Planning Human-Robot Interaction for Social Navigation in Crowded Environments

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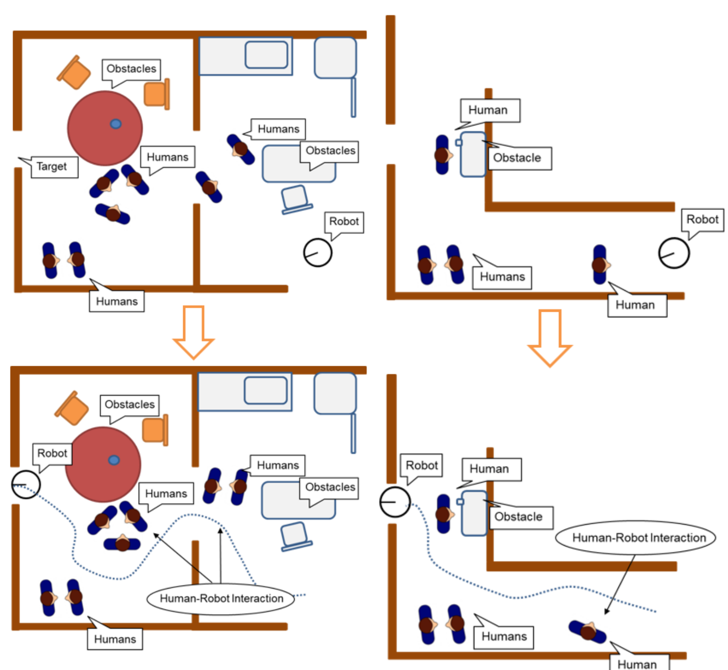
Abstract. Navigation is one of the crucial skills autonomous robots need to perform daily tasks, and many of the rest depend on it. In this paper, we argue that this dependence goes both ways in advanced social autonomous robots. Manipulation, perception, and most importantly human-robot interaction are some of the skills in which navigation might rely on. This paper is focused on the dependence on human-robot interaction and uses two particular scenarios of growing complexity as an example: asking for collaboration to enter a room and asking for permission to navigate between two people which are talking. In the first scenario, the person physically blocks the path to the adjacent room, so it would be impossible for the robot to navigate to such room. Even though in the second scenario the people talking do not block the path to the other room, from a social point of view, interrupting an ongoing conversation without noticing is undesirable. In this paper we propose a navigation planning domain and a set of software agents which allow the robot to navigate in crowded environments in a socially acceptable way, asking for cooperation or permission when necessary. The paper provides quantitative experimental results including social navigation metrics and the results of a Likert-scale satisfaction questionnaire.

1 Introduction

A future where humans and robots coexist appears to be getting increasingly close. In fact, some applications in which social robots help humans in their daily tasks already exist. For instance, social robots in therapy or education have proven feasible and successful in use[1]. Other social robots are being developed to provide the elderly with assistance at home or in nursing homes, and even to provide health specialists with help during their working hours. Many of these applications for robots require them to work alongside people as capable and socially smart partners.

In these scenarios, navigation is one of the most important tasks social robots need to perform. In fact, mapping, localisation and path planning, which are the foundations of robot navigation, have been among the most significant research lines for years. The field of social navigation is experiencing a remarkable growth because in environments with humans where some of the elements (objects and people) are dynamic, humans' comfortability, safety and intentions must be prioritised. Social navigation adapts robot navigation to scenarios with people by following social norms. For instance, robots should avoid getting to close to people or disturbing people who are not willing to interact with them.

In our previous work [2], a social path planner for modelling robot navigation in populated environments was proposed. In [3] and [4] an algorithm for human-centred navigation where a novel method for clustering groups of people in the robot's surrounding was used. According to these clusters, a social map was defined. Other works such as [5] also generate similar maps. Unfortunately, sometimes avoiding disturbing people while navigating makes impossible for the robot to reach its desired destination (*e.g.*, when a person blocks a door, or when the only path would require the robot to navigate between people which are interacting). Current algorithms have serious problems to find solutions, and frequently social robots cannot find a way to reach their destinations. The paper at hand extends previous works [3,4] and focuses on a social planning strategy for situations where people block the path and there are no alternative paths.



