2020 IEEE International Conference on
Autonomous Robot Systems and Competitions (ICARSC)
April 15-16, Ponta Delgada, Portugal

Human-aware Robot Navigation based on Time-dependent Social Interaction Spaces: a use case for assistive robotics

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***Abstract*—Social navigation in care-giving environments - nursing homes, geriatric residences, for example - is an essential task for future generations of service robots. Navigating in a complex environment with elderly people, clinical staff or companions implies the need to adapt to social conventions the planned routes, the velocity of approach to people and the spaces of interaction between robot-human, human-human and human-object. Currently, navigation algorithms do not take into account the social complexity of the scenarios like, for example, their relationship with the hour of the day or the activities carried out in these scenarios. This article presents a first approach to the idea of time-dependent social mapping, where the planning of the social route by the robot takes into consideration variables that depend on the time and schedules of use of certain spaces. To this end, this article describes how the spaces of human-object interaction vary as a function of time and how this affects the social navigation planned by the robot. Several use cases have been performed in a simulated environment to asses the improvements in the robot social navigation using these temporal variables.**

I. Introduction

The use of social robots in assisted living environments for older people will become a reality in the coming years [1]. Currently, there are many situations in which human-robot collaboration is demanded. In a care-giving center, for instance, possible scenarios include physical or cognitive activities proposed by assistive robots, the accompaniment side-by-side of the elderly person while walking, clinical staff support [1]. In these situations, planning and following paths in a social-aware fashion is essential to achieve social acceptability [2].

Most of the works in the literature are based on the *proxemics*: the robot moves through the environment without disturbing people's personal spaces or interrupting their interaction with other people or objects in the environment [3]. Planning of paths in these situations is usually solved following *social mapping* techniques that map regions in the environment where the robot should not navigate [4]. Social mappings extend metric and semantic maps including social information of the environment [4]. Consider the scene depicted in Fig. 1a: in it, the robot plans a route in a care-giving environment taking into account people who might be interacting with some of the objects. The space of interaction associated with an object is known as *affordance* [5]. In Fig. 1a, around the object *table*, its interaction space has been drawn in red during a group therapy session with elderly people. Consequently, the robot avoids this area in its trajectory. However, object's interaction space should not be static but should vary over time. In the above illustrative example, the object *table* is not always being used, in fact, its use depends on the therapeutic sessions schedule. Fig. 1b represents this second situation, where the robot plans a different trajectory, based on the activities schedule, without the risk of invading the object affordances.

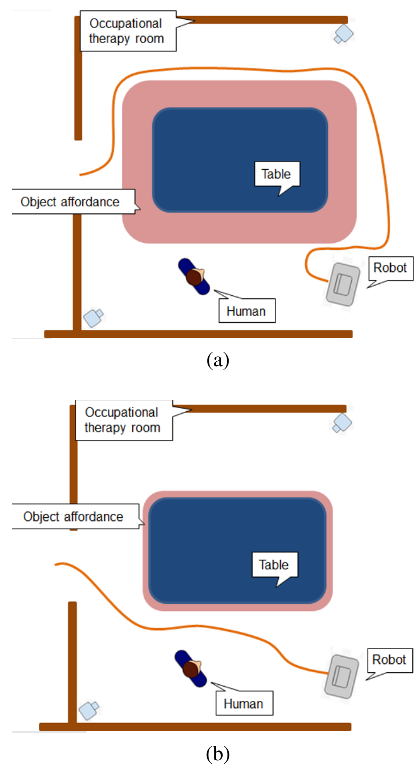

Fig. 1: Two different everyday scenarios: a) At the time of planning, the socially accepted path, the robot takes into account that there is scheduled a therapy in the room; b) Unlike the previous case, in this new scenario there is not scheduled therapies in this room.

The scenario described in Fig.1 can be extended to other real situations in care-giving centers where activities are governed by schedules established by the clinical or administrative staff. If a robot includes schedules in its plans, the routes can be easily adapted, achieving a higher degree of social acceptance. This article presents a first approach to the idea of a time-dependent social mapping, where the planning of routes includes the use of the spaces over time, restricting or penalizing its route in some areas depending of the activities

*This work has been partially supported by the Extremaduran Goverment project GR15120, IB18056 and by the FEDER project 0043-EUROAGE-4-E (Interreg V-A Portugal-Spain - POCTEP).

