A Flexible and Adaptive Spatial Density Model for Context-aware Social Mapping: towards a more realistic Social Navigation

Araceli Vega-Magro[1], Luis J. Manso[2], Pablo Bustos[1] and Pedro Núñez[1*]

***Abstract*— Social navigation is a topic with enormous interest in autonomous robotics. Robots are gradually being used in human environments, working individually or collaborating with humans in their daily tasks. Robots in these scenarios have to be able to behave in a socially acceptable way and, for this reason, the way in which robots move has to adapt to humans and context. Proxemics has been extensively studied with the aim of improving social navigation. However, these works do not take into account that, in several situations, the personal space of the humans depends on the context (*e.g.*, this human space is not the same in a narrow corridor than in a wide room). This work proposes the definition of an adaptive and flexible space density function that allows, on the one hand, to describe the comfort space of individuals during an interaction and, on the other hand, dynamically adapt its value in terms of the space that surrounds this interaction. In order to validate the performance, this article describes a set of simulated experiments where the robustness and improvements of the approach are tested in different environments.**

I. Introduction

It seems unthinkable a future world without robots working directly with humans at home, offices or hospitals. In recent years, social robotics has experienced remarkable growth, but there are still many open problems, such as human-robot interaction, affective behavior or human aware navigation among others.

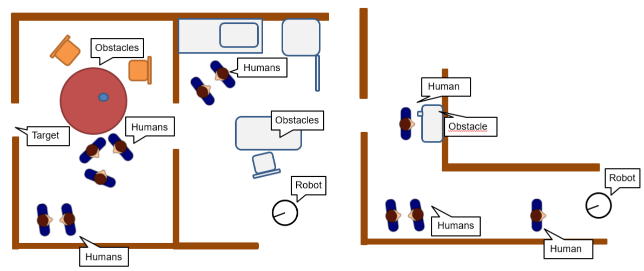
In particular, human-centered navigation, also named social navigation, is nowadays a topic of growing interest. In [1] authors describe the problem of human-centered robot navigation as an evolution from *metric mapping*, *semantic mapping*, *social mapping*, and finally, *behavioral mapping*. In each of these phases or stages, the robot expands its knowledge about the human-populated environment, from the information of its own external sensors (metric map), to the behavior that is specified with each entity or groups of entities on the map (behavioral map).

In this regard social navigation is usually studied as a social mapping problem: most approaches address the problem of social mapping by modeling the comfort space of the human being, which is usually is based on the well-known theories on proxemics [2]. According to these theories, in previous works such as [3] or [4], a spatial density function

*This work has been partially supported by the MICINN Project TIN2015-65686-C5-5-R, by the Extremaduran Goverment project GR15120, by the Red de Excelencia "Red de Agentes Físicos" TIN2015-71693-REDT, FEDER project 0043-EUROAGE-4-E (Interreg POCTEP Program) and MEC project PHBP14/00083.

[1]Robotics and Artificial Vision Laboratory (RoboLab), University of Extremadura, 10003 Cáceres, Spain. pnuntru@unex.es

[2]School of Engineering and Applied Science, Aston University, Birmingham, United Kingdom.



(a) (b)

Fig. 1: The robot has to choose the best route and navigate in typical scenarios by using its social rules (a) office environment composed of two rooms; and (b) narrow corridor.

that allows defining comfort zones around people was proposed. This function provides for a mathematical model to cluster people in the environment and defines spaces where robot navigation is forbidden. Similar to other works in the literature, this personal space is fixed and does not depend on the spatial context and human intention.

Suppose the cases illustrated in Fig. 1. Do they represent the same situation? In both images, the robot must socially navigate in human-populated scenarios from its initial position to the target. However, spatial context is different. Fig. 1a shows a typical office environment with two rooms and different objects placed on it. In this situation, robot plans a social path taking into account the personal spaces (comfort zones), and it is expected that the mobile platform successfully navigates to the target. By applying this same idea in the scenario described in Fig. 1b, a blocked path is built in the corridor. In human-human interaction, without dialogue, humans can contract its comfort areas if the final goal is to cross. Thus, it would be interesting if the robot also can adapt its personal spaces in a flexible and automatic way in order to navigate without dialogue.

The **main contribution** of this work, which extends the previous one described in [3], is the proposal of an **adaptive and flexible spatial density function** for context-aware social mapping. The main difference between this previous work is that this new function allows to: i) describe the comfort zones of individuals during an interaction; and ii) dynamically adapt its parameters depending on the spatial context and human intention.