(a) Office environment composed of two rooms

(b) Narrow corridor

Fig. 1: Examples of scenarios in which robots have navigate using social rules.

Consider the cases illustrated in Fig. 1. In both images the robot must navigate in human-populated scenarios from its initial position to a target position, and there are blocked areas in the routes planned. In Fig. 1a the human next to the door blocks the path; in a similar scenario, in Fig. 1b two people are interacting and the social map generated by our clustering algorithm also blocks the robot path. As the **main contribution** of this paper, we propose a social navigation planning domain and a set of software agents which allow robots to navigate in human-populated environments in a socially acceptable way, asking for permission or cooperation when necessary.

This paper is organized as follows: after discussing known approaches to human-centered navigation for robot navigation in Section 2, Section 3 presents the cognitive architecture CORTEX, which consists of a network of software agents that allows executing complex tasks involving skills such as human perception or robot navigation. In Section 4 we describe the proposed navigation planning domain. Section 5 presents the experimental results. Section 6 describes the conclusions drawn and future work.

2 Background

The debate between the use of grid-based vs. topological maps [6] has existed, including on whether or not using maps at all. While robots have been able to perform rather complex tasks without representations of any kind, when robots are supposed to perform them efficiently, map-less approaches becomes hard to support. Considerably rich and structured world models, with a higher *semantic* load than two-dimensional grids became frequently necessary to use in these cases. Suggesting scenarios in which a structured representation is necessary is not hard, just consider a dialogue between a robot and a person; interpreting human commands such as “pick up the red ball and bring it to my sister” is a good example. The robot would require information about kinship and the balls that they have seen (there might be more than one). This kind of information is required for almost all HRI skill. *Social mapping*, was introduced in [5]. It deals with the problem of human-aware robot navigation and considers factors like human comfort, sociability, predictability, safety and naturalness [7]. More recently, the concept of *behavioral mapping* has been introduced in [8], where the authors extend social mapping to a behavioral model acting as a mediator that facilitates seamless cooperation among the humans.

Robot navigation in crowded environments has been extensively studied in the last years and several theories and methods have been proposed since then. Particularly interesting reviews have been presented in [7,9] and more recently [10]. Classic social navigation paradigms are based on using well-known navigation algorithms, and therefore adding social conventions and/or social constraints. Under this prism, different works such as [11,12], have shown that the same proxemic zones that exist in human-human interaction can also be applied to human-robot interaction scenarios. A broad survey and discussion regarding the social concepts of proxemics theory applied in the context of human-aware autonomous navigation was presented in [9]. A proxemic-based adaptive spatial density function was defined for clustering groups of people and define forbidden spaces in [3].

As the number of skills robots have increases human-robot collaboration becomes more feasible. In [13], the requirements for effective human-robot collaboration in interactive navigation scenarios are listed. Additionally, authors present three different human-robot collaborative planners. However, they only focus on secure navigation and not on HRI. Other works such as [14], anticipate the human trajectory in order to update social constraints during robot navigation. Similar works are presented in [15]. Again, authors do not take into account interaction with people for robot navigation. Planning for HRI has been used in manipulation tasks [16] and task allocation in collaborative industrial assembly processes. However, there are no works where HRI has been used to improve robot navigation in crowed environment using social conventions. This paper introduces a planning domain for social navigation where HRI is crucial for solving real situations where the robot's path is blocked due to social limitations. The goal is for the robot to execute actions that optimise social navigation and human satisfaction.

3 Cognitive Architecture for social navigation

To properly understand the proposal at hand it is necessary to familiarise with CORTEX, the cognitive architecture used [17]. Social robotics systems are getting more and more complex: different robotic skills are needed in order to achieve the tasks that robots are currently expected to do. The robotics cognitive architecture CORTEX is defined structurally as a network of cooperative *software agents* connected through a *shared representation* (see Fig. 2). This shared representation was defined in [17], as *"a directed multi-labelled graph where nodes represent symbolic or geometric entities and edges represent symbolic or geometric relationships"*.

