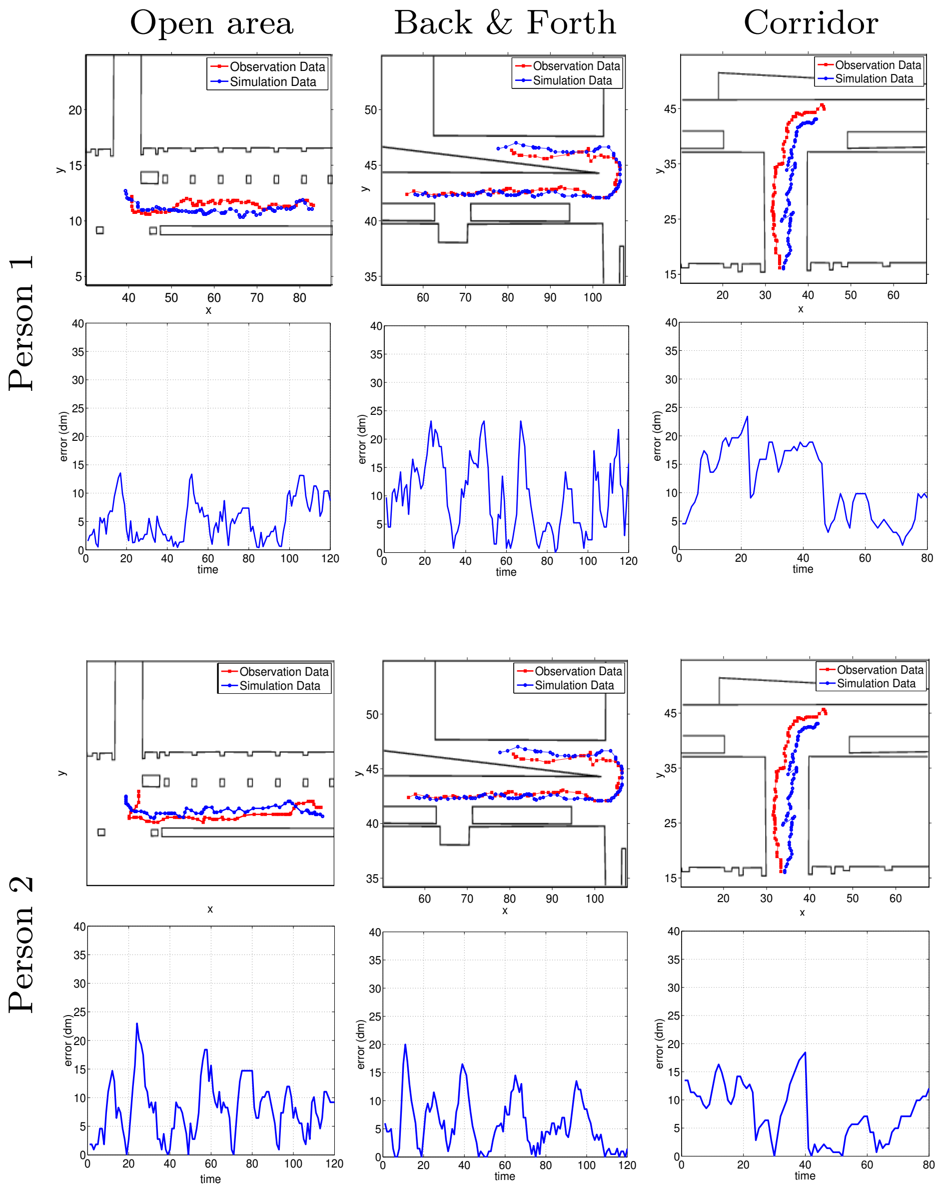

Figure 4.14: **Validating People Motion Model.** For each pair of images, the first plot represents the simulated and true trajectories of two different pedestrians. The second plot depicts the evolution of the error. In each column row a different situation is shown: open areas, going back and forth, and narrow corridors.

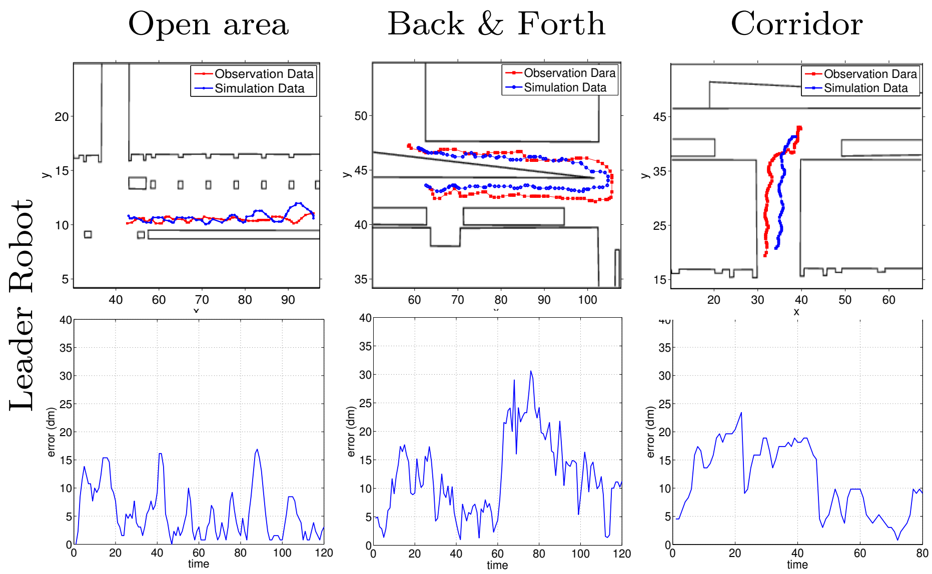

Figure 4.15: **Validating Leader Robot Motion Model.** ***Top:*** Images that represent the paths carried out by the leader robot and the person who performed this role. ***Bottom:*** The error comparison of the two behaviors.

We tested the three different situations shown in Fig. 4.13: the group moving in an open area with no obstacles; the group going forth and back; and the group walking through a narrow corridor.

Figures 4.14–4.16 summarize the results of the experiments in the three situations. For each figure, the plots on top represent the true and simulated paths, and the graphs on bottom represent the accuracy error of our simulation at different time instances.

In Fig. 4.14 we plot the trajectories estimated for two different pedestrians and their respective estimations with the Discrete Time Motion model we have proposed in this chapter. Note that the error is relatively large only for the first few iterations. This is because these frames correspond to a situation in which both the persons and guides are still and suddenly start walking. This creates large accelerations which are not correctly predicted by our model. Yet, after a few frames the error decreases to very low values, below 50 cm.

Fig. 4.15 shows the accuracy of the path estimated for the leader robot going in front of the group. The trajectory of this robot is computed using path planning, and

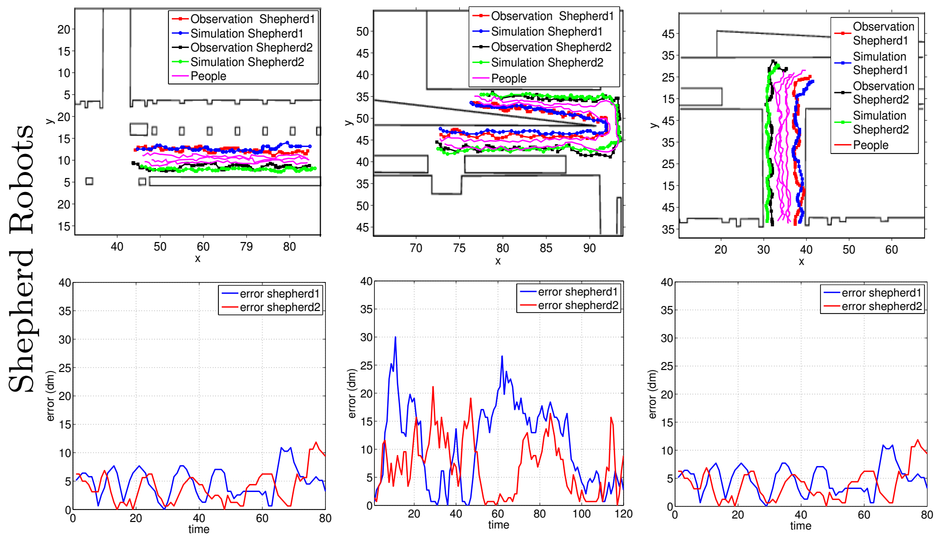

Figure 4.16: **Validating Shepherd Robot Motion Models.** ***Top:*** Images that represent the paths carried out by the leader robot and the person who performed this role. ***Bottom:*** The error comparison of the two behaviors. The case of the "back and forth" is especially interesting, it is example in which one of the pedestrians leaves the group. Note how one of the shepherds changes its trajectory to intercept this person and return him/her back to the group formation.

we favor rectilinear paths when no obstacles are found. There is just a slight error when compared to the person playing the role of leader robot, as completely rectilinear paths are difficult to follow for a human. Yet, both behaviors are very similar.

Finally, in Fig. 4.16 we show the trajectories of the shepherd robots, which were going at the back of the group, following the leader while preventing the people from the group to leave. Different situations are represented. At the top graphs, all the pedestrians follow the leader and no special action needs to be taken by the shepherds. In the second row images, one of the shepherds follows the members of the group walking normally, and the other shepherd focuses on bringing back one person who left the formation. In the bottom graphs, all persons follow the leader, and again, the shepherds follow normal trajectories. In all cases, the simulated paths are very close to the real ones, with an average error below 1 meter.

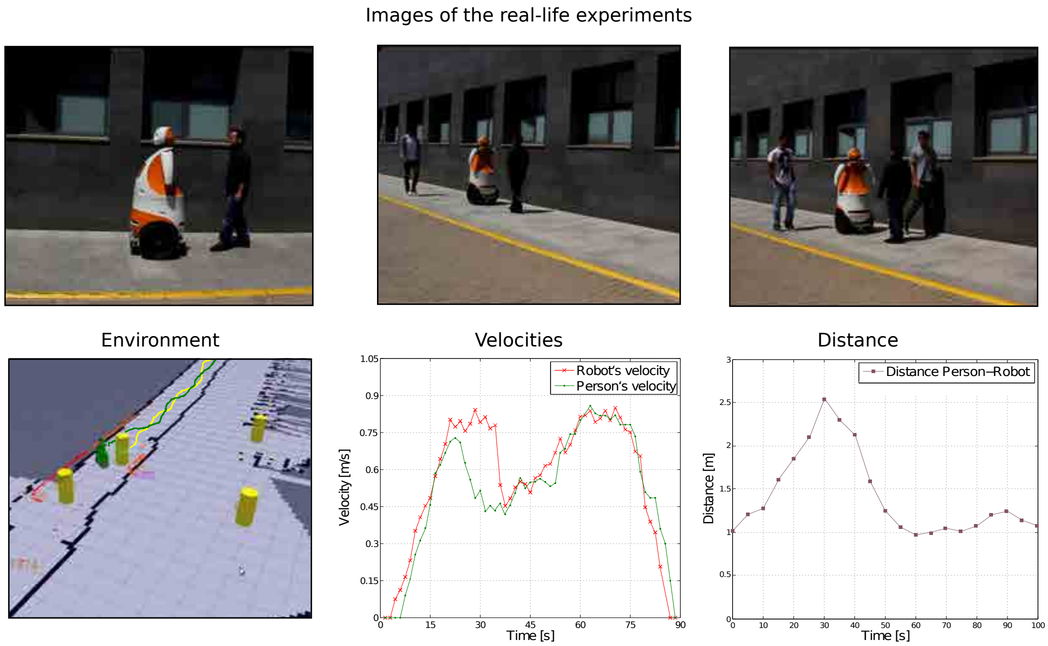

Figure 4.17: **Real-life experiments of Leader task.** ***Top:*** Some images of the experiments performed with Tibi in the BRL. ***Bottom:*** Path performed in the environment, human and robot's velocity, and distances between Tibi and the volunteer.

4.6.3 Real Experiments

The model described in this chapter has a set of limitations we came across while testing our model in real-life scenarios and which led us to continue testing through simulations. For instance, robots cannot accelerate or go faster than people in a safe way; robot's localization in dense environments has not been tested widely; and, we did not find robust methods to detect people's poses.

Nevertheless, we performed a set of experiments where our robots Tibi and Dabo carried out guidance task. So far, our robots are not able to communicate between them, therefore, we have yielded two sets of experiments:the leader task and shepherd task.

In the first set of experiments, Tibi carried out the leader task in the BRL, see Fig. 4.17-*Top*. Tibi was able to guide a person in a area of the BRL using the Discrete Time Motion model. Tibi adjusted its velocity according to human's motion and uttered some sentences in order to encourage people to follow its path.

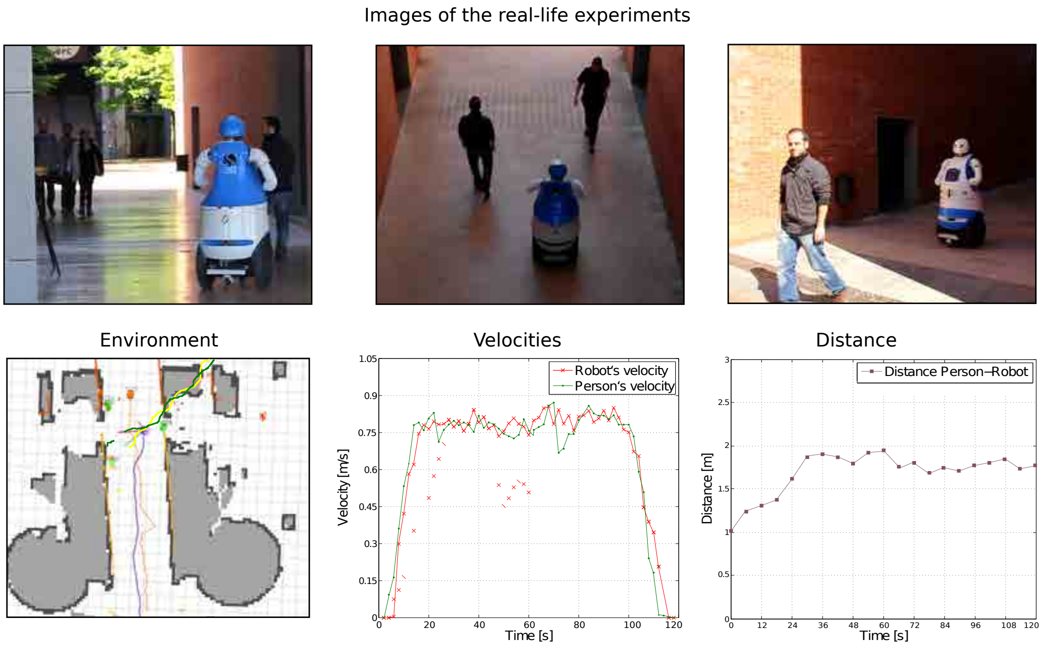

Figure 4.18: **Real-life experiments of Shepherd task.** ***Top:*** Some images of the experiments performed with Dabo in the BRL. ***Bottom:*** Path performed in the environment, human and robot's velocity, and distances between Tibi and the volunteer.

In the second part of the experiments, we evaluated the behavior of Dabo performing the shepherd task, see Fig. 4.18. Dabo carried out its task, followed the volunteer and modified its velocity in accordance with human's behaviors.

In conclusion, we yielded a set of real-life experiments in order to evaluate robots' behavior while guiding a person with out robot Tibi and Dabo. Although we use a single robot due to technological constraint, we plan to implement the cooperative behavior of a set of robots guiding a group of people to verify the functionality of our model.

4.7 Summary

We have presented a new framework to guide people in urban areas with a set of mobile robots working in a cooperative manner. In contrast to existing approaches, our method can tackle more realistic situations, such as dealing with large environments with obstacles, or regrouping people who left the group. We presented various results in different situations: guiding in open areas, in areas with a single obstacle, and urban areas with a large number of obstacles. In all of these experiments we showed that the robots can perform very satisfactorily and approaching realistic situations.

Moreover, this chapter describes the validation process of the simulation model that have been used to explore the new possibilities of interaction when humans are guided by teams of robots that work cooperatively in urban areas. The set of experiments, which have been recorded as video sequences, show a group of people being guided by a team of three people (who play the role of the guide robots). The video sequences were recorded in the Barcelona Robot Lab, where people move in the urban space following diverse trajectories. The motion (pose and velocity) of people and robots extracted from the video sequences were compared against the predictions of the DTM model. Finally, we checked the proper functioning of the model by studying the position error differences of the recorded and simulated sequences. Furthermore, we perform a set of simple real-life experiments where our robots Tibi and Dabo carried out the task of leader or shepherd in the Barcelona Robot Lab.

Chapter 5

Local Optimization of Robots Movements using Prediction and Anticipation Model

Success is not achieved only with special qualities.
It is primarily a work record, method and organization

J.P. Sergent

This chapter proposes a new model for guiding people in urban settings using multiple robots that work cooperatively. More specifically, this investigation describes the circumstances in which people might stray from the formation when following different robots' instructions. To this end, we introduce a "prediction and anticipation model" that predicts the position of the group using a Particle Filter, while determining the optimal robot behavior to help people stay in the group in areas where they may become distracted. As a result, this chapter presents a novel approach to locally optimize the work performed by robots and people using the minimum robots' work criterion and determining human-friendly types of movements. The guidance missions were carried out in urban areas that included multiple conflict areas and obstacles. We also provide an analysis of robots' behavioral reactions to people by simulating different situations in the locations that were used for the investigation. The method was tested through simulations that took into account the difficulties and technological constraints derived from real-life situations. Despite these problematic issues, we were able to demonstrate the robots' effect on people in real-life situations in terms of pushing and dragging forces. The work in this chapter has been presented in [50, 55, 57].

5.1 Introduction

In recent years, research and wide-spread interest in the interaction between robots and humans have increased rapidly, in the academic sphere as well as in laboratories, private companies, and the media. The applications of this field are very diverse, ranging from developing automatic exploration sites [165] to using robot formations to transport and evacuate people in emergency situations [23]. Researchers are also hard at work on crafting robots that can operate as team members [148], therapists [28] and in robotics services [89].

Within the area of social and cooperative robots, the nature of interactions between a group of people and a set of accompanying robots has become a primary point of interest. As previously described, our findings are based on the behavior of a team of robots which operate cooperatively to accompany a group of people from a designated starting point to a specific destination within an urban area.

In Chapter 4, we introduced a representative model of the environment in which robots were able to perform their assigned tasks. In the present chapter, the investigation takes this one step further by presenting a "Prediction and Anticipation Model" (PAM). This model projects the behavior of a group of people (prediction) using a particle filter [7]. It also enables us to determine the particular distribution of robots that can be used to best prevent people from straying from the formation in specific areas of a map (anticipation). By using the Prediction and Anticipation Model, we were able to prevent people from straying from the guided group and, thus facilitate the task of the robots. Furthermore, we develop techniques to locally optimize the work performed by robots and people alike, and therefore obtain a human-friendly motion.

To test the proper functioning of the model, we conducted several simulations. We were not able to test the complete method in real-life scenarios due to technological constraints and safety concerns (due to a lack of robots equipped with high acceleration capabilities and that were also deemed safe to navigate in urban sites). Despite these factors, we were able to successfully evaluate the effect of a robot's pushing and dragging forces on people in real-life situations using one of our robots (Tibi).

In the simulations, a group of people were led by a group of robots in an urban area that involved navigation through and around several cross-streets, buildings and obstacles. The simulations that were performed encompassed a variety of different factors including: *(i)* number of people being accompanied, *(ii)* different layout scenarios within the environment (for example, corridors, open areas or intersections), and *(iii)* situations in which a specific number of people strayed from the designated path at the same time. In the simulations, we compared two alternative strategies: *(i)* placing a robot of the initial formation in the conflict area, in order to prevent people from straying, and inviting people to return to the formation using voice instructions via the PAM model. *(ii)* Wherever participants strayed, we studied the robots' behavior and evaluated how they were able to solve this kind of herding task without necessarily having anticipated the situation. In each of these two strategies, we measured the time it took to perform the task and assessed the robots' performance in order to determine the best strategy for each situation.

We also conducted real-life experiments to analyze the robots' impact on people when they are guided by the pushing and dragging forces that exist between robots and humans, or even between humans and humans. These forces have been identified and quantified in prior studies of pedestrians in crowds and in evacuation scenarios [76, 149]. To ensure that the above mentioned model was valid for our study, we conducted a series of real-life experiments that include either: a robot approaching a moving person from different angles at speeds, or a person following a robot. We compared the results of these tests with those yielded by the simulations, in order to demonstrate the proper functionality of the model.

5.2 Chapter's Overview

As stated earlier, this chapter describes a new model that has been designed to accompany people using a team of robots which work cooperatively to perform the assigned task. One of the main issues which arises when humans are asked to follow robots' instructions in a given task is the fact that people might stray from the robot formation.

On the one hand, the main focus of this study is on the "Prediction and Anticipation Model" (PAM) of human behavioral motion. We introduce a model which suggests a probable position of the members of the group using a Particle Filter (prediction), and it attempts to determine the optimal number of robots needed using the **minimum robot energy (or work) criterion**, depending on the number of individuals present and the environment in which they find themselves. We then go on to analyze the areas of the established map which could cause confusion in the group or result in general group dispersion, and explore ways of preventing people from straying from the path by considering the optimal formation of the robots in terms of the task that needs to be performed (anticipation).

On the other hand, although robots might be able to anticipate human actions, people might also move away from the group spontaneously. In light of this, our work introduces a novel approach to locally optimize the work performed by robots and obtain a human-friendly motion (basically, ensuring that robots do not intrude on the humans' personal space). We consider situations in which individuals can move away from the formation, or in which they must be regrouped by multiple mobile robots working cooperatively. These issues are addressed by introducing a new cost function which minimizes the work required by robots to lead and regroup people.

5.2.1 Problem Constraints and Model Assumptions

This subsection describes the limitations we came across while testing our model in real-life scenarios and which led us to continue testing exclusively through simulations. We will also explain the model assumptions we adopted for the simulations.

There are at least two types of problem constraints. The first derives from robots' perception systems and motions; the second one is the result of human behavioral reactions to the robots' instructions. The effects of these limitations on our study are summarized below:

- Robots cannot accelerate or go faster than people in a safe way. This means our robots cannot usually follow people's behavioral reactions.
- The localization of urban robots in dense environments has not been tested widely, and existing methods are not yet robust enough.

- No robust methods exist to detect people's poses (position and orientation) when they move in a group. From the point of view of a robot on one of the sides of the group, some individuals are inevitably partially or completely out of sight. If the group has a small number of people the chances of achieving accurate pose detection are high, but if there are many people, detection becomes very difficult. Since our method is based on estimating the pose of each person of the group, pose detection is key to our research.

