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Social Robot Navigation adapted to Time-dependent Affordance Spaces: a Use Case for Caregiving Centers

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***Abstract*— The use of socially assistive robots in real environments, such as nursing homes or geriatric residences, is spreading in recent years. Social robot navigation in these complex environments, with multiple users and dynamic objects, is an essential task for the next generation of service robots. This navigation must respect social rules, for example not to interrupt an interaction between two people or between a person and an object. Current navigation frameworks in robotics literature do not take into account the social complexity of the scenarios like, for example, the relation of the objects and their use by people with time. This article presents an approach to the idea of time-dependent social mapping. The main novelty is the definition and development of time-dependent affordance spaces. Each object has a zone that vary in function of time and the activities scheduled by the center's staff. Therefore, the planning of the best path by the robot takes into consideration this variation on time achieving a higher degree of social navigation. Several use cases have been performed in a simulated scenario to asses the robustness and validity of the proposal using these temporal variables.**

I. INTRODUCTION

Social robots will be a reality in caregiving centers in the near future [1]. Human-robot interaction is needed to perform complex tasks, and most of them need robust navigation that implies planning in a socially aware manner [10].

The predominant approach in literature to solve this type of problem is based on *proxemics*: the robot navigates in the environment without disturbing people's personal spaces or interrupting their interaction with other people or objects [2]. *Social mapping* techniques are used to solved these situations. Social mapping extend metric and semantic maps including social information of the environment [3]. Usually, the regions in the environment where the robot should not go through are mapped as banned regions.

In the scene depicted in Fig. 1. The robot plans a path that not only takes into account the free space, but also takes into account other constraints related to objects, people and their interaction. According to the definition of *affordance* [5], understood as the space of interaction associated with an object, this could be vary in function of time. Or, in other words, this space of interaction could be mapped as banned regions or a free regions in function of time. In Fig. 1a, around the object *table*, its affordance space has been drawn in red (banned region) during a therapy session with elderly people. Consequently, the robot avoids this area in its path planning. The object *table* is not always being used, in fact, its use depends on the therapeutic sessions scheduled. The second situation is represented in Fig. 1b, where the robot plans a different trajectory, based on the activities scheduled, without the risk of invading the object affordance space.

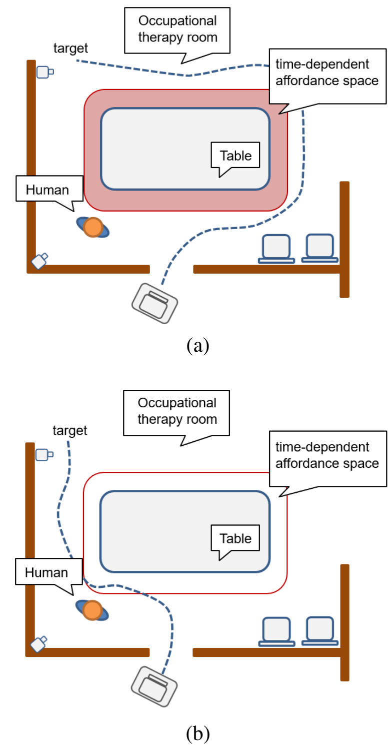

Fig. 1: Two distinct situations in the same room: a) The robot knows that there is an activity at that time and planning a path according to the situation; b) In the second situation, there is no therapy, and the robot uses the affordance space to plan the path.

This work presents an approach to the idea of a time-dependent social mapping, where the planning of routes includes the use of the objects affordance spaces over time, restricting or releasing some areas according to the activities 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, the paper describes this new model for the definition of the time-dependent affordance spaces.

This article is organized as follows: In section II a discussion of previous works is provided. Section III presents

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an overview of the proposed. Next, Section IV describes the new model of affordance spaces, including its dependence over time. Section V presents the socially-accepted path-planning algorithm proposed. Finally, Section VI shows the experimental results obtained and Section VII summarizes the main conclusions and future directions.

II. Related Work

Navigation in human environments is related to human's perception of robot's intelligence [6]. Path-planning must take into account people, objects and their interactions and including social conventions [10].

