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Proposta de Tesi Doctoral

SOCIAL ROBOT NAVIGATION

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Contents

1 Introduction

The deployment of service robots in urban environments is a challenging task and remains as an open issue for the robotics community. The requirements for a successful execution of such tasks are quite rigorous: robots, necessarily, must behave naturally to other persons, since urban environments are designed for people, and at the same time, safety must be considered as a top priority. Thereby, social acceptance and human safety become the key criteria for a social robot navigation in typically human environments, such as streets, shopping malls or open spaces. These two requirements inevitably entail a more intelligent and aware robot navigation if we want robots to be accepted by people in their ordinary everyday.

Tackling the social navigation problem by only relying on a robust navigation is not enough, although this topic has grown enormously in the few past years. Thus, the understanding of human motion in urban environments is of extreme importance in order to adapt service robots to typical human environments and not in the contrary. In addition, an adequate measure of the performance should consider social acceptance and human safety instead of time of execution, considered in other typical navigation approaches.

All those arguments motivate the research of a unified social-aware framework for the deployment of social robots in urban environments, that recognizes and identifies the social obligations for a new generation of robots truly accepted in human urban settings.

A prerequisite to more social and intelligent robots boils down to the development of new prediction tools, like a long-term prediction. We define the term "human intentionality long-term prediction" as a tool to forecast intentions or motivations that drive human behaviors.

There are a number of real world applications where motion intentionality can be applied, besides our original motivation. For example, human motion scene surveillance, where we can detect abnormal trajectories making use of prediction information, and thus identifying all those erratic trajectories; human tracking, to obtain a robust tracking of human motion; robot navigation in crowded human environments, in order to adjust robot navigation to be aware of human motion; or social interaction, to improve the social interaction between robots and humans. All these issues require prediction information, preferably a long-term prediction.

In general, the analysis of future scenarios is typically done using short-term prediction, which is a propagation of the current state into a certain time horizon, but it has several limitations, specially appreciable on more complex environments.

2 Objectives

As stated before, the main motivation of the present Ph.D. thesis is the study of an integrated social-aware framework for the deployment of social robots in urban environments. This framework, will lead to the obtainment of new methods to correctly deploy service robots, that were not considered by state of the art approaches. The general social-awareness navigation framework consists of prediction algorithms, social models of interaction, navigation algorithms, planning techniques and performance functions that take into account human acceptance and safety.

In brief, in this thesis we have the objectives to develop new methods in:

- Robot social-awareness navigation framework.
- Human motion trajectory predictor.
- Extended social force model.
- Robot social-awareness navigation methods.

The research in general of prediction techniques is one of the parts of the framework, and thus, one of the objectives of the thesis that permit the forecasting of a scene evolution in the future. More concretely the objective is the study of new long-term human motion intentionality predictors based on geometry criteria, and prediction of trajectories in urban scenarios.

In addition, one of the objectives of this Ph.D. thesis is the study of robot models for motion interaction in both indoor and outdoor environments, between robots to persons and persons to persons. In order to model these social interactions, we will make use of the Social Force Model (SFM) introduced by Helbing [28]. Specifically, the proposed work presents a powerful scheme for robot's human-awareness navigation based on the social-forces concept. Our objective is to completely describe a urban scene: static obstacles, pedestrians and the social motion interactions that take place, and that describe future pedestrian trajectories, as well as the impact produced by the robot movement while navigating in such environments.

By making use of intentionality prediction, this thesis aims to obtain a human motion model to cope with the current problems of robot navigation in urban environments. That entails the integration of prediction information and an extended social force model in addition to original approaches to this issue. Due to the nature of human behavior, we need a set of tools, aside from typical polls, to provide information of the performance of service robots, which is a specially troublesome task when humans are part of the system. To this end, we will study metric functions capable of measure human responses for either robot navigation as well as robot companion tasks.

3 Expected contributions

This Ph.D. work seeks to contribute to the understanding of the deployment of service robots in urban scenarios, paying special attention to robot safety and to the acceptance among pedestrians.