- There is not currently enough data on people's reactions to robots' motion instructions. Instructions like "please return to the group" or "do not go away" might cause different reactive motions in different touring situations.

Because of these limitations, and due to the lack of knowledge of other real-life experimental works, we have made the following assumptions in our model:

- People in a guided tour "usually" follow the group leader. In this case, the leader is a robot.

- People understand, agree with and follow the robot's instructions and motions (for example, when a robot approaches a person who has moved away, the person follows the robot's instructions and movements).

- The number of people who move away from the formation is no more that one or two people.

- When one or more robots are used to block one area to form a barrier people do not attempt to cross the robot barrier.

- After 15 minutes of a robot guidance, 26% of people stray from the group, see [125] for additional information.

- Robots know the pose (position and orientation) of each person in the group.

- Robots are always localized keeping in mind the constraints of the physical environment.

- Robots can communicate between them and send and receive information.

- Robots have a map of the environment in which the tour or visit is going to take place.
- Robots have enough acceleration capacity and speed to safely reach a person, who has strayed.

The first four assumptions are usually demonstrated by people who follow the "citizen rules" of common civic behavior and who are not in a state of panic or engaging in an act of vandalism. As a result, we are assuming people understand and obey the tour guides. The fifth assumption has been observed in social studies carried out on human motion behavior [125]. The sixth assumption is difficult to verify at the present time because, although there exist several algorithms which can detect people's position, the methods are not yet precise and robust enough for situations in which people are partially or completely out of the robots's field of vision, for example [95]. The next three assumptions are valid and have been tested in outdoor real-life scenarios [27]. The last assumption is also complicated and, although there are many good and fast robots with excellent navigation methods [166], there are no safe robust methods that have been tested in real-life experiments with people. Moreover, robots currently do not have the adequate acceleration and prediction methods to follow people's random and spontaneous changes of motion.

5.2.2 Chapter Topics and Contributions

The contributions and topics described in this Chapter are presented below, see Fig. 5.1.

- *Representation of people's motion*: Before working with real robots and real people, we first must develop some simulation results. In order to do this, we needed to model people's motion by using the concepts introduced in the investigation carried out by Helbing et al., which studied the dynamics of pedestrian crowds from the "social force model" point of view [75], this theory has been introduced in Chapter 3. The meaning of "social force model" does not refer to a social robot's behavior, but rather to the existence of a non-physical force (push, drag or traverse) robots can exert to move or drag people. More specifically, this work describes the pedestrians' motion based on a social force model which result from

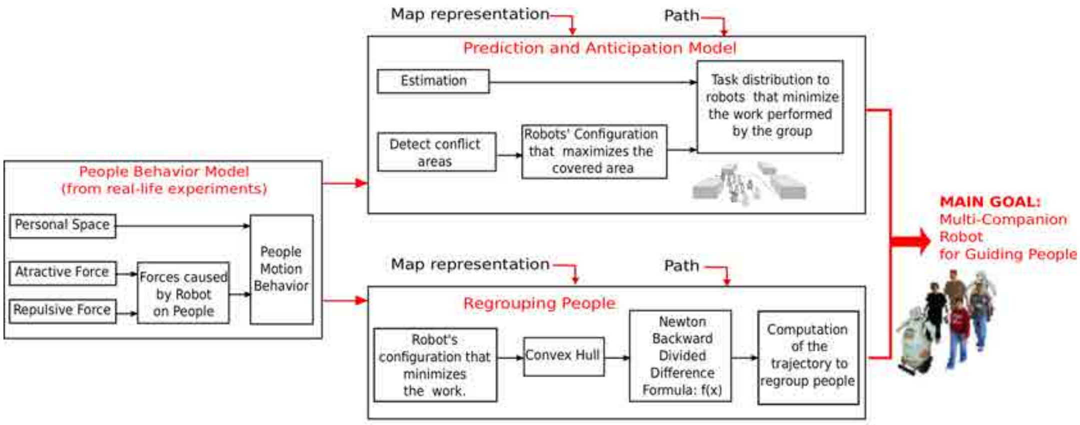

Figure 5.1: **Overview of the study presented.** An essential part of our work was to simulate people's movements and to show humans' reactions depending on the stimulus provoked on them. We also offer solutions to two different problems that were found while carrying out the mission of guiding people. First, we show the PAM model, to prevent group dispersion, we identify areas where people might get lost, and robots are located there to bring them back to the formation. Secondly, if someone moves away from the group, the behavior of the robots to accompany him/her back to the formation is shown. For both problems, we use a function that minimizes the cost of work of robots and humans in order to make the interaction between them as pleasant as possible.

the internal motivations of the individuals performing certain movements [177]. This theory has been presented previously in Section 4.3.

- *Prevent group dispersion*: As indicated earlier, our work focuses on the behavior of robots when guiding a group of people in urban areas. One of the main challenges when robots try to perform this task is the possibility that one or more people will move away from the group, either out of boredom or due to his/her interest in something which lies away from the group's path.

  To use the model presented in this work, Prediction and Anticipation Model (PAM), we needed to know the layout of the urban map, the path that would be taken, the final destination of the guided group, and the estimated positions of the people and robots. The first component of the model is the prediction, which anticipates the movements that will be made by both the humans and robots.

The second component, anticipation, detects the conflict areas (where people are prone to stray) and calculates the number of robots that should cover the conflict area. The Prediction and Anticipation Model (PAM) uses the previously gathered data (i.e. people's and robots' positions, detection of conflict areas, etc.) to compute the possible distribution of robots in order to cover the conflict areas and guide the people to the final destination. Because we needed to minimize the number of robots and wasted energy, the PAM is designed to seek out the number of robots and determine their respective tasks so as to minimize the work done by robots and people.

- *Detection of conflict areas*: As previously indicated, one of the key components of our work is the robots' ability to anticipate human movements. Therefore, it is crucial to understand the environment in which the group moves. As a result, we needed to know the set of robots and people that would be situated in the hallways, open spaces, intersections and other settings. We also describe a function which determines the density of obstacles that surround the group during their movement along the path. In the areas with open spaces and a low density of obstacles, the probability that a person will move away is high and, thus, these areas were treated as conflict areas in our investigation.

- *Minimum work performed by robots and people*: We present a function which determines the optimal configuration of robots (defined as the behavior of all the members of the group). That configuration should not only minimize the work performed by the robots, but also make the interaction between robots and people as "comfortable" as possible, in terms of motion (in this context, the word "comfortable" denotes that the robots will not try to intrude on people's personal space). This function can be used in two different stages of the simulations: *(i)* once we have determined that areas in which people are more likely stray, we can asses which robot ought to be sent to the area; and, *(ii)* when that person leaves the group, we can also calculate which robot should be sent to find and accompany him/her back to the formation. In both cases, we determined the strategy for assigning robots' tasks which required the least amount of work and also led to the minimum displacement problems in the guidance task. Moreover, robots had to be able to perform all their tasks while navigating quietly, avoiding obstacles, and not intruding on people's personal space.

- *Regrouping people*: In our work, we allowed for the possibility that one or more people would move away from the group. The system would then need to assign a robot to perform the task of retrieving him/her. By using the function introduced above, we computed the behavior of the team of robots to redirect the person who has strayed. Once the configuration with minimal work cost was determined, we could compute the robot's trajectory to regroup the people.

5.3 Prediction and Anticipation Model

One of the main issue when robots try to perform the task of guiding a group of people, is the possibility that one or more people move away from the group, either out of boredom or due to his/her interest in something lying outside the given path.

In the previous Chapter 4, we presented how robots should behave when they accompany groups of people, or which strategy the group of robots should follow when a person moves away. In the present Chapter, we go one step further, presenting a model designed to prevent people from moving away from the formation. Therefore, the model for this study must incorporate both information about the environment as well as people's behavior within that environment, so robots are able to anticipate the problem of losing people.

To apply the Prediction and Anticipation Model (PAM), the layout of the urban map must be known a priori, the path to the final destination of the guided group and the estimated positions of the people and robots. The first component of the model is the Prediction, which is used to foresee the people's and robots' motion some steps ahead. The second component, Anticipation, identifies the conflict areas (where people can move away) and computes the number of robots that should cover that conflict area. The PAM then uses this data (people's and robots' positions, detection of conflict areas) to calculate the distribution of robots to cover the conflict areas and guide the people to the destination. The PAM also decides the number and distribution of robots in a way that minimizes the work done by robots and people, see Fig. 5.2.

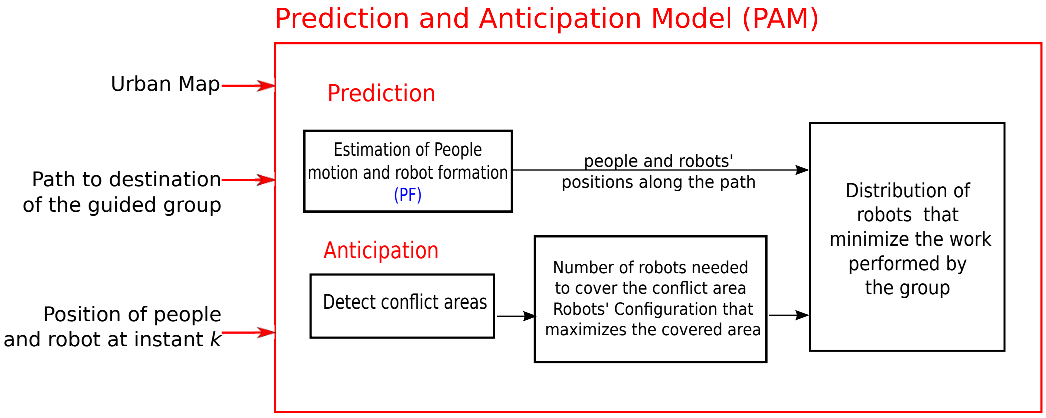

Figure 5.2: **Components of the PAM model.** The first component estimates people and robots' positions along the path by using a particle filter. The second components is anticipation, which detects the areas on the map where people might get distracted and move away, it also computes the configuration of robots which maximizes the covered area. Using the junction of the two components, the distribution of robots that minimizes the work performed by both robots and people is obtained.

5.3.1 Prediction

As previously mentioned, a key aspect of a guiding mission is to prevent people from straying from the group. To achieve this aim, the model must estimate people's positions and velocities with a Particle Filter (PF), in this case a Gaussian Particle Filter (GPF).

We have modified part of the measurement update algorithm [7] to prevent humans and robots from colliding with each other and with obstacles, based on the findings in earlier studies [106]. Furthermore, we use the information on people's motions in the Particle Filter to estimate the position of the group over time. The computation to estimate people/robots' positions is sequential, it starts from the leader robot, then people of the group, and finally shepherd robots. In each step of the process, the people/robot position (personal space occupancy) is updated. In the sampling process, we do not consider the particles that are located in positions already occupied by the vital space of other members of the team. So, position estimations where two different people/robots overlap the personal space occupancy of other people/robots are not allowed at any time.

An extensive description of the method has been presented in the previous Chapter 4, in Section 4.5.

Using this method, we can predict where the group of people will be at certain times in the future. Moreover, once the prediction of people's motion behavior is computed, the group of robots can enable us to determine the locations on the path where people are most likely to stray.

5.3.2 Anticipation

Once the model has predicted the people's position, it must identify the potential conflict areas, and determine where the robots should move in order to prevent straying and assign the robots positions in order to be able to guide the group of people.

Thus, the model is able to compute the optimal number of robots needed and structure of their formation so as to minimize the work they must perform. The presented model is applicable to any urban area. To study potential conflict areas, we have taken into account five different kinds of settings: open areas, entering a hallway, leaving a hallway, crossing intersections with three streets and crossing intersections with four streets.Other possibilities which may be considered are merely combinations of the above mentioned conditions.

In this Chapter, it is assumed the map on which robots perform their task it is already known as well as the path the group should follow. Therefore, the first step of the method consists of being aware of the open spaces (the areas in the map where there are no obstacles or their density is very low) along the planned path, as well as, hallways, open areas or intersections. After that, the obstacles are modeled as Gaussian functions,

$$T_o(\boldsymbol{\mu}_o, \Sigma_o)(\boldsymbol{p}) = \frac{1}{|\boldsymbol{\Sigma}_o|^{1/2}(2\pi)^{n/2}} e^{-\frac{1}{2}(\boldsymbol{p}-\boldsymbol{\mu}_o)^T \boldsymbol{\Sigma}_o^{-1}(\boldsymbol{p}-\boldsymbol{\mu}_o)} \tag{5.1}$$

Then, the probability map consist of a set of Gaussian functions where the obstacles are located, and the rest of the map will be represented as a zero-function. The function $H(map)$ is the occupied space of the obstacles and is calculated by adding all the Gaussian functions representing the obstacles:

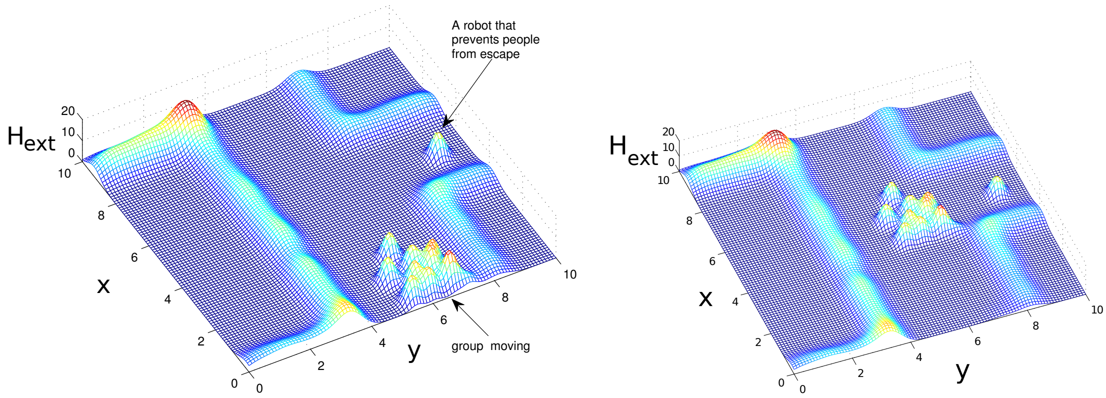

Figure 5.3: **Gaussian Functions.** Graphical representation of Eq. 5.3 using Gaussian functions of a group of people moving in an urban area. ***Left:*** The group starts moving, on the bottom of the y-axis, then the Prediction and Anticipation Model detects that one person can move away from the formation in the next corner, computes which robot can be sent and sends an auxiliary robot to that corner to prevent from people moving away. ***Right:*** The group passes along the crossing area but, as a robot is located in that area, people cannot move away.

$$H(map) = \sum_{p \in \mathcal{O}} T_o(\boldsymbol{\mu}_o, \boldsymbol{\Sigma}_o) \tag{5.2}$$

where, $\mathcal{O}$ is the set of obstacles in the environment, $\boldsymbol{p} \in \mathcal{O}$, means that point $\boldsymbol{p}$ is located inside an obstacle.

Moreover, we have also defined the robots as Gaussian functions, so, Eq. 5.2 can be extended to include the robots as well:

$$H_{ext}(map, conf) = \sum_{\boldsymbol{p} \in \mathcal{O}} T_{\boldsymbol{o}}(\boldsymbol{\mu}_{\boldsymbol{o}}, \boldsymbol{\Sigma}_{\boldsymbol{o}}) + \sum_{p \in \mathcal{R}} T_r(\boldsymbol{\mu}_r, \boldsymbol{\Sigma}_r) \tag{5.3}$$

where $conf$ is the set of robots' positions. In Fig. 5.3 there is an example of this representation. Therefore, robots can be seen as obstacles, since they can block the passage and act as a barrier.

According to [66], when pedestrians move in groups, the people formation can be considered as rows of 2 to 4 people (the distances between them are shown in Table 5.1). The parameters of this table are: taking the values between brackets as the standard deviation error of the mean; φ_{ij} is the angle between the walking direction of the person

Angle and distance measures between people in a group			
		$l\varphi_{ij}$ (deg)	d_{ij} (m)
size=2	p_1p_2	98.8 (±1.12)	0.78 (±0.02)
size=3	p_1p_2	97.8 (±5.14)	0.79 (±0.05)
	p_2p_3	87.1 (±4.46)	0.81 (±0.10)
size=4	p_1p_2	99.2 (±6.33)	0.87 (±0.06)
	p_2p_3	87.7 (±6.54)	0.93 (±0.09)
	p_3p_4	85.4 (±5.01)	0.80 (±0.05)

Table 5.1: **Angle and Distance measures:** Average angle and distance values between group members for each group size [66].

p_i and the segment formed by person p_i and person p_j; and d_{ij} is the distance between p_i and p_j.

Taking into account these measurements, if N_p is the number of people who are being accompanied by robots, it can be assumed that group's width is $k * d_{side}$, where k is the number of people in a row, and d_{site} is the distance between two people, see Table 5.1. Furthermore, the length of the group is $N_p/3 * d_{front}$, where d_{front} is the distance between one person and another who is in front of him/her. This measurement is defined by the personal space of a person described in Section 4.3.

Once the map of obstacles and the group size have been computed, the density of the obstacles along the path that the group will follow can be calculated. Since the group will move at a constant speed, we can compute at each instant t, the density of obstacles that a group of people will find along a specific path on the map.

First, we have to predict the position and velocity of the center of the group, $\boldsymbol{g}_t$. Here, we combine the social force model presented in Section 3.3 with a Kalman Filter.

Let $\boldsymbol{g}_t = (x_{g_t}, y_{g_t}, \dot{x}_{g_t}, \dot{y}_{g_t})^T = (\mathbf{x}_{g_t}, \mathbf{v}_{g_t})^T$ be the state of the center of the group at time t and $\boldsymbol{\Sigma}_t$ its 4×4 covariance matrix estimate. The term $\mathbf{x}_{g_t}$ represents the position and $\mathbf{v}_{g_t}$ the velocity of the pedestrian in Cartesian space. The constant velocity motion model is then defined as

$$p(\boldsymbol{g}_t|\boldsymbol{g}_{t-1}) = \mathcal{N}(\boldsymbol{g}_t; \boldsymbol{A}\boldsymbol{g}_{t-1}, \boldsymbol{A}\boldsymbol{\Sigma}_{t-1}\boldsymbol{A}^T + \boldsymbol{Q}) \tag{5.4}$$

where $\boldsymbol{A}$ is the state transition matrix. The matrix $\boldsymbol{Q}$ represents the acceleration capabilities of humans. We extend this model by considering how the state of the pedestrian at a generic time t is influenced by its previous state and static obstacles $\mathcal{O}$. As mentioned earlier, the basic equation of motion for a pedestrian is given by a social force term:

$$\frac{d}{dt}\mathbf{v}_{g_t} = \frac{\boldsymbol{F}}{m} \tag{5.5}$$

The force term $\boldsymbol{F}$, is computed as described in Eq. 3.3. Moreover, we use a discrete time approximation of Eq. 5.5 within a fixed interval of time Δt to obtain $\boldsymbol{g}_t$, where

$$\boldsymbol{g}_t = \boldsymbol{\Upsilon}(\boldsymbol{g}_{t-1}, \mathcal{O}) = \begin{bmatrix} \mathbf{x}_{g_{t-1}} + \mathbf{v}_{g_{t-1}}\Delta t + \frac{1}{2}\frac{\boldsymbol{F}}{m}\Delta t^2 \\ \mathbf{v}_{g_{t-1}}\Delta t + \frac{\boldsymbol{F}}{m}\Delta t \end{bmatrix} \tag{5.6}$$

This equation describes how the motion of the center of the group evolves over time. The change in motion is a reactive behavior from interaction forces and physical constraints from the environment. Assuming that the motion is affected by Gaussian noise with zero mean and with covariance matrix $\boldsymbol{Q}$, we can the define

$$p(\boldsymbol{g}_t|\boldsymbol{g}_{t-1}, \mathcal{O}) = \mathcal{N}(\boldsymbol{g}_t; \Upsilon(\boldsymbol{g}_{t-1}, \mathcal{O}), \boldsymbol{J}_{\boldsymbol{\Upsilon}}\boldsymbol{\Sigma}_{t-1}\boldsymbol{J}_{\boldsymbol{\Upsilon}}{}^T + \boldsymbol{Q}) \tag{5.7}$$

where $\boldsymbol{J}_{\boldsymbol{\Upsilon}} = \frac{\partial \boldsymbol{\Upsilon}(\cdot)}{\partial \boldsymbol{g}}$ is the Jacobian of $\boldsymbol{\Upsilon}(\cdot)$ evaluated at $\boldsymbol{g}_{t-1}$.

Second, once the prediction of group's position is computed along the time t, we can now define density of obstacles that a group of people will find along a specific path on the map. Thus, this function D_t is computed as follows:

$$D_t(group\_size, map) = \int_{\boldsymbol{x}\in\mathcal{G}_t} H(\boldsymbol{x})d\boldsymbol{x} \tag{5.8}$$

where $\mathcal{G}_t$ is the space occupied by the intersection of the set of obstacles and group's position at time t. Therefore, $\boldsymbol{x} \in \mathcal{G}_t$ means that the density of obstacles is computed in the area occupied by the group, see Fig. 5.4. Thus, for those areas where the density of obstacles is low, the probability that people will move away is high. Moreover, according to [125], when people are being guided by a robot, for instance, in a museum, after 15 minutes, people's interest wanes, and about 26% of its members stray from the path. Therefore, in the present work, we consider that in free areas, up to 26% of the members can move away. If the value of D_t is low in a specific area, it means there are many open zones and the robots must remain attentive to human reactions. Using this model, we can determine the optimal robots' motion behaviors in different environments for guiding purposes.

Next, Eq. 5.8 is extended to determine the configuration of the robots that best ensures that robots will cover the conflict areas -i.e., block the area in order to help people to remain in the group. We associate a scalar value with the group by using the function $D_{t_{ext}}(conf, group)$, where $conf$ is the set of positions of the robots and $group$ is the position of the group of people being accompanied. This function indicates that the higher the value of $D_{t_{ext}}$, the more control is needed. Thus, for the particular configuration of robots $conf$, the function $D_{t_{ext}}$ will be:

$$D_{t_{ext}}(conf, map) = \int_{\boldsymbol{x} \in \mathcal{G}_t} H_{ext}(\boldsymbol{x}) \ \ dx \tag{5.9}$$

where $\mathcal{G}_t$ is the area occupied by the group of people and robots at time t. So, the configuration of robots that will be considered is the one that maximizes Eq. 5.9:

$$C = argmax\{D_{t_{ext}}(conf, map)\}, \forall \text{ configurations} \tag{5.10}$$

According to this strategy, the areas where people are likely to move away are covered. For groups of 6 or more people, the probability that more than one person will move away at the same place in different directions is high. For smaller groups, we only need to position a single robot in the open zones. That is, those zones which have a small value for the function D_t. However, for large groups, it is not enough to place just a single robot in such areas. As the robots know the map a priori, when they accompany large groups some might be positioned so as to form a barrier and prevent people from straying. Other strategies might be also used here, for example, a robot with an extensible arm or a rope might be employed.

