A Proposal for the Design of a Semantic Social Path Planner using CORTEX

Pedro Núñez, Luis J. Manso, Pablo Bustos, Paulo Drews-Jr, Douglas G. Macharet

***Abstract*—Path planning is one of the basic and widely studied problems in robotics navigation, being its aim to determine the path from one coordinate location to another along a set of way-points. Traditionally, this problem has been addressed using the geometric world, that is, 2D or 3D coordinates from a geometric map. New generation of robots should be able to plan this path also taking into account social conventions, which is commonly called social navigation. This paper describes the ongoing work of a new proposal for the path planning problem where the semantic knowledge of the robot surrounding and different social rules are used to determine the best route from the robot to the target poses. In this work, a specific type of semantic map is described, which integrates both, geometrical information and semantic knowledge. The proposal uses CORTEX, an agent-based Robotics Cognitive Architecture which provides a set of different agents in the deliberative-reactive spectrum. The proposal is going to be tested in two different social robots within the NAVLOC project[1].**

***Index Terms*—Path planning, social navigation, human-robot interaction**

I. Introduction

SOCIAL robotics is witnessing a remarkable growth in the recent years. In a not very far future, social robots will perform everyday tasks in offices, hospitals homes or museums. These actual scenarios are usually complex and dynamic, that is, people, objects or other robots move around the robot and, therefore, the environment in an instant of time is not the same after some days, hours or even some minutes. In the social context where these robots are going to work, there exist different capabilities and skills that are expected, such as human or object avoiding collisions, localization, path planning, human-robot interaction or object recognition.

Most of the solutions proposed in the literature for these typical problems, especially for navigation tasks, are addressed using representations of the spatial structure of the environment. These solutions provide a robot with more or less efficient methods to carry out some tasks in static and simple scenarios. However, using only a spatial representation of the environment is difficult to navigate successfully. This tendency is now changing, and the scientific community is experiencing an increasing interest in so-called semantic solutions, which integrate semantic knowledge and geometrical information.

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[1]Brazil-Spain cooperation on navigation and localization for autonomous robots on underwater and terrestrial environments

Recently, the term *social navigation* in robotics has been introduced as a way to relate human-robot interaction and the robot navigation in human scenarios. The main goal of social navigation is to develop methods in order to make robot behavior, in particular robot navigation, socially accepted [1]. In the case of the socially-aware path planning problem, which is expected to become an increasingly important task in next social robots generation [2], the robot should decide the best route to the target poses following social rules (*e.g.*, to gracefully approach people, or to wittily enter and exit from a conversation).

To determine the best social route from the robot to the target poses, this work proposes a new design of a path planning algorithm based on semantic knowledge of the environment robot and the use of socially accepted rules. Classical path planning approaches assume geometrical information from the environment, that is, they use spatial representation of the environment (*e.g.*, topological, feature-based or occupancy grid maps), and reason about the best route using this spatial memory. On the contrary, the semantic social path planning approach described in this paper firstly introduces a high-level and long-life knowledge captured by the robot from the environment, in a similar way that the human point-of-view, and after, it introduces socially accepted rules to the semantic knowledge during the planning task. The main advantages of the semantic approach are robustness, ease of human-robot communication and a more understandable access to robot's inner functioning for debugging. It can be more robust to localization errors than classical path planning algorithms based on low-level geometric descriptors, since it adds as a new source of information the position of known objects along the path. Moreover, using semantic way-points, robots and humans can share routes since their way-points would be described using objects and labels instead of two-dimensional coordinates given in an arbitrary reference frame.

New generations of social robots should be able to generate different routes during an interaction with humans and also exhibit proactive social behaviors. In this context, the cognitive architecture CORTEX used in this paper and defined in [3], is based on a collection of agents (*i.e.*, semi-autonomous functional units that collaborate by means of a common representation in their pursue of a common goal) that can operate anywhere in the deliberative-reactive spectrum. In this architecture there exist navigation, perceptual and human-robot interaction agents, among others, thereby facilitating the combined use of semantic knowledge and social rules.