In the last decade, social navigation has been extensively studied, and various techniques have been proposed. Several authors suggest models of social rules using cost functions adding social conventions, social constraints, or both as a usual solution [7], [8]. In [7], for example, the authors combine social conventions such as overtaking a person on the right with classic path-planning algorithms such as A*. In [8], the authors 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 [3], [9], for instance, by using the proxemics concept, areas in people's surroundings where the robot cannot navigate are defined. Furthermore, other works use the term activity space or object affordance to restrict or even block the robot's navigation creating regions around objects [10], [5]. Recently the idea of spaces for interaction and how they could be used to define social paths have been proposed [11]. However, all previous authors and works consider these social maps as static, and there is no dependence over time or other type of situations. Several of these concepts are used in this article where, as main novelty, it is defined these spaces of interaction of the object as time-dependent affordance spaces, taking into account the activities agenda of an elderly care center.

III. Overview of the Social Navigation Framework

Our proposal is based on Deep State Representation (DSR), a shared representation of the environment, and the CORTEX cognitive architecture described in [12], to allow the incorporation of several sources of information into a common knowledge. 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 edges are the relationship between them (e.g., "in", "connected", etc). 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 another room). Fig. 2 displays an example of the multi-labelled graph for an eldercare facility.

Fig. 3 shows the proposal overview. The social navigation agent builds the social map according to the DSR. Various sources update the DSR. The human-observer agent is in charge of detecting and tracking people. The object-recognition agent is responsible for detecting objects and monitoring their pose. The time dependence is provided by the center's professionals trough the activities agenda. The weights of each node depend on the social map generated by the cognitive architecture. Lastly, the social path is planned using the Dijkstra algorithm with a free-space graph.

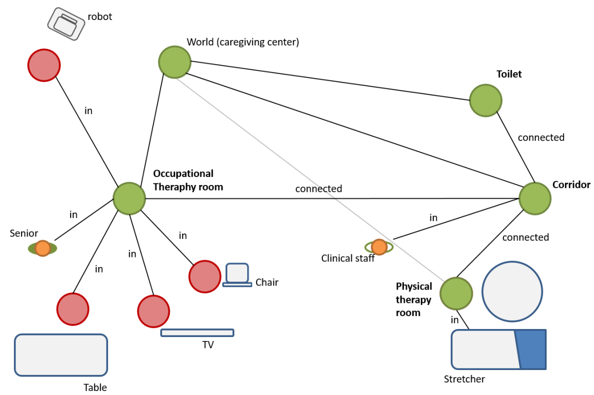


Fig. 2: DSR example for a caregiving center.

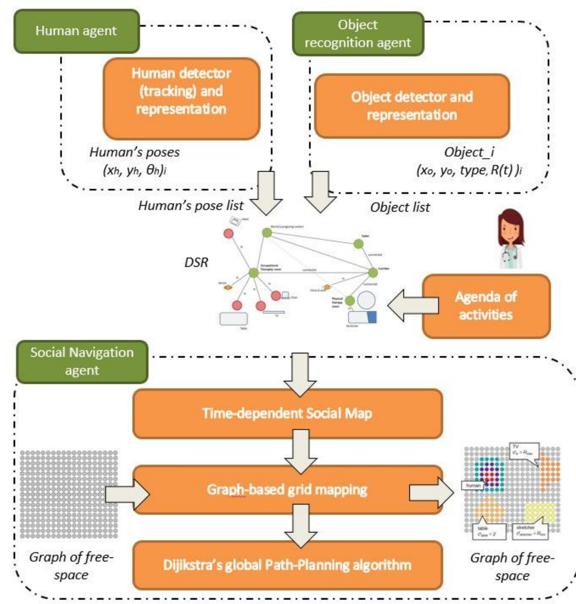


Fig. 3: Overview of the proposed system.

IV. Time-Dependent Social Map

To path-planning in real environments with people and objects, the proposed work builds a social map of the robot's surroundings. This involves the definition of time-dependent affordance spaces associated with objects and personal spaces associated with people.