Another issue to be determined is the best distribution of the robots to perform this task. In order to do that, we studied the work performed by the group. In the

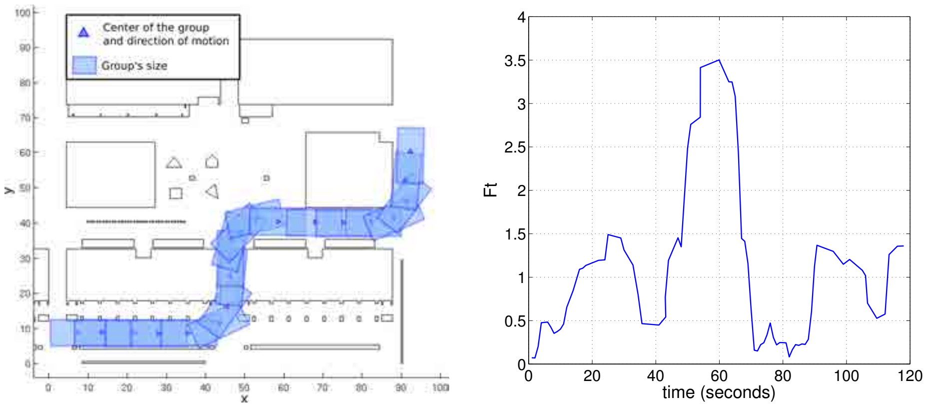

Figure 5.4: **Density of obstacles a long the path.** Graphical representation of a group of people moving through an area with obstacles and crossing areas. ***Left:*** path that the group will follow, fuzzy rectangles are the estimation of the group size, triangles are the mean position of the group and the direction of motion. ***Right:*** The graph that indicates the density of obstacles along the path using Eq. 5.8.

next section, we present a model that locally optimizes the work carried out by the robots in a way that achieved the minimum displacement of humans during a guiding mission.

5.4 Optimal Robot Task Assignment for the Cooperative Mission

In the previous section, we outlined how we determined the areas where people are more likely to move away depending on the density of obstacles along the path. The next step is to decide which robots should be sent to these areas depending on the group's motion and the position of the robots. In this section, we introduce a function based on the **minimum robot energy (or work) criterion** which determines the robots' optimal configuration (as it relates to the group of motion tasks assigned to each robot). We also tried to minimize the work performed by robots and achieve the minimum distances of displacement by the people. The following function can be used to solve two different tasks:

- Once the areas where people could stray have been identified, it must be determined which robots will be sent.

- If someone (a person or group of two people) leaves the group, it must be computed which robot should be sent to bring the person back to the formation.

In both cases, we identify the best strategy for the following situation: "Given a fixed number of robots (usually 2 or 3), assign robots' tasks which will minimize the work that will be required by them and, also, produce the minimum displacement problems for guiding people". Moreover, robots must be able to perform all their motion tasks while they navigate, avoid obstacles, and refrain from intruding on people's personal space.

In the case where we use two robots, one will be the leader and the second one will perform the task of regrouping and herding the people. If we use three robots, one will be the leader, and the other two will be used for regrouping or herding people. The leader of the robots is not predefined, in fact, the robots can change roles depending on the evaluation of the cost function. The robot tasks that have to be delegated in this stage are as follows:

- *Leader task*: The leader robot computes a path planning and moves to the next point. We also assume that there exists a *drag force* which will attract people behind the robot. Here, the robot only has to move from the present position to the next one on along guiding path. If a robot that is not the leader assumes the leading role, this robot will have to move to the leader's present position before performing its task.

- *Robot acting as a barrier task*: As we explained in the previous section, it is more likely for people to become dispersed within certain areas on the map, therefore, in those areas where the density of obstacles is low, one or more robots should be sent to prevent people from straying. Here, it is assumed that the robots that perform this task well act as a repelling force pushing people to follow the group and preventing them from walking away from the formation.

- *Looking for a person who goes away task*: The robot moves to the estimated position of the person who has strayed from the formation. In this case, the robot must compute all possible paths to reach the estimated position and then assume the one which minimizes the itinerary. In our simulations, we used a selection of points on the environment where people are more likely to move away.

- *Pushing task*: The robot pushes a person who has strayed so he/she returns to the crowd formation. Since "push" has several meanings, the more direct one denotes the act of physically push a person, a more gentler method is to give instructions and accompany the person back to the group. This task can be also applied when a robot pushes a person (or people) who is (or are) following the formation in order to regroup people when the formation has fallen apart. We assume a repelling force which pushes the person to follow the robot's direction.

- *Crowd traversing task*: The robot has to move through the formation to achieve the estimated position of the person who strays from the crowd formation. This task implies that the robot has to push people away from their path, which creates a set of repulsion forces between the robot and the people. This particular situation is not addressed in the present work, due to safety concerns.

The cost function, described below, is computed based on the work performed, and can be divided into two blocks: *(i)* Robot work motion, and *(ii)* Human work motion.

In order to compute the dragging, pushing and crowd traversing forces, we use the equations defined in previous investigations on human behavior with other individuals [75]. People's movements are determined by their desired speed and the goal they wish to reach. In our case, the direction of the person movement $\boldsymbol{e}_{p_i}(t)$ is given by:

$$\boldsymbol{e}_{p_i}(t) = \boldsymbol{e}_{R_i}(t) + \boldsymbol{\xi}(t) \tag{5.11}$$

where $\boldsymbol{\xi}$ is the noise. Usually, people do not have a concrete goal and should follow the leader robot, thus, the person's direction is determined by the robot's movement or the person who they have in front of them, if the robot is not in their visual field.

In the following sections, we describe the different forces behind the computation of the cost function.

5.4.1 Robot Work Motion

Working with autonomous mobile robots, the robot R_i work motion is expressed as:

$$\begin{aligned}\boldsymbol{f}_{R_i}^{mot} &= m_{R_i}\boldsymbol{a}_{R_i}\\ \boldsymbol{W}_{R_i}^{mot} &= \boldsymbol{f}_{R_i}^{mot}\Delta s_{R_i}\end{aligned} \tag{5.12}$$

where m_{R_i} is the mass of the R_i robot, $\boldsymbol{a}_{R_i}$ its acceleration and Δs_{R_i} the space traversed by the robot to achieve its goal.

5.4.2 Human Work Motion

In Human Robot Interaction, it is necessary to consider the *dragging*, *pushing* and *crowd intrusion forces* produced by a certain robot's motion which can affect people. This component is called *Human Work Motion*, and it is the cost of people's movements as a result of robot's motions. As described earlier in this chapter, the group follows the robot guide/leader, and a set of robots help to achieve their goal. The effect of robots on people as forces is as follows:

- Leader robot: attractive (dragging) force, inversely proportional to distance.
- Shepherding robot: Repulsive (pushing, traversing) force, which has a repulsive effect on people's personal space.

5.4.2.1 Dragging Work

The dragging force is necessary when the leader robot guides the group of people from one place to another. It acts as an attractive force, hence the force applied by robot leader $\mathcal{L}$ to each person p_i is:

$$\boldsymbol{f}_{\mathcal{L}i}^{drag}(t) = -C_{\mathcal{L}i}\boldsymbol{n}_{\mathcal{L}i}(t) = -C_{\mathcal{L}i}\frac{\boldsymbol{r}_{\mathcal{L}}(t) - \boldsymbol{r}_{p_i}(t)}{d_{\mathcal{L}i}(t)} \tag{5.13}$$

$$d_{\mathcal{L}i}(t) = \|\boldsymbol{r}_{\mathcal{L}}(t) - \boldsymbol{r}_{p_i}(t)\| \tag{5.14}$$

where $d_{\mathcal{L}i}(t)$ is the distance between person p_i and robot $\mathcal{L}$ at instant t. See [74] for more information about the parameter $C_{\mathcal{L}i}$, which reflects the attraction coefficient over the individual p_i, and depends on the distance between the robot leader and person p_i.

Thus, the dragging work, which the leader robot exerts on each individual, is defined by:

$$\boldsymbol{W}_{drag} = \sum_{\forall\ p_i} \boldsymbol{f}_{\mathcal{L}i}^{drag} \Delta s_i \tag{5.15}$$

Where Δs_i is the distance traveled by the person p_i.

5.4.2.2 Pushing Work

The *Pushing force* is understood to be the repulsive effect yielded by the shepherding robot on the group of people in order to regroup a person or prevent people from moving away by using a robot as a barrier. This repulsive force is caused by the robots' movements into people's personal space which is five feet around the humans body. This territorial effect might be described as a repulsive social force:

$$\boldsymbol{f}_{ij}^{push} = A_i exp^{(r_{ij}-d_{ij})/B_i} \boldsymbol{n}_{ij} \left(\lambda_i + (1+\lambda_i) \frac{1+cos(\varphi_{ij})}{2} \right) \tag{5.16}$$

Where A_i is the interaction strength, r_{ij} the sum of the radii of robot shepherd $\mathcal{S}_i$ and person p_j, usually people have a radius of one meter and robots 1.5 m, B_i is the parameter of repulsive interaction, $d_{ij}(t) = \left\| \boldsymbol{r}_{\mathcal{S}_i}(t) - \boldsymbol{r}_{p_j}(t) \right\|$ is the distance from the mass center of robot $\mathcal{S}_i$ and person p_j. Finally, by choising $\lambda < 1$, the parameter reflects the situation in front of a pedestrian, it has a larger impact on their behavior than things happening behind them. The angle $\varphi_{ij}(t)$ denotes the angle between the direction $\boldsymbol{e}_i(t)$ of motion and the direction $-\boldsymbol{n}_{ij}(t)$ of the object exerting the repulsive force, see [74].

So we can write pushing work by:

$$\boldsymbol{W}_{push} = \sum_{\forall\ p_j\ \in \mathcal{P}_i} \boldsymbol{f}_{ij}^{push}(t) \Delta s_j \tag{5.17}$$

Where $\mathcal{P}_i$ is the set of people in which one of the shepherd robots has invaded the person's personal space. If an individual is more than two meters away from the robot, it is considered that the robot has not intruded on his/her personal space.

5.4.2.3 Traversing Work

And last but not least, the *Traversing force* is determined by the forces applied by the robot when traversing the crowd. For safety reasons, in this research, it has been decided the value of this force would be infinity to ensure that a robot would not cross the crowd or cause any damage.

5.4.3 Total Cost for One Robot

The cost function for robot R_i, given a specific task, is the following:

$$\boldsymbol{W}_{R_i} = \delta_{mot}\,\boldsymbol{W}_{R_i}^{mot} + \delta_{drag}\,\boldsymbol{W}_{R_i}^{drag} + \delta_{push}\,\boldsymbol{W}_{R_i}^{push} + \delta_{trav}\,\boldsymbol{W}_{R_i}^{trav} \tag{5.18}$$

$$\text{where } \delta_k \;=\; \begin{cases} 1 \text{ if this task is assigned} \\ 0 \text{ if this task is not assigned} \end{cases}$$

Where k could be *pushing, dragging, traversing* or *motion.* For each period of time, the leader and shepherd robots will be given a task in the guiding mission, which will require one or several robot work motions and human works motions.

5.4.4 Local Optimal Robot Task Assignment

At this point, we are able to compute a local optimal task assignment for the robots completing the guiding task. In this case, we mean "local" and not "global" optimal robot task assignment because we are only working with a short period of time ahead, when an event happens or can happen; for example, when a person strays from the group or where potential conflict areas in which people are more likely to stray are located. The local optimal robot task assignment will be one which minimizes the assigned work cost required to accomplish the local task, and it is computed as follows:

$$C = argmin\{\boldsymbol{W}_{total}(c)\}, \; \forall \text{ configuration c} \tag{5.19}$$

where the *configuration* indicates how the tasks are distributed among the robots, and $\boldsymbol{W}_{total}(c) = \sum_{\forall \mathrm{C}} \boldsymbol{W}_i$ is the total cost for the c robots that are working cooperatively. Eq. 5.19 computes the best configuration based on the **minimum robot motion energy (or work) criterion**.

Using C we can identify the motion tasks for each robot and establish their trajectories in order to achieve their goals. A typical mission is to retrieve a person who has strayed from the group. In this case, the output of the configuration is that one robot has to reach the person who is moving away; once the robot has reached him/her it must apply a *Pushing force* to lead the person back to the group position. The scenario is adjusted in the case that several people move away in different directions at the same time. If there are enough robots, the model computes the robot's optimal configuration and assigns each one the goal of reaching the assigned person and leading him/her back to the group. If the number of people moving away in different directions is greater than the number of shepherd robots available, then, there is neither an optimal solution nor a good solution. This problem can only be resolved by the following means: when one shepherd robot is available, if the person is still in an area of the map where the robot can detect him/her, the best task assignment will be computed and robots will be set to achieve their goals. However, if this person cannot be detected, the problem has no possible solution.

Table 5.2 presents robots' tasks and behaviors, as well as, the forces that are applied in each case. The computation of the configurations and the procedure that should be followed by the robots is explained in the following section.

The various issues which emerge from the determination of this local optimal solution are as follows:

- The method employed has a time complexity of $N_R!$, where N_R is the number of robots used for guiding. Although we have not analyzed other faster methods (from the complexity point of view) in this work, there are various ways of reducing this time complexity using the environment or robot formation heuristics.

- The method finds a local optimal solution when the number of robots is greater than the number of persons who move away from the group. Otherwise, there is no local optimal solution.
- The method sequentially assigns the robots to follow the group of people who have strayed, or to prevent people from straying. If there are several configurations with the same cost function value, the system will automatically choose the first solution. In the case where there are two solutions where either the leader or a shepherding robot can be used to reach a person the method will select the latter.
- The scalability of the method depends on the number of people being guided and the number of robots present. If the number of robots and people are high, then due to the time complexity issue, the method might be too slow.

5.5 Computation of the Robot Configurations for Group Reunification

One of the most common problems which arises when robots guide a group of people occurs when one or more people move away from the group and need to be retrieved, either because they are interested in an object lying outside the trajectory of the group, or because they become distracted. In this section we describe the method of reintegrating people who have strayed from the group using the cost function described above.

When this problem occurs, the robots must adjust their goals. For instance, one of the shepherd robots can change its direction, instead of following leader's trajectory, or the leader robot can become a shepherd robot. Therefore, it is necessary to evaluate the cost and the consequences of such changes in robot roles and trajectories. In Table 5.2 we describe the robots' forces and behavior in each guiding task.

In order to compute the best configuration C which minimizes the total robot cost in a regrouping task, the system must predict, for each configuration of robots, people's positions and motion vectors [7], as well as how much work each robot must do to perform its task. People's motion is predicted with a particle filter which considers

Tasks and Behaviors			
Task	**Robot**	**Forces Applied**	**Behavior**
Guide the group	Leader	f^{drag}	Act as a tour guide
	Shepherd	f^{drag} f^{push} f^{trav}	Interchange the role with the robot leader
		f^{drag}	Act as a tour guide.
Join the group	Leader	f^{drag}	Reduce the velocity
	Shepherd	f^{push}	Increase the velocity
Rescue people	Leader	f^{drag}	All the group follows the leader.
		f^{drag} f^{push} f^{trav}	Robot leader interchange its role with shepherd robots.
	Shepherd	f^{puch} f^{drag} f^{trav}	Compute the trajectory for reconduct people.
Barrier in a cross	Leader	f^{drag}	Follows the trajectory till the goal
	Shepherd	f^{push}	Robot moves toward the corner and wait for the group passes.
Narrow corridor	Leader	f^{drag}	Follows the trajectory till the goal.
	Shepherd	f^{push}	Wait all the group enters the narrow corridor.

Table 5.2: **Tasks and Behaviors**: Description of robots' forces and behaviors in each guiding tasks.

all the positions of people and robots as well as the obstacles in the environment. To compute the work that each robot must carry out, Eq. 5.18, the system has to compute the robot work motion, and the robot work required by Helbings' forces. The robot work motion must take into account the trajectory the robot has to take in order to reach the person who is moving away. There are various trajectories the robot has to perform: (i) if the person who is moving away is within the robot's field of vision, and there are no obstacles, then the trajectory is a straight line; (ii) if the person who moves away is on the same side of the robot, but there are obstacles, then the trajectory must account for these obstacles, that has been introduced previously in Section 4.4; (iii) if

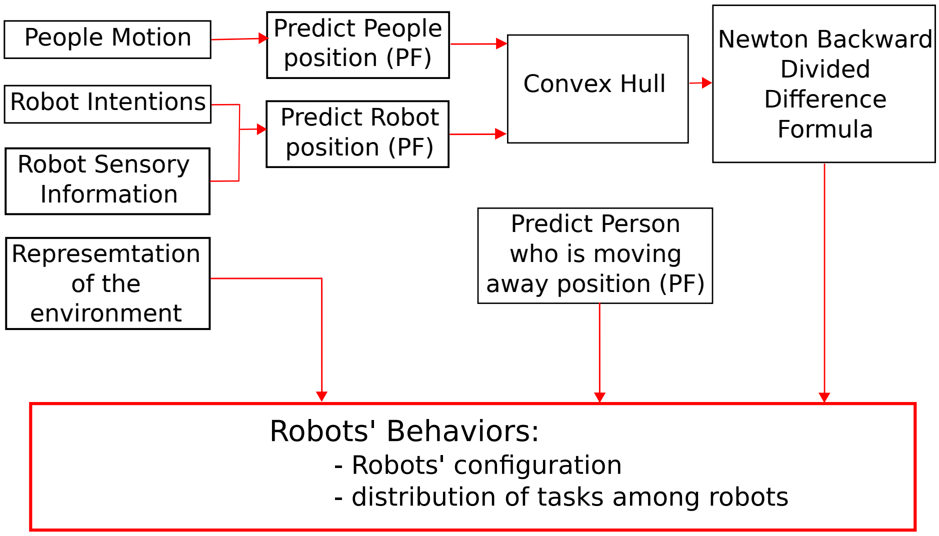

Figure 5.5: **Method of reintegrating people who have strayed from the group.** Procedure for calculating the path that a robot should follow to the position of the person who is moving away. Using the particle filter the positions of robots and people are computed. Considering the position of the group of people who are following the leader and the robots which are accompanying the group, the convex hull is computed (here, the person who is moving away is not considered, and the robot which will develop this task neither). Then, the function which interpolates the points in the convex hull is computed using Newton Backward Difference Formula. Finally, the trajectory the robot should follow is: firstly, the tangent function of the function f(x) and passing through this robot, and, secondly, the tangent function of the function f(x) and the person who is moving away.

the person who strays is on the opposite side of the group of people being guided, in relationship to the robot, then the robot has to determine first the proper trajectory to go around the group of people and then compute the trajectory depending on whether it is more similar to case (i) or case (ii).

A discussion of the second part of case (iii) can be found in Section 4.4, so here we shall only explain the first part of case (iii) here. In order to compute the trajectory in order to go around the group of people, we must calculate the convex hull of the people's and robots' positions: $\{\boldsymbol{r}_{p_i}\}_{i=1}^{N_P} \cup \{\boldsymbol{r}_{r_i}\}_{i=1}^{N_R}$. If we treat the group of people moving away in the same direction as a single element, then we might use its arithmetic center as the position of the group. Next, the function that interpolates the points in the convex hull is computed for each robot using the Newton Backward Divided Difference Formula,

Algorithm 4 Schematic strategy for regrouping people

```
Estimate people's position and directions.
if There are people moving away then
    for Each robot do
        Compute convex hull with robots and people's position:{r_{p_i}}_{i=1}^{N_p} ∪ {r_{r_i}}_{i=1}^{N_R}
```

$$\left\{ \sum_{i=1}^{N_p} \alpha_i \boldsymbol{r}_{p_i} + \sum_{j=1}^{N_R} \alpha_j \boldsymbol{r}_{r_j} \mid (\forall i, \forall j \,:\, \alpha_i, \alpha_j \leq 0) \wedge \sum_{i=1}^{N_p} \alpha_i + \sum_{j=1}^{N_R} \alpha_j = 1 \right\} \quad (5.20)$$

```
        Interpolate the function f(x) with the points on convex hull.
        Compute the trajectory, which will be the f(x)'s tangent passing through the
        escaping group.
        Compute the cost function.
    end for
    Choose the configuration such that, minimizes global cost function.
    Move Robots.
else
    Continue moving the group.
end if
```

which consider only those people in the area between the robot, the convex hull and the group that is moving away, such that we arrive at the function $f(x)$, see Fig. 5.5. Then we compute the trajectory of the robot, denoted as the tangent of $f(x)$, that passes through the center position of the moving group. This procedure is computed each interval of time k until the robot arrives at the moving group and the group is redirected toward the formation to be followed, see Fig. 5.5. To compute the total amount of required work we compared different trajectories and selected the one that yields a lower cost function.

In the simulation section of this chapter, we present the results of these cost function calculations, and describe a comparative study of different trajectories. In Algorithm 4 we introduce a schematic procedure to be followed by the group of robots.

5.6 Real-life Experiments to Verify Human Reactive Behavior

The aim of this study is to describe how a group of robots working cooperatively can effectively accompany a group of people. We focus on two key issues: preventing people from straying from the formation and studying the behavior of the team of robots when one or more people of the group move away.

In this section, we demonstrate that the Helbing et al. model of forces is applicable to our study. To verify these forces, we have conducted a series of real-life experiments using our own robot, called Tibi, see Fig. 5.6, and a group of volunteers who had not worked with service robots previously. We selected this group of volunteers so that they had no prior contact with robots and had not been conditioned by them. We conducted a set of experiments in which the robot approaches a person from different angles and at different speeds. The robot was controlled by teleoperation, but the volunteers were not aware of this fact. The results of these experiments enabled us to determine the personal space a person requires when he/she interacts with a robot, and allowed us to assess the effects of pushing and dragging forces on human individuals.

5.6.1 Tibi Robot

For the experiments, we used Tibi robot, pictured in Fig. 5.6, which has been introduced previously in Section 3.6.1.

The Tibi robot was designed to interact with different people in open spaces. The robot is socially accepted, and humans take an interest in interacting with it, robot's design must be well-rendered, and, its movements should be smooth. Moreover, it should know the personal space required by humans, so as to avoid invading on it and causing a negative reaction in people with whom it interacts.

Below, we present the methods and results of a series of experiments conducted with the robot Tibi. These experiments have been designed to analyze people's reactions when Tibi approached them (push force), when they walked together (push force) or when a person followed a robot (dragging force).