In the proposal of a flexible and adaptive spatial density function for social navigation, different CORTEX agents are involved. First, in the higher layer of the architecture the robot must have the capability of detecting objects in the path and updating the symbolic model accordingly. Additionally, the skill of detecting humans is also mandatory because robots need to know about humans to get commands, avoid collisions and provide feedback. The final, and most important agent for social navigation, is the one implementing the navigation algorithms that allows robots to navigate from a point to another in a secure and social manner (implementation of the path-planning, localization and SLAM algorithms, among other).

3.1 Deep State Representation

The concept of *deep representations* was initially described by Beetz et al. [18] and it advocates the integrated representation of robot's knowledge at various

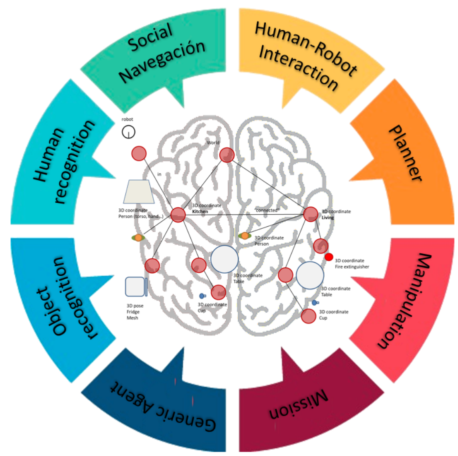


Fig. 2: Diagram of CORTEX with the main software agents involved in this work. The shared representation of the environment is represented in the centre.

levels of abstraction in a unique, articulated structure such as a graph. Based on this concept, a new shared representation, *Deep State Representation (DSR)*, to hold the robot's belief as a combination of symbolic and geometric information, is proposed in [17]. This new structure represents knowledge about the robot itself and the world around it in a flexible and scalable way.

3.2 Agents

An agent within CORTEX is defined as *a computational entity in charge of a well-defined functionality, whether it be reactive, deliberative of hybrid, that interacts with other agents inside a well-defined framework, to enact a larger system*. In CORTEX, agents define the classic functionalities or skills of cognitive robotics architectures, such as navigation, manipulation, person perception, object perception, dialogue, reasoning, planning, symbolic learning or executing. These agents operate in a goal-oriented regime and their goals can come from outside through the agent interface, and can also be part of the agent normal operation. Next, a description of the main software agents needed for social navigation is shown:

Human detection and representation The person detector agent responsible for detecting and tracking the people in front of the robot. Humans do not usually want their personal space being invaded by robots. The presence of humans in the robots' path or in their environment may determine changes in the navigation route in order to make it socially acceptable. The person detector agent acquires the information using an RGBD sensor. For each detected person the agent inserts in the DSR the pose of its torso, its upper limbs, and the head. The lower limbs are ignored because they do not provide as much social information as the head, the upper limbs and the torso do [17]. The torso is used to avoid entering the personal space of humans and as an indicator of the possible directions in which they might walk.

Human-Robot Interaction The conversation agent performs speech-based human-robot interaction. In social environments, HRI provides tools to the robot and/or human to communicate and collaborate. Therefore, this agent is used to include information in the model when humans tell robots about unknown objects and to properly acquire commands. Automatic Speech Recognition and Text-to-Speech algorithms allow robot to send and receive information to/from humans during its social navigation.

Executive The Executive is responsible for computing plans to achieve the current mission, managing the changes made to the DSR by the agents as a result of their interaction with the world, and monitoring the execution of the plan. The active agents collaborate executing the actions in the plan steps as long as they consider them valid (it must be taken into account that agents might have a reactive part). Each time a structural change is included in the model, the Executive uses the domain knowledge, the current model, the target and the previous plan to update the current plan accordingly. The Executive agent is able use different planners. Currently AGGL [19] and PDDL-based [20] planners are supported.

Social Navigation Navigation is in charge of performing local navigation, complying with social rules and including the location of the robot in the DSR. Global path planning is performed by the symbolic planner used by the executive.