A. Social mapping: time-dependent affordance spaces

The literature defines the idea of *Affordance Space* to indicates areas where humans normally perform activities with objects [5]. These spaces are related to how people

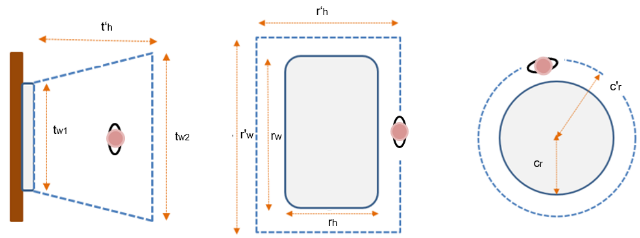


Fig. 4: Three types of objects and their affordance spaces

interact with objects; for example, the interaction with a table is different from the interaction with a chair. These spaces are also called *Activity spaces* usually represented in a semantic map, which allows the semantics of space to be taken into account in the planning of socially acceptable navigation solutions. However, these spaces no vary and have been fixed a priori. To achieve a better social path planning our proposal makes the values of these spaces time-dependent.

Therefore, let $O_M = \{o_1, ..., o_M\}$ be the set of M objects with which humans can interact in the environment. Each object $o_k \in O_M$ stores its pose $p_{o_k} = (x, y, \theta_k)$, its affordance space A_{o_k}, which is associated with the space needed to interact with this object and its time-dependence $R_{o_k}(t)$,

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

Distinct objects have different affordance spaces, A_{o_k}, and are defined for each object $o_k \in O_M$. These areas have been defined according to the type of object and how thee interaction is performed (Fig.4). The three types used here are described below:

- *Trapezoidal shapes*: Object like TVs are common in caregiving center. This type of objects are modeled as an isosceles trapezoid with height t'_h and widths (t'_{w1}, t'_{w2}), as described in [10].

$$a_t = t'_h \cdot \frac{t'_{w1} + t'_{w2}}{2} \quad (1)$$

- *Rectangle shapes*: 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.

$$a_r = r'_h \cdot r'_w \quad (2)$$

- *Circular shapes*: Objects like circular tables are also common in caregiving centers. These objects are modeled as a circle with center in p_{o_k} and radius c'_r.

$$a_c = \pi \cdot {c'_r}^2 \quad (3)$$

This affordance space for each object is used by the navigation algorithm at time t and it is associated with different costs in the free-space graph used for navigation. Activities for each object are scheduled by the center's staff providing at start and end time. As mentioned before, each object has associated a time-dependent function $R_{o_k}(t)$.

$R_{o_k}(t)$ ranges from $R_{min} \leq R_{o_k}(t) \leq R_{max}$, where R_{min} means that the object does not have any activity scheduled at that time t and the robot can use this affordance space to path-planning and navigate. When the start time of the activity is approaching, the value of $R_{o_k}(t)$ increases, changing the cost of the affordance space in the free-space graph used for navigation. Finally, R_{max} means that the object has an activity scheduled at time t and the robot cannot use this affordance space to path-planning and navigate (Fig. 6).

B. Social mapping: personal spaces

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. 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 [10]:

$$g_{h_i}(x, y) = exp^{-(\gamma_1(x-x_i)^2 + \gamma_2(x-x_i)(y-y_i) + \gamma_3(y-y_i)^2)} \quad (4)$$

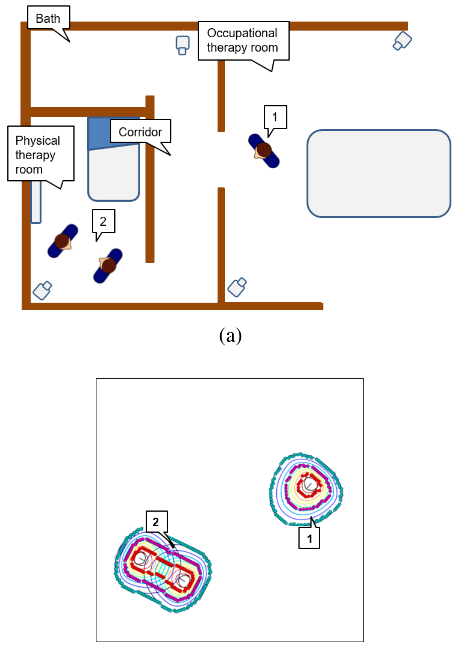
, where the coefficients γ_1, γ_2 and γ_3 are associated to the rotation of the function β_i. Let σ_s be the variance on the left and right directions ($\beta_i \pm \pi/2$), which defines the variance along the β_i direction (σ_h), or the variance to the rear (σ_r), this function β_i is defined next:

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

Once people have been detected is grouping by performing a Gaussian Mixture [10]. Fig. 5a shows a person, labeled as '1', and its personal space modeled by the assymetric Gaussian (Fig. 5b). Fig. 5a also shows two people labeled as '2' and its personal spaces clustered a Gaussian Mixture (Fig. 5b).