Figure 5.6: **People walking with Tibi Robot.** ***Left:*** Tibi walks side by side with the volunteer. ***Center:*** Robot walks behind the person pushing him/her (the Helbings' pushing force is applied). ***Right:*** Tibi walks in front the person and, here, the dragging force is applied.

5.6.2 Experiment Structure and Design

To perform the experiments, we had the participation of fifteen volunteers aged from 20 to 40 years old. We performed two different sets of real-life experiments: the first set aimed to obtain the persons' personal space preferences when the individual stood at a certain point and was approached by the robot; the second set was designed to determine the distances between the robot and the person for the dragging and pushing forces. In the first set, the person stood at a certain point and the robot approached him/her at different speeds and angles, when the person felt the robot too close, he/she could start walking away. This reaction manifests the parameters of the person's preferences for personal space when he/she interacts with the Tibi robot.

In the second set of experiments, we analyzed the behavior of people when accompanied by Tibi. In this set of experiments we measured the distances between the robot and the person when the pushing forces or the dragging forces were applied in three distinct situations. In the first scenario the robot was the leader and the person followed the robot propelled by the dragging force; in the second, the robot was located behind the person and forced the person to move via the pushing force; and in the third, the robot was located at the person's side and forced him/her to move via the pushing force. Here, though the robot and the human have followed the same path,

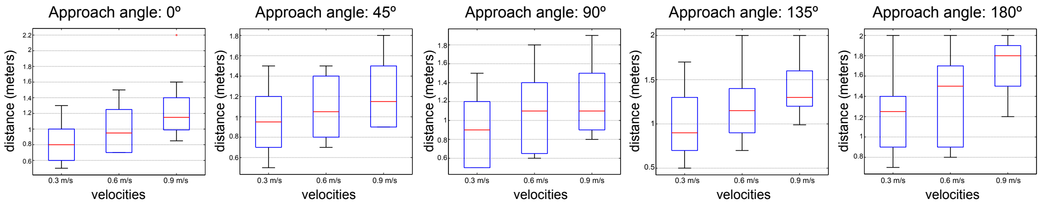

Figure 5.7: **First set of experiments:** the person stands at a certain fixed point and does not move up until the robot is too close. The graphs show the distances between the robot and the person (y-axis) at different speeds (x-axis) before he/she moved due to the robot is too close. The graphs show the mean, variance and quartiles of the data obtained in the experiments at different approach angles.

Tibi moved at different speeds, and it performed the role of the leader or shepherd, see Fig. 5.6.

The results and conclusions of the set of experiments are described in the following subsection.

5.6.3 Human Behavioral Responses to Robot Motions

As mentioned above, the first part of the experiments performed aimed to determine the personal space desired by people when they interact with the robot. To that end, we conducted a series of tests in which the robot moved towards a person at different speeds (0.3 m/s, 0.6 m/s and 0.9 m/s) and at different angles ($0^o, 45^o, 90^o, 135^o$ and 180^o).

Fig. 5.7 shows the distances between the robot and a person, where different speeds and angles were considered. Note that as speed increases the distances become greater, and the size of the personal space increases proportionally. The distances also vary, depending on the angle of approach. The results are summarized in Fig. 5.8, which shows the size of personal space desired, depending on the robot's velocity. In Table 5.3 depicts the distances of the person's vital space, for each speed and angle value.

In the second part of the experiments, we evaluated the effect of the leader robot and the shepherd robot when they accompanied people. We also studied the participants' behavior when they were accompanied by Tibi. In the first situation, the robot assumed the role of the leader, and the participants had to follow him. Fig. 5.9 shows the distances between the person and the robot along the way. The robot accelerated and

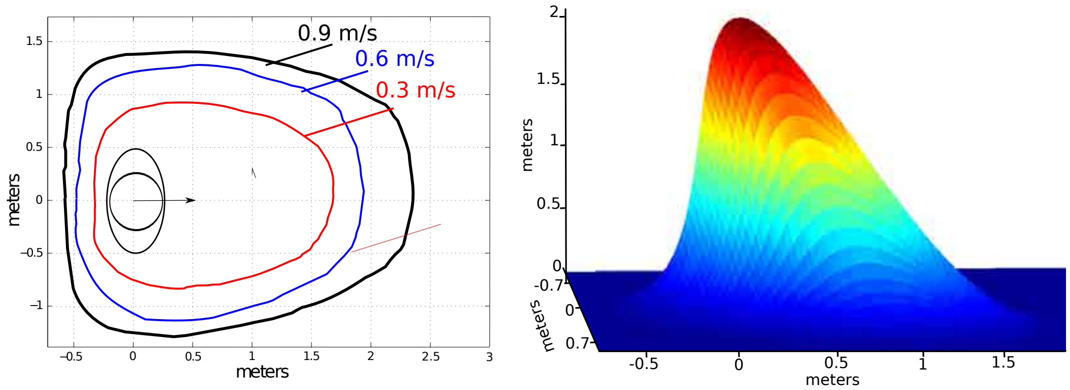

Figure 5.8: **Personal space:** Summary of the personal area of a person provoked by the approach of the Tibi robot at different speed of the robot motion.

People's Personal Space			
	Tibi's velocity of approach		
	vel.=0.3 m/s	vel.=0.6 m/s	vel.=0.9 m/s
α = 0 (deg)	0.30 ($\pm$0.20)	0.50 ($\pm$0.30)	0.70 ($\pm$0.25)
α = 45 (deg)	0.50 ($\pm$0.25)	0.65 ($\pm$0.30)	1.00 ($\pm$0.35)
α = 90 (deg)	0.70 ($\pm$0.30)	1.10 ($\pm$0.35)	1.50 ($\pm$0.40)
α = 135 (deg)	1.30 ($\pm$0.30)	1.80 ($\pm$0.40)	2.15 ($\pm$0.45)
α = 180 (deg)	1.60 ($\pm$0.25)	2.00 ($\pm$0.40)	2.30 ($\pm$0.30)

Table 5.3: **Personal Space Distances.** Average distance values between Tibi and volunteers, in meters.

decelerated, the remaining distance is constant, within certain parameters. This shows the force of attraction of the leader and suggests that people follow the path of the leader.

In Fig. 5.10 the different results that were obtained are presented: the distance between a volunteer and the robot, and the robot and a volunteer's speed and acceleration while Tibi performed the leader role. It is shown that during the process of guiding the distances were maintained and the human attempts to imitate the velocity of the robot, and therefore, if the robot accelerates the person increases its speed, and analogously if the robot reduces its velocity.

Lastly, we studied people's behavior when the robots played the role of shepherd.

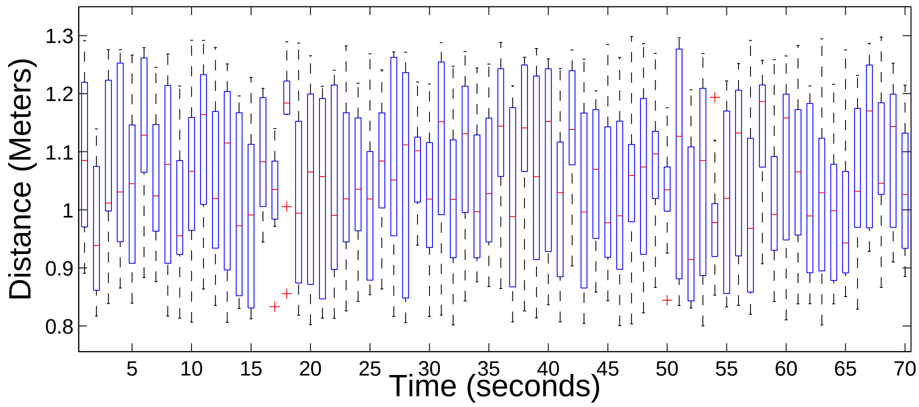

Figure 5.9: **Second set of experiments:** The robot is the leader and the person follows the robot provoked by the dragging force. The graph shows the distance between the leader robot and people (y-axis) during a period of time (x-axis) where the robot accelerated and decelerated. It can be observed that the distances varied between 0.85 m to 1.27 m.

In this scenario, Tibi shifted to people's sides or positioned itself behind them while moving at different speeds. In Fig. 5.12, the robot was positioned behind people. When the robot's speed was too slow, 0.4 m/s, the human's interest decreased and the person strayed from the robot. However, if the robot moved faster, at 0.8 m/s, the person felt that the robot was pushing him/her and he/she tried to keep the distance constant.

According to [14], the mean comfortable speed ranges from 1.272 m/s to 1.462 m/s, for this reason, we do not allow the robot to reach speeds greater than 1 m/s. When volunteers were asked if they felt comfortable with a robot walking behind them at speeds close to 0.8 m/s, they said they felt safe and walked until the robot stopped moving. In addition, we conducted a study comparing the behavior of the volunteers when they have a robot behind them or another person following them. Fig. 5.11 shows the trajectories performed in both cases and the distances measured during the path. It was found that if the speeds are between 0.7 m/s and 1 m/s behaviors are very similar.

Finally, Fig. 5.13 shows that when the robot walks side by side with the person, the distances are smaller, probably because people have less safety concerns in the company of the robots. Also, in this situatiom, the robot is accompanying the person instead of pushing him/her.

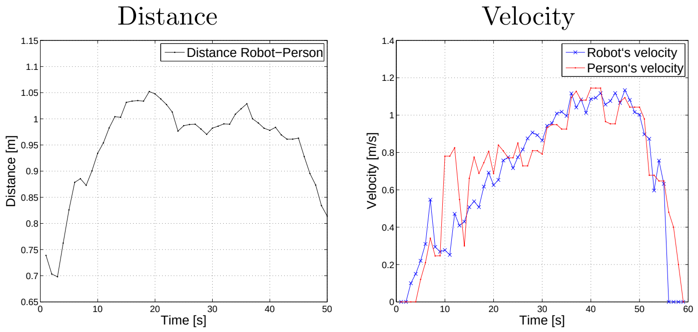

Figure 5.10: **Distance, velocity and acceleration.** Robot acts as a leader while a person follows it. Distance, velocity and acceleration of the robot and the person during the guiding process.

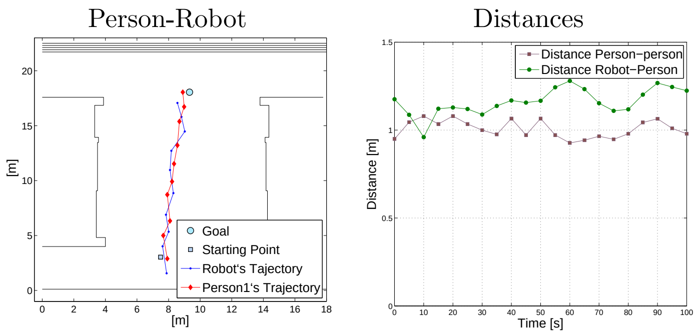

Figure 5.11: **Comparison of the trajectories:** ***Left*** : Robot navigates behind a volunteer. ***Center*** : Distances between the volunteer and the robot (or another person). ***Right*** : A person walks behind the volunteer.

In conclusion, we computed the personal space desired within the company of our robot Tibi, and we analyzed the effects of the dragging and pushing forces, depending on robot's movements and depending on robot's role, as a leader or shepherd. These observations were then incorporated into our simulations to verify the functionality of our model. The following sections present the simulation results in light of the values obtained in these experiments.

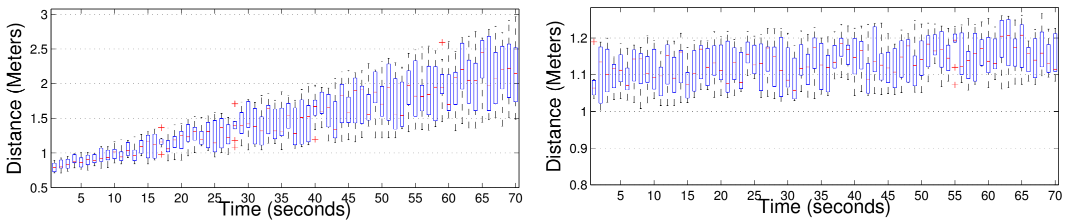

Figure 5.12: **Second set of experiments:** The robot is located behind the person and forces the person to start moving due to the pushing force. The graphs show the distance between the shepherd robot and people (y-axis) during a period of time (x-axis). ***Left:*** If the robot's speed is too slow (0.4 m/s), persons' interest decreases and the person does not feel the robot is pushing and then, he/she starts moving independently of robot speed – the distance between the robot and the person increases during the walking period. ***Right:*** If the robot speed is higher (0.8 m/s), then the person feels that the robot is pushing him/her and the person tries to maintain a constant distance between them.

5.7 Simulations in the Barcelona Robot Lab

In this section, we explain two series of three simulations conducted using the PAM model. The first set of simulations was conducted using the map of the Barcelona Robot Lab. The second set focused only on analyzing the regrouping task. The simulations used the map of the Barcelona Robot Lab which measures about 10000 m^2. This urban area is located in the North Campus of the Universitat Politècnica de Catalunya (UPC). The urban area includes corridors, open areas and intersection areas, as well as, static obstacles (buildings, benches or potted plants), and dynamic obstacles (mobile robots and people in motion). We then compared the results from the simulations conducted with and without the PAM model.

The simulations dealt with groups of people who followed the models described by Helbing et al. [75]; additionally, we assumed the participation of a group of two or three robots which move according to the Discrete Time Motion Model (DTM) [58], and behave according to the computation of the configurations explained in Section 5.5.

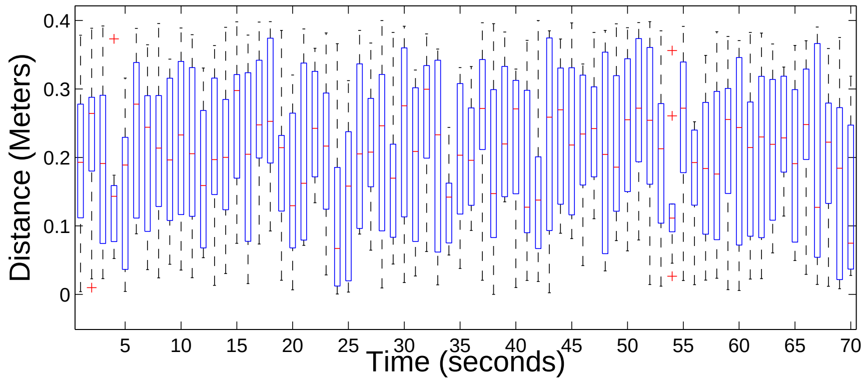

Figure 5.13: **Second set of experiments:** the robot and the person are side by side, and the person walks due to the pushing force. The graph shows the distance between the shepherd robot and people (y-axis) during a period of time (x-axis). Notice that distances between the robot and the person are between 0.2 m and 0.37 m.

5.7.1 Simulations using the PAM model

We performed several simulations in the map of the Barcelona Robot Lab in which two or three robots guided a group of people. The robots were supposed to reach a specific target position in the map and react to unexpected situations. For each simulation, we compared the results with and without the PAM model described above. With the PAM model the simulated robots were able to anticipate the problem of people moving away and avoid losing a member of the group. If the robots do not use this model, then, the time of regrouping was much higher because they had to look for the people who had moved away, instead of preventing them to leave the group.

In the first simulation, two robots guided a group of five people along a path where there were two areas where people could move away, see Fig. 5.14. We compared whether the robots behave in accordance with the Prediction and Anticipation Model or not, where the behavior of people who do not move away remains constant. Fig. 5.14-*Left* shows that when the PAM model is used the group follows the path and nobody leaves the formation, but where the PAM model is not applied there are two areas where people move away and robots must look for them and bring them back to the formation. In Fig. 5.14-*Center*, the covariance of the size of the group is plotted. Note that, if the robots are able to anticipate human motion behavior, they can prevent

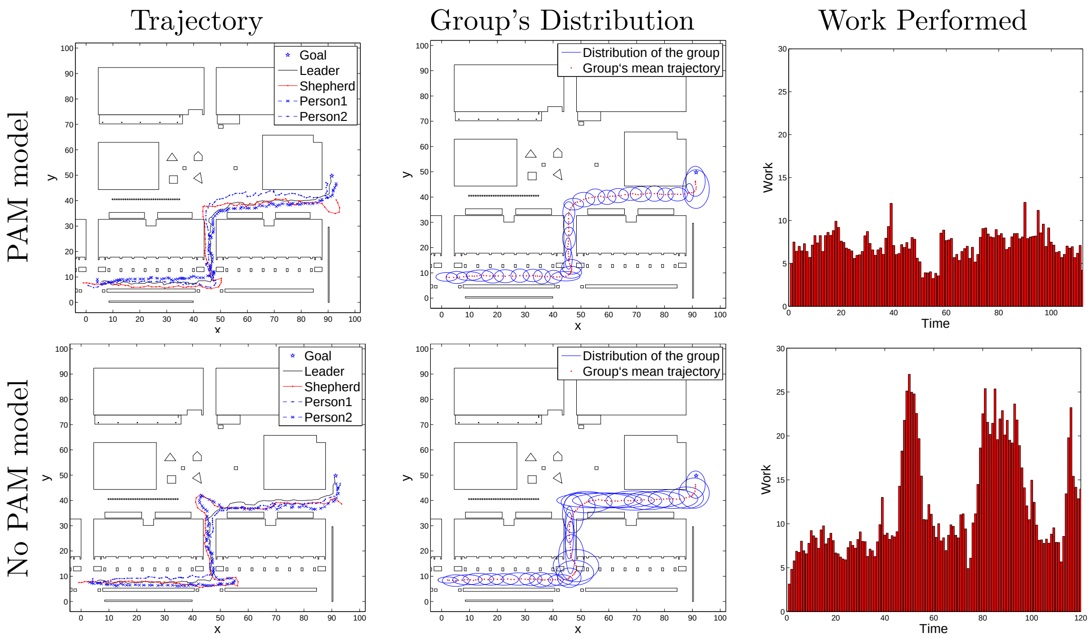

Figure 5.14: **Simulation #1:** Graphic summary of people and robots' path for the first simulation, using the Prediction and Anticipation model (top), and without considering it (bottom). ***Left:*** Final trajectories of the simulated people and robots. ***Center:*** Trajectory of the whole group, shown as mean path and covariance. The increase of the covariance size is produced when a person leaves the group. ***Right:*** Graph of the Work performed by the group.

them from straying and, thus, maintaining the covariance of the group. However, if the robots have to wait for someone to stray before taking action, the size of the covariance grows.

Anticipating or expecting someone to stray, can be seen on the graphs that show the work required by the robots (and people) to maintain the group of people on the desired path. In other words, the work required by the robots to look for one or more people who stray from the group, is much lower if robots can anticipate and help people to follow the path by avoiding dispersions, see Fig. 5.14-*Right*. Also note that in this visual aid the two peaks of the work performed, correspond to the two instants of time in which a person leaves the group and must be accompanied back.

In the second simulation, three robots guide a group of seven people along a path within an area where people can move away in different directions, see Fig. 5.15. Again, we used this scenario to compare trends in the robots' behavior with and without the

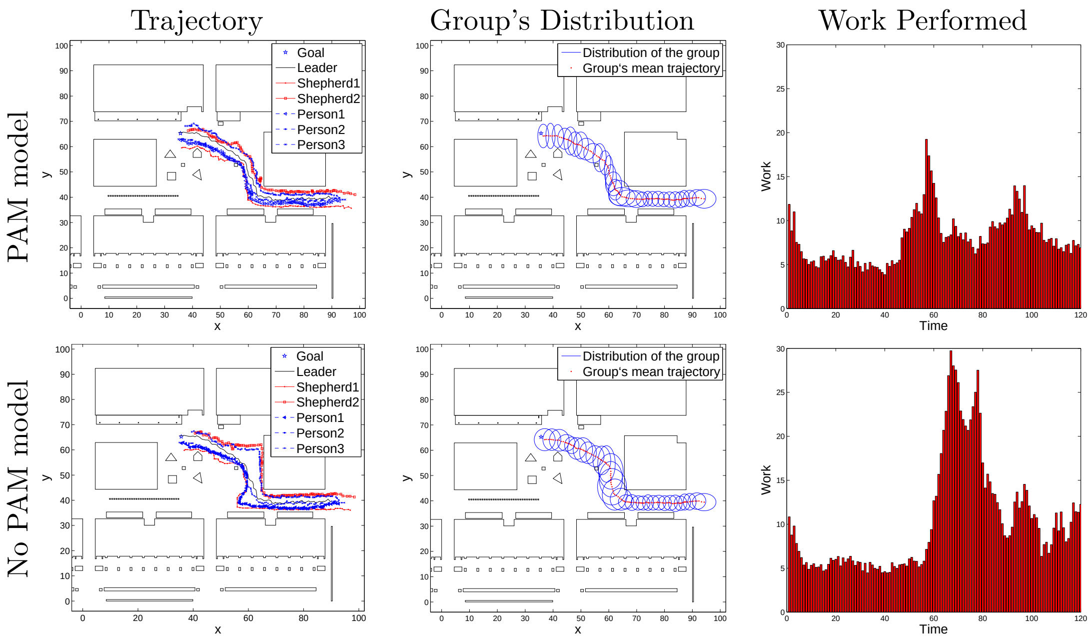

Figure 5.15: **Simulation #2:** Summary of people and robots' path for the second simulation. ***Top:*** Using the Prediction and Anticipation model. ***Bottom:*** Without considering PAM.

application of the Prediction and Anticipation Model. In both cases, the behavior of people who did not move away remained constant. In Fig. 5.15-*Left* it is demonstrated that when the PAM model is used, the group follows the path and nobody leaves the formation. However, where the model is not used, there is an area in which two people move away in different directions and the robots must look for them and return them to the group. In Fig. 5.15-*Center*, the covariance of the group is plotted, and it can be seen that the covariance is larger when the PAM model is not employed.

Fig. 5.15-*Right* represents the work performed by the group, where it can be observed that the work is lower when robots can anticipate stray movements and help people to follow the path by preventing dispersions. Note that the peak of the function corresponds to the moment in time in which two people leave the group and they must be accompanied back through the deployment of two shepherd robots.