This paper is organized as follows: after discussing known approaches to human-centered navigation in Section II, Section III presents the cognitive architecture CORTEX, which consists of a set of software agents for implementing complex robotic tasks, such as human and object perception or robot navigation. In Section IV an overview of the proposed flexible and adaptive spatial density model is described. Section V points out the experimental results, and finally, Section VI describes the conclusions and future work of the approach.

II. Related Work

Most of classical robot navigation algorithms have considered all obstacles of similar relevance, including people. Social robots, on the contrary, must consider humans special entities, evaluating their level of comfort with respect to the robot's path. The social robot navigation problem has been extensively studied in the last years and different approaches have been proposed ([5], [6] and more recently [7] are interesting reviews for readers). The concept of *social mapping*, as was described in [8], was introduced to define personal spaces that model socially acceptable behaviors for robots during navigation: the problem of human-aware robot navigation must consider factors like human safety, comfort, sociability and /or naturalness [5].

When a social robot plans the best route in human-populated scenarios, it must avoid passing between people talking or crossing very close to a person. In order to manage the shared space between humans and robots, different works in the literature have demonstrated that the same proxemic areas that exist in human-human interaction can also be applied to human-robot interaction scenarios [9], [10], [11]. Under this prism, the notion of personal space model has been incorporated in the path planning step in order to create acceptable behaviours for robots during their navigation (human avoiding, social space or social path-planning behaviors). Authors in [12], propose a framework which is able to model context-dependent human spatial interactions, encoded in the form of a social map. This social map is obtained by solving a learning problem using Kernel Principal Component Analysis (KPCA), and later the social borders are calculated as isocontours of the learned implicit function. In [13] it is proposed a perceptual model that takes into account the relative pose between robot and human, the human gestures and the speech volume for building the social space. Recently, a human-centered robot navigation strategy where the human space is modeled according to proxemics theory was presented in [14].

In most real-world scenarios, humans in the environment are interacting with each other. In [3], also based on the proxemics, an adaptive spatial density function was defined for clustering groups of people, which later define forbidden spaces for robot's navigation. Most works based on proxemics, do not take into account that these social zones often depend on the human intentions and the environment ($e.g.$, if human want to cross social robot - human intention - in a narrow corridor -environment-, comfort area must reduce). This idea was briefly described in [1], where authors extended the previous work [12] and suggested a skew-normal probability density in order to model the social space. The proposed approach goes further and it defines a new spatial density function that extends the previous work [3], [4] in order to satisfy these real scenarios. The proposal uses a flexible mathematical model based upon the use of a modified two-dimensional Gaussian function [15] to dynamically model the personal space of an individual adapting its shape to the spatial context. The model can be incorporated in any navigation architecture in order to socially navigate among humans.

III. Deep State Representation and Agents

Previously to the description of the proposal, the cognitive architecture CORTEX is briefly described [16]. Current social robotics systems are getting more and more complex: different robot skills are needed in order to achieve typical tasks. The robotics cognitive architecture CORTEX is defined structurally as a configuration of software agents connected through a shared representation. This shared representation was first-time defined in [16], as *a directed multi-labelled graph where nodes represent symbolic or geometric entities and edges represent symbolic and geometric relationships*.

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* [16]. In CORTEX, higher-level 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. In this paper, different specific agents within CORTEX 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. It implements the path-planning, localization and SLAM algorithms, among others. Fig. 2, illustrates the current CORTEX cognitive architecture [16].

IV. Proposed approach

The description of the proposal follows the next steps: i) detecting and tracking humans in the environment; ii) Personal space modeling by using an asymmetric Gaussian [15]; and iii) adapting the personal space associated to each person to human intention and spatial context.

A. People detection and tracking

Human detection and tracking is one of the most difficult problem in robotics himself, especially in complex real world scenes that commonly involve multiple people. Considering $S \subset \mathbb{R}^2$ the space of the global map, a human i is represented by its pose (position and orientation), $\mathbf{h_i} = (x_i\ y_i\ \theta_i)^T$, being $(x_i\ \ y_i)^T \in S$ and $\theta_i \in [0, 2\pi)$. In this work is assumed