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 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.

Lastly, the interaction space surrounding a person is classified into four zones, according to the degree of 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 [9].



(a)

(b)

Fig. 5: A typical scenario with people in an eldercare center; b) their correspondent asymmetric Gaussian have been drawn and labeled with the same number. Note that there is a Gaussian clustering of two persons labeled as '2'.

The public zone is the remaining free space. These contours, which are created by choosing different values of the density threshold ϕ, are illustrated in Fig. 5b.

V. Socially-acceptable path-planning algorithm

Robot's environment is represented by a uniform graph composed of obstacle-free nodes, that have a different finite traversal cost. This graph is used to estimate the optimal path using traditional Dijkstra'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.Initially, all nodes have equal availabilty 1 and cost 1. Fig. 7a displays the initial free-space graph.

Dijkstra's algorithm calculates the cost from the origin to the target node, taking into account the nodes' cost. A path is the sum of each node's cost traversed, and the path with the lowest total cost is selected.

B. Social graph-based grid mapping

The free-space graph include the affordance spaces of the objects and the personal spaces to represent the social map of interaction.

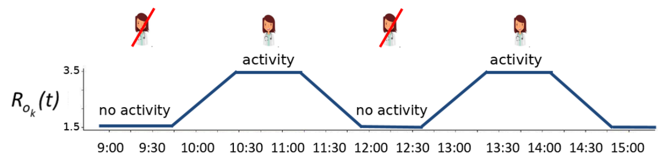


Fig. 6: Representation of the time-dependent affordance space function $R_{(t)}$.

1) Time-dependent affordance spaces of objects: Being A the matrix formed by the availability of each node and C the matrix formed by the costs and considering the set of shapes used to define the affordance spaces, this paper modifies the node's availability and cost, according to the time-dependent affordance spaces proposed.

Firstly, for each object is defined a polygon P_o, that represents the availability, a_{o_i}, of all the nodes $n_i \in A$ contained in the space formed by the polygon P_o. The availability of the nodes of each object, a_{oi} in the matrix A, is set to *occupied*, $a_{o_i} = occupied$, while availability of the rest of nodes is not modified.

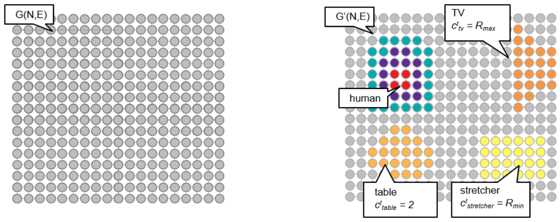
Secondly, let $L^t{}_o = \{A^t{}_{o_1}, ..., A^t{}_{o_M}\}$ be the set of polylines that describe the time-dependent affordance space for each object. For each $A^t{}_{o_k}$ is defined a polygon $P^t{}_{o_k}$ formed by the points of the polyline, which maps these points with the costs of the nodes in the free-space graph. Accordingly, the cost of the nodes in the matrix C are set to $c^t_{o_k} = R_{(t)}$ in the free-space graph, these values are associated to the scheduled activities for each object.

Figure 6 represent how the cost changes progressively in function of time. Starting at $c^t_{o_k} = 1.5$, which means that no activity is scheduled and ending at $c^t_{o_k} = 3.5$, which means that there is an activity. It should be noted that it is greater than 1 when there is no activity. This contributes to respect the shape of the object's affordance space during navigation, for example, in the case of a table. The penalization in the cost does not prevent it from crossing the affordance space when necessary, for example, in the case of a TV. Consequently, the robot exhibits better social navigation.