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978-1-7281-7078-7/20/$31.00 ©2020 IEEE

scheduled. This social information is added on top of the free-space graph which is later used for path planning and navigation. As a main contribution, this paper describes this new model for the definition of the time-dependent social interaction spaces that can be used in most of the navigation algorithms based on proxemics.

This paper is organised as follows: In section II a discussion of previous works related to robot navigation in human-environments is provided. Section III presents an overview of the proposed social navigation architecture, including time-dependent social interaction spaces. Next, Section IV describes the new model of social interaction spaces, including its dependence over time. In Section V, the socially-accepted path-planning algorithm presented in this paper. Finally, Section VI outlines the experimental results are outlined and Section VII summarises the conclusions and future works.

II. Related works

Path-planning in human environments is an essential task for future generation of social robots. The way in which a robot navigates in real environments, such as an elderly care center, has a strongly effect on the perceived intelligence [6]. A path that explicitly takes into account people and interactions human-human and human-objects in the environment should not only consider, for instance, minimizing the distance traveled to the target or the time consumption, but also social rules (*e.g.*, keeping a comfortable distance from humans or not disturbing people during an interaction with objects in the environment [2]).

Social navigation started being extensively studied in the last decade and several methods have been proposed since then. Some authors propose models of social rules by using cost functions [7], [8]. A typical solution is to add 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. In [8], they use potential fields and a proxemics model in order to define regions where robot is able to navigate.

In this respect, most works in the literature use the concept of *social mapping* to define social interaction spaces in which robot navigation is forbidden or penalized [4]. In [4], [9], [10], for instance, authors define areas in people surroundings in which robot's navigation is forbidden by using the concept of proxemics. In addition, other works use the term object affordances and/or activity spaces, and prevent robots from navigating near them creating regions where navigation is also forbidden or penalized [11], [5]. Recently, in the work presented in [12], the concept of interaction spaces and their use to define social paths was introduced. However, all previous authors and works consider these social maps as static, and there is no dependence over time or other kind of situations. Some of these concepts are used in this article where, as main novelty, it is defined the time-dependence of these spaces of interaction, taking into account the activities agenda of an elderly care center. The proposal uses the classical Dijkstra's algorithm, where weights of the graphs are modified in order to take into account the social map of the environment and its dependence overt time.

III. Overview of the social navigation framework

Robot social navigation in elderly care centers, where all activities are scheduled by the center's professionals, requires a reformulation of the classic social navigation algorithm, as well as the use of an evolved hardware and software architecture. This work uses a shared representation of the environment (Deep State Representation, DSR) and the CORTEX cognitive architecture described in [13]. DSR is a multi-labelled graph that defines the information of the environment: rooms, humans, objects, as well as the robot, among others. In this graph, nodes are the elements, and arcs are the relationship between them (e.g., "in", "connected", etc) [13]. Software agents interact with this DSR to include new nodes (e.g., a new person come in the robot's room, or a new object is detected) or update relationships (e.g., two people starts an interaction or the robot moves to other room). Fig. 2 illustrates a simplified example of the multi-labelled graph for an elderly care center.

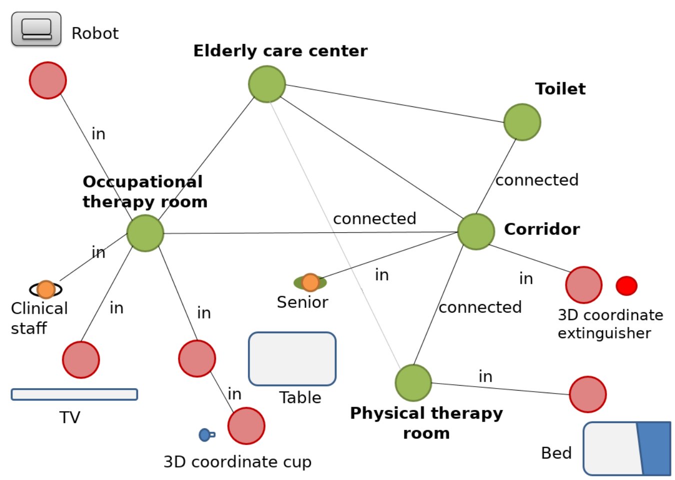


Fig. 2: An example of the Deep State Representation in a real elderly care center.