In the third simulation, three robots guide a group of seven people along a path within an area where people can move away in different directions, see Fig. 5.16. Again, a comparison is made between the robots' behavior with and without the employment of the Prediction and Anticipation Model. Fig. 5.16-*Left* demonstrates that when the

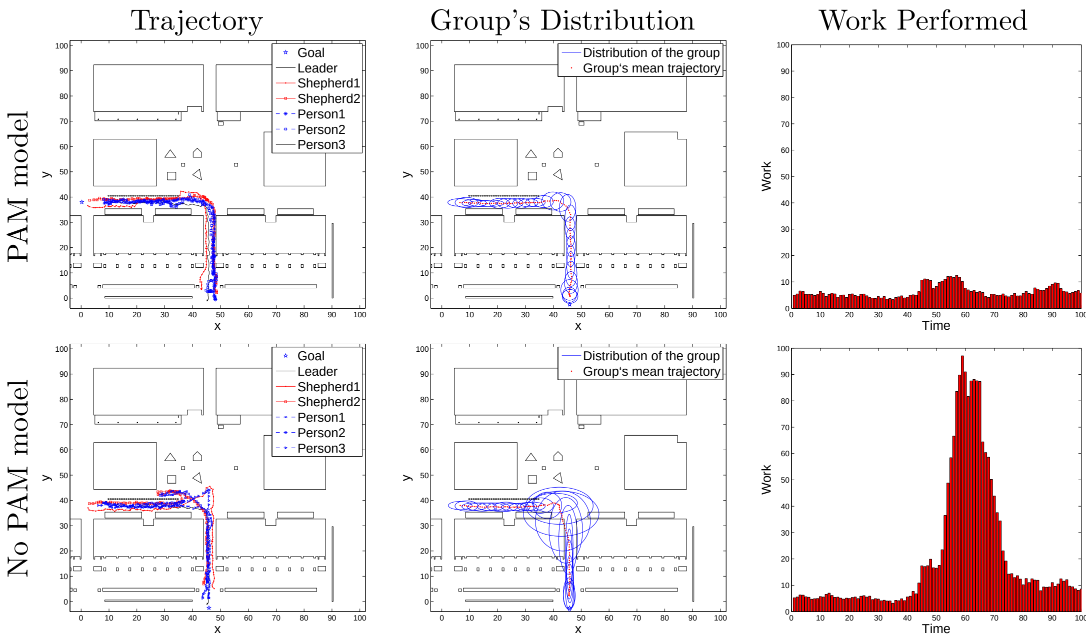

Figure 5.16: **Simulation #3:** Summary of people and robots' path for the third simulation. ***Top:*** Using the Prediction and Anticipation model. ***Bottom:*** Without considering PAM.

PAM model is used, the group follows the path and nobody leaves the formation; however, where the model is not used, there is an area in which two people move away in different directions and the two shepherd robots must look for them and return them to the group. Fig. 5.16-*Center* plots the covariance of the group.

In Fig. 5.16-*Right*, the work performed by the group is presented. It shows that the work is lower when robots are able to help people follow the path and preventing dispersions. It must be mentioned, although there are no shepherd robots in the back of the formation, people are still attracted by the humans who they have in front, and, thus, they follow the group and do not disperse.

In summary, we may conclude that, through the application of the prediction and anticipation model, robots are able to help people to follow the path, managing to prevent people from straying while carrying out their work at a lower cost.

5.7.2 Simulations of Regrouping People

In this subsection, we analyze the performance of the regrouping task, through three simulations conducted in open areas and at intersection.

In the first simulation, two robots guide a group of five people in an open area without obstacles, see Fig. 5.17. The positions of the two simulated robots are plotted with circles, the placement of the five people is indicated by asterisks. As mentioned above, when the robots detect that people are moving away, or an open area exists that may lead to dispersion, they must determine the optimal configuration of robots to perform the task of returning the people to the group and/or preventing them from straying. The following are the possible configurations for regrouping people with two robots, one leader and one shepherd: *(i)* The shepherd robot takes care of regrouping people who have moved away following the left path Fig. 5.17-*1st*. *(ii)* Shepherd robot takes care of regrouping people who have moved away following the right path Fig. 5.17-*2nd*. *(iii)* and *(iv)* the shepherd robot takes the role of leader, left and right trajectory respectively, and the leader robot moves toward the person who has strayed. In all four cases, we assume that the shepherd robot is able to explain to the group that it has assumed the role of the leader Fig. 5.17-*3rd* and *4th*. *(v)* The leader robot regroups the formation, and thus the entire group moves toward the person who has strayed Fig. 5.17-*5th*. For all five possible configurations the system computes the work cost, Fig. 5.17-*Right*. Note that the first configuration is the one which requires the lowest work cost.

In the second simulation, three robots guide a group of eight people in a street crossing area, see Fig. 5.18. In this case the simulated robots must regroup two people who stray towards different directions at the same time. The following are the possible configurations for regrouping two different people with two shepherd robots and one leader: *(i)* the shepherd1 robot takes care of regrouping person1 and the shepherd2 robot takes care of regrouping person2, Fig. 5.18-*1st*. *(ii)* The shepherd2 robot takes care of regrouping person1 and the shepherd1 robot takes care of regrouping person2, Fig. 5.18-*2nd*. *(iii)* The shepherd1 robot assumes the role of leader, while the leader robot moves toward person1, and the shepherd2 robot regroups person2. *(iv)* The shepherd1 robot assumes the role of leader, the leader robot moves toward the person2, and the shepherd2 robot regroups person1. *(v)* The shepherd2 robot assumes the role

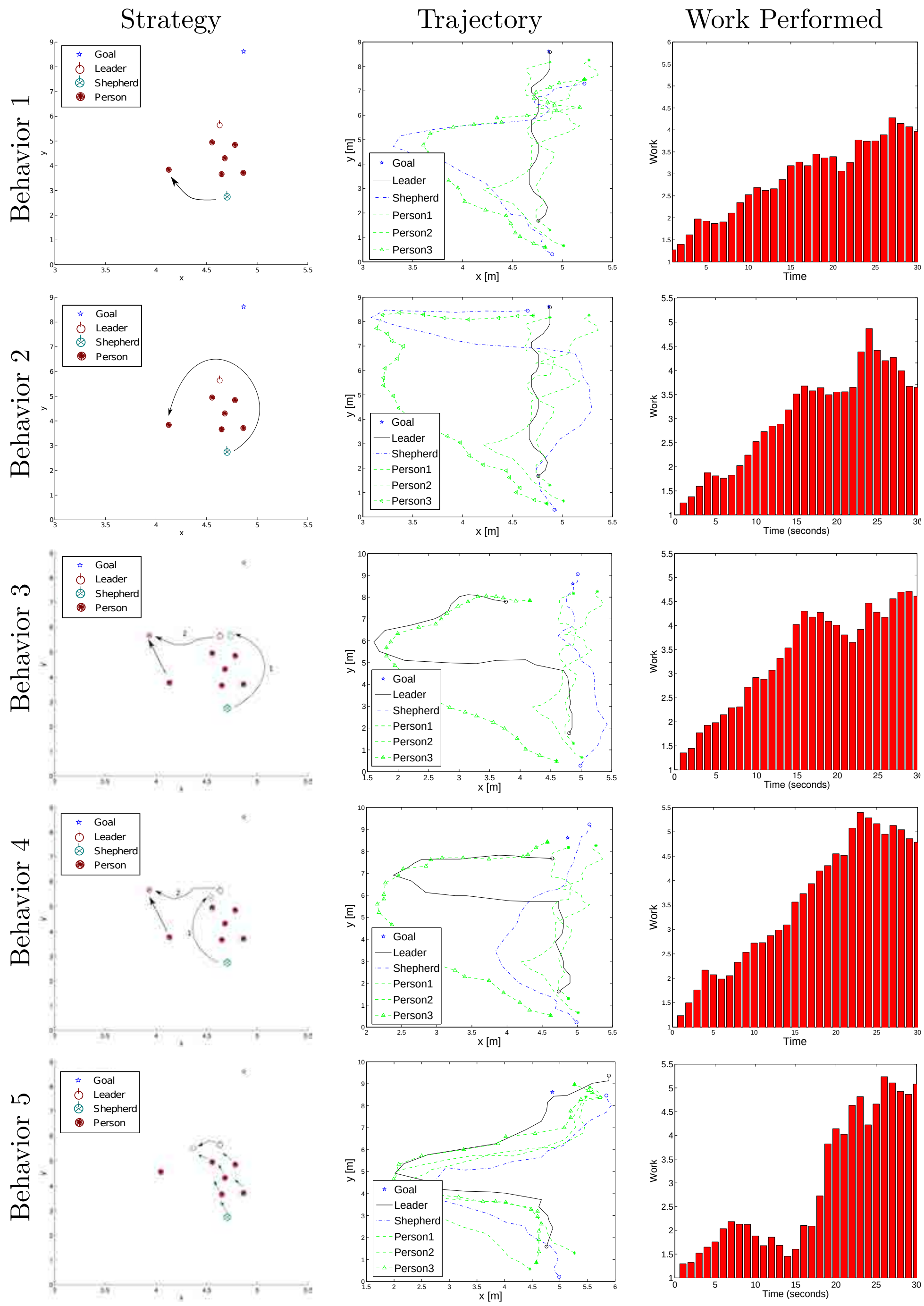

Figure 5.17: **Simulation of the Regrouping #1.** ***Left*** : Different strategies that robots can follow. ***Center:*** Trajectories the group follows. ***Right:*** Work performed by the group.

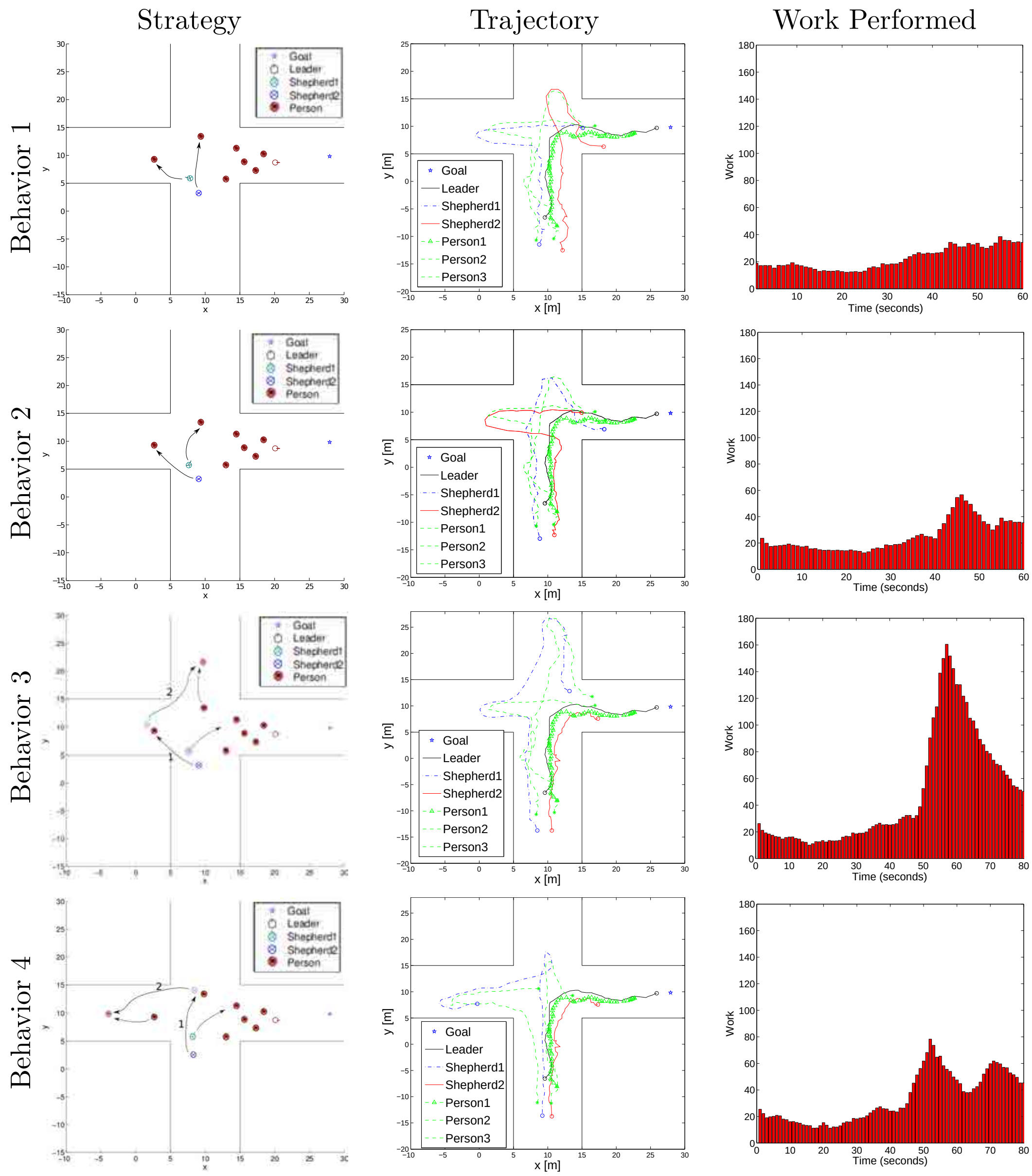

Figure 5.18: **Simulations of Regrouping #2.** ***Left*** : Different strategies robots can follow. ***Center:*** Trajectories the group follows. ***Right:*** Work performed by the group.

of leader, the leader robot moves toward the person2, and the shepherd1 robot regroups person1. *(vi)* The shepherd2 robot assumes the role of leader, the leader robot moves toward the person1, and the shepherd1 robot regroups person2. *(vii)* The leader robot regroups the formation and the entire group moves toward the people who have strayed.

(viii) The leader robot regroups the formation and the entire group moves toward people who have strayed. It should be mentioned that in this specific example, situations *(iii)*-*(viii)* cannot be considered, because if the leader robot moves toward the people who are moving away, it implies that it would have to cross through the group, but we have already established that the transverse force has not been considered in these experiments.

Finally, there are strategies by which we may compute the cost of looking for a single person. When the person has rejoined the group, the work cost is recalculated to accommodate the regrouping of the second person. This strategy implies that the two shepherd robots are not going to look simultaneously for all the people moving away at a given point. Fig. 5.18-*3rd* and *4th* provide two examples of this strategy.

Fig. 5.18-*Right* shows the work cost calculated for these possible configurations. Note that the first configuration is the one which corresponds to the lowest cost. We also observed that the strategies that first compute the cost of regrouping one person only and then address the other people who have strayed are much more costly than other strategies.

Finally, in the third simulation, two robots guide a group of five people in a crossing area, see Fig. 5.19. The following are the possible configurations for regrouping people with two robots, one leader and one shepherd robot: *(i)* The shepherd robot takes care of regrouping people who have strayed following the right path Fig. 5.19-*1st*. *(ii)* The shepherd robot takes care of regrouping people who have strayed away following the left path, Fig. 5.19-*2nd*. *(iii)* The leader robot regroups the formation and the entire group moves toward the person who has strayed, Fig. 5.19-*3rd*. In *(iv) and (v)* the shepherd robot assumes the role of leader, left and right trajectories respectively, and the leader robot moves toward the person who is moving away. In these cases, we assume that the shepherd robot is able to explain that it has taken the role of the leader Fig. 5.19-*4th* and *5th*. Fig. 5.19-*Right* shows the work cost calculated for all possible configurations. Note that third configuration is the associated with the lowest cost.

In summary, we have presented different scenarios and several strategies with respect to the cost function in order to determine the ways in which robots can perform the given task cooperatively with the minimum work expended.

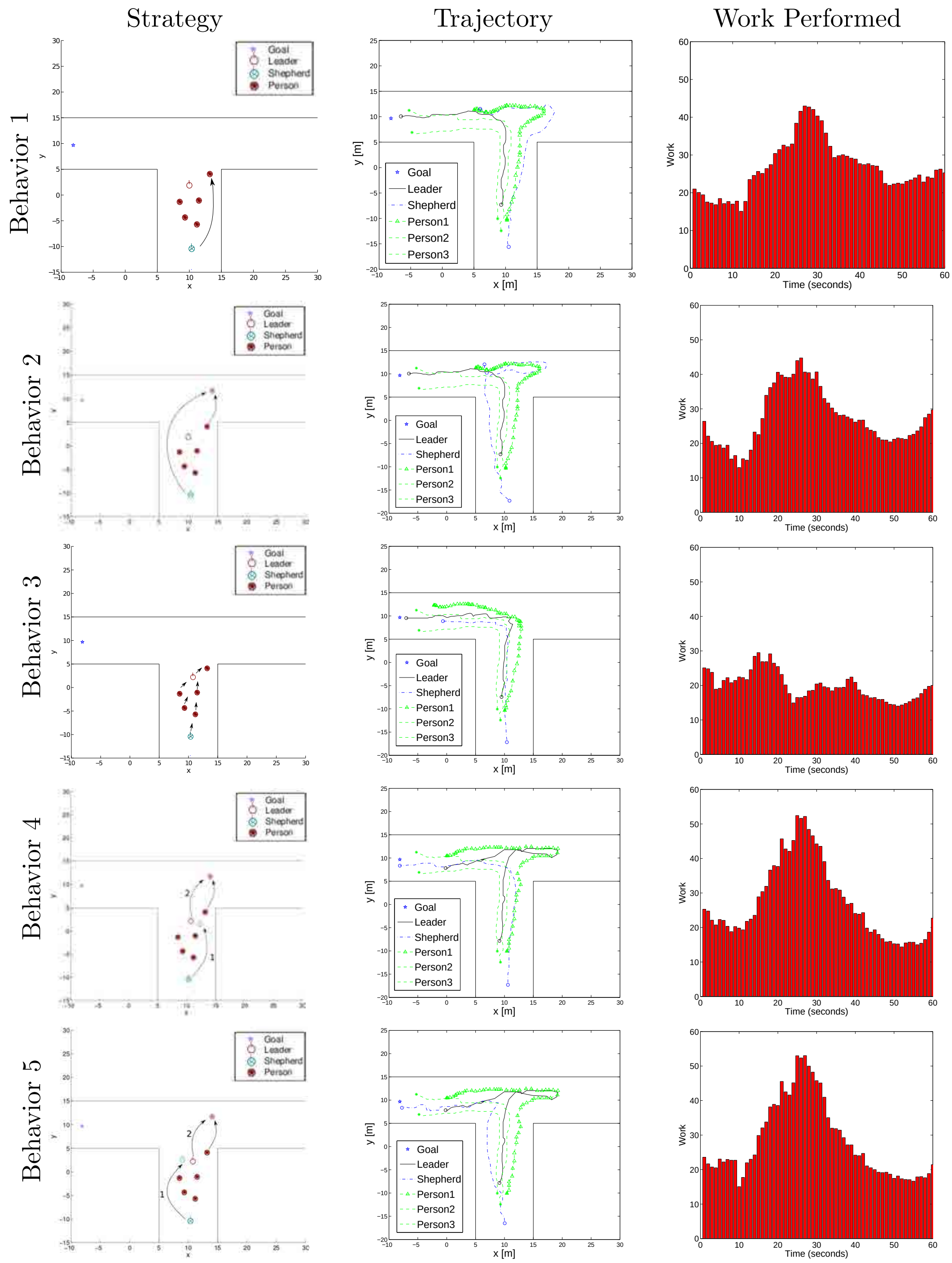

Figure 5.19: **Simulation of the Regrouping #3.** ***Left:*** Different strategies that robots can follow. ***Center:*** Trajectories the group follows. ***Right:*** Work performed by the group.

5.8 Discussion

We developed the Prediction and Anticipation Model, in order to guide people using multiple robots working cooperatively on a given task. We have also introduced the minimum robot motion energy criterion to assess the task assignment that might minimize the work required by people and robots during the guiding mission. Although the PAM model has been applied exclusively to people-guiding missions within the context of this chapter, we believe it can be extended to other tasks that demand cooperation between robots and people, for example, robots gardening or robots cleaning in urban areas.

We have identified other works that use robots functioning cooperatively to guide people [115], nevertheless, they do not tackle the problem of people straying from the formation. However, there are various methods for guiding people in museums using a single robot, as well as, guiding people inside a certain area using robot formation techniques or even guiding ducks within a controlled environment. Not all of these methods may be applied to the issue we mainly address in this work, since they do not allow people to stray from the group. Moreover, these techniques do not use the anticipation strategy to determine the best configuration of robots to carry out the mission.

We demonstrate the guiding mission using this model by conducting simulations instead of real-life experiments. The main reason for this decision is due to the complexity of conducting these experiments with the available technology. For example, the robots that exist nowadays do not move fast enough and do not navigate safely enough to follow people's random motions in an urban area. Nor may people's motions be completely and accurate detected when robots and persons are moving together in a group. These technological limitations will be overcome in the near future and we do not consider them to be significant challenges for the discipline in general. Furthermore, we have validated Helbing's forces using our robot Tibi and were able to calculate people's personal space when they interacted with Tibi.

Because we have not demonstrated these trends in real-life experiments, we have had to make a series of assumptions on human motion behavior when people are guided by robots. Although one might believe that these assumptions are strong, we think they are valid wherever people cooperate with robots. Even if said assumptions are not partially or totally demonstrable in real-life scenarios, the minimum robot motion criterion can still be applied; we need only to include other criteria that consider human behavioral movement. These new criteria will need to be incorporated into the selection of the optimal robots configuration.

The proposed approach has some drawbacks, as described below. One drawback is time complexity of the optimal robot task assignment. As we mentioned earlier, this time complexity is $N_R!$, meaning which, it grows factorially. We have not intended to look for techniques that reduce this time complexity, for example using heuristics, but this will be a task for a future work. Another drawback is the requirement of having to know the pose of all the people that move in the group. We think that we do not need all the poses, we only need the poses of the people that are in the border of the group, but this will be modified in the near future. At last, there is the drawback of the validation in real-life scenarios.

Lastly, we must note that the PAM model can be applied to real-life missions. Typical missions may include guiding tourists at a certain site; accompanying professional visitors in opened or close environments; service tasks such as cleaning or gardening in urban areas, etc.; and carrying out military missions. In all these tasks, people are gathered in small or large groups, and some of the participants may stray out of fatigue, boredom, injury, distraction, or for personal needs (such as finding a rest room). We have not considered situations in which the people in the group are in a state of panic or engaged in vandalism.

5.9 Summary

This chapter has presented a new model, called Prediction and Anticipation Model, which was developed to guide people using multiple robots that work cooperatively.

Unlike other existing works, our method can be applied in realistic situations such as dealing with large environments with obstacles, or regrouping people who have left the group. For that reason, this work can be applied to certain specific real robot applications, for instance, guiding tourists, accompanying professional visitors or acting as a robot companion.

We have described the findings from various simulations conducted in open areas with obstacles and considered different people's behavioral movements. In each simulation, we were able to show that, by using the PAM model, the robots could act early enough and were able to prevent people from getting lost or straying from the group. We assert that these same results can be extended to urban areas with a large number of obstacles. Although we have only assessed the functionality of the PAM model through simulations, we have conducted real-life experiments to validate the Helbing's forces using our Tibi robot, and assessed the preferred dimensions of personal space, data which was then incorporated into our simulations.

Finally, we have identified three areas for further research: the first consists of adding into the particle filter sampling process the social force model, the second involves conducting real-life experiments in the Barcelona Robot Lab; and the third is to adjust the assumptions that were made in this work so that we might analyze new robot motion behaviors and strategies.