The social navigation algorithm implemented is an evolution of the work presented in [3]. Currently, the Dijkstra algorithm is used to determine the shortest path between the position of the robot and its target, and the elastic band algorithm [21] is used to optimize the trajectory.

The robot calculates the initial trajectory based on a free space graph formed by occupied and free points. Each point has a social cost that represents how inconvenient it is for humans to see the robot go through each point. This cost is used to weight the edges of the graph. The cost of a path is the sum of the costs of the points that compose it. The navigation algorithm uses the Dijkstra algorithm to find the shortest route between the points of the graph, based on the cost of the path. Once the path is computed, the robot optimizes the trajectory using the elastic bands algorithm, which consists in the calculation of attraction and repulsion forces to get the robot away from the obstacles on the road.

In environments with humans, the robot creates a social map based on the description of the personal space of the humans present. Three social zones have been defined around the person: intimate zone, personal zone and social zone.

These spaces were introduced in [22]. The free space graph is adapted to these zones by modifying the costs of the points contained in said areas. By increasing the cost of the personal and social zones, robots will try to avoid these areas in the planning of the shortest route. The intimate zone is considered a forbidden setting as occupied the points of the graph contained in that area. Fig. 3 shows a free space graph and the defined zones, characterized by asymmetric Gaussian curves.

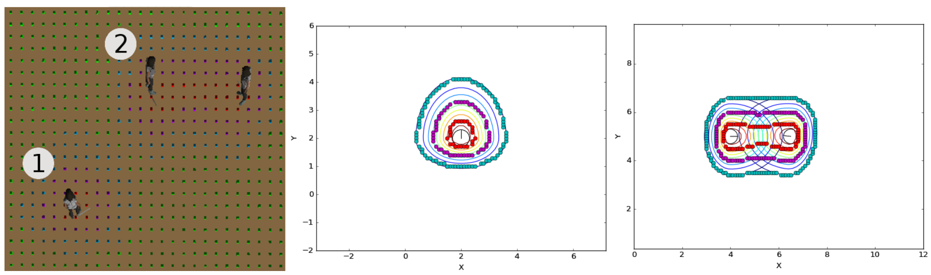


Fig. 3: Free space graph and the social zones defined. In colour red is shown the intimate area, in purple the personal area and in colour blue the social one. Number one shows the social zones for an individual human and number two shows the cluster of two persons interacting.

If there is an interaction between the humans present, the planner groups them together, in such a way that it is forbidden to pass between them, ensuring that the robot does not interrupt the interaction.

Regarding localization algorithms, the navigation agent is algorithm-independent. It has been used with different ones with different properties, so the algorithm can be changed depending on the characteristics of the environment.

4 Planning Human-Robot interaction

As in any other context, planning human-aware navigation tasks entails defining the elements of the planning problem: an initial world model, a mission, and a set of actions (*i.e.*, the planning domain). In traditional automated planning, the initial world model is composed of a set of symbols and a set of n-ary predicates that are used to provide information regarding such symbols. In CORTEX, planning is performed similarly with the symbolic information in the DSR, using the nodes of the representation as symbols and the edges of the graph as predicates. The fact that the predicates in CORTEX are limited to the edges in the DSR limits the usage of predicates to unary and binary ones, but it also facilitates the visualization of the symbolic world model representation [19]. The remaining of this section describes the symbols and predicates (nodes and edges used in the DSR) that support estimating the best plan to make the robot achieve its navigation tasks. In this paper the term predicate and edge will be used indistinctly.

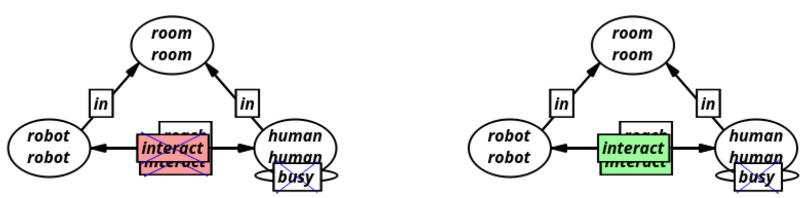
4.1 Symbols and predicates

For navigation purposes, the robot uses three types of symbols: *human*, *robot*, and *room*. This paper investigates the case where only a *robot* is found in the model, but the existence of several humans and rooms is possible.