The overview of the proposal is described in Fig. 3. The social path is planned by using a classical Djisktra algorithm that uses a free-space graph of the environment. In this graph, the weights of each node depend on the social map generated by the cognitive architecture. This social map is built by the social navigation agent according to the DSR, which has been previously provided by two different agents: the human-observer agent and the object recognition agent. The first one, the human-observer agent is in charge of detecting and tracking people in the scene. The object-recognition agent is responsible for detecting objects and monitoring their pose in the environment. Finally, the time dependence of this social map is provided by the center's professionals.

IV. Time-depending social interaction spaces

To plan a path in real environments with people the proposed work builds a social map of the robot's surroundings.

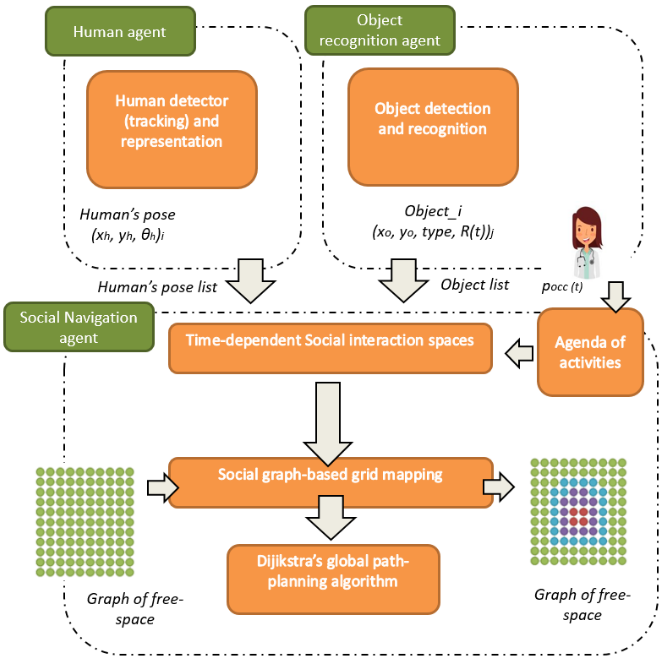


Fig. 3: Overview of the proposed system

This involves the definition of social interaction spaces associated with people and objects and, in this last case, its dependence over time. Each of the modules is described below:

A. Social mapping: people in the environment

Let $H_N = \{h_1, h_2 ... h_N\}$ be a set of N humans detected by the human-observer agent, where $h_i = (x, y, \theta)$ is the pose of the i-th human in the environment[1]. To model the interaction space of each person h_i an asymmetric 2-D Gaussian curve $g_i(x, y)$ is used, as described in [11]:

$$g_{h_i}(x, y) = exp^{-(\gamma_1(x-x_i)^2+\gamma_2(x-x_i)(y-y_i)+\gamma_3(y-y_i)^2)} \quad (1)$$

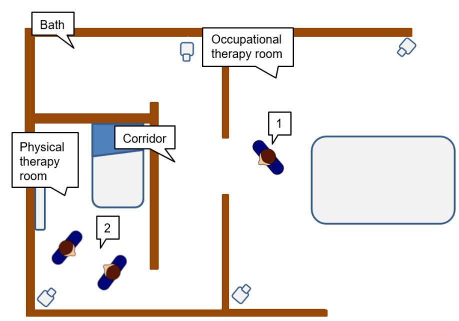
, where the coefficients γ_1, γ_2 and γ_3 are associated to the rotation of the function β_i. Fig. 4a shows a person, labeled as '1', and its personal space modeled by the assymetric Gaussian described in [11]. Let σ_s be the variance on the left and right directions ($\beta_i \pm \pi/2$), which defines the variance along the β_i direction (σ_h), or the variance to the rear (σ_r), this function β_i is defined next:

$$\begin{aligned}
\gamma_1(\beta_i) &= \frac{cos(\beta_i)^2}{2\sigma^2} + \frac{sin(\beta_i)^2}{2\sigma_s^2} \\
\gamma_2(\beta_i) &= \frac{sin(2\beta_i)}{4\sigma^2} - \frac{sin(2\beta_i)}{4\sigma_s^2} \\
\gamma_3(\beta_i) &= \frac{sin(\beta_i)^2}{2\sigma^2} + \frac{cos(\beta_i)^2}{2\sigma_s^2}
\end{aligned}$$

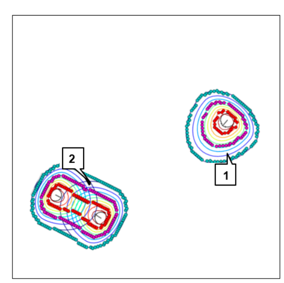
[1]The actual detection of humans is out of the scope of the paper. In the experiments carried out it was performed by the CORTEX architecture.