The use of semantic knowledge, thus, may enable a social robot to work in a more intelligent and robust manner [5].

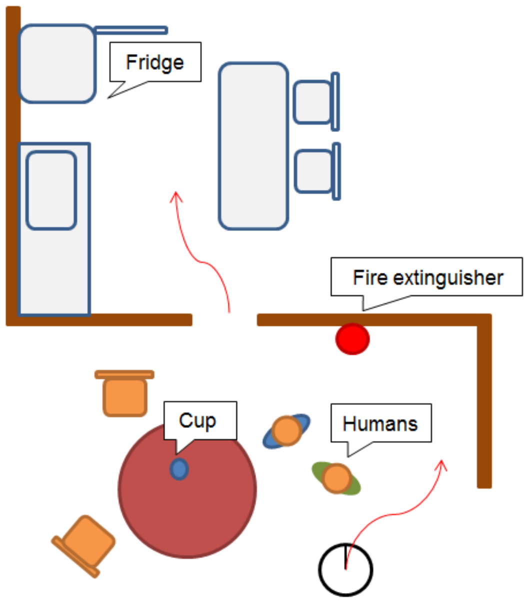


Fig. 1. Brief description of the semantic social path-planning problem. The robot has to choose the best route from the living-room to the kitchen by using its semantic knowledge (*e.g.*, cup, fire extinguisher and fridge) and social rules (*e.g.*, humans along the path)

Fig. 1 illustrates the problem to solve: the robot located in the living-room has to choose the best route from its pose to the target along a complex dynamic environment with people. In this study case, the robot's target is 'kitchen'. The robot has knowledge about different objects with label 'kitchen' (*e.g.*, fridge). Therefore, the best route has to be chosen from the 'living-room' to the 'kitchen'. Here, it uses perceptual agents in order to perceive the environment and detect objects from it (semantic knowledge), and also uses human-robot interaction agents to infer or apply social rules. Obviously, there exist navigation agents that allow the robot to navigate in a secure way.

What does a social robot need for a social semantic path planning algorithm? The next list summarizes the main items:

- A navigation system that smoothly integrates local and global constraints.
- Semantic description and recognition of objects and humans in the robot's surroundings.
- Automatic Speech Recognition (ASR) and Text-To-Speech (TTS) algorithms (Human-Robot Interaction), and optionally the capability to enhance dialogs with accompanying movements of the head and arms to express emotions.

This article is structured as follows: Section II provides a brief summary about similar works in this field of research. In Section III, a description of CORTEX cognitive architecture and the hybrid representation are made. Section IV provides the proposal description along the main agents involved. The description of the semantic social path planning is described in Section V. Finally, the main conclusions are detailed in Section VII.

II. Related Work

How autonomous robots move in human environments has a strongly effect on the perceived intelligence of the robotic system [6]. Independently of the physical capabilities of robots (navigation of wheeled robots are completely different to biped ones), social navigation started being extensively studied in the last years and several methods have been proposed from then. On one hand, some authors propose models of social conventions and rules by using cost functions [7], [8]. A typical solution is to propose a classic navigation method, adding social conventions and/or social constraints. In [7], for instance, the authors use a classical A* path planner in conjunction with social conventions, like to pass a person on the right. Other work as [8] uses potential fields and a proxemics model[2]. On the other hand, several authors use human intentions in order to model the social navigation [10]. In [10], authors propose a local navigation method and a human intention analysis using face orientation in order to modify the trajectory, which they called as Modified Social Force Model (MSFM) with three types of human intentions: avoid, unavoid and approach.

All the aforementioned methods need global path planners in order to choose the best route from the robot to the target and then, they apply social conventions and constraints to modify this path. Classical global path planners use a spatial representation of the robot's surrounding, that is, the path-planning problem requires a map of the environment. Numerous path-planning algorithm have been proposed in the literature, from classical Dijkstra or A* algorithms to other more complex systems. An interesting review of path planning algorithms was writing by LaValle et al. [11], who also propose the Rapidly-exploring Random Trees (RRT) method. This method, in conjunction with the Probabilistic Road Map algorithm (PRM) algorithm [12] is used in the cognitive architecture CORTEX [3].