To this end, we require new social tools to provide the required amount of "intelligence" to the social robots behavior. We expect to do a contribution proposing a new general long-term prediction algorithm.

In the present thesis project, we expect to enrich the Social Force Model (SFM) introduced by Helbing [28] to model the social interactions under the presence of a social robot, and thus we aim to obtain the robot-person interaction force parameters specifically suited for our robotic platform Tibi [49].

We will propose a powerful scheme for robot's social navigation based on the social-forces concept and the human motion predictor. A social aware navigation is also well suited for a robot companion task and we expect to contribute on this issue based on our general social navigation scheme.

Moreover, we expect to contribute with new metrics to evaluate in general the robot's performance, based on vital spaces and comfortableness criteria. Since the verification of man-in-the-loop systems is fuzzy, an analytical metric that justifies the behavior of social robots is more than desirable.

Additionally, we expect to apply of those techniques into the robot companion task and contribute to the problem with an alternative new approach.

4 State of the art

A review of the current state of the art on the more significant contributions is provided. This section is divided in three parts: human motion prediction, social robot navigation, including the classical navigation approaches and a review of the robot companion task.

4.1 Human motion prediction

Concerning the wide variety of human motion predictors in the literature, two major human motion predictors (HMP) groups can be distinguished: a geometric-based group and a place dependent-based group. For the latter group, we have to learn the prediction model for each one of the environments where the HMP is used. The geometric-based group does not always need to learn the human motion intentionality (HMI) for each specific environment, although training is also required in one way or another.

Bennewitz *et al.* [4], propose a place-dependent method in which they analyze a collection of people's motion behaviors in an indoor environment by a clustering technique that uses the Expectation-Maximization algorithm.

Once they learn the classes of motion trajectories, they use these primitive trajectories as patterns for human motion trajectory association, and thus, inferring HMI. One of the main disadvantages of the place-dependent methods, as we will discuss later, is the lack of flexibility on abnormal observations, that is, all those erratic trajectories due to a person stopping or changing its destination. Our algorithm is able to quickly adapt to changes in intentionality and perform successfully.

Vasquez *et al.* [59] cluster different motion patterns by a dissimilarity measure which allows the use of pairwise clustering algorithms in order to group observed trajectories into patterns. Chen *et al.* [8] propose a clustering method and three different prediction strategies based on the quality of the matching.

Using heuristics and geometric criteria, Foka *et al.* [19] propose a geometric-based method for human motion prediction that uses human motion intentionality in terms of goals. Prediction is done by identifying final destinations based on the instantaneous tangent angle in combination with a grid-based probability assignation to all final destinations. It has been used for on-line prediction for robot navigation in dynamic environments. Another geometrical approach proposed by Ferrer *et al.* [16] predicts future trajectories by minimizing the variance of curvature of forecast paths.

A mixed approach, proposed by Ziebart *et al.* [64] uses both place dependent and geometric criteria. They use a reward function to generate the optimal paths towards a destination. This method can also be used as a modeling of route preferences as well as for inferring destinations. This method requires intensive place-dependent training, which is an important drawback for the generalization of its use as a predictor.

Dee *et al.* [11] propose a vision-based prediction to infer intentionality, characterized as the combination of obstacles and free space pixels under the field of view of the person. Liu *et al.* [37] propose a method for long term prediction using localization awareness.

4.2 Social robot navigation

Robot navigation is a mature field of robotics; there exist many works that demonstrate that robots are able to navigate in many environments [7, 36, 30]. However, nowadays robots navigate in pedestrian areas, therefore, more social-interactive approaches are required. Potential Field methods keep a great synergy with the social forces as we will discuss later [31, 6]. The proposed work is greatly based on this navigation approach but focusing on the social acceptance and safety.