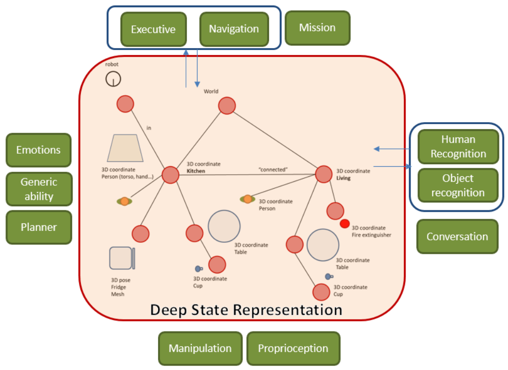


Fig. 2: Main agents within CORTEX involved in this proposal are highlighted in red. A more detailed description about CORTEX and DSR can be found in [16].

that human pose is detected and tracked by robot perception system at real time (*i.e.*, human recognition agent [16]).

B. Personal space modeling

In order to model the personal space of each individual, an asymmetric 2-dimensional Gaussian function is used [15]. This function associates the distance between a point $\mathbf{p} = (x\ y)^T \in S$ and the person's position, h_i, with a real value $g_i \in [0, 1]$. The expression for the function cost is

$$g_{h_i}(x, y) = exp^{-(k_1(x-x_i)^2 + k_2(x-x_i)(y-y_i) + k_3(y-y_i)^2)} \quad (1)$$

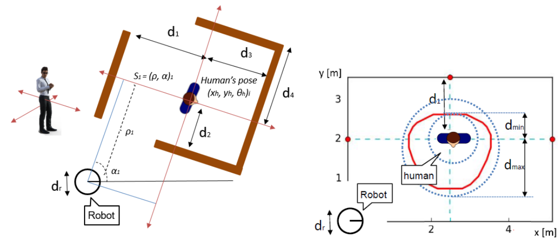
being k_1, k_2 and k_3 the coefficients used to take into account the rotation of the function β_i, defined by the relations

$$\begin{aligned} k_1(\beta_i) &= \frac{cos(\beta_i)^2}{2\sigma^2} + \frac{sin(\beta_i)^2}{2\sigma_s^2} \\ k_2(\beta_i) &= \frac{sin(2\beta_i)}{4\sigma^2} - \frac{sin(2\beta_i)}{4\sigma_s^2} \\ k_3(\beta_i) &= \frac{sin(\beta_i)^2}{2\sigma^2} + \frac{cos(\beta_i)^2}{2\sigma_s^2} \end{aligned}$$

where σ_s is the variance to the sides ($\beta_i \pm \pi/2$ direction) and represents the variance along the β_i direction (σ_h) or the variance to the rear (σ_r) (see [15]). The cost function is aligned to the person's heading, that is, θ_i, and normalized to 1. By varying σ_s, σ_h and σ_r the shape of the personal space model can be easily modified.

C. Environment-dependent personal space modeling

Once the personal space $g_{h_i}(x, y)$ is defined for each human h_i, next stage involves the adaptation of the Gaussian shape to the context of the interaction and also to the environment. First, the proposal evaluates distances from human pose $h_i = (x_h, y_h, \theta_h)$ to walls in four different orientations θ_i=$(0, \pi/2, \pi, 3\pi/2)$ being θ_i=0 the same as the orientation of the person. Then, for each distance, the algorithm evaluates if the robot is able to navigate in this space. If not, the human adapts the comfort space by varying the corresponding variance of the asymmetric Gaussian function σ (*i.e.*, σ_s, σ_h and/or σ_r). This algorithm is detailed next:



(a) (b)

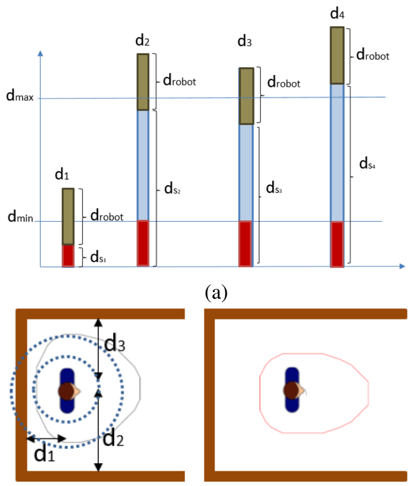
Fig. 3: Description of the method for measuring distances between human and walls. (a) The intersection between the walls and the lines S_1 and S_2 define distances d_i; and (b) distances used in the proposed work in order to adapt the personal space to the environment.