Recently, several advances in semantic planning have been achieved. In fact, social robots that incorporate capabilities for task planning and storing some semantic knowledge in their maps are commonly used (*e.g.*, classification of spaces, such as rooms, corridors or garden, and labels of places and/or objects) [15], [5]. By using this semantic knowledge, robots are able to navigate or planning tasks. In several works is used voice interactions with robots in order to build the semantic map. This same problem is autonomously acquired by the robot in most recent works (see Kostavelis's survey [15]). In this paper, a 3D object detection and representation autonomous agent is used.

Finally, one of the main problem to solve is the cognitive architecture the robot is equipped with and also the kind of semantic and spatial information the robot has to store. Different proposals can be found in the literature, most of them by separately storing symbolic and metric information. Symbolic knowledge representation, such as the works proposed in [16] and [17], have been at the core of Artificial Intelligence since its beginnings. Recently, works that integrate

[2]Proxemics is defined as the study of humankinds perception and use of space [9]

spatial and symbolic knowledge in a unified representation are more frequent in the literature, and have a distinctive start in the *deep representation* concept introduced in [18]. Examples of these deep representations are [18], [19], [3]. In the proposal described in this paper, the robot uses the CORTEX architecture, which has demonstrated to be a robust and efficient agent-based architecture for robotics applications and is based on a set of agents interacting through a deep state representation [3].

III. Deep State Representation and Cortex

The concept of *deep representations* was initially described by Beetz et al. [18]: *representations that combine various levels of abstraction, ranging, for example, from the continuous limb motions required to perform an activity to atomic high-level actions, subactivities, and activities*. Deep representation advocates the integrated representation of robots knowledge at various levels of abstraction in a unique, articulated structure such as a graph. Based on this definition, in [3] it is proposed a new shared representation to hold the robots belief as a combination of symbolic and geometric information. This structure represents knowledge about the robot itself and the world around it. From an engineering point of view this representation is flexible and scalable. Formally, a deep state representation was defined as *a directed multi-labelled graph where nodes represent symbolic or geometric entities and edges represent symbolic and geometric relationships*.

The robotics cognitive architecture CORTEX is defined structurally as a configuration of software agents connected through a deep state representation that is called DSR, where an agent is defined in [3] 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*. The CORTEX architecture is implemented on top of the component-oriented robotics framework RoboComp [14]. In CORTEX, higher-level agents define the classic functionalities of cognitive robotics architectures, such as navigation, manipulation, person perception, object perception, dialoguing, reasoning, planning, symbolic learning or executing. The choice of these functionalities is by no means a closed issue in Cognitive Robotics but it is clearly a discussion outside the scope of this paper. These agents operate in a goal-oriented regime [16] and their goals can come from outside through the agent interface, and can also be part of the agent normal operation.

In Fig. 2 an overview of the DSR and its location within the cognitive architecture CORTEX is drawn. Different agents, such as navigation, person detector or planner are also shown. DSR is illustrated as a a graph where all the robot knowledge about its surrounding is represented. The next sections describe the design of the semantic social path planner using the cognitive architecture CORTEX, analyzing the agents involved and the relationships between them in three different cases of study.

IV. Agents

In order to plan the best social route from the robot pose to the target, different specific agents within CORTEX are involved. First, 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 allow robots to navigate from a point to another in a secure and social manner. In the next subsections, a brief description of the main agents involved in the proposal is provided. These agents are highlighted in Fig. 3, which illustrates the current CORTEX cognitive architecture [3].