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 [52]; the Dynamic Window Approach [21]; or randomized kinodynamic planning using rapidly-exploring Random Trees [34]. Other algorithms consider obstacles moving over time [32, 41]. Finally, several approaches consider both vehicle dynamics and dynamic obstacles [18, 46]. While all of these algorithms may be used to generate varying degrees of safe and effective obstacle avoidance, none of them explicitly account 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 [35, 3], 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 [43]; tending toward the right side of a hallway, particularly when passing people [45]; and approaching people to join conversational groups [2]. Museum tour guide robots are often given the capability to detect and attempt to handle people who are blocking their paths [7, 44, 56]. In [48], 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 [54].

Safety and reliability are key factors 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 [1], the notion of safety is studied in detail with respect to all relevant aspects of Human-Robot Interaction.

4.3 Robot social-awareness navigation in an accompany task

In recent years, human-robot interaction has become a very active research field, nevertheless, there is not extensive research on motion planning in the presence of humans. Some methods have been developed to allow robots to navigate around people while performing specific tasks. Some of these tasks include tending toward the right side of a hallway [45] and standing in line [43]. Museum tour guide robots are often given the capability to detect and attempt to deal with people who are blocking their paths on a case-by-case basis, [7].

Several groups have begun to address questions relating to plan complete paths around people, rather than relying on solely reactive behaviors. In [51], a method for a robot to change its velocity near people has been developed. While this method begins to address ideas of planning around people, it does not directly consider social conventions. In contrast, in [53], the HumanAware Motion Planner considers both the safety and reliability of the robots movement and human comfort, it attempts to keep the robot in front of people and visible at all times. However, the paths that the planner generates may be very unnatural due to its attempts to stay visible to people.

In most works, unlike the present thesis project, safety is assured by not allowing humans to approach robots. However, this method cannot be used if the robot has to assist a human. In [1], the notion of safety is studied in detail with all of its aspects in Human Robot Interaction.

Two different aspects of human's safety have been studied in [65]: "physical" safety and "mental" safety. With this distinction, the notion of safety includes physical aspects and psychological effects of the robots motions on humans. Physical safety is necessary for the human-robot interaction. Normally, physical safety is 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 [27]. A robot should comply to similar conventions [20]. In human robot interaction, the spatial formation around a robot has been studied in relation to initiating interaction [42]. A classification of people's motion towards a robot was presented in [5]. In [55], 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 [39]. 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 considered explicitly, this method guarantees a motion without collision by taking into account the dynamics of the environment.

Moreover, an increasing area of interest in the HRI field, is the development of autonomous companion robots [10]. Furthermore, researchers are making efforts on performing human-robot interaction in a more natural way. A robot companion should detect the human operator and conduct his/her commands [26].

Human-robot interaction research in the field of companion robots is still new in comparison to traditional service robotics, such as robots serving food in hospitals or providing specific security services. Therefore, prior research in this particular field is relatively minimal [62].

Vaughan introduced a complete robot system which controlled the behavior of another intelligent system with the presence of variability, uncertainty and noise [60]. 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 instead 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 posited 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. Another works on this direction include [24, 25, 22, 23]

Most of the current research predominantly studies robots that participate in social-human interactions as companions [29]. Many studies have investigated people's attitudes towards robots and their perception of robots. In [9], it was shown 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 mediating factors, which can impact this preference, such as a persons experience with robots [33], gender [9] or in which part of the room she was standing or sitting [61]. Satake et al. [50] proposed an approach model for robots which should initiate interaction in a shopping mall.

In [47], a new perspective to the different uses and identities of a companion robot has been brought, moreover it also describes the advantages and disadvantages of this type of companion. The "Robotic Butler/Maid" was able to perform domestic task, but also caused difficulties in relationships at home by being too efficient and making people feel redundant. In [10], 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 be able 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 considered. The principal goal of the motion planner is to take human movements into account in order to ensure their safety.