1) Calculation of the distance to walls: The object perception agent in CORTEX is in charge of recognizing and estimating the pose of objects in the environment [16]. For each object detected by the robot, the agent defines a new node in the DSR, and saves not only its pose but also its shape (*e.g.*, sphere, cylinder, plane, cube, etc). On the contrary, rooms are assumed to be known by the robot, and they are defined as nodes in the DSR. These nodes are characterized by the set of walls (planes) that describe the room. The robot is always localised in the environment thanks to the navigation agent in CORTEX.

If a human h_i is inside a room or a corridor, the algorithm evaluates the distance from human position to walls. First, Let $R_i = \{\omega_1, \omega_2, ...\omega_n\}$ be the room where person h_i is located, being ω_k the wall k that composes the complete room (*e.g.*, a corridor has a minimum of two walls, while on the contrary in a typical room there are four different walls). Each wall ω_k is described by a plane $p_{\omega_k} \in \mathbb{R}^3$ referenced to the robot pose (origin of the reference frame).

In order to measure distances to each wall, the proposed algorithm generates two different straight lines, S_1 and S_2, being S_j defined as $S_j = (\rho, \alpha)_j$, where ρ is the length of the normal drawn from the origin (*i.e.*, robot) to the line, which subtend an angle α with the positive direction of x-axis. In Fig. 3a is shown a human located in a room R composed of four walls $R_1 = \{\omega_1, \omega_2, \omega_3, \omega_4\}$ and where $S_1 = (\rho, \alpha)_1$ is also drawn. Next, intersection point between S_1 (and S_2) and the plane p_{ω_k} define the distance d_k from the human position to ω_k. In Fig. 3a four different distances are shown: line S_1 defines two different distances, d_1 and d_3, while S_2 defines the distances d_2 and d_4 (intersection between S_2 and walls ω_2 and ω_4, respectively). The set of all the distances from human to walls defines the distance vector d_T.

2) Evaluation of the spatial context: Once the distance vector d_T has been calculated, the next step is to evaluate if the personal space must adapt its shape to the spatial context. Let d_r be the diameter of the robot plus a safety margin. Besides, let d_{min} and d_{max} be the minimum and maximum distances that define the comfort zone, respectively. These values are presented in 3b as circumferences with center



(a)

(b)

Fig. 4: Evaluation of the spatial context in a typical narrow corridor. (a) Four bars associated to each distance d_i are drawn. Distance d_{s_i} identify the need of modifying the comfort zone. (b) d_{s_2} and d_{s_3} involve a modification of the personal space in this scenario.

$h_i(x,y)$ and radius d_{min} and d_{max}. For each $d_i \in d_T$, the proposed method calculates the distance d_s:

$$d_{s_i} = d_i - d_r \tag{2}$$

Let's consider different values of d_{s_i}. If $d_{min} \leq d_{s_i} \leq d_{max}$, it is need to adjust the comfort area in order to allows robot navigation. On the contrary, if $d_{s_i} \leq d_{min}$, robot is unable to navigate in this orientation. Finally, if $d_{s_i} \geq d_{max}$, there is no need to modify the shape of the personal space. Fig. 4a graphically describes the evaluation of the spatial context. Four bars, associated to each distance $d_i \in d_T$, are shown. For each d_i, d_{s_i} is also drawn. Only d_{s_2} and d_{s_3} involve a modification of the personal space. In Fig. 4b, the new Gaussian is presented after consider the spatial context of the human-robot interaction.

3) Environment-dependent personal space: In this stage the personal space model is adapted to the spatial-context. As was described in IV-B, the model used in this approach is an asymmetric Gaussian $g_{h_i}(x,y)$ defined by σ_s, σ_h and σ_r. By varying some of these values, $g_{h_i}(x,y)$ adapts its shape to the environment. Let $g'_{h_i}(x,y)$ be the new model, where now σ_s, σ_h and σ_r are dependent of the spatial context (*i.e.*, $\sigma(d_s)$). This dependence is modeled as non-linear regression $\sigma(d_s) = a \cdot {d_s}^b$, being a and b parameters that define the shape of the curve and the magnitude of the $\sigma(d_s)$ value. Finally, this personal space describes a region where robots' navigation is forbidden, such was described in [3].

V. Experiments

To evaluate the performance of the proposed algorithm, firstly a set of parameters has to be tuned such that the algorithm adapts the personal space to the spatial context. A set of simulated scenarios were used to validate the results of the proposed system. The algorithms have been developed in C++ software and the benchmark tests have been performed on a PC with processor Intel Core i5 2.4GHz with 4Gb of DDR3 RAM and GNU-Linux Ubuntu 16.10.