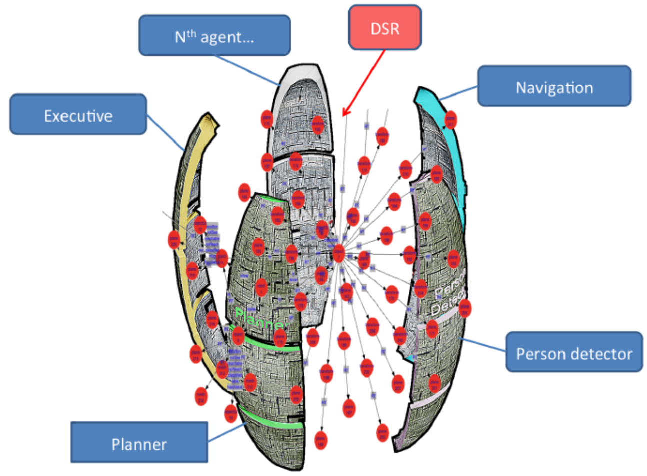


Fig. 2. An overview of the DSR and its location within the cognitive architecture CORTEX [3]

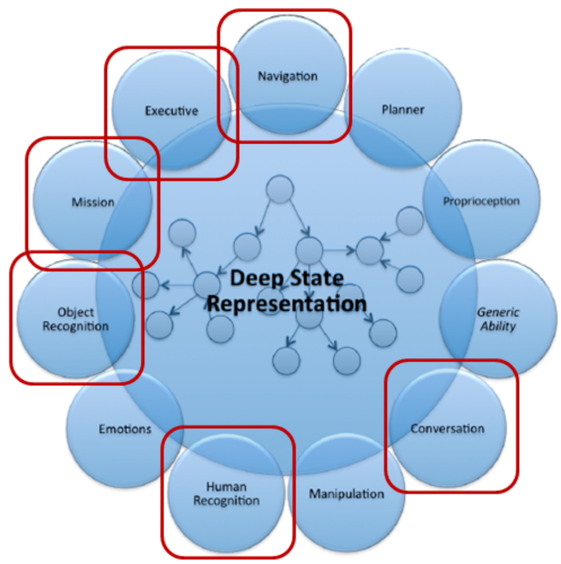


Fig. 3. Main agents within CORTEX involved in the semantic social path planning described in this proposal are highlighted in red.

A. Object detection and representation

The object perception agent is in charge of recognizing and estimating the pose of objects and visual marks in the environment. For each object or mark detected it describes within the model (DSR) not only the pose but also its type.

These kind of elements are useful for the robot in several scenarios. First of all, the targets will usually be objects and qualitative positions (*e.g.*, in front of something, close to something, between two objects) taking the objects as reference instead of just some coordinates. Humans will seldom ask the robot to go to a coordinate because they do not necessarily need to know the reference frame used by the robots and, more importantly, because it is not comfortable for humans to provide targets in such a way.

Synthetic visual marks are detected using the AprilTags library [20]. Arbitrary visual marks will be detected using the OpenCV library [21] and 3D objects are currently being detected using an object recognition pipeline based on the PointClouds library [22]. The poses of the detected objects are referenced to known objects (in the DSR) that support them, such as a known table under a target cup. Once referenced, the kinematic relations embedded in DSR allow the computation of any object's pose from any reference frame easily.

B. Person detector

Person detector is the agent responsible for detecting and tracking the people in front of the robot. Humans do not usually enjoy its 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. In social navigation, a human can also interact with the robot and give it orders, or the robots, in their way to their target, might be able to communicate with people to provide information or ask for help.

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 [3]. These elements can be used to infer the objects referenced by the humans when they point or look at them. 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.

C. Conversation

The conversation agent performs human-robot interaction (HRI). 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 both send and receive information to/from humans in the environment during its social navigation.

D. Mission

This agent is used as a means to provide missions to the executive agent and to visualize the DSR. It has two graphic views. A graph-like view and a 3D geometric view [3].

E. Executive

The Executive is responsible of planning feasible 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 might use different planners. Currently AGGL [4] and PDDL-based [23] planners are supported.

F. 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.

Two poses are maintained by the robot: the pose obtained from the local odometry, and the pose provided by a localization algorithm based on external geometric laser features. Given their properties, each of these poses is useful for a particular purpose. Odometry provides good information relative to the robot's position in the short term, while localization provides good information for mid and long term positioning. Additionally, the space walked by the robot in the last seconds is also included.

Regarding localization algorithms, the navigation agent is algorithm-independent. It has been used with different algorithms showing different properties, which can be selected to fit different kinds of environments.