5 Human motion intentionality prediction

We proposed a new human motion intentionality indicator [17], denominated Bayesian Human Motion Intentionality Prediction (BHMIP), which is a geometric-based long-term predictor. The new prediction indicator should be capable of quantifying the human motion intentionality (HMI) implicit on a trajectory with respect to the current position and orientation. This intentionality indicator should capture the probability that a human trajectory reaches a destination point d_m, which is a clear indicator for the inherent intentionality. To achieve this, we define the variable ϕ_{nm}, which is the angle between the current orientation of the target n and the vector to the destination point d_m, a relative measure of the orientation with respect to a destination (see Fig. 1-*Left:* for clarification).

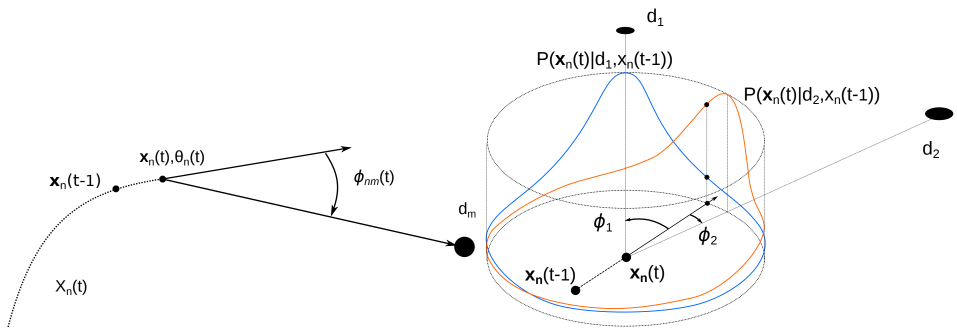

Figure 1: *Left:* The angle ϕ_{nm} is defined as the angle described by the orientation vector of the target n at time t and the $\mathbf{x_n}(t) \rightarrow d_m$ vector. *Right:* Different probability functions shifted depending on their respective destinations.

As it can be seen in Fig. 1, $\phi_{nm}(t)$ is the angle defined by the first derivative of the current trajectory and the $\mathbf{x_n}(t) \rightarrow d_m$ vector. By doing this, $\phi_{nm}(t)$ becomes a measure relative to a destination, while $\theta(t)$ is a global measure of the target orientation. This difference will allow us to obtain a good characterization of the human motion intentionality.

We model the probability $P(\mathbf{x_n}(t)|\mathbf{x_n}(t{-}1), d_m)$ as a Gaussian function. In Fig. 1-*Right:* is depicted an example of this probability function to two destinations centered at the position $\mathbf{x_n}(t)$.

Using the Bayes theorem we can compute the *posterior* probability that the destination d_m, given the current and previous positions of the trajectory $X_n(t)$:

$$P(d_m|X_n(t)) = \frac{P(X_n(t)|d_m)P(d_m)}{P(X_n(t))} \tag{1}$$

where $P(d_m)$ is the prior probability to reach the destination d_m and the joint probability $P(X_n(t)|d_m)$ can be formulated as:

$$P(X_n(t)|d_m) = P(\mathbf{x_n}(1)|d_m) \prod_{\tau=2}^{t} P(\mathbf{x_n}(\tau)|d_m, \mathbf{x_n}(\tau{-}1)) \tag{2}$$

By replacing Eq. (2) into the Eq. (1), we can obtain a compact formulation of the BHMIP.

A comparison of the BHMIP is done with other well known methods for long-term prediction using the Edinburgh Informatics Forum pedestrian database [40] and the Freiburg People Tracker database [38]. For a more detailed discussion of the BHMIP intentionality predictor and the validation of the model, see [17].