Chapter 6

Proactive Behavior of an Autonomous Mobile Robot

If you are proactive, you don't have to wait for circumstances or other people to create perspective expanding experiences. You can consciously create your own.

Stephen R. Covey

In recent years, researchers have made great efforts to enable autonomous social robots to interact with people. However, there remain many unresolved questions about the social capacities robots should have in order to interact more naturally. The ultimate goal of our research was to enable robots to interact naturally with people when carrying out the accompanying task. In this chapter, we present the results of several experiments conducted at the Barcelona Robot Lab, in which we studied various aspects of the interaction between a mobile robot and untrained human volunteers. First, we proposed different pro-active behaviors for robots to use when approaching a person and engaging with him/her. To do so, we provided the robot with several perception and action skills, such as that of detecting people, planning an approach, and verbally communicating its intention to initiate a conversation. To verify that a relationship was effectively formed, and to manifest that people were interested in the robot, we offered our volunteers the opportunity to assist the robot in a task. We also developed additional communication skills to allow people to assist the robot and help it to enhance its facial recognition system. During this online assisted stage, the robot was able to communicate to people and, in doing so, improve its visual skills. The work in this chapter has been presented in [44, 59, 171].

6.1 Introduction

One major topic within the field of human-robot interaction research is the issue of giving the robots the ability to initiate interaction with a human. Generally, it is thought that social robots can engage in the same way people do, using human-like physical signals and gestures [122]. Recent studies show that robots are also able to encourage people to initiate interaction [29, 72], expecting people to approach them instead of initiating it themselves [100].

Satake et al. [145] proposed a model of approaching behavior to initiate a conversation with walking pedestrians. Researchers have also attempted to identify the most advantageous moment for starting the interaction or engagement [150], finding most often that it should occur when (or just moments before) both human and robot perceive that they are sharing a conversation. Fogarty et al. [45] proposed models for estimating the best times to interrupt a person within an office environment.

Recent efforts have also focused on creating robots that are able to start conversations with humans in a friendly and natural manner [120]. The present thesis takes this a step further, by looking at how robots can seek assistance from the person, after initiating a conversation and engaging meaningfully with him/her. Specifically, we show how the robot and person perform a collaborative task, in which the robot asks the human to help it improve its facial recognition system.

The contributions of this chapter are therefore twofold. Firstly, we introduce a framework wherein a mobile robot is able to initiate a dialogue with a person and develop an engagement, focusing on the way the robot initiates the conversation in a manner perceived as natural by the person. Specifically, we look at the human communication model proposed by Clark [25], based on the notion that people in a conversation perceive the roles of other persons, such as a speaker, listener, and side participants. In order to perform this initial task, we furnished the robot with a simple visual module for detecting human faces in real-time, with the caveat that faces have to be in a non-occluded and frontal position.

Figure 6.1: **Human-Robot Interaction and Communication.** ***Left:*** Tibi mobile robot approaches a person to initiate a conversation. ***Right:*** After the first contact, the person assists Tibi to improve its visual skills. A Wii's remote controller is used to help to validate and improve the visual detector.

Our next contribution was to introduce a second robot-human communication framework, once the engagement has been initiated, wherein the human can naturally help the robot improve the performance of its facial recognition module. We used an online learning algorithm [171], and incorporated the human's assistance, which enhances the performance and robustness of the initial face detector, by allowing the robot to detect faces in adverse conditions, i.e., when detection of visual targets is hindered by abrupt changes in light or partial occlusions. In addition, the robot was able to learn the person's identity in order to engage in coherent dialogues with him/her in the future. In this online and real-time assisted algorithm, the human plays the role of a teacher, guiding the robot through its learning process, and correcting the output of the facial recognition system. The amount of human intervention falls in intensity over time, and usually after a few seconds the robot's visual system becomes significantly more robust and reliable. Fig. 6.1 shows three different frames from a typical teaching process between a person and our robot, Tibi.

The robot's ability to approach people and learn to use human assistance leads to a number of possible applications. Among the most promising of these is the robot's capacity to independently look for people who can assist it, so as to progressively improve upon its skills throughout the interaction process. Because validating a few faces proposed by the facial recognition module requires very simple communication, this learning stage can be performed by any non-expert person.

6.2 Chapter's Overview

The sections below describe the architecture we developed to provide autonomous mobile robots with pro-active behaviors. Our goal was to study previous approaches and take them one step further, by encouraging the robot to actively seek human interaction and ask the person to help it improve its visual detection skills. The main obstacle in this scenario was the possibility that the person did not understand that the robot was trying to initiate a conversation with him/her. Humans typically initiate conversation by eye gaze [64], and in a real environment, it is very difficult for a robot to recognize this social gesture. Because of this, we relied more heavily on body's position, gestures, and verbal cues. Once the human has effectively understood the robot's intentions, he/she could follow a specially-made, simple, and efficient communication protocol for teaching the robot. The protocol, developed specially for the purposes of this stage of the study, involved the following key components, see Fig. 6.2:

- *The robot's ability to pro-actively seek interaction*: One of the main purposes of this study was to identify the optimal robot behavior for initiating interaction with a human. To do so, we analyzed three variations on this behavior, looking at scenarios in which: (1) The robot uses only verbal cues to communicate with the participant; (2) The robot uses both verbal and non-verbal cues (e.g., gestures and eye gazes); and (3) The robot uses verbal and non-verbal cues and actually approaches humans.

- *Online human-assisted face recognition*: Once the robot has engaged with a human, we proposed an approach in which the robot was able to enhance its visual skills using the human's help. Following each interaction, we were able to prove that the robot's skills were visibly improved.

- *Tibi's emotions*: To synthesize Tibi's emotions of happiness, sadness and anger, we used the emotion model of the three dimensions of emotion [146]. This model characterizes emotions in terms of *stance*, *valence* and *arousal*.

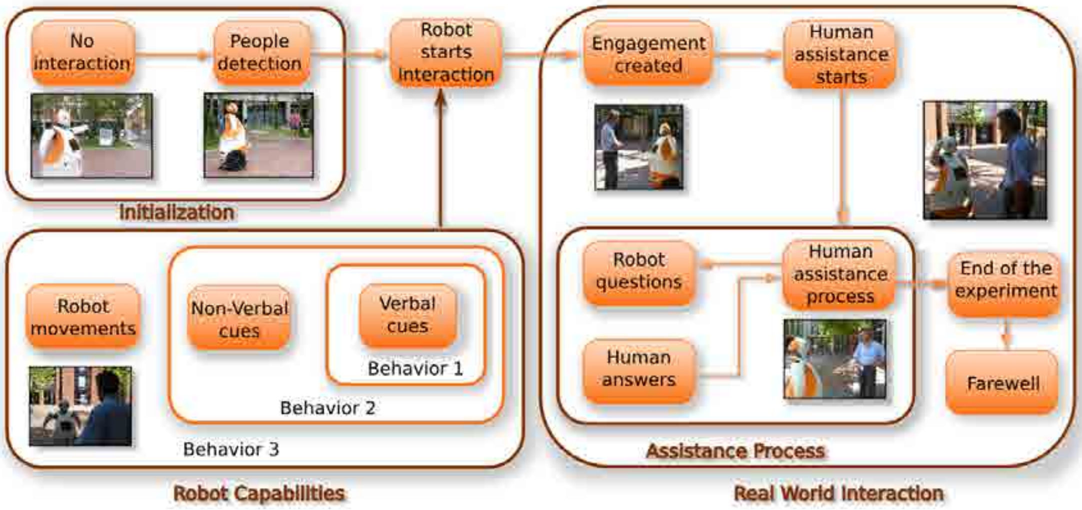

Figure 6.2: **Approach Overview.** Sketch of the experiments performed to analyze different robot behaviors.

- *User study of robot's behavior*: We also conducted a user study to determine whether the robot's behavior was perceived as socially appropriate by the experiment participants. We also looked at various key aspects of the interaction between a mobile robot and untrained human volunteers.

6.3 Robot's Behavior

In this section, we describe the different behaviors enacted by the robot during the experiments. First, we show how the robot pro-actively seeks interaction; later we introduce an approach in which the robot is able to enhance its skills by accessing the human's assistance.

6.3.1 Robot's Proactively Seeking Interaction

Recent studies have focused on developing robots able to encourage people to initiate interaction [29, 72]. The most common strategy for robots thus far has been to expect people to approach them to initiate a dialogue. In contrast, as shown in Fig. 6.1, our

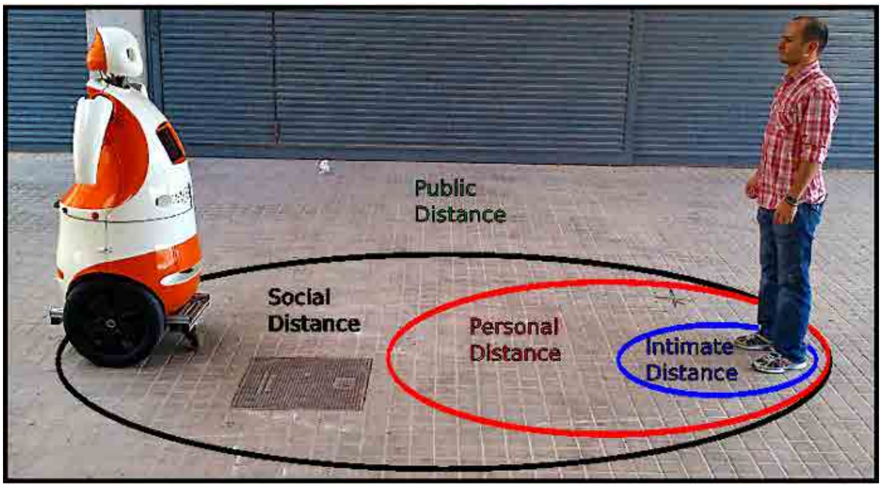

Figure 6.3: **Levels of Engagement.** Robot-to-person levels of distance, to distinguish levels of engagement while interacting.

research introduces a mobile robot that is able to approach people in a safe and friendly manner so as to begin a conversation.

The strategy for creating people-to-robot engagements is more pro-active than models which merely wait for the person to begin the interaction. In addition, the robot's ability to approach people opens up a wide range of possible applications. These include an invitation service, wherein a robot approaches people to offer city information and invite them on a tour; or the application proposed later in this chapter, where we use this pro-active behavior to improve the robot's perception skills by enabling it to learn from the human it engages with.

In order to allow the robot to independently initiate interaction with humans, we used a laser range scanner to detect people in the space [6].

After this initial localization phase, the robot approaches the person, always respecting common conventions of people's personal space. The robot is also able to respond appropriately to human reactions. For example, if after the initial approach, the robot invites the chosen person to come closer, and he/she does not notice, the robot will repeat the invitation. However, if the human simply declines to come closer, the robot will choose another volunteer. The robot will not begin the interaction process until the person visibly shows interest in the robot.

Assistance Expressions	
Invitation to create and engagement	Hey, how are you? I am Tibi. I'm trying to learn to detect faces, will you help me?
	Hi, I am Tibi, I'd like to learn how to recognize different objects, can you be my teacher?
Invitation to continue the interaction	Please, don't go. It will take just two minutes.
	Let me explain you the purpose of the experiment, and then, you can decide if you want to stay.

Table 6.1: **Phrases Uttered by Tibi.** Sample robot phrases to start interaction with a person.

The use of space we incorporated was based on the conceptual framework known as "proxemics," proposed by Hall [70]. This investigation establishes the following taxonomy of distances between persons within a group of people:

- Intimate distance: the presence of another person is unmistakable, close friends or lovers (0-45cm).
- Personal distance: comfortable spacing, friends (45cm-1.22m).
- Social distance: limited involvement, non-friends interaction (1.22m-3m).
- Public distance: outside circle of involvement, public speaking (>3m).

Based on these proxemics, Michalowski et al. [118] classified the space around a robot in order to distinguish human levels of engagement while interacting with or in the presence of a robot. Fig. 6.3 plots these four levels of distance and their corresponding engagements. In the present work, our robot uses the proxemics shown in Table 6.1 to try to maintain a "social distance" in the initial approach, assuming a "personal distance" only when the person has accepted the invitation to interact.

The active robot's behavior is carried out by developing a state machine, as shown in Fig. 6.4. Finite state machines (FSMs) are widely used in many reactive systems to describe the dynamic behavior of an entity. The theoretical concepts of FSMs and an entity's specification, in terms of state transition diagrams, have been used for quite some time [62]. A deterministic finite state machine is a quintuple $(\mathcal{K}, \mathcal{H}, s_0, \varkappa, \mathcal{F})$, where: $\mathcal{K}$ is a finite, non-empty set of symbols; $\mathcal{H}$ is a finite, non-empty set of states;

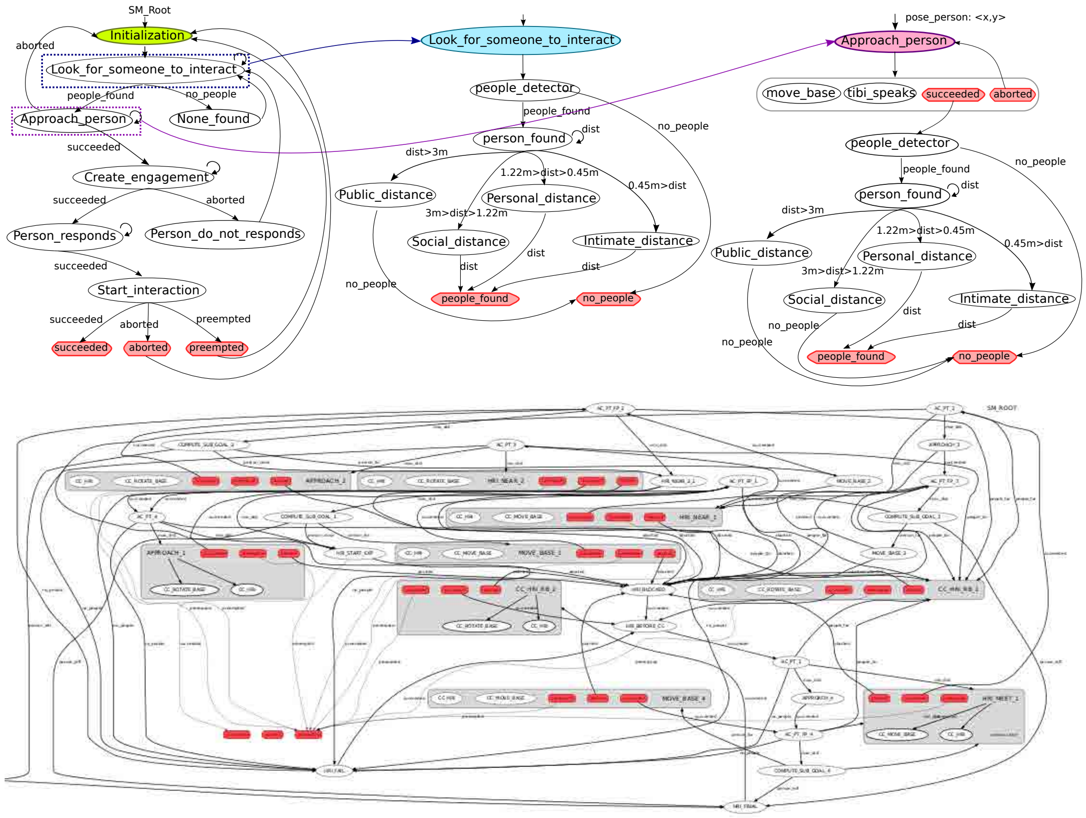

Figure 6.4: **Example of a state machine.** The robot attempts to create an engagement with a person. ***Top:*** Different components of the state machine. ***Bottom:*** The full state machine for this experiment.

s_0 is an initial state, $s_0 \in \mathcal{H}$; $\varkappa$ is the state-transition function, $\varkappa : \mathcal{H} \times \mathcal{K} \to \mathcal{H}$; and $\mathcal{F}$ is the set of final states, a (possibly empty) subset of $\mathcal{H}$.

This state machine allows the robot to respond appropriately to people's behavior. The robot is able to determine if humans are interested in initiating interaction simply by tracking their positions.

One of the main objectives of our study was to determine the optimal mode of robot behavior for initiating interaction with a human. Conducting a review of the literature on empathy and pro-social behavior [26], we were able to identify three different modes of behavior, wherein: (1) The robot uses only verbal cues to communicate with the participants; (2) The robot uses both verbal cues and non-verbal cues (gestures and eye gazes); and (3) The robot performs verbal and non-verbal cues, and effectively

Figure 6.5: **Tibi Gestures.** Movements performed by Tibi during experiments. ***Left:*** Three different emotional expressions. ***Right:*** Two actions.

approaches humans.

Once initial interaction is established and the human has accepted, the goal is then for the robot to approach him/her, moving from a "public distance" level to a "personal distance" level. In order to encourage the person to move even closer, the robot performs the following actions, depending on the aforementioned behaviors:

- *Verbal communication:* Encouragement comments, such as "Don't be afraid, I just want to talk with you", "Can you teach me to detect faces?"
- *Non-verbal communication:* Gestures, arms and neck movements. A few samples are shown in Fig. 6.5.
- *Robot motions:* The robot approaches the person until reaching a "social distance".

Each of these strategies will have a different impact on different users. For that reason, we performed a set of experiments to analyze the relative acceptability of each behavior model. A diagram of the different strategies is illustrated in Fig. 6.2.

6.3.1.1 Emotion Synthesis System

Emotions play a significant role in human behavior, communication and interaction [5]. Accordingly, the robot's emotions are important in our system. The robot expresses its emotional status by speech and gestures.

In order to synthesize Tibi's emotions of happiness, sadness and anger, we used the emotion model of the three dimensions of emotion [146]. This model characterizes emotions in terms of *stance* (open/close), *valence* (negative/positive) and *arousal*

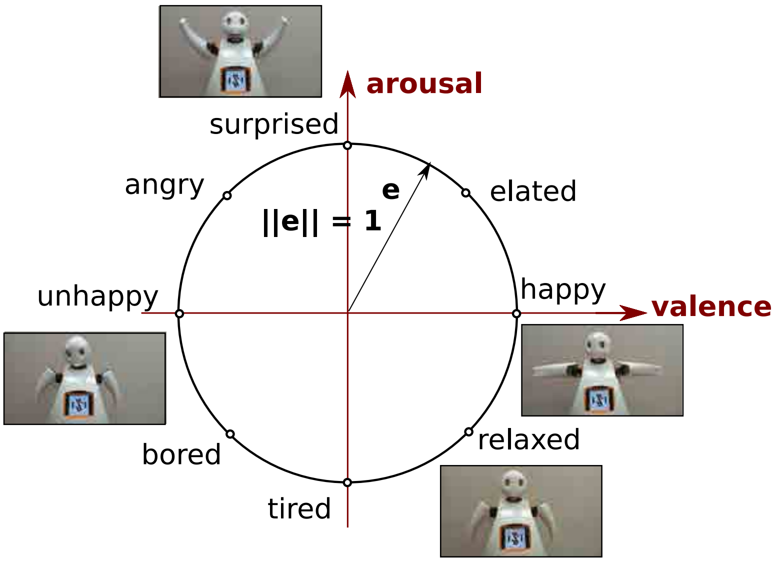

Figure 6.6: **Emotion space.** This representation is used to define the actual emotional state of Tibi; every emotion can be described by the parameters arousal and valence.

(low/high), thereby, it allows the robot to derive emotions from physiological variables. Our system relies on an open stance because Tibi is motivated to be openly involved in interaction with humans, see Fig. 6.6.

Arousal factor

The arousal factor is determined by the human and the human's responses, and by factors such as whether Tibi finds the human, and whether the human responds. For the implementation of the arousal factor, the intensity of the perceived stimuli is required. Furthermore, the perception system is able to rate the current state of engagement between the human and Tibi.

In order to define the intensity of perceived humans is used. In the current implementation the distance is used to measure the intensity. For this computations the distance zones are used, see Fig. 6.3.

The intensity of a human perceived in the public zone is rated as zero, whereas a person entered the intimate zone is assigned to the maximum intensity. The relative intensity of a person is more interesting than the absolute value. If a human enters the personal zone (coming from the social zone) its intensity will increase and the arousal

Algorithm 5 The intensity of perceived people is computed depending on their distance to Tibi.

for Each perceived person **do**
  Compute corresponding distance zone
end for
Intensity $i = 0$
for Each distance zone **do**
  switch distance zone
    case social zone
      Compute i

$$i+ = (p\_p(t) - p\_p(t-1)) \cdot z\_l \tag{6.1}$$

    end case
    case personal zone
      Compute i

$$i+ = (p\_p(t) - p\_p(t-1)) \cdot z\_l \tag{6.2}$$

    end case
    case intimate zone
      Compute i

$$i+ = p\_p(t) \cdot z\_l \tag{6.3}$$

    end case
    otherwise
      no changes of i
    end case
  end switch
end for

should be increased as well. Assuming that the volunteer remains in the personal zone its intensity will remain the same, but the arousal should not increase anymore, otherwise one would become frightened all the time.

To avoid these problems, the relative intensity is used for the social zone and for the public zone. Therefore, only changes in the intensity are considered for calculating the arousal. This is slightly different for the intimate zone. Thus, for the intimate zone the absolute intensity is used. Based on these assumptions, the global intensity of the currently detected people can be calculated. The currently perceived people located in a specific distance zone are represented by $p\_p(t)$, whereas the previously people located in this zone are described by recognized $p\_p(t-1)$. For every zone a specific intensity level is used represented by zone level. In the current implementation these zone levels (z_l) are defined as follows: Public zone $z\_l = 0$, social zone $z\_l = 0.25$, personal zone $z\_l = 0.5$, and intimate zone $z\_l = 1$. This process is presented in Algorithm 5.

Algorithm 6 Arousal ($A(t)$)

if $i > 0$ **then**

$$A(t) = A(t-1) + weight \cdot \frac{i}{\#\ p\_p} \tag{6.4}$$

else

$$A(t) = A(t-1) - step \tag{6.5}$$

end if

limit $A(t)$ to the interval $[-1, 1]$

The arousal factor is determined by the human and the human's responses, and by factors such as whether Tibi finds the human, and whether the human responds. If Tibi fails to find the human, the intensity decreases and, therefore, the arousal is lower. When Tibi finds the human and asks the human something, the arousal decreases if the human says nothing to the robot for a long time. Low arousal increases the emotion of sadness. High arousal increases the emotions of happiness and anger by determining whether the human's response is positive or negative.

If a certain object has already been recognized before, difference between the current situation and the previous one is rather small and therefore, the relative intensity value is rather small, too. Based on these definitions of the objects' intensities the robot's arousal can be calculated according to Algorithm 5. At first the global intensity of all currently perceived objects is calculated.