Once people have been detected, the algorithm clusters humans in the environment according their distances by performing a Gaussian Mixture ([11]) (two people, labeled as '2', have been clustered in Fig. 4b). The personal space function g_{h_i} of each individual i in the environment is added and a Global Space function $G(p)$ is built. From this function, a contour J_i is established as a function of the density threshold ϕ. Finally, the contours of these forbidden regions are defined by a set of k polygonal chain (*i.e.*, polyline) $L_k = \{l_1, ..., l_k\}$, where k is the number of regions detected by the algorithm. The curve l_i is described as $l_i = \{a_1, ..., a_m\}$, being $a_i = (x, y)_i$ the vertices of the curve, which are located in the contour of the region J_i.

Finally, the last step classifies the space around a person into four zones, depending on social interaction: public, social, personal and intimate zones. Each human h_i in the environment will have three associated spaces: the intimate space, defined by the polyline $L_k{}^{intimate}$; the personal space, defined by $L_k{}^{personal}$; and the social space, delimited by $L_k{}^{social}$, each of them being larger than the previous one, as it was introduced in [10]. The public zone will be the remaining free space. These contours, which are created by choosing different values of the density threshold ϕ, are illustrated in Fig. 4: in color red is shown the intimate space, in purple the personal one and as blue color the social space.



(a)



(b)

Fig. 4: a) People in a simulated caregiving environment; b) asymmetric Gaussian associated to person '1' and clustering of the group of two people labeled as '2' in Fig. 4a.

B. Social mapping: Space Affordances and Activity Spaces

In caregiving centers is common to perform physical or cognitive therapies where people - elderly or professional - interact with objects. Robots should be able to detect these situations before planning their path. In this sense, literature defines the concept of *Space Affordances* to refers areas where humans usually perform particular activities [5] (*i.e.*, in interactive scenarios, these spaces are related to objects with which people interact, for example, the space near a TV or a table where people are in a specific therapy). These spaces are called *Activity spaces* when people are interacting with them. In this paper, these spaces are not fixed spaces and are time-depending.

Let $O_M = \{o_1, ..., o_M\}$ be the set of M objects with which humans interact in the environment. Each object $o_k \in O_M$ stores the interaction space i_{o_k} as an attribute, which is associated to the space required to interact with this object, the time-dependence $R_{o_k}(t)$ and also its pose $p_{o_k} = (x, y, \theta_k)$,

$$o_k = (p_{o_k}, R_{o_k}(t), i_{o_k})$$

Different objects in the environments have different interaction spaces i_{o_k}. For instance, when using the table for therapies, a smaller space is needed in comparison to when watching television because this last can be done from a farther distance. Besides, these spaces are also associated with the activities scheduling of the center, $R_{o_k}(t)$. $R_{o_k}(t)$ is a mathematical function depending over time that is scheduled by the center's professionals, where $0 \leq R_{o_k}(t) \leq R_{max}$.

The *Space Affordance* A_{o_k} is defined for each object $o_k \in O_M$ by using i_{o_k} and $R_{o_k}(t)$. In this paper, these spaces have been modeled depending of the shape of the object and the way that people interact with, and are classified as: i) poster or TV similar shapes; ii) rectangle shapes (*e.g.*, tables o beds); and iii) circular shape objects (*e.g.*, tables). Fig. 5 illustrates the space affordance of each object.