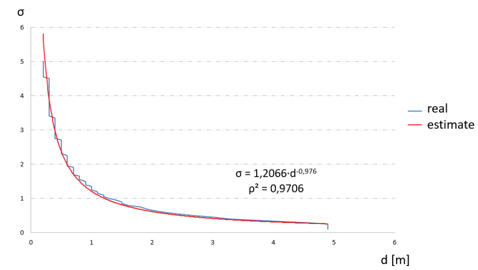


Fig. 5: Power regression used to model the dependence between $sigma$ and the distance to the sides, back and front.

A. Adaptive and flexible spatial density function assessment

The proposed system has several parameters that have to be tuned to properly adjust the flexible and adaptive spatial density function to the spatial context and the people-clustering algorithm.

- a and b, from $\sigma(d_s) = a \cdot d_s^b$: parameters that define the shape of the curve and the magnitude of the $\sigma(d_s)$ value.
- d_l: the maximum Euclidean distance between consecutive vertices in the polyline. A specific value is proposed.
- δ: the density threshold. The value proposed depends how the humans are interacting (see the formations proposed in [17]).

The a and b parameters have been chosen as the coefficient that better fit the data to the curve giving by the expression $\sigma = a \cdot d_s^b$. A set of σ_h values are used in order to get the corresponding contours of the asymmetric gaussian $g_h(x,y)$ (see Eq. (1)). By fixing the height of the cost function, these contours define different distances as is shown in Fig. 5. This same experiments have been made for σ_r and σ_s with identical results. From these data, $a = 1.2$ and $b = -0.976$, where $R^2 = 0,97$.

The distance threshold parameter d_l allows adjusting the density of vertices in the polyline. The smaller the value of d_l the higher the detail of the shape of the forbidden area. In order to choose an appropriate d_l value, several simulated experiments with different individuals were conducted. The tests showed that below $10cm$ approximately, decreasing the value of the parameter did not considerably affect the shape of the resulting forbidden area. The conclusion drawn from the experiments is that d_l can be safely fixed to $10cm$.

B. Evaluation of the proposal

1) Validation of the flexible spatial density function: In order to evaluate the proposal, firstly a basic simulated scenario has been created. This consists of a square room without objects, with dimensions $5\,\mathrm{m} \times 5\,\mathrm{m}$ and the presence of a human. This room has mobile walls, in that way it is possible to reduce the distances from the human to each wall. Fig. 6 shows the results of the proposed algorithm for adapting the personal space to the spatial context. In Fig. 6a, four different tests are illustrated, where the distance to the wall in front of the person is increased (from left to the right). The contour map of the personal space is shown in Fig. 6a, where is drawn as the gaussian function $g'_h(x,y)$ adapts correctly to the context. Results are also presented in Table I for the original cost function $g'_h(x,y)$ and for the function $g'_h(x,y)$, being $d_r = 0,8$m and d_{min} and d_{max} equal to 0,6m and 1,3m, respectively. In this table is also indicated if the robot crosses between the human and the wall. As is shown in Table I, the flexible spatial density function $g'_h(x,y)$ adapts correctly to the spatial context. Similar results are illustrated in Fig. 6b and Fig. 6c and described in Table II (being $d_r = 0,8$m and d_{min} and d_{max} equal to 0,3m and 0,6m, respectively) and Table III (where $d_r = 0,8$m and d_{min} and d_{max} equal to 0,5m and 1m, respectively).

TABLE I: Comparative results of the cost function defined in [3] and the proposed in this paper, by varying the distance to the wall in front of the person.

Heading							
gh(x,y)			g'h(x,y)				
d_3	d_s	cross?	d_3	d_s	d'_s	σ_h	cross?
2,5	1,7	YES	2,5	1,7	1,3	1	YES
2,05	1,25	NO	2,05	1,25	1,2	1,05	YES
1,95	1,15	NO	1,95	1,15	1,1	1,10	YES
1,85	1,05	NO	1,85	1,05	1	1,21	YES
1,75	0,95	NO	1,75	0,95	0,9	1,34	YES
1,65	0,85	NO	1,65	0,85	0,8	1,50	YES
1,55	0,75	NO	1,55	0,75	0,7	1,71	YES
1,45	0,65	NO	1,45	0,65	0,6	1,99	YES
1,35	0,55	NO	1,35	0,55	1,3	1,00	NO

TABLE II: Comparative results of the cost functions by varying the distance to the wall to the right of the person.