To normalize the intensity to the range of $[0, 1]$ the intensity value is divided by the number of currently perceived people. If a certain intensity has been detected, the previous arousal value $A(t-1)$ is increased depending on the global intensity and a specific weight that indicates how fast the arousal value increases. In this work, the weight is set to 1. If no intensity is measured the arousal value is decreased. The value for decreasing is represented by step. Inspired in [78], the current step is set to 0.25. Finally the arousal value is limited to the range of [-1, 1], Algorithm 6 describes the process to compute the arousal value. In Fig. 6.7, plots of the stimulus intensity and arousal value are depicted given the distance between Tibi and a person.

Valence factor

Valence represents the robot's satisfaction with current situation. For example

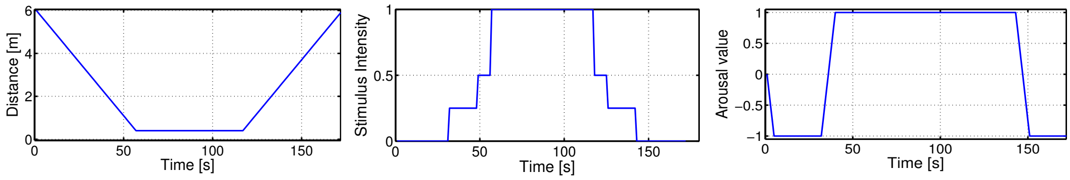

Figure 6.7: **Arousal value.** ***Left:*** Distance between a volunteer and Tibi during the experiment. ***Center:*** Intensity stimulus with $weight = 1$ and $step = 0.25$. ***Right:*** Arousal value.

achieving a goal increases the valence. This depends on the current achievement of the internal goals of the robot. For instance, if the robot is currently pursuing one goal, the valence depends on the rating of the achievement of this goal. If the goal is almost achieved, the valence will be rather high; if the robot is far away from achieving this goal the valence is low. If the robot is pursuing multiple goals, the valence is calculated depending on the achievement of all of these goals.

In this thesis, valence factor is determined by whether the human responds appropriately to the robot's requests. When Tibi waits for a "*yes*" or "*no*" answer, if the human says something unexpected that Tibi can't understand, the user responds negatively. A negative response increases the emotion of anger; a positive response increases the emotion of happiness.

6.3.2 Online Human-Assisted Face Recognition

Once the robot has initiated engagement with a human, we outlined an approach in which the human helps the robot to enhance its visual skills.

To allow our robot to benefit from the human's assistance, we equipped it with a screen that depicts the results of the classifier. When one of the frames in the input video contains a face about whose identify the robot is not confident, it asks for the human's help, through a set of precise and non-technical "*yes*" or "*no*" questions, answered using the Wii remote control. Table 6.2 shows some examples of these questions. The Wii remote control is introduced by the robot, who then is able to explain that someone running the experiment will give the participants the Wii remote control and show them how it works.

Assistance Expressions	
Assistance	Is your face inside the rectangle? I'm not sure if I see you, am I?
No detection	I can't see you, move a little bit. Can you stand in front of me?
Farewell	Thank you for your help, nice to meet you. I hope to see you soon.

Table 6.2: **Assistance Expression.** Sample phrases uttered by the robot when updating the visual classifier.

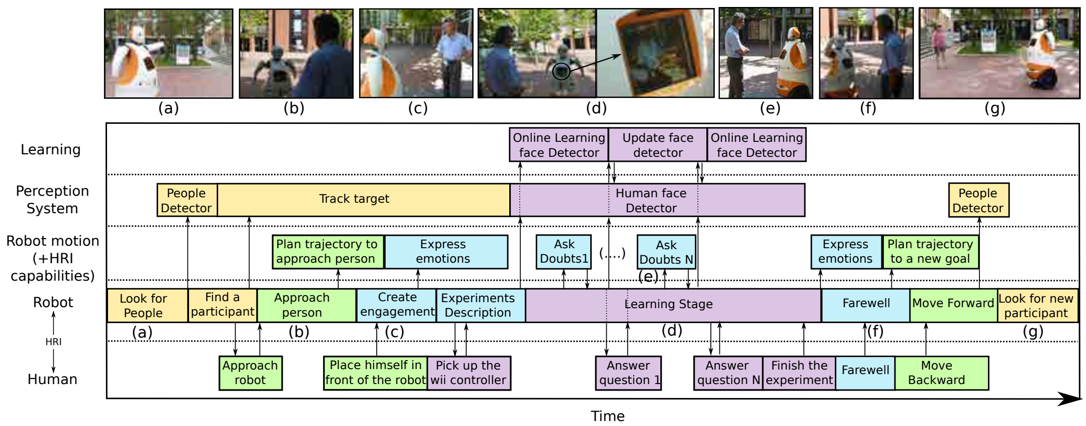

Figure 6.8: **Diagram of the interaction.** Internal elements of Tibi and a person during the experiments.

Finally, in Fig. 6.8, the illustration of the whole interaction between Tibi and a volunteer and the internal elements are presented.

6.4 Real-Life Experiments

Before using the user study to determine whether different robot behaviors are socially appropriate to humans, we conducted real-life experiments to evaluate the robot's behavior. The approach proposed below was effectively tested in the BRL.

Real-world experimentation showed unexpected obstacles that had not come up during the simulations. We observed severe limitations of the perception system, laser people detector, and tracker. People were not always properly detected, and the data

Figure 6.9: **Real-life experiments:** Some examples of the real experiments conducted.

association was occasionally wrong. However, an in-depth discussion of the perception system falls outside the scope of the present thesis.

6.4.1 Robot Proactively Seeking Interaction

We carried out 40 experiments with different volunteers. In each instance, the robot was able to approach the participants and initiate engagement. Fig. 6.9 depicts examples of the experiments performed with several volunteers in different urban environments.

Fig. 6.10 shows two samples of the paths taken by robots when approaching a person. The left image shows the robot inviting the person, in-motion, to begin the interaction; on the right, the person is simply waiting for Tibi.

Once a significant number of real experiments with different volunteers were conducted, we observed that the system worked, and the robot was able to approach humans and begin interactions with untrained people. We used these findings to proceed to conduct a user study, designed to determine whether the robot's behavior was socially acceptable to humans. This component is described in depth in Section 6.5.

6.4.2 Human-Assisted Face Recognition

The human-assisted facial recognition system was evaluated in terms of the degree of human intervention and its effects on human-robot interaction. We focused specifically on the duration of the established interactions and the level of users' comfort therein.

The classifier used in the detection phase yields a score $\varsigma \in [0, 1]$, which represents the classifier confidence. Generally, when $\varsigma > 0.5$ the detection is assigned to a positive class. However, there is an interval ϑ in which the system is unable to assign the detection to a positive or negative value. In these cases, our approach is to ask the user

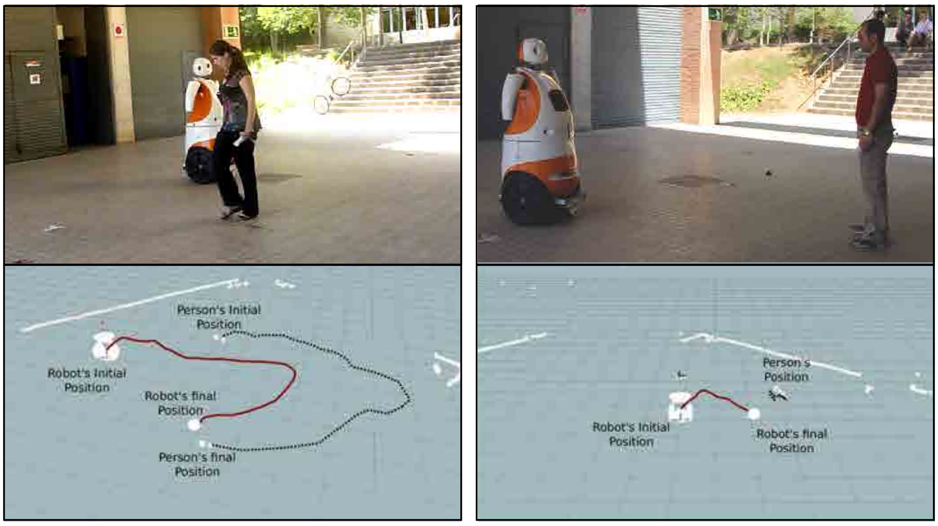

Figure 6.10: **Tibi initiates an interaction.** The robot approaches two different people and begins an interaction with them. ***Left:*** Tibi follows the person in motion and invites her to initiate the interaction. ***Right:*** The person waits for Tibi.

if the detection is positive (i.e., correct) or negative, and thus enhance the detections. By conducting these experiments, we attempted to discover the range and degree of human assistance in which the interaction becomes more effective. Fig. 6.11 shows different volunteers assisting Tibi robot.

Fig. 6.12 shows the impact of the human assistance on human-robot interaction. The figure on the right reflects the percentage of human intervention for different assistance intervals ϑ. It shows that the percentage of assistance increases as the interval grows larger, suggesting that the greater the distance, the more active people will be in the interaction, the more they will help the robot to learn and recognize faces, and the more effort they will make generally in the engagement. This results in shorter interactions, seeing as people grow tired and quickly lose interest in helping the robot to enhance its facial recognition skills. Fig. 6.12-*Left* shows this behavior by illustrating the average interaction and assistance times. As the degree of human assistance grows larger (and with it, interval size), the interaction time between robot and humans becomes shorter. It is also noteworthy that the interaction time with a smaller percentage of human intervention is relatively short. This is because when human participation is minimal (i.e., when human users seldom help the robot), people also lose interest in

Figure 6.11: **Human assistance**. ***Top:*** People assisting Tibi robot in outdoor scenarios. ***Bottom:*** Tibi's field of vision. The output of the recognition system is shown by rectangles. Correct detections are represented by green boxes; blue boxes indicate when the system is not confident and requires the help of a human.

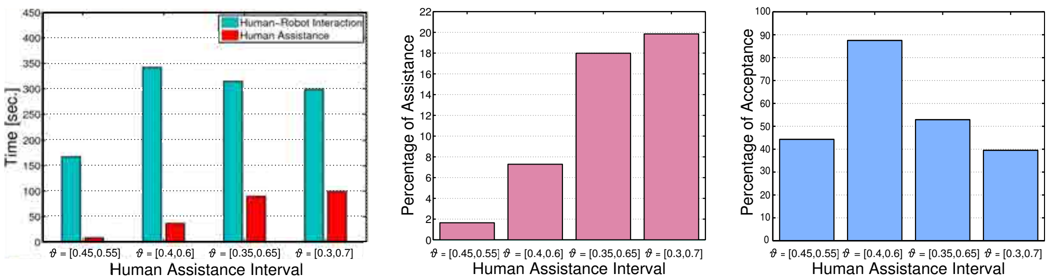

Figure 6.12: **Human Assistance Results**. ***Left:*** Average times spent for human-robot interaction and human-assistance. ***Center:*** Percentage of human assistance in the face recognition system according to varying assistance intervals. ***Right:*** Percentage of users' acceptance.

the cooperative and interactive task of face learning and recognition. The illustration on the right of Fig. 6.12 depicts the percentage of human acceptance of the robot's behavior. We found that a satisfactory compromise between the human's effort and interaction time is achieved for an assistance interval of $\vartheta = [0.4, 0.6]$.

6.5 User study

The results presented above demonstrate that the robot is able to approach people and initiate interaction. A user study was also conducted to determine whether the three strategies presented above are perceived by people as socially appropriate.

The hypothesis we endeavored to test was as follows: "Participants will perceive a difference between the three robot behaviors and will assist at a greater rate when the robot is able to move and approach people according to accepted social conventions."

6.5.1 Procedure

The urban area considered for the tests is the Barcelona Robot Lab in the campus of the Universitat Politècnica de Catalunya (UPC), with an approximate size 10.000 m^2, introduced in Section 3.6.1. During the experiments, the robot was randomly navigating across this area while looking for people to initiate the interaction. For the experiments, we use a mobile service robot, Tibi, specially designed to operate in urban pedestrian areas.

The Tibi robot is equipped with multiple sensors, including a Bumblebee stereo camera and three lasers. In order to initially detect the persons at large ranges we use the front laser mounted at 40 cm above the ground. This just yields a rough estimation of the person's pose. The precise localization of his/her face is performed with one of the stereo cameras. In addition, a touch screen is located at the front of the robot, it is used to communicate with people.

6.5.2 Results

In the experiments, we compared the different robot behaviors for initiating interaction, as described in Section 6.3. At first, the robot used only verbal instructions to attract people's attention. Later, it was allowed to rotate so as to focus more closely on people's positions. Lastly, the robot was able to move towards the people to interact with them. Assistance could begin only once engagement had been initiated.

We selected 30 people (16 women, 14 men) on the University Campus to participate in the experiments. Participants were ranging in age from 20 to 65 years (M = 39.24, SD = 12.86), and represented a variety of university majors and occupations including computer science, mathematics, biology, finance and chemistry. For each participant, we randomly activated one of the three robot behaviors for initiating interaction. Then, each participant helped the robot to improve its visual skills. Again, none of the participants had previous experience working or interacting with robots.

Survey's Questions	
General Robot Behavior Scale	Cronbach's alpha = 0.74
How comfortable did you feel near the robot?	
How safe did you feel around the robot?	
How human-like did the robot behave?	
Robot's Sociability Scale	Cronbach's alpha = 0.82
How social was the robot's behavior?	
How natural was the robot's behavior?	
How well did the robot's movements adhere to human social norms?	
Robot's Intelligence Scale	Cronbach's alpha = 0.79
How intelligent did the robot behave?	
How well could the robot anticipate to your movements?	

Table 6.3: **Questionnaire.** Survey questions asked of each participant. All questions were asked on a 7-point scale from "Not at all" to "Very much".

Participants were asked to complete a variety of surveys. Our independent variables considered whether the robot approached the person or if it only used voice instructions. The main dependent variables involved participants' perceptions of the robot's persuasiveness, their compliance with the robot's suggestions, and their perceptions of the robot's social and intellectual characteristics. Each of these fields, was evaluated by every participant using a questionnaire to fill out after the experiment, based on [91]. Some questions are presented in Table 6.3. The questions were answered on a Linkert-scale from 1 to 7 (1 being "Not at all" ; 7 being "Very much"). We conducted a variance analysis (ANOVA) measurement for the evaluation score. Participants were also invited to submit additional comments on each robot behavior.

Social Scales

Participants were asked to answer nine questions, as shown in Table 6.3, following their encounter with the robot in each mode of behavior. To analyze their responses, we grouped the survey questions into two scales: the first measured overall robot behavior, while the second evaluated more specific questions on the robot's movement. Both scales surpassed the commonly-used 0.7 level of reliability (Cronbach's alpha).

Each scale response was computed by averaging the results of the survey questions comprising the scale. ANOVAs were run on each scale to highlight differences between the three robot behaviors.

Below, we provide the results of comparing the following three robot behaviors: *(B1)* the robot only uses verbal communication; *(B2)* the robot uses both verbal communication and gestures; and *(B3)* the robot uses verbal, nonverbal communication and may approach the person.

For the global evaluation score plotted in Fig. 6.13-*Left*, repeated ANOVA measures were conducted. A significant main effect was found, $F(2, 27) = 38.23$, $p < 0.001$, $\eta^2 = 0.27$. Multiple comparisons with the Bonferroni method revealed that the score for *B3* is significantly higher than both behaviors *B1* ($p < 0.001$) and *B2* ($p < 0.001$). No significant difference was found between *B1* and *B2* ($p = 0.224$).

To analyze the source of the difference, additional scores were examined. For the sociability of the robot (Fig. 6.13-*Center*) a repeated-measures analysis of variance revealed a significant main effect, $F(2, 27) = 139.30$, $p < 0.001$, partial $\eta^2 = 0.1$. Pairwise comparison with Bonferroni showed a remarkable difference between the three strategies as well. *B1* vs. *B2*: $p < 0.01$; *B1* vs. *B3*: $p < 0.001$; *B2* vs. *B3*: $p < 0.001$.

Finally, for the robot's intelligence (Fig 6.13-*Right*), a repeated-measures analysis of variance revealed a significant main effect, $F(2, 27) = 27.15$ $p < 0.001$, partial $\eta^2 = 0.33$. Pairwise comparison with Bonferroni revealed that the score for *B3* is significantly higher than both *B1* ($p < 0.001$) and *B2* ($p = 0.0015$) strategies. No significant difference was found between *B1* and *B2* ($p = 0.33$).

In summary, from our analysis of the three different behaviors, we may conclude that when the robot uses verbal and non-verbal communication, and is able to approach the person, it has the largest rate of acceptance by humans. Under these circumstances, people generally perceived the robot to be more intelligent, seeing as it could detect and approach them; they also believed that it had better social skills.

Participants Comments

Each questionnaire included several blank lines underneath the social scales, where participants could record additional thoughts on the experiments. While we did not explicitly codify and analyze these comments, they do provide further insight into the effect of the three robot behaviors.

Comments when the robot uses only verbal communication *(B1)* : Many

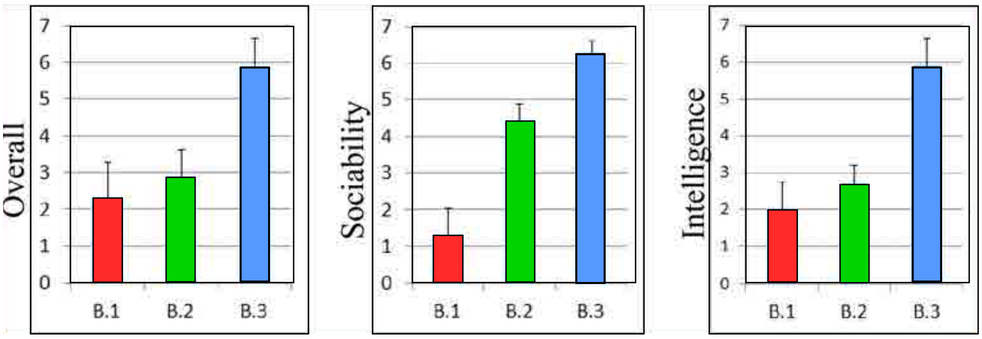

Figure 6.13: **HRI Results.** Degree of acceptance of the three robot's behaviors. ***Left***: Global evaluation of the strategies. ***Center:*** Robot's sociability. ***Right:*** Robot's intelligence, as perceived by the humans.

of the comments received reflect that the robot did not attract the attention of volunteers. Participants noted:

"I didn't think the robot was talking to me, because it wasn't moving."

"The only quality I can attribute to him is that he knew when I was walking around him."

"The fact that the robot didn't move made it difficult for me to know whether it was interacting with me or not."

"The robot attracted my attention because it's cute, but not because of its behavior."

Note that the comments on this behavior indicate that participants felt that the robot did not try to initiate engagement with them.

Comments when the robot uses both verbal communication and gestures *(B2)* : Many of the comments reflect that the robot did not attract participants' attention to a satisfactory degree. Tibi was considered a social robot, but was not perceived as intelligent:

"I like when she gestures, and attracts my attention, but I would have preferred that the robot also approached me, not just waited for me to act."

"I love when the robot greets me when I pass nearby, I find it very sociable."

"If Tibi was able to move, it would draw more attention and hold my interest, yet

I find it very interesting that I could play the role of a teacher."

"I like that the robot comes do me and doesn't wait for me to approach it before speaking to me."

Note that the comments on this behavior generally indicate that although participants felt that the robot tried to initiate an engagement with them, it was not enough, and most participants wondered if Tibi was moving independently.

Comments when robot uses verbal, nonverbal communication, and was free to approach the person *(B3)* : Many of these comments indicated that participants felt that the robot tried to initiate engagement with them, and they were generally interested in the robot's skills:

"This is the first time I find myself around a robot who interrupts me in order to help me; it's very original."

"Tibi is very polite, and I find it charming that it follows me around until I pay attention."

"I felt that Tibi obeyed social conventions by approaching me and starting the interaction."

"Does it mean that Tibi will be here alone? That's original but may be dangerous for her."

"I feel that the robot is very intelligent because she knows when I'm nearby and approaches me in order to interact. I'd like to know what else she can do." (emphasis in original)

"It's funny that Tibi gets mad when I ignore her; it would be interesting to see if she remembered me next time she sees me."

Note that the comments on this behavior indicated that participants felt that the robot tried create an engagement with them. Moreover, Tibi behaved in a socially acceptable manner and generally understood if people wanted to interact with her or not.

6.5.3 Discussion

The findings presented in the previous section reinforce the idea that the robot's ability to initiate engagement is an important skill in a robot's natural interaction with people. Overall, people were surprised to find a robot in a public space, and they were astonished when the robot caught their attention. Moreover, they enjoyed helping the robot to detect their faces and were surprised to see how the robot progressively improved its skills with their help.

The experiments we conducted yielded conclusive results. We found that people felt their interaction with the robot was more natural when the robot communicated through gestures, verbal cues, and motion. Detailed analysis showed that these capacities improved human's perception of the robot's intelligence and sociability. We also found that the amount of speech and comments made by the robot seems to be appropriate for this type of scenario. Furthermore, people felt comfortable using the Wii remote control to communicate with the robot.

We were also able to effectively demonstrate that human assistance helps to build the skills to detect individuals' faces and identify specific objects. The whole process was performed very efficiently and with minimal human effort. The results show that the use of a social robot piques people's interest and encourages them to help the robot improve its visual skills.

We noticed that very few participants were capable of specifically listing the robot's disadvantages, but most provided helpful suggestions when asked about possible improvements for Tibi. People noted an interest in communicating with the robot via voice commands, believing that kind of communication to be more comfortable. They also suggested that it would be interesting if they could teach the robot to identify new objects by pointing them at the robot's screen. Both of these remarks will be incorporated in our future research.

Finally, we must address some of the cultural limitations of our project. The parameters and definitions for human personal space, employed in the first set of experiments, are specific to European peoples and to the design of our own robot. Therefore, if this experiment had to be adapted in other cultures, its parameters would need to be adjusted accordingly. In addition, the proposed model of interaction was tested in a specific scenario, and so its application in other situations is limited. It is possible that context and environment significantly affect humans' preference for a specific mode of robot behavior. For example, in a business environment, a mobile robot approaching people could be annoying, as its interruptions could disturb people. We believe that the University Campus is rather neutral, and can thus reflect general trends in interaction in many daily use scenarios. Yet, this question warrants further study.

6.6 Summary

We have presented an autonomous mobile robot seeking interaction for human-assisted learning. The contributions of this chapter are two-fold. First, we have studied different robot behaviors to initiate interaction with humans. The robot was able to autonomously approach a person and create an engagement with him/her.

Secondly, once the engagement was created, people could assist the social robot to improve its visual skills. Following the assisted learning stage, the robot was able to detect people by using its visual skills even under challenging scenarios, such as when the objects were partially hidden or appeared with major alterations in their appearance.