- *Poster or TV similar shapes*: This kind of objects are modeled as a symmetrical trapezoid with height t'_h and widths (t_{w1}, t_{w2}), as described in [11]. Time-dependence is included in the parameters t'_h and t_{w2} by using the following equations:

$$t_{w2} = (t_{w1} \cdot t'_h)/4 \tag{2}$$

$$t'_h = a_h \cdot R(t) \tag{3}$$

- *Rectangle shape objects*: Objects like tables, beds or stretchers are rectangular objects typically used in caregiving centers. These objects are modeled as a rectangle with height r'_h and width r'_w (see Fig. 5). In a similar way, time-dependence is also included as:

$$r'_h = r_h \cdot (1 + R(t)/4) \tag{4}$$

$$r'_w = r_w \cdot (1 + R(t)/4) \tag{5}$$

- *Circular shape objects*: Objects like circular tables are also common in caregiving centers. In this papers they are modeled as a circle with center in p_{o_k} and radius c'_r. Its dependence over time is also included as:

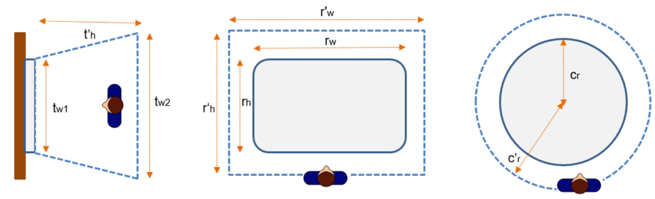


Fig. 5: Social interaction modeling: the Space Affordance of an interactive object is modeled by: a symmetrical trapezoid (left); a rectangle (middle); and circular shapes (right)

$$c'_r = c_r \cdot (1 + R(t)/4) \tag{6}$$

Finally, the last step classifies the space around each object at an instant time t into three regions, depending on its dependence over time (*i.e.*, no activity scheduled in the room, unknown or activity scheduled in it). For each region, a polyline is defined $L^t_{o_k}$. The set $L^t_o = \{L^t_{o_1}, ..., L^t_{o_M}\}$ describes the set of polylines used by the navigation algorithm at an instant time t and they are associated with different costs in the free-space graph used for navigation.

V. Socially-acceptable path-planning algorithm

This section describes the social path-planning algorithm proposed in this paper. Robot's environment is represented by a uniform graph composed of obstacle-free nodes, that have a constant finite traversal cost, and non-free nodes, which have an infinite one. The approach described in this work modifies the costs according to the social map. This final graph is used to estimate the optimal path using classical Dijisktra's algorithm.

A. Graph-based grid mapping

Space is represented by a graph $G(N, E)$ of n nodes, regularly distributed in the environment. Each node n_i has two parameters: availability, a_n, and cost, c_n. The availability of a node is a boolean variable whose value is 1 if the space is free, 0 otherwise. The cost, c_i, indicates the traversal cost of a node, i.e., what it takes for the robot to visit that node (high values of c_i indicates that the robot should avoid this path). Initially, all nodes have the same cost 1. Fig. 6a shows an original free-space graph in which all nodes have the same cost and availability (as there are no obstacles in the area depicted).

The classical Dijkstra algorithm is employed for determining the shortest path between an initial position and a target to which the robot must travel. Given a node of origin, the algorithm calculates the cost from origin the to the target node taking into account the cost of the nodes. The cost of a path is the sum of the cost of the nodes that compose it.

B. Social graph-based grid mapping

The free space graph is modified to include the social spaces of interaction: firstly, those associated with the interaction between one person and another -or groups of people-, and

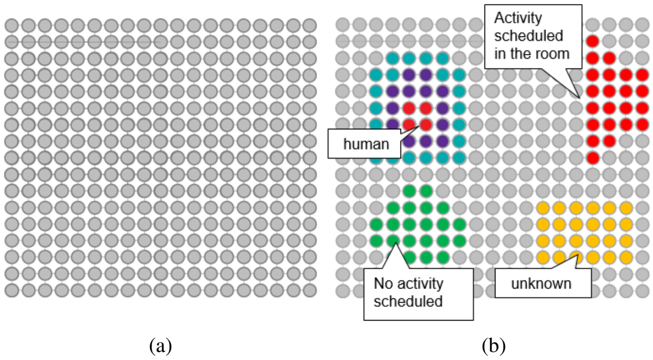


Fig. 6: Graph-based grid mapping: a) original free-space graph; and b) final free-space graph, after including the social interaction space associated to a person.

secondly, those associated with the interaction between people and objects.

1) Personal Space mapping: Being A the matrix formed by the availability of each node of the free space graph and C the matrix formed by the costs and considering the set of polygonal curves defined bellow, $L_k{}^{intimate}$, $L_k{}^{personal}$ and $L_k{}^{social}$, this paper present the modification of the cost and availability of the nodes of the graph according to these interaction spaces.