6 Extended social force model and navigation

We propose a novel robot social navigation for both indoor and outdoor environments, where robots are expected to interact naturally in typically human environments. In order to model the social interactions, we use the Social Force Model (SFM) introduced by Helbing [28] or Zanlungo [63], but these models only take into account a person to person interaction. We propose to extend the SFM to a consider robot to person interactions. In general, the formulation of the social forces is as follows:

$$\boldsymbol{F}_i^{int} = \sum_{j \in P} \boldsymbol{f}_{i,j}^{int} + \sum_{o \in O} \boldsymbol{f}_{i,o}^{int} + \boldsymbol{f}_{i,r}^{int} \tag{3}$$

where, P is the set of people moving in the environment where the human interacts and O is the set of obstacles. In addition, 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_i, 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. 2-*Left:*. The blue arrow represents the force aiming to 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 the forces is represented as the black arrow $\boldsymbol{F}_i$.

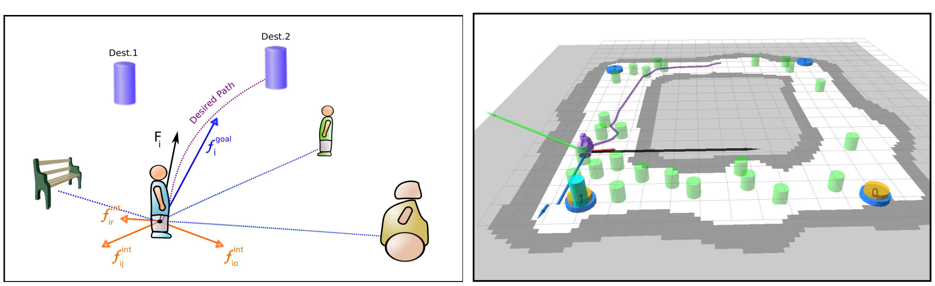

Figure 2: *Left:* Diagram of the social forces corresponding to the person p_i. *Right:* Simulation environment to obtain the θ parameters.

We propose a novel approach to the robot navigation issue, understood as an instantaneous reaction to sensory information, driven by the social-forces centered at the robot. More precisely, we aim to obtain a short-term goal-driven robot navigation ruled by the SFM. The combination of the social forces, which include goal and interacting forces, describes the resultant force governing the robot movement:

$$\boldsymbol{F}_r = \alpha \ \boldsymbol{f}_{r,dest}^{goal} + \gamma \ \boldsymbol{F}_r^{per} + \delta \ \boldsymbol{F}_r^{obs} \tag{4}$$

Once calculated the resultant social-force, the robot behaves consequently to these external stimuli and propagates its state according to this force value. The method requires a new metric, inspired in the classical definition of mechanical work: the *social work* to evaluate the navigation performance in a social manner. In Fig. 2-*Right:* we can observe an example of a social-navigation in a reduced urban environment and a set of virtual persons. The outcome of each simulations depends on its inner parameters, and thus we require a great number of them to obtain a good estimation of the θ parameters by minimizing the *social work* carried out. Real experiments in the BRL were also performed, for more information, see [14].

7 Robot social-awareness navigation in an accompany task

The robot companion task is treated as a specific application of the social navigation

In contrast to the social navigation, two different goals appear. Firstly, a force makes the robot drive towards the predicted destination $\boldsymbol{f}_{r,dest}^{goal}$. Furthermore, the robot must approach the person who accompanies, and hence a second goal pushes 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:

$$\boldsymbol{F}^r = \alpha \ \boldsymbol{f}_{r,dest}^{goal} + \beta \, \boldsymbol{f}_{r,i}^{goal} + \gamma \ \boldsymbol{F}_r^{per} + \delta \ \boldsymbol{F}_r^{obs} \tag{5}$$

The set of parameters $\{\alpha, \beta, \gamma, \delta\}$ is obtained, firstly by optimizing the robot companion behavior extensively in thousands of simulations and after by using an interactive learning approach with set of volunteers in a real scenario.

We additionally formulate a performance metric that has the maximum performance in the area of human's field of view and where the interaction between the robot and the human is maximal. Additionally, the area corresponding to the back of the person is considered as a partial success, since this area is less tolerable by humans. Finally, in the area described further than three meters there is no interaction, and therefore its performance is zero. Real experiments were carried out intensively, as can be seen in Fig. 3.