Both contributions have been extensively and rigorously tested in a real environment. The findings suggest that allowing the robot to take initiative when communicating with people generally increased the number of human-to-robot interactions. This, in its turn, allows humans to help robots improve their visual skills, and engage in subsequent and more predictable interactions.

Chapter 7

Conclusions and Future Work

It's more fun to arrive at a conclusion than to justify it.

Malcolm S. Forbes

Ending a dissertation gives the chance to write a valuable set of conclusions about the work in order to share them with the scientific community. Furthermore, a thesis also opens new questions to be studied, and it is also important to clearly define which are these new topics to be addressed by future works.

7.1 Conclusions

This thesis has tackled several challenging issues in the field of cooperative social robots. It has described an innovative framework which allows robots to interact naturally with humans and their environments, effectively navigating, guiding, or accompanying people within urban settings. In this sense, this work effectively addresses four principal concerns: *(i)* the concept of social companion robots accompanying people; *(ii)* the discrete time motion model for escorting a group of people using several robots which behave in a cooperative and safe manner; *(iii)* the Prediction and Anticipation Model (PAM), which helps to prevent people from straying from the formation, and to determine the optimal robot behavior for helping people stay in the group in specific areas where they may become distracted; and *(iv)* the nature of the robots' ability to effectively engage with humans. We demonstrated these behaviors both in simulations and in user studies with our robots, Tibi and Dabo. This chapter presents the conclusions yielded by the approaches we proposed in order to investigate the aforementioned tasks.

The first major contribution of this thesis is the innovative robot-companion approach based on the newly founded Extended Social-Forces Model. By studying how people navigate around one another, we were able to formulate a key set of social forces, represented as mathematical constraints. We presented a powerful scheme for robots' behavior in terms of motion based on the social-forces concept (Section 3.5.3). This socially behavior is well-suited for tasks of robot companionship, a better performance has been demonstrated if human interactions are taken into account.

We also introduced a robot companion metric (Section 3.5.1). Since it is difficult to effectively evaluate any system in which natural human behavior plays a role, we needed to develop an analytical metric to justify the behavior of our robot companion approach. This assessment is based on the notion of "proxemics", as proposed by Hall [70], and ensures that the robot's navigation is socially acceptable to the person being accompanied, as well as to other pedestrians in the vicinity. It also works to prevent the robot from invading the human's personal space.

In order to refine the robot's behavioral skills, we employed an interactive learning method. This strengthens the model by generating instances of controlled interaction which enhance the social acceptability of the companion robot's behavior. We believe that human feedback for parameter learning is a key component to the development of robots specially designed to interact with people (see Section 3.5.2).

To validate the model, we performed an extensive set of simulations and real-life experiments in a an urban environment. We noted several practical applications of our experiments, among them, robots guiding tourists around a city, or accompanying professional visitors. Our overall validation of the approach in real scenarios was informed by feedback information received directly from the volunteers themselves. These contributions have been presented in [41, 44, 49].

The second principal contribution of this thesis is the development of a new framework for guiding people in urban areas with a set of cooperative mobile robots, Chapter 4. The proposed approach offers several significant advantages, as compared with those outlined in prior studies. Firstly, it allows a group of people to be guided within both open and closed areas, potentially containing obstacles; secondly, it uses several cooperative robots; and thirdly, it includes features that enable the robots to keep people from leaving the crowd group, by approaching them in a friendly and safe manner.

Our design assigned one of the robots to be the leader, or tour guide. This head robot was placed at the front of the group and its role was to predict the trajectory of the people and the other robots. These follower robots, or “shepherds”, were responsible for guiding the people, preventing them from leaving the group, and following the path as determined by the leader.

At the core of our approach, we proposed a “Discrete Time Motion” (DTM) model, which works to represent human and robot motions, Section 4.4, in order to predict people’s movements, so as to plan a route and provide the robots with concrete motion instructions. Moreover, the interaction with the obstacles of the environment is considered through a potential field, wherein both the people’s and the robots’ positions are represented by continuous and derivable functions.

Another key feature of our model is the realism we achieved in our dynamic models for both robots and people. Both models were validated through video sequences of groups of people performing different kinds of motions. The models we proposed were in fact very good close approximations of these real situations.

In contrast to previous approaches, our method can tackle realistic scenarios, such as large environments containing obstacles, or situations in which people naturally stray from the group. We presented various results in situations wherein robots guide people in open areas, areas with a single obstacle, and urban areas with a large number of obstacles and other hazards. In all of these experiments, we were able to show that the robots could perform satisfactorily and be competent guiding people in realistic situations.

Moreover, we described the validation process of the simulated model that explores new possibilities for interaction when humans are guided by teams of robots working cooperatively in urban settings. In our experiments, a group of people was guided by a team of three robots. We recorded their motions on video in the Barcelona Robot Lab, an urban space wherein they followed diverse trajectories. The motions of both the people and the robots, which were extracted from the video sequences, were later compared against the predictions yielded by the DTM model. This work has been published in [56, 58].

The third contribution of this thesis is the development of a “Prediction and Anticipation Model”, which was designed to guide people using multiple robots working together cooperatively (see Section 5.3). This model projects the behavior of a group of people (prediction) using a particle filter. It also enables us to determine the optimal distribution of robots for preventing people from straying from the formation in specific areas of the map (anticipation). Using this model enabled us to keep people from straying from the guided group, and thus to facilitate the task of the robots. Furthermore, we found that we could locally optimize the work performed by robots and people alike, and thereby yielding a more human-friendly motion.

We conducted several simulations to test the proper functioning of the model. Due to technological constraints and safety concerns, we were not able to test the complete method in real-life scenarios; this constitutes a large component of our future research. Despite this limitation, we were able to successfully evaluate the effect of a robot’s pushing and dragging forces on people in real-life situations using one of our robots.

This dissertation describes and interprets the findings yielded by various simulations conducted in open areas littered with obstacles and characterized by individuals’ behavioral movements. In each simulation, we were able to show that, by using the PAM model, the robots could act preemptively to prevent people from getting lost or straying from the group, and we believe that the same results can be replicated in urban areas with a large number of obstacles. Although thus far we have only assessed the functionality of the PAM model in simulations, we conducted real-life experiments to validate Helbing’s forces using our robot, Tibi. We also assessed the participants’ preferred dimensions of personal space, data which was then incorporated into our simulations. These concepts have been presented in [50, 55, 57].

Finally, *the forth contribution of this thesis* is the framework for an autonomous mobile robot capable of interacting to acquire human-assisted learning (see Chapter 6). First, we studied different robot behaviors for initiating interaction with humans, wherein the robot was able to autonomously approach a person and successfully engage with him/her (see Section 6.3.1). To refine this, we looked into the human communication model proposed by Clark [25], based on the notion that people in a conversation perceive the roles of other individuals, such as a speaker, listener, and side participants. On the basis of this insight, we furnished our robot with a simple visual module for detecting human faces in real-time, with the caveat that the faces had to be in a non-occluded and frontal position in order to be perceived accurately.

Once contact was initiated, people were given the opportunity to assist the robot to improve its visual skills. After this assisted learning stage, the robot was able to detect people by using its visual skills, even under challenging scenarios, such as when objects were partially occluded, or appeared with major changes in their appearance (Section 6.3.2).

We tested both contributions extensively and rigorously in real environments. Our findings suggest that allowing the robot to take the initiative generally increased the number of human-to-robot interactions. This increase, in turn, allows humans to help robots improve their visual skills, and engage in subsequent and more predictable interactions. These contributions have been presented in [44, 59, 171].

Overall, our research demonstrates the need for robots that are able to operate acceptably around people; to behave in accordance with social norms while accompanying and guiding them; and to acquire acceptable behaviors in their presence. Moreover, our work shows that cooperation amongst a group of robots optimizes the performance of the robots and the people alike, therefore generating a human-friendly motion. Finally, while much research remains to be done, we believe that this work will be greatly beneficial to future robots, as well as to the people who work with them.

7.2 Future Work

Although several problems regarding the cooperation of robots to accompany and guiding people were addressed in this dissertation, there are still some important issues to be addressed in the future. This chapter is aimed at discussing new possible routes of research arising from the work presented in the previous chapters, taking into consideration the current and future requirements to be fulfilled in order to build smarter and friendlier robot companions.

7.2.1 Limitations of the current work

The focus of this thesis has been on the development of a framework that allows robots to interact naturally with humans and their environment, while robots navigate, guide or accompany people in a cooperative way in urban settings. However, the current implementation of different methods has several limitations that must be addressed before the framework can be used as part of a complete system. In particular, the primary limitation relates to people detection and tracking.

7.2.1.1 People detection and tracking

This subsection describes the limitations we came across while testing our model in real-life scenarios and which led us to continue testing exclusively through simulations.

No robust methods exist to detect people's poses –position and orientation– when they move in a group in pedestrians areas. From the point of view of a robot on one of the sides of the group, some individuals are inevitably partially or completely occluded. If the group has a small number of people the chances of achieving accurate pose detection are high, but if there are many people, detection becomes very difficult. Since our method is based on estimating the pose of each person of the group, pose detection is key to our research.

Since in this dissertation people must be treated as social entities, and not just obstacles, robots must be able to accurately detect where people are in the environment. Unfortunately, the laser-based detection and tracking system we currently employ (see Section 3.4) performs quite poorly in real world escenarios. The tracker could be improved in many ways, we are planning to use a multi-sensor approach to better determine the locations of pedestrians in the environment. For instance, by combining the laser range scanners with a vision system able to detect people by shape, the tracker could achieve higher accuracy.

7.2.1.2 Additional real-life experiments

While this dissertation has presented a wide range of results from simulations, and most robots' behaviors were addressed in real-life experiments, the cooperative behavior of a group of robots was addressed in a simple scenario, Section 4.6.3.

Experimental work using teams of robots in real scenarios is necessary. As it has been mentioned in Section 5.2.1, there are some drawbacks that made it difficult to carry out more sets of real-life experiments. The analysis made allows us to conclude that several drawbacks, common to most strategies, still remain. Among others, future work will focus on factors such as: resource utilization, interference, communication load or workload among robots when performing the cooperative tasks.

Finally, there is a problem constraint which derives from robots' motions. Robots cannot accelerate or go faster than people in a safe way. This means our robots cannot usually follow people's behavioral reactions. Currently, there is not enough data on people's reactions to robots' motion instructions. Instructions like "please return to the group" or "do not go away" might cause different reactive motions in different touring situations.

7.2.2 Future lines of research

We believe that the methods presented in this thesis can introduce new lines of research. Firstly, from Chapter 3, robots behavior in terms of motion can be enhanced by making robots' navigation more natural, sociable and comfortable for humans. Moreover, in this thesis robots navigate in urban environments with pedestrians in the surroundings, therefore, we believe their navigation systems must understand the social conventions followed by people. Secondly, a task that we think could be represented with the frameworks mentioned in Chapters 4 and 5 is emergency evacuation robots. New people's behavior must be considered, such as panic situation, thus, a set of robots could evacuate groups of people if it is required. Finally, continuing the work presented in Chapter 6, we aim to find new methods for robot interactive learning through human assistance.

7.2.2.1 Understanding human interaction for social autonomous navigation

Nowadays, a mobile robot must be able to successfully navigate in the environment where it is working, many different algorithms for obstacle avoidance have been developed. The presence of humans requires novel approaches in terms of robot navigation. Allowing robots navigate among humans opens different interaction possibilities for robots.

Most of the works on human-aware robot navigation attempted to improve robot acceptance, but the methods might vary. Some of them try to minimize stress, in order to make the interaction more comfortable for pedestrians [29, 39]. Others aspire to make robots behave more natural and sociable according to cultural conventions [11].

Moreover, robots behavior should follow social conventions, respecting proximity constraints, avoiding people interacting or joining a group engaged in conversation without disturbing. The sociology literature often refers to the concept of personal space proposed by Hall [70].

For instance, if the robot aims to join a group, it must get permission from the group to be integrated. In order to develop social robots, the notion of human to human interaction needs to be included.

As future work, we plan to improve the robot's behavior presented in Chapter 3, and obtain robots which are able to navigate in a more comfortable, natural and sociable way while accompany/guide a group of people.

7.2.2.2 Emergency evacuation robots

Robots are becoming popular tools for traditional search and rescue missions [23]. Several studies have been performed in order to investigate how people react in emergency situations [155]. Emergency evacuation robots offer many advantages over traditional methods of notification and guidance. In particular, during an emergency situation the only notification that people receive is a buzzing alarm, and the guidance they receive comes from stationary signs and their own recollection. Emergency personnel can assist, but they need time to arrive at the site and they take a great risk by entering a building during an emergency. Robots can be stored inside and become active as soon as an evacuation is called. They can approach people and guide them out of the building with no danger to emergency personnel.

For that reason, we aspire to build a framework to make robots capable of evacuating people as an expansion of the models presented in Chapters 4 and 5. To solve this task, people's behavior such as panic situation must be considered, and new robots' strategies have to be studied, thus, a set of robots could evacuate groups of people if it is required.

7.2.2.3 Robot interactive learning through human assistance

Humans live interacting with other people and perform tasks in individual and collective ways everyday. Robotic researchers are interested in designing robots that can interact with people in the same way as humans do. In order to reach this goal, robots must learn from the interaction with humans and learn humans skills used in everyday life. The learned social behaviors could be used in a wide range of real-world scenarios, such as, domestic tasks, shopping, assistance, guidance, entertainment, surveillance, or rescue.

There are many examples where these interactions occur, but some of them are very basic and people do not realize the extreme difficulty that entails executing such tasks for a robot. The navigation in crowded environments, or the social engagement to initiate a conversation, are typical examples.

Continuing the work presented in Chapter 6, we plan to develop new techniques to learn from the interaction with humans using multi-modal interaction. The models can be learned off-line or on-line, and humans can use the information coming from inputs and the outputs to train the system again in order to improve the models. We expect that with these new techniques, the multi-modal interactive system can improve the accuracy and robustness of the methods.

Appendix A

Tibi and Dabo Mobile Robots

Two mobile service robots, designed to operate in urban, pedestrian areas, were bought and properly modified and equipped for the URUS (Ubiquitous Networking Robotics for Urban Sites) project [143]. These are Tibi and Dabo, pictured in Fig. A.1. They are based on two-wheeled, self-balancing Segway RMP200 platforms, and as such are highly mobile, with a small footprint, a nominal speed up to 4.4m/s, and the ability to rotate on the spot (while stationary). The Segway RMP200 is, in many ways, an ideal platform to run in urban areas. Humanoid robots are not yet equipped to operate in outdoor environments, and four-wheeled vehicles have a much larger footprint and are more restricted in their mobility.

Moreover, Segway robots can carry heavy payloads, up to 45 kg for this model. On the downside, two-wheeled platforms are statically (and dynamically) unstable, keeping their balance using gyroscopic sensors to track and correct their tilt. The robot will pitch forward or backward to accelerate or decelerate, or simply to keep its balance while stationary. This behavior presents two issues for their use in robotics.

The Tibi and Dabo robots have a height of 165 cm, occupy a clearance space of 80 cm, and weight 110 kg. It is equipped with multiple sensors, as well as, a Bumblebee stereo camera and three lasers.

They are equipped with the following sensors, see Fig. A.2:

- Two Hokuyo UTM-30LX 2D laser range sensors used to detect obstacles and people, giving scans over a local horizontal plane at 40cm above the ground,

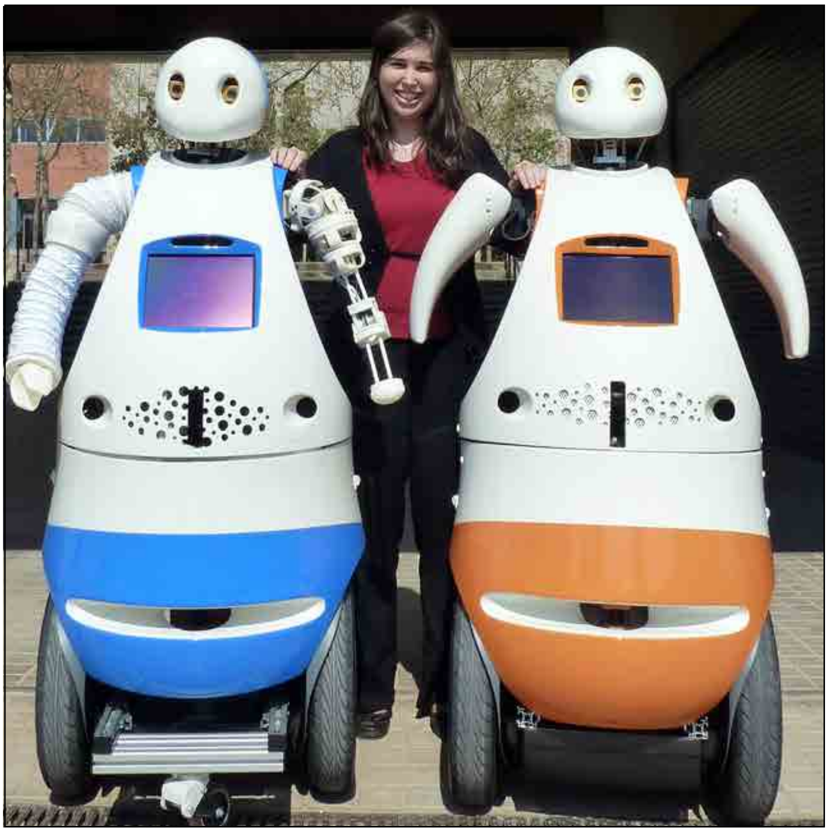

Figure A.1: **Tibi and Dabo robots.**

facing forward and backward.

- A stereo Bumblebee camera located in the eyes is used for computer vision purposes.
- A touchable screen to communicate with people.
- A speaker, movable arms and head to express emotions.
- Two on-board computers (Intel Core 2 Quad CPU 2.66 and 3.00 GHz) manage all the running processes and sensor signals, and a laptop is used for external monitoring.

Moreover, Tibi and Dabo were designed to interact with different people in open spaces. The robots are socially accepted, and humans take an interest in interacting with them, robots' design are well-rendered, and, their movements are smooth.

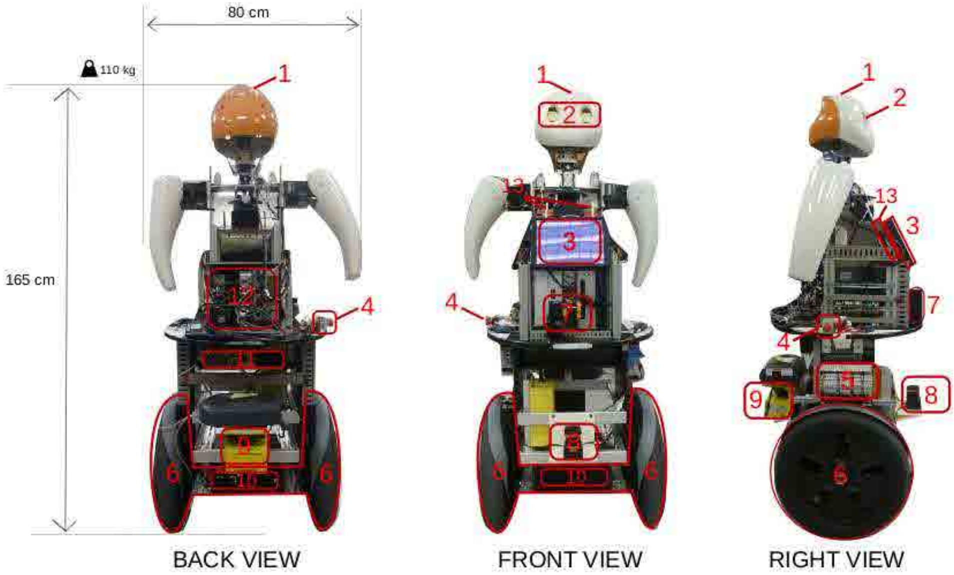

Figure A.2: **Components of the Tibi Robot:** (1) the head; (2) Bumblebee stereo cameras; (3) monitor; (4) emergency stop button; (5) maneuvering buttons; (6) Segway wheels; (7) vertical front laser for navigation; (8) horizontal front laser for navigation and localization; (9) horizontal back laser for navigation and localization; (10) Segway batteries and controller; (11) additional batteries; (12) on board computers; (13) wireless antenna.

Appendix B

Analysis of Variance

To evaluate the questionnaires, a single factor analysis of variance (ANOVA) has been computed, according to [13]. This method compares the mean values of several groups to test whether the probability that the means of all groups are equal is below a certain threshold. For the surveys conducted in the context of this dissertation in Chapters 3 and 6, the different groups are the robot's behaviors, and the means are calculated from the ratings given by the participants in the evaluation. A precondition for the anova is that the sample set is normally distributed. Furthermore, the homogeneity of variances is required.

To run the anova, a hypothesis H_0 is made that says all means are equal: $\mu_1 = \mu_2 = \ldots = \mu_r$, where r denotes the number of groups.

For the ANOVA overall distribution of the means is divided into two sub-distributions, one between the groups in this thesis, between the different behaviors, and another one within the group, here the ratings for a particular behavior. The distribution between the groups is represented by the sum of squares for treatments c(SS_T), the square sum of the deviation of the single means from the overall mean. The distribution within a group is represented by sum of squares for errors (SS_E), the square sum of the deviation of the single values from the mean within a group.

SS_T and SS_E are obtained as follows:

$$SS_T = \sum_{j=1}^{r} n_j(\hat{X}_j - \hat{X})^2 \tag{B.1}$$

$$SS_E = \sum_{j=1}^{r}\sum_{i=1}^{n_j}(X_{ji} - \hat{X}_j)^2 \tag{B.2}$$

where, r represents the number of groups $X_1, X_2, \ldots, X_r$; and n_i the number of elements within the ith group, $X_{i1}, X_{i2}, \ldots, X_{in_i}$. Therefore, the overall number of elements $n = n_1 + n_2 + \ldots + n_r$. Furthermore, $\hat{X}_j$ and $\hat{X}$ are defined as follows:

$$\hat{X}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} X_{ji}, \quad j = 1, \ldots, r \tag{B.3}$$

$$\hat{X} = \frac{1}{n}\sum_{j=1}^{r}\sum_{i=1}^{n_j} X_{ji} = \frac{1}{n}\sum_{j=1}^{r} n_j\hat{X}_j \tag{B.4}$$

Then, the test value T is computed as:

$$T = \frac{SS_T}{SS_E} \tag{B.5}$$

T is compared to the theoretical value from the F-Distribution table $Fr-1, n-r, \alpha$ (α level of significance). If $T > Fr-1, n-r, \alpha$, H_0 is rejected falsely with a probability of α. This means in the context of the experiments from Chapters 3 and 6 that it is known that there are significant differences between the ratings for the different behaviors.

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