The robot and each person must be located within an existing room; for this purpose an *in* predicate (edge in the DSR) is used. Robots and humans might be paying attention to other robots and humans; for this purpose an *interact* predicate is used. Humans might block the path of the robot, physically or socially (*i.e.*, robots are not supposed to interfere visually when two people interact). Physical blocking is represented using *block* edges, while social blocking is represented using *softblock* edges. To represent that a robot is close enough to establish social interaction with a human the robot includes *reach* predicates. The following section describes the most relevant actions of the human-aware navigation domain. The actions described in the domain will help the reader understand the meaning and usage of these predicates.

4.2 Navigation domain

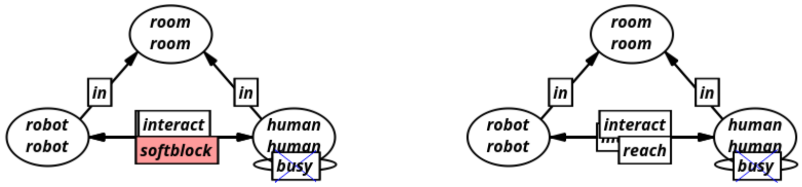
The whole navigation domain is composed of 12 actions. The three most important are described in this section: engageHuman, askForPermissionToPass, and askForCollaborationToPass.



(a) Action's LHS (b) Action's RHS

Fig. 4: Action *engage*.

engageHuman In this proposal the first step to ask for help or permission when navigating is engaging human interaction. This very goal is the purpose of the *engageHuman* action. The action (see Fig. 4) states that if a human is reachable the robot can interact with such person unless its symbol is marked as busy (which is done when a human explicitly says that she or he does not want to be disturbed). The effect of the correct execution of the action is two new *interact* edges, one from the human to the robot and *vice versa*.

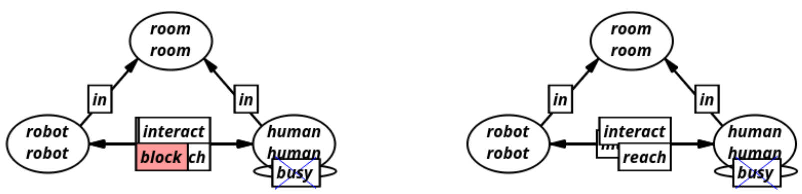


(a) Action's LHS

(b) Action's RHS

Fig. 5: Action *askForPermissionToPass*.

askForPermissionToPass Once the robot is interacting with a particular human it can ask for permission to pass in the case it needs to cross the viewpoint of two humans which are interacting among themselves. This would also apply in other use cases when, for example, humans are watching television. The precondition for the robot to be able to execute the *askForPermissionToPass* action would be the existence of a human blocking its path *socially* (predicate *softblock*) in the same room where it is located with whom the robot should be interacting. The outcome of the successful execution of the action is that the human stops blocking the way of the robot socially. See figure 5 for the visual definition of the action.



(a) Action's LHS

(b) Action's RHS

Fig. 6: Action *askForCollaboration*.

askForCollaboration The action *askForCollaboration* is similar to the previous action *askForPermission*. The only difference is that in this case the human blocks the way physically and not socially. Therefore, in this case the robot asks the human to move and waits. See figure 6 for the visual definition of the action.

4.3 Missions

The missions are defined as in other systems, describing a subset of existing symbols and the predicates that should be true. The two types of experiment performed require the robot to go from one room (id 3) to an adjacent room (room id 5), even though there are people blocking its way physically or socially.

In both cases the goal is the same, "go to room 5", so the mission has two symbols, the robot and the room 5, and a predicate that should be true *(in robot_1 room_5)*.

5 Experimental results

A set of simulated scenarios were used to validate the results of the proposed navigation planning domain. The algorithms have been developed in C++ and the tests have been performed in a PC with anIntel Core i5 processor with 4Gb of DDR3 RAM and Ubuntu GNU/Linux 16.10. We evaluate both, quantitative and qualitative experimental results, including social navigation metrics and the results of a Likert-scale satisfaction questionnaire. We use a simulated version of the robot Viriato, a social robot equipped with an RGBD camera and laser range sensor.