In first place, considering only the intimate space around the person h_i, for each polyline $l_i^{intimate}$ is defined a polygon $P_i^{intimate}$ formed by the points of the polyline. The availability a_{h_i} of all the nodes $N_i \in N$ contained in the space formed by $P_i^{intimate}$ is set to occupied, $a_{h_i} = occupied$. This means that the robot will not be able to invade this space, as it would disturb the person. For personal and social spaces, the availability of the nodes of the graph is not be modified, but its cost will be changed.

Considering the personal space around the human h_i, for each polyline $l_i^{personal}$ a polygon $P_i^{personal}$ has been defined. The cost c_{h_i} of all the nodes $n_i \in N$, contained in the space formed by $P_i^{personal}$ will be modified and set to $c_{h_i} = 4.0$. In the same manner, for the social space, a polygon P_i^{social} is defined for each polyline $l_i^{personal}$. All the nodes $N_i \in N$ contained in the space formed by P_i^{social} will have cost $c_{h_i} = 2.0$. The public space will be the rest of the graph whose costs remain unchanged. Fig. 6b show the final free-space graph, where the costs of nodes are modified according to the social spaces of interaction.

Intimate areas are forbidden for navigation. Personal and social spaces are available, but their costs are higher, being personal spaces more expensive than social spaces. This way, when the robot plans the shortest path, it will move away from the person. The social and personal spaces are not considered occupied so if the robot does not have enough space to navigate, for example in a corridor, it won't be blocked, but it will navigate through the social space, even if its cost is higher. If the robot does not have another alternative, it will cross the personal space, but it will never cross the intimate one.

2) Space Affordances of objects: This same technique has been used for *Space Affordances*. Let $L^t{}_o = A^t{}_{o_1}, ..., A^t{}_{o_M}$ be the set of polylines that describe *Affordance* of each object over time. For each $A^t{}_{o_k}$ the polygon $P^t{}_i$ is built. The availability, a_{o_k} of the nodes in the graph within the objects are set to *occupied*, $a_{o_k} = occupied$ while availability of the rest of nodes is not modified. Regarding to cost of nodes in the free-space graph, these values are associated to its dependence over time ($i.e.$, no activity scheduled in the room ($c^t_{o_k} = 1.5$) , unknown ($c^t_{o_k} = 2.5$) or activity scheduled in it ($c^t_{o_k} = 3$). Thus, nodes of the free space graph $N_i \in N$ contained in P^t_i are modified in order to set its cost to these values according to the activities agenda. Fig. 6b shows three different objects and their space affordances with different colors depending of the activities scheduling.

VI. Experimental Results

A set of simulated caregiving scenarios have been used to validate the results of the proposed social navigation system. The algorithms have been developed in C++ and the tests have been performed in a PC with an Intel Core i5 processor with 4Gb of DDR3 RAM and Ubuntu GNU/Linux 18.10.

In order to assess the validity of the proposed navigation approach, the methodology has been evaluated accordingly to the following metrics: (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 [14], [15])

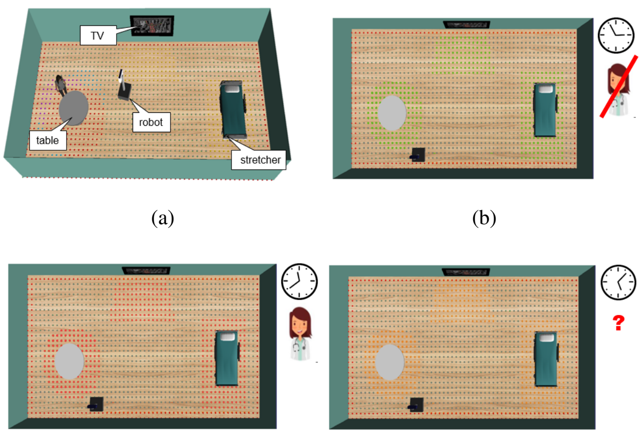
The first experiment is illustrated in Fig. 7 and evaluates the approach described in this paper for building time-dependent social interaction spaces. In Fig. 7a a physical therapy room with three objects is shown (a TV, a circular table and a stretcher). Previously, the activities scheduling of this room has been set by the center's professionals. Fig. 7b, Fig. 7c and Fig. 7d show three different instant times of the social interactions spaces of the objects. As appreciated, the cost of the graph is different according to the activities agenda.