Thus, nodes of the free space graph $n_i \in C$ contained in P^t_i are modified in order to set its cost to these values. Fig. 7b shows three different objects and their space affordances with different colors depending of the value of $c^t_{o_k}$. To simplify the representation, we have defined four colors that correspond to the discretization in four intervals of the values of $c^t_{o_k}$, namely, yellow if $(1.5 \leq c^t_{o_k} \leq 2.0)$, dark yellow if $(2.0 \leq c^t_{o_k} \leq 2.5)$, orange if $(2.5 \leq c^t_{o_k} \leq 3.0)$, dark orange if $(3.0 \leq c^t_{o_k} \leq 3.5)$.

2) Personal Space mapping: Being A the matrix formed by the availability of each node and C the matrix formed by the costs and considering the set of polygonal curves that define the personal space of a human as: *intimate*, *personal* and *social*, this paper also present the modification of the cost and availability of the nodes of the free-space graph according to these personal spaces.

Let $H_i = \{L_i{}^{intimate}, L_i{}^{personal}, L_i{}^{social}\}$ be the set of polylines that describe the personal space for each human.



(a) (b)

Fig. 7: a) Example of the free-space graph; b) result of including the time-dependent affordance spaces and personal spaces in the free-space graph.

For each polyline L_i is defined a polygon P_i formed by the points of the polyline. Accordingly, $P_i^{intimate}$, $P_i^{personal}$ and P_i^{social} are built. The availability a_{h_i} of all the nodes $n_i \in A$ 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 in the graph will not change, but their cost will. For personal and social spaces, $P_i^{personal}$ and P_i^{social} respectively, the cost c_{h_i} of all the nodes $n_i \in C$, contained in the space formed by $P_i^{personal}$ have been set to a value four times higher than the free node, $c_{h_i^{personal}} = 4.0$ and two times higher for the nodes contained in P_i^{social}, $c_{h_i^{social}} = 2.0$ (see Fig. 7a).

Intimate areas are forbidden for navigation. Starting from the free-space, the cost doubles when the robot needs to use a more personal space in its path-planning or navigation. In this way, when the robot plans the shortest path, it will move away, reasonably, from the person, exhibiting a better human-aware navigation.

VI. Experimental Results

A use case is illustrated in Fig. 9 and evaluates the approach described in this paper for building time-dependent affordance spaces. The caregiving center is composed by a occupational therapy room with two objects, a TV and a circular table, and a physical therapy room with a stretcher.

The agenda has been set by the center's professionals and is composed of two activities: the first one is a serious game that needs the television to be performed and it is scheduled from 11am to 12pm. The robot's task is to move to a position close to the TV before the first activity ends. The second one is a therapy that needs the table to be performed and it is scheduled from 12pm to 14pm. The robot's task is to move to a position close to the table once of the activity has started. Consequently, Fig. 8 shows, in the upper part, the graph of the function $R_{o_{tv}(t)}$ generated for the television and, in the middle part, the function $R_{o_{table}}(t)$ generated for the table. Both functions reach R_{max} during the time of the activity. It is also observed that the graph of the function $R_{o_{stretcher}}(t)$ remains constant, set to R_{min}, since there is no activity scheduled for that object.

From Fig. 9a to Fig. 9d four snapshots of the use case are shown. Fig. 9 is linked to Fig. 8 by the numerical labels inside the speech balloons. This means that the snapshot shown in Fig. 9a was taken at the time 1 shown in Fig. 8. Therefore, Fig. 9a shows the path that the robot would plan at 9:30 am. In Fig. 8 the therapist icon is crossed out to point out that there is no activity scheduled for that object at that time. It is observed that the path crosses the affordance space of the television, because it has no activity planned at that time. Fig. 9b shows the path that the robot would plan at 10:45 am. Although the activity has not yet begun, the therapist icon is not crossed out to indicate that an activity will soon begin. It can be seen that the path slightly crosses the affordance space of the television, since, although it does not have any activity planned at that time, it will start soon. Fig. 9c is similar to the previous one, however, as the activity has already begun, the path moves further away from the television and never invading its affordance space. Then, the robot's task is to navigate to the right side of the television following the path described in Fig. 9c. Continuing as before, Fig. 9d shows the path that the robot plan at 13:15 am. This is the last hypothetical planning before navigate to the table. Then, the robot's task is to navigate to a position near the table following the path described in Fig. 9d.

In the use case described, the influence of the time-dependent affordance space on the shortest path planning by the robot is clearly appreciated. The combination of the variation of the planned path in function of time and personal spaces achieves a behaviour more in line with our social conventions [1].