While it can be used with any local navigation system, the navigation agent has been only tested with the path-planning algorithm proposed in [24], an algorithm based on the elastic-band representation, with successful results. The proposal presented in this paper extends the geometrical path-planning to a social semantic algorithm, which is described in the next section.

V. SOCIAL SEMANTIC PATH PLANNING IN CORTEX COGNITIVE ARCHITECTURE

In this section the semantic social path planning algorithm is described. An overview of the system is shown in Fig. 4. As illustrated in the figure, the complete system is composed of a global semantic path planner followed by a local geometrical path planner. Both of them are affected by a social navigation model. The semantic path planner chooses the optimal route, that consists of a list of labeled objects in the map. Then, the robot plans a local geometrical navigation from its current pose to the next object in the list. This path is affected by the

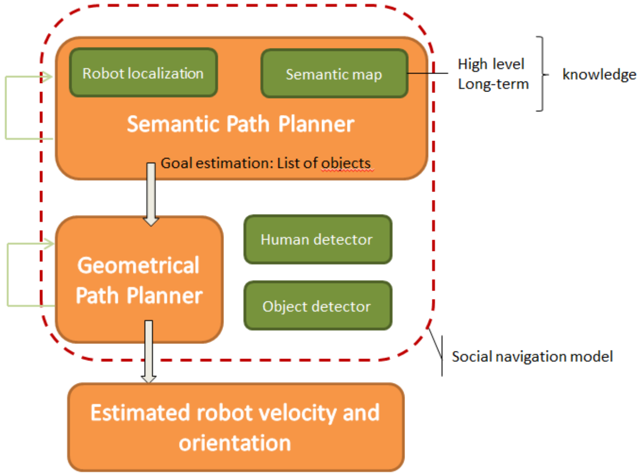


Fig. 4. The overall blocking diagram of the proposed system.

social navigation model, and if necessary, the local (or global) route is re-planned. All agents described in previous section are concurrently running in the navigation process.

A. Semantic Path Planning

Global path planning at a symbolic level is performed by the planner included in the executive. The semantic path planner is based on the use of a two-hierarchies architecture, similar to that one presented in [5]. Both, the spatial and semantic properties of each object within DSR allow the planner to choose the best global route. Let $O = \{o_1, o_2, ..., o_n\}$ being the list of n objects o_i within the semantic map of the robot, that is, its high level and long-term knowledge. Each object o_i is characterized by a duple $o_i = \{m_i, s_i\}$, where m_i is the metric representation of the object ($i.e.$, rotation and translation matrices from its parent node) and s_i is the semantic information associated to the object ($i.e.$, label). Each object has a parent node, which usually represents the room where the object is located. Rooms are also nodes of the graph, that are connected if they are sharing a door. Thus, the semantic path planning algorithm chooses the best route from the graph, that is, the list of rooms that the robot has to visit, and then, generates a list of j objects (waypoints) for the local planner, $\Gamma_R = \{o'_1, o'_2, ...o'_j\}$, being $o'_j \in O$. Thus, global navigation is achieved by using consecutive objects from Γ_R.

B. Geometrical path Planning

Once the robot is assigned the path Γ_R, the geometrical path-planner should accomplish the navigation between two consecutive objects, o'_{k-1} and o'_k. The geometrical path-planning algorithm of the proposal is based on the use of graphs as a representation of free space and of elastic-bands [24] as an adaptable representation of the current path. Elastic bands work as a glue filling the gap between the internal representation of the path and the constraints imposed by the world physics. In order to build a graph representing the overall free space, the probabilistic road map algorithm, PRM, is used [12] along with a preexisting map and a collision detection algorithm. To complete this schema, the RRT algorithm [11] is also included in the system to complete the paths when unconnected islands remain in the PRM graph or to connect the robot's current position and robot's final position with nodes in the graph. The object perception agent is directly involved in the path following process: when the robot detects the object o'_k, a new target is generated, being the new local route defined by the nodes o'_k and o'_{k+1}.