5.1 Description of the experiments

The simulated scenario is a $65m^2$ two-room apartment equipped with a kitchen and a living room, where two different tests are described[1]: i) First, a human blocks the path in the corridor; and ii) two people talk in a vis-a-vis formation blocking the robot path. The robot Viriato navigates through this apartment to several positions. Fig. 7 summarises the tests in six steps: In Fig. 7.1 the robot starts its route. Its first target is located in the corridor. In Fig. 7.2 the robot plans its path and navigates to the human. After asking for collaboration, the robot navigates to the first target (Fig. 7.3). In the second test (Fig. 7.4), the robot has the target in the second room, plans its path and initiates a conversation with people (Fig. 7.5). Finally, once the robot asks for permission to pass, it navigates to its target position.

An example of the HRI planning is shown in Fig. 8: our social robot (labeled as '1') has an approach behavior with which it can initiate conversation with people (labeled as '2'). As the path is blocked, the robot asks for cooperation (labeled as '3'). Once the path is free, our social robot navigates until its target (labeled as '4'). A zoom of this test in '2' and '3' robot position is drawn on the right, where the changes in the graph of free space are illustrated.

In order to assess the effectiveness of the proposed navigation approach, the methodology has been evaluated accordingly to these metrics in both static scenarios: (i) average minimum distance to a human during navigation, d_{min}; (ii) distance traveled, d_t; (iii) navigation time, τ; (iv) cumulative heading changes, CHC; and (v) personal space intrusions, Ψ. These metrics have been already established by the scientific community (see [8,23]). Results are summarised in Table 1 and Table 2.

To assess the satisfaction of the humans regarding the robot's behavior and HRI abilities, a Likert scale-based questionnaire was provided to a total of 34

[1] A video of the experiments is located on goo.gl/KdGYBN

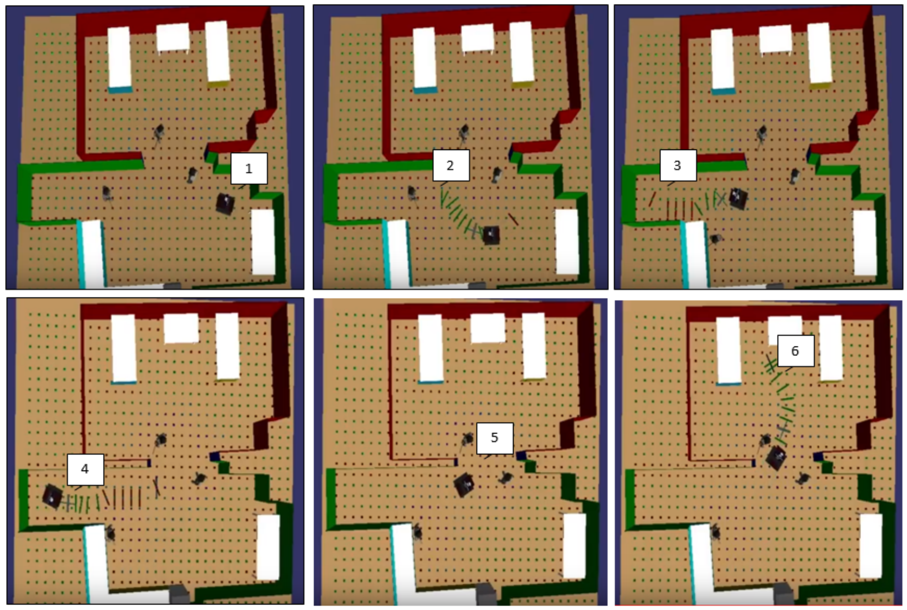


Fig. 7: The tests used in this paper in six steps

participants. The results of the questionnaire, including the questions are shown in table 3.