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) average minimum distance to objects $(d_{Stretcher}, d_{Table}, d_{TV})$; (iii) distance traveled, d_t; (iv) cumulative heading changes, CHC; and (v) personal space intrusions, Ψ. These metrics have been already established by the scientific community (see [13], [14]). It can be seen in Table I how the two paths performed by the robot completely respect human personal spaces, navigating only in public space. In fact, the percentage of the path that going through personal spaces $(L_{intimate}, L_{personal}, L_{social})$, is remained at 0%, consequently public space, Ψ (Public), is remained at 100% during the two trajectories. Similarly, navigation respects the minimum distances to objects according to the activities schudeled in the center's agenda. In fact the minimum distance $(0.62m)$ to the TV is reached when the robot starts the second path, since it should turn completely to start the second path, getting little closer to the TV than at the end of the first path $(0.84m)$.

In order to demonstrate the robustness of the proposal, a longer video is included where the robot navigates to random positions in the center, while the tasks programmed in the different objects also vary randomly. Also, a person

[1] Link to the experiment: https://www.youtube.com/watch?v=FsfsK7eVYVI

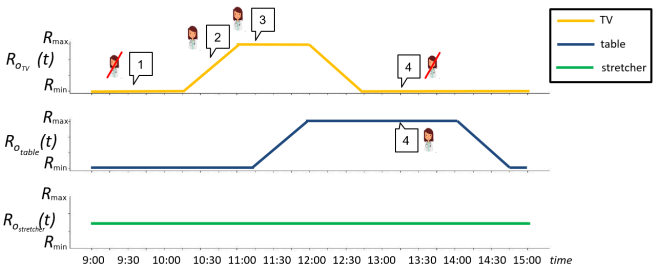
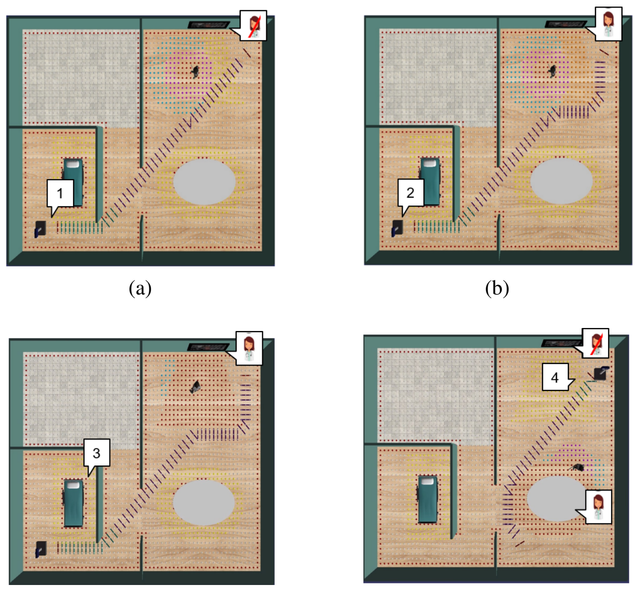


Fig. 8: $R_{(t)}$ functions to time-dependent affordance spaces for the objects described in the experiments.

TABLE I: Navigation results

PATH 1		PATH 2	
Parameter	Value (σ)	Parameter	Value (σ)
τ *(s)*	36.37	τ *(s)*	24.76
CHC	18.20	*CHC*	9.75
d_{min} *Person (m)*	2.19	d_{min} *Person 1 (m)*	1.75
d_{min} *Stretcher (m)*	1.06	d_{min} *Stretcher (m)*	3.44
d_{min} *Table (m)*	1.60	d_{min} *Table (m)*	1.45
d_{min} *TV (m)*	0.84	d_{min} *TV (m)*	0.62
Ψ $L_{Intimate}$ *(%)*	0.0	Ψ $L_{Intimate}$ *(%)*	0.0
Ψ $L_{Personal}$ *(%)*	0.0	Ψ $L_{Personal}$ *(%)*	0.0
Ψ L_{Social} *(%)*	0.0	Ψ L_{Social} *(%)*	0.0
Ψ *(Public) (%)*	100	Ψ *(Public) (%)*	100



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

Fig. 9: Time-dependent affordance spaces for the use case. a) Path at 9:30 am, no activity scheduled b) Path at 10:45 am, serious game activity will start soon on TV c) Path at 11:15 am, serious game activity has started on TV d) Path at 13:15 am, serious game activity has ended and the activity at the table has begun.

is included to show how their personal spaces are taken into account in the navigation [2].