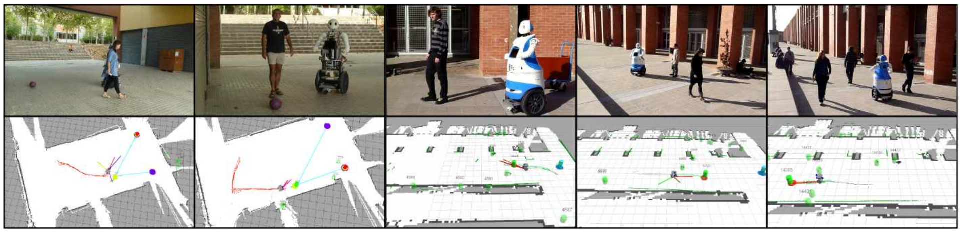

Figure 3: Real-life experiments: Some examples of the conducted real experiments. *Top:* Dabo accompanying a person to a desired goal. *Bottom:* The same scene using the system interface.

8 Publications

A list of currently accepted or submitted publications resulting from the proposed research.

Conferences

[16] G. Ferrer, and A. Sanfeliu. Comparative analysis of human motion trajectory prediction using minimum variance curvature, In *6th ACM/IEEE International Conference on Human-Robot Interaction (HRI),* Lausanne, Switzerland, 2011. ACM

[13] G. Ferrer, A. Garrell, and A. Sanfeliu. Robot companion: A social-force based approach with human awareness-navigation in crowded environments. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2013, submitted.

[14] G. Ferrer, A. Garrell, and A. Sanfeliu. Social-Awareness Robot Navigation in Urban Environments. In *European Conference on Mobile Robotics, ECMR.* 2013, submitted.

Journals

[57] E. Trulls, A. Corominas Murtra, J. Pérez-Ibarz, G. Ferrer, D. Vasquez, J. M. Mirats Tur and A. Sanfeliu. Autonomous navigation for mobile service robots in urban pedestrian environments, *Journal of Field Robotics* 28(3): 329-354, 2011.

[17] G. Ferrer, and A. Sanfeliu. Bayesian human motion intentionality prediction in urban environments. *Pattern Recognition Letters* to appear.

[12] G. Ferrer, A. Garrell, F. Herrero, and A. Sanfeliu. Robot Companion: A Social-Awareness Navigation approach using Human Motion

Prediction and Social Forces. *IEEE Transactions on Robotics*, 2013, submitted.

Book Chapters

[15] 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*, pp. 185203, Springer, 2013.

9 Working plan

The working plan includes past work and the expected future work, with the aim of fulfilling the initial objectives. A number of seven tasks are defined, most of them are self contained and only two of them are divided into subtasks.

A brief description of each task is provided, but it is only intended to be an orientation of the work required and the objectives of each task.

Task 1: Literature review

The literature review is an important task, that makes reference to the reading and understanding of other works and publications related to the different topics included in this thesis project. Accordingly, the lecture of other works or papers is recursive throughout the thesis work, although during certain periods of time, this tasks is carried out more intensively. The literature review includes topics such as human motion prediction, robot navigation, robot companion, which are the core research areas proposed in this thesis project.

Task 2: Human motion intentionality prediction

This section is divided in two subsections, which are different approaches to solve the same problem.

Task 2.1: Minimum curvature prediction

This task obtains a prediction algorithm making use of the curvature of trajectories in order to obtain a motion prediction. It includes the formulation of the predictor and the validation of the approach using a well-known database.

Task 2.2: BHMIP prediction

The Bayesian human motion intentionality prediction is based on orientation features of the pedestrians and their relative positions in a certain scene, as explained in Sec. 5. This task includes the formulation of the approach, a validation of the approach using two well-known databases and a implementation of the method, as a `C++` library for real experimentation in other tasks.

Task 3: Human motion trajectory prediction

This task seeks to obtain a formulation of the propagation of the trajectories, given the intentionality information obtained in the previous task, and additionally a `C++` library implementation. A validation using two well-known databases and experimentation in real scenes is required.