6 Conclusions and future works

This paper provided a detailed introduction to the problem which autonomous navigation aims to solve, with a special emphasis on human-aware navigation. Despite there are many approaches to human-aware navigation, this is the first work focused on planning navigation tasks in collaboration with humans taking human social rules into account (see the *askForPermission* action).

This paper provided qualitative and quantitative results for the experiments conducted. The quantitative data support the claim that the robot does not interfere with humans, keeping a good distance and navigating properly (*e.g.*, a small Cumulative Heading Changes -CHC- value). The results of the questionnaire evince that humans are satisfied with the overall robot's behavior.

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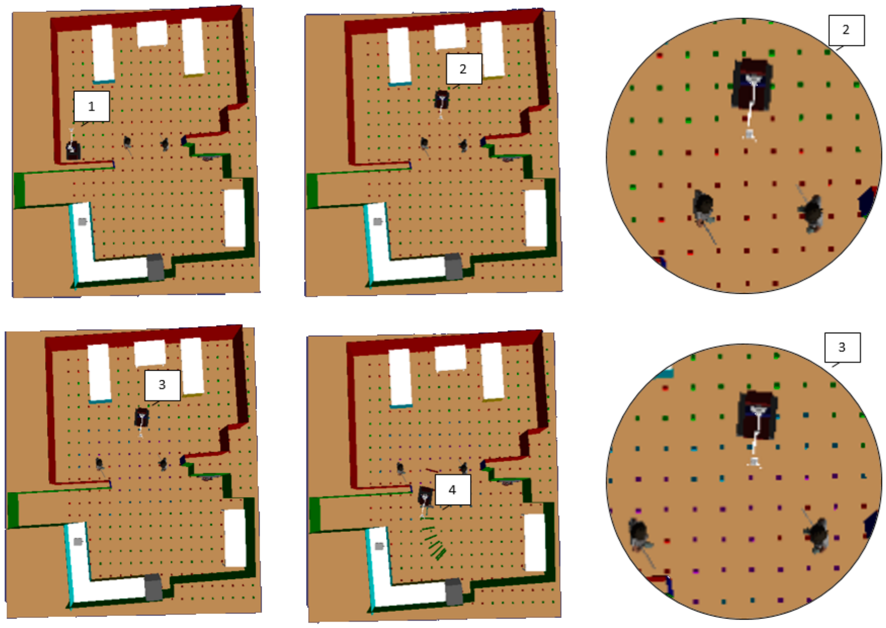

Fig. 8: An example of the HRI planning described in this paper: ask for collaboration.

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Table 1: First experiment

Parameter	Social navigation architecture
d_t *(m)*	11.68 (2.00)
τ*(s)*	46.06 (14.75)
CHC	0.76 (0.15)
d_{min} *Person 1 (m)*	10.26 (0.54)
d_{min} *Person 2 (m)*	11.01 (0.42)
d_{min} *Person 3 (m)*	11.96 (0.39)
Ψ *(Intimate) (%)*	0.0 (0.0)
Ψ *(Personal)(%)*	0.0 (0.0)
Ψ *(Social + Public)(%)*	100.0 (0.0)

Table 2: Second experiment

Parameter	Social navigation architecture
d_t*(m)*	10.58 (1.75)
τ *(s)*	44.8 (12.52)
CHC	1.37 (0.18)
d_{min} *Person 1 (m)*	8.94 (0.58)
d_{min} *Person 2 (m)*	14.59 (1.14)
d_{min} *Person 3 (m)*	10.64 (1.31)
Ψ *(Intimate) (%)*	0.0 (0.0)
Ψ *(Personal)(%)*	0.0 (0.0)
Ψ *(Social + Public) (%)*	100.0 (0.0)

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Table 3: Satisfaction questionnaire.

Question	avg. answer (σ)
Robot's behavior is socially appropriate in exp. 1	4.41 (0.54)
Robot's behavior is socially appropriate in exp. 2	4.47 (0.40)
Robot's behavior is friendly in exp. 1	3.79 (0.60)
Robot's behavior is friendly in exp. 2	4.05 (0.52)
The robot understands the social context and the interaction in exp. 1	4.32 (0.62)
The robot understands the social context and the interaction in exp. 2	4.37 (0.71)

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