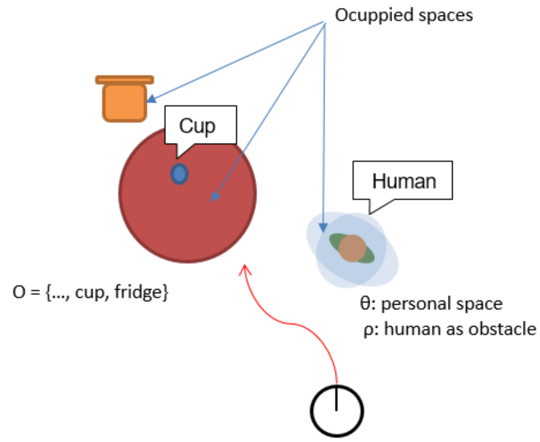
C. Social Navigation Model

In order to mathematically formulate the socially-acceptable path planning algorithm, let denote $H = \{H_1, H_2, ...H_n\}$ the set composed by n humans in the environment. Each human, H_i, in the DSR is represented by the pose of its torso, its upper limbs, and the head. These elements can be used for defining a personal space θ_i and a social interaction intention ρ_i. Both θ_i and ρ_i are detected by the human detector agent, and are included in the DSR as information associated to human H_i. On one hand, and similar to the work presented in [2], θ_i is defined as Gaussian Mixture Model of two 3D Gaussian functions, one for the front of the individual, and other for its rear part. By adjusting the covariance matrices of these two gaussians, one can modify the personal space model. On the other hand, ρ_i describes the different cases where a human wants or not to interact with the robot during the path: i) human does not want to interact ($i.e.$, human is considered as obstacle); ii) human wants to interact with the robot, and then, the robot has to approach human, interact and finish the communication. In this respect, depending of the ρ_i value, the final path may be modified. For instance, if the human is considered as obstacle, the graph in the geometrical local navigator has to be updated in order to avoid this new obstacle (see Fig. 5(a)). On the contrary, if the human wants to interact with the robot, a new object $o'_k = H_i$ is included in the list of nodes to reach, being H_i the next target (see Fig. 5(b)).

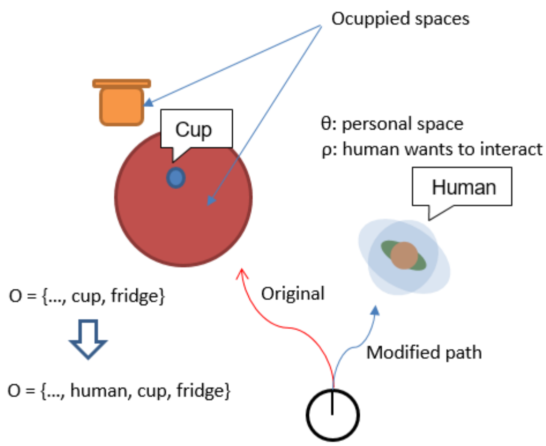
VI. Cases of Study

Within the 'BS-NAVLOC' project, this paper proposes three different cases of study. All of them are examples of robots navigating in indoor environments, and the main goal is to demonstrate that the semantic social path planning algorithm proposed in this paper, using the CORTEX cognitive architecture, may be performed in different robotics platforms in a near future and with successful results. In this section, the ongoing work is presented, describing briefly the DSR and the relationships between the involved agents.

The proposal of semantic social path-planning algorithm is going to be tested in two different robots (Fig. 6). The first robot is the DOKBot, from VerLab at the University Federal of Minas Gerais, which consists of a Pioneer 2-AT robotics platform equipped with different perceptual sensors, such as laser, RGB cameras and microphones (see Fig. 6(a)). This robot was originally designed for semiautomatic telepresence purposes. The second autonomous system is Shelly, an anthropometric social robot that is currently being used in RoboLab,



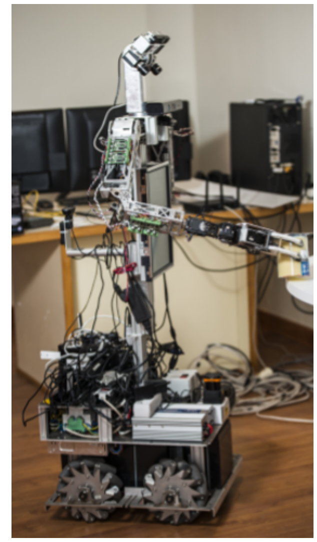
(a)