Task 4: Extended social force model

The Social forces model task is understood as the study, in general, of the interaction that takes places in a urban environment between persons. We aim to extend this model to take into account robot-person interactions. This task additionally includes the implementation of a complete social virtual scene, corresponding to the social-forces obtained, into a `C++` library and a simulated environment called "scene simulation". This task additionally requires experimentation in real conditions to validate the extended interaction model that we seek to obtain.

Task 5: Social robot navigation

In this task we require to integrate into a unified robot navigation framework, most of the developed tools developed in this thesis, whic are described above in the previous tasks. This integration entails a more "intelligent" behavior than other classical robot navigation approaches.

Task 5.1: Reactive social navigation

A first approach to the social navigation is proposed as a simplified reactive scheme. This task consists of the formulation of the robot navigation, a new metric, inspired in the classical definition of mechanical work: the *social work* to evaluate the navigation performance in a social manner. Simulations using the "scene simulation" gives an initial estimation of the system parameters, and afterward we need an implementation for our real robots Tibi and Dabo (Sec. 10) aside from experimentation in a real environment like the BRL.

Task 5.2: Social navigation planning

The second iteration of the social robot navigation, in which instead of a reactive scheme, we obtain the robot trajectory considering a finite time horizon and prediction information. The task requirements, similar to task 5.1, consists of a formulation of the problem, an implementation in `C++`, prior optimization in the "scene simulation", and validation in real urban environments like the BRL for the Tibi and Dabo robots.

Task 5.3: Smoothed navigation

The third iteration of the social navigation, where we specially consider cinematic restrictions of the robotic platform and a smoothing of the robot trajectory. The task requirements are the same as tasks 5.1 and 5.2.

Task 6: Robot social-awareness navigation in an accompany task

The robot companion task, briefly described in Sec. 7, consists of a formulation of the problem, in terms of social forces, a performance metric in order to measure the approach. Additionally, we require an implementation in `C++` of the method, a prior optimization in the "scene simulation" accompanying a person, an interactive learning with persons in a real environment and a validation in real urban environments like the BRL for the Tibi and Dabo robots.

Task 7: Elaboration of the PhD thesis document and defense

The last task of the thesis project consists of the elaboration of the final document and the preparation of the public defense of the thesis.