The second test represents a more complex scenario composed of different rooms, objects and people, and where the activity scheduling is also modified (see Fig. 8). The robot plans a social path from its current pose to a pose in other room. In the first test, $R_{o_k}(t)$ = 1, that is, there is an activity scheduled in the physical therapy room; In the second test $R_{o_k}(t)$ = 0.25 ($i.e.$, there is not an scheduled activity in this same room). Other rooms are set to $R_{o_k}(t)$ = 0.25 for both two tests. In Fig. 8b and Fig. 8c the social paths planned by the robot are drawn in red color. Table I summarizes the results of the proposed solutions for the tests described in this section.[2]

VII. Conclusions and Future works

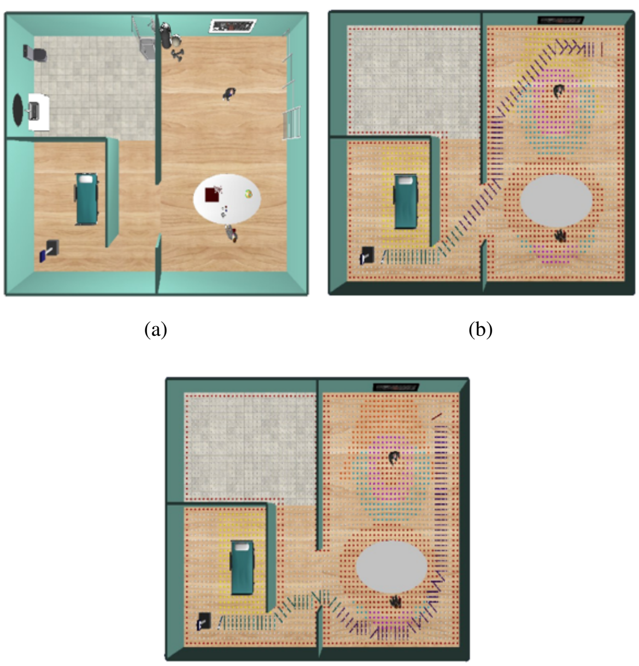
Human-aware robot navigation is a complex skill that has to take into account real situations that involve human-robot

[2]Experimental results video: https://youtu.be/YvZen-tXwDQ



(a) (b) (c) (d)

Fig. 7: First test: a) simulated physical therapy room with three objects inside. b) Spaces of interaction and its costs in the graph (in green) if there is not activities scheduled in the room; c) if the agenda is unknown (in orange color); and d) if there is activities scheduled in the room (in red).



(a) (b) (c)

Fig. 8: Second test: a) simulated physical caregiving center with three rooms. b) navigation in a room without activities scheduled by the center's professionals; and c) robot navigation in this same room with activities in the agenda.

or human-object interactions. In the case, for instance, of care environments, some of these interactions are associated to activities scheduled by center's professionals. Taking into account this time-dependence in the social path planning algorithm is the main aim of the approach described in this paper. The algorithm is based on the well-known Djisktra's

TABLE I: Navigation results with space affordances

NO THERAPY		THERAPY HOUR	
Parameter	Value (σ)	Parameter	Value (σ)
d_t *(m)*	14.03m	d_t	17.40m
τ	101.79s	τ	124.24s
CHC	0.47 (0.11)	*CHC*	1.75 (0.05)
d_{min} *Person 1 (m)*	1.39 (39.40)	d_{min} *Person 1 (m)*	1.89 (64.15)
d_{min} *Person 2 (m)*	3.147 (68.18)	d_{min} *Person 2 (m)*	1.07 (39.00)
Ψ *(Intimate) (%)*	0.0 (0.0)	Ψ *(Intimate) (%)*	0.0 (0.0)
Ψ *(Personal)(%)*	0.0 (0.0)	Ψ *(Personal)(%)*	0 (0.0)
Ψ *(Social)(%)*	0.0 (0.0)	Ψ *(Social)(%)*	0.0 (0.0)
Ψ *(Public)(%)*	65.01 (1.5)	Ψ *(Public)(%)*	98.39 (1.36)
Ψ *(Affordances) (%)*	34.98 (1.5)	Ψ *(Affordances) (%)*	1.64 (1.36)

algorithm, where the original free space graph is modified according to time-dependent social interaction spaces.

Although the results demonstrate the validity of the approach, future research lines consider the use of a real robot and questionnaires to gather information on the acceptability of the planned paths.

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