VII. Conclusions and Future Works

Human-aware robot navigation is a difficult skill because the circumstances in which the human-robot, human-human, or human-object interactions happen, require a navigation system capable of detecting and responding according to those situations. In eldercare centers, it is possible to associate some of the interactions associated with objects with the daily agenda of therapeutic activities. Including this time dependency in the path planning process is the major innovation proposed here. Resting on Dijkstra's algorithm, the enhancement modifies the value of the free space graph according to time-dependent affordance spaces, improving the social robot navigation.

As future work, we intend to study the degree of adaptation to our social conventions of the paths executed by the robot through qualitative research. We are also studying whether the incorporation of time into personal spaces can improve our line of research on social navigation.

[2]Link to the experiment: `https://www.youtube.com/watch?v=gkx-ya2-yEo`

References

[1] P. Flandorfer. Population Ageing and Socially Assistive Robots for Elderly Persons: The Importance of Sociodemographic Factors for User Acceptance. International Journal of Population Research, 2012.

[2] J. Gomez, N. Mavridis and S. Garrido. Social Path Planning: Generic Human-Robot Interaction Framework for Robotic Navigation Tasks. Workshop on Cognitive Robotics Systems: Replicating Human Actions and Activities at IROS 2013.

[3] K. Charalampous, I. Kostavelis and A. Gasteratos. Robot navigation in large-scale social maps: An action recognition approach. Expert Systems with Applications. Vol 66. pp 261 –273. 2016. Elsevier.

[4] Charalampous, K., Kostavelis, I. adn Gasteratos, A. Recent trends in social aware robot navigation: A survey. Robotics and Autonomous Systems. Elsevier B.V. https://doi.org/10.1016/j.robot.2017.03.002

[5] J. Rios-Martinez. Socially-Aware Robot Navigation: combining Risk Assessment and Social Conventions. Hal.Inria Frace, 2013.

[6] Althaus, P., Ishiguro, H., Kanda, T., Miyashita, T., Christensen, H.I.: Navigation for HumanRobot Interaction Tasks. IEEE International Conference on Robotics and Automation. Volume 1, pp. 1894, 1989, (2004).

[7] Kirby, R., Simmons, R., Forlizzi, J.: COMPANION: A Constraint-Optimizing Method for Person-Acceptable Navigation. IEEE International Symposium on Robot and Human Interactive Communication, (2009).

[8] Tranberg Hansen, S., Svenstrup, M., Andersen, H.J., Bak, T.: Adaptive Human Aware Navigation Based on Motion Pattern Analysis. IEEE International Symposium on Robot and Human Interactive Communication, (2009).

[9] J. Rios-Martinez, A. Spalanzani, and C. Laugier. From proxemics theory to socially-aware navigation: A survey. International Journal of Social Robotics. Vol 7. n2. pp 137–153. 2015. Springer.

[10] A. Vega, L.J. Manso, P. Bustos, P. Núñez D.G. Macharet. Socially Aware Robot Navigation System in Human-populated and Interactive Environments based on an Adaptive Spatial Density Function and Space Affordances. Pattern Recognition Letters. Vol. 1, Pages 72-84, 2019

[11] Weihua C., Tie Z., and Yanbiao, Z.: Mobile robot path planning based on social interaction space in social environment. International Journal of Advanced Robotic Systems. Volume 1, pp 1–10, (2018).

[12] Calderita, L.V. Deep State Representation: an unified internal representation for the robotics cognitive architecture CORTEX. PhD thesis, Universidad de Extremadura, 2016.

[13] Okal, B., Arras, K.: Learning socially normative robot navigation behaviors with bayesian inverse reinforcement learning. IEEE International Conference on Robotics and Automation, pp 2889 – 2895, (2016).

[14] Kostavelis, I.: Robot Behavioral Mapping: A Representation that Consolidates the Human-robot Coexistence. Robotics and Automation Engineering. Volume 1, pp 1–3, (2017).