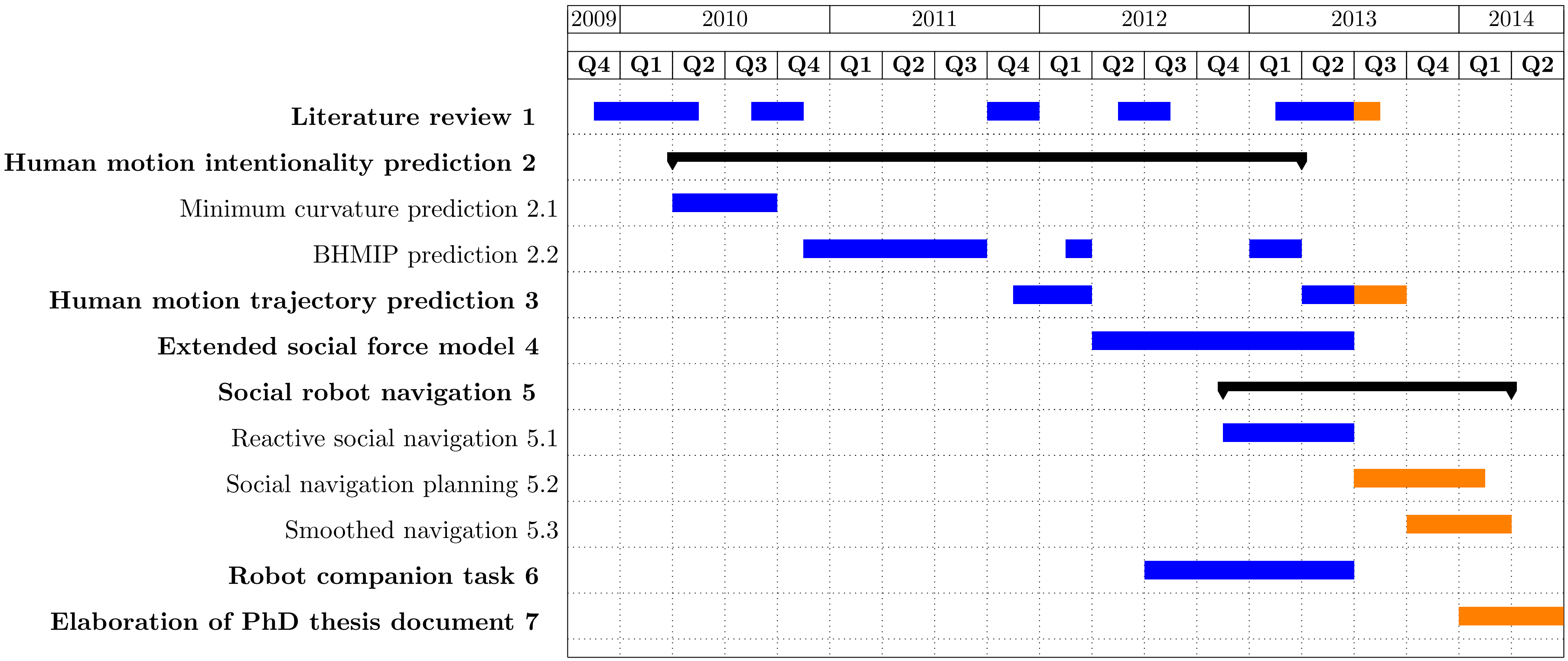

Figure 4: Work plan of the proposed work

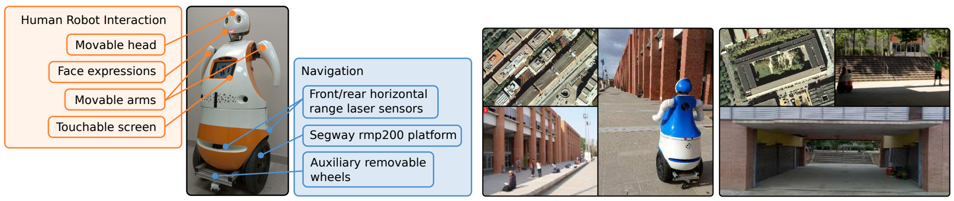

Figure 5: **Left.** Mobile Dabo robot platform used in the experiments. **Right.** Barcelona Robot Lab, North campus of the UPC on the *Left* and the FME Lab, South Campus of the UPC on the *Right*.

10 Resources

In order to conduct all the experiments and to test the approach presented, we have used two twin mobile service robots developed for the URUS project [58], called Tibi and Dabo (Fig. 5-*Left*), designed to work in urban pedestrian areas and interact with people.

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

As social robots, Tibi and Dabo are meant to interact with people. They have several interaction elements to perform more friendly interactions, as a touchable screen, speaker, movable arms and head, and LED illuminated face expressions. Power is supplied by two sets of batteries, one for the segway platform and one for the computers and sensors, giving about a 5h full working autonomy. Two onboard 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. The systems run Ubuntu-Linux and use a middleware called ROS, a software developmental environment for robot system integration that provides a useful and large set of libraries and tools. Fig. 5-*Left* shows one of the robots and some of its components.

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

The BRL (Fig. 5-*Right*) is a large section of the campus that was outfitted as an experimental area, covering over 10.000 m^2, including six buildings and a square, with multiple ramps, staircases and typical obstacles such as bulletin boards, bicycle stands, trashcans or flower pots. The FME lab (Fig. 5-*Right*) consists of a tree area and a pavement area separated each other by stairs.

11 References

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