(b)

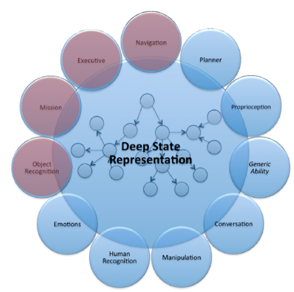
Fig. 5. Social navigation model proposed in this paper: a) human does not want to interact with the robot; and b) the human wants to interact.

(a)



(b)

Fig. 6. The semantic social path-planner within CORTEX is going to be integrated in two different robots: a) DOKBot robot, from VerLab research group at the University Federal of Minas Gerais; b) Shelly robot, from RoboLab research group at the University of Extremadura.



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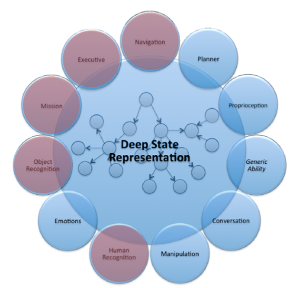

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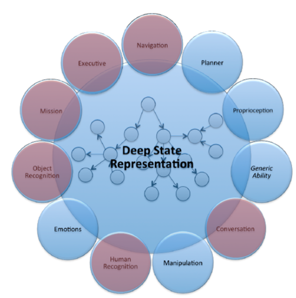

(c)

Fig. 7. Agents involved in the cases of study described in this paper. a) semantic path planning; b) semantic social path planning; and c) semantic social path planning with HRI.

at the University of Extremadura. This robot was designed to help in daily life tasks. It is composed of an omnidirectional base, two 7-DOF arms with two-fingered grippers and a RGB-D camera attached to a pan-tilt-yaw structure. It has another RGB-D camera on the upper part of the torso which is used to detect human bodies and a lidar for navigation. This robot is illustrated in Fig. 6(b).

Next, the experimental scenarios are described. They have been designed from low-complexity to high-complexity levels:

- Semantic Path Planning. In this experiment, the robot chooses the best route from a room to another. In this scenario, there is not people in the path, and thus, only the semantic knowledge of the rooms is used. Fig. 7(a) shows the agents involved in this scenario.
- Semantic social path planning. This experimental scenario consists on a semantic social navigation. Similar to the previous case of study, the robot has to navigate between two different rooms in an indoor and human environment. In this respect, people walk or stand in the robot path, and thus, the robot has to modify the route in order to be socially accepted. The set of agents involved in this case of study is illustrated in Fig. 7(b).
- Semantic social path planning with HRI In this case of study, the robot first interacts with the human in order to know what is the next room to visit, and also, other humans interact with the autonomous agent during the path. In this HRI, the robot may modify partial or fully its route. Finally, in Fig. 7(c), the agents involved in CORTEX are highlighted.

VII. Conclusions and future works

This paper presents the ongoing work, within the NAVLOC project, of a proposal for the design of a semantic social path-planning algorithm. The approach is based on the use of a global semantic path-planner in conjunction with a social navigation model. The theoretical proposal achieves the main goal of this kind of algorithm, that is, the robot is able to choose the best route from its current position to another position in a dynamic and complex scenario by using its high level knowledge and by applying social rules in order to be socially accepted. High functionality and robustness are guaranteed by using the cognitive architecture CORTEX and the Deep State Representation.

As it was aforementioned, this paper describes the ongoing work, where three different experimental scenarios are also described in order to test the proposed social navigation algorithm in future works. Currently, both spanish and brasilian researching teams, are working in integrating CORTEX in the two robots presented in this paper, Shelly and DOKbot.

Acknowledgments

This work has been partially supported by the MICINN Project TIN2015-65686-C5-5-R, by the Extremaduran Goverment project GR15120, by MEC project PHBP14/00083 and by CAPES-DGPU 7523/14-9.

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