Sides							
gh(x,y)			g'h(x,y)				
d_2	d_s	cross?	d_2	d_s	d'_s	σ_r	cross?
1,9	1,1	YES	1,9	0,9	1	1,33*	YES
1,8	1	NO	1,8	0,85	0,95	1,05	YES
1,7	0,9	NO	1,7	0,85	0,85	1,41	YES
1,6	0,8	NO	1,6	0,85	0,75	1,60	YES
1,5	0,7	NO	1,5	0,85	0,65	1,84	YES
1,4	0,6	NO	1,4	0,85	0,55	2,16	YES
1,3	0,5	NO	1,3	-	1**	1,33	NO

TABLE III: Comparative results of the cost functions by varying the distance to the wall to the rear of the person.

Rear							
gh(x,y)			g'h(x,y)				
d_1	d_s	cross?	d_1	d_s	d'_s	σ_r	cross?
1,5	0,7	YES	1,5	0,7	0,85	1	YES
1,4	0,6	NO	1,4	0,6	0,55	1,05	YES
1,3	0,5	NO	1,3	0,5	0,45	2,63	YES
1,2	0,4	NO	1,2	0,4	0,35	3,36	YES
1,1	0,3	NO	1,1	0,3	0,6*	2,00	NO

2) Validation of the social mapping in two use cases: The proposal has also been evaluated in two use cases: i) a person who crosses a robot in a corridor where there are also objects, and ii) a robot that accompanies a person in an apartment with objects. In both experiments the adaptation of the personal space has been validated, as well as the free space for robot navigation. A comparative study with the original spatial density model has been included. These two use cases are drawn in Fig. 7. Three different humans' poses are used in the experiments, as is marked in Fig. 7a and Fig. 7b. For each pose, the distance vector d_T, σ'_h, σ'_s and σ'_r (and its original values) are provided. Table IV describes the results for the use case defined in Fig. 7a. As is shown in Table IV, in the three poses the personal space is correctly adapted to the spatial context and the robot can use the free space in its path planner algorithm. On the contrary, using the original function the robot is blocked during its path. Similar results are shown in Table V, where the improvements of the algorithm using the proposed function are also shown.

TABLE IV: Results for the use case described in 7a.

$g_h(x,y)$					$g'_h(x,y)$			
d_T	σ_h	σ_r	σ_s	cross?	σ'_h	σ'_r	σ'_s	cross?
d_1 = 1.5				YES				YES
d_2 =1	1	2	1,33	NO	1,84	2	1,33	NO
d_3 =1.5				NO				YES
d_4 = *				YES				YES
d_1 = 5,5				YES				YES
d_2 = 1,1	1	2	1,33	NO	1	2	2,16	NO
d_3 = *				YES				YES
d_4 = 1,4				NO				YES
d_1 = 5,5				YES				YES
d_2 =1,1	1	2	1,33	NO	1	2	1,33	NO
d_3 = *				YES				YES
d_4 = 2,4				YES				YES

TABLE V: Results for the use case described in 7b.

$g_h(x,y)$					$g'_h(x,y)$			
d_T	σ_h	σ_r	σ_s	cross?	σ'_h	σ'_r	σ'_s	cross?
d_1 = *				YES				YES
d_2 = 1,41	1	2	1,33	NO	1,36	2	2,1	YES
d_3 =1,73				NO				YES
d_4 =1,41				NO				YES
d_1 = 1,5				YES				YES
d_2 = 1,35	1	2	1,33	NO	1	2	2,3	YES
d_3 = 2,89				YES				YES
d_4 = 0,38				NO				NO
d_1 =2,16				YES				YES
d_2 = 4,87	1	2	1,33	YES	1	2	1,55	YES
d_3 = 3,25				YES				YES
d_4 = 1,62				NO				YES

VI. Conclusions and Future Work

This article presents a novel approach for context-aware social mapping. This work extends the previous one described in [3], where now it uses a flexible spatial density model in order to automatically adapt the personal space to spatial context and human intention. The proposal dynamically describes the comfort zones for people in the robot environment and it is independent of the navigation architecture. Experimental results demonstrate the improvements and robustness of the approach for social mapping compared to previous works [3].

Future research directions include the extension of the methodology to deal with populated environments and the interaction between humans and objects in the scene. This methodology must be applied and validated in a real-world scenario to study, under realistic conditions, the actual reaction of human subjects regarding safety and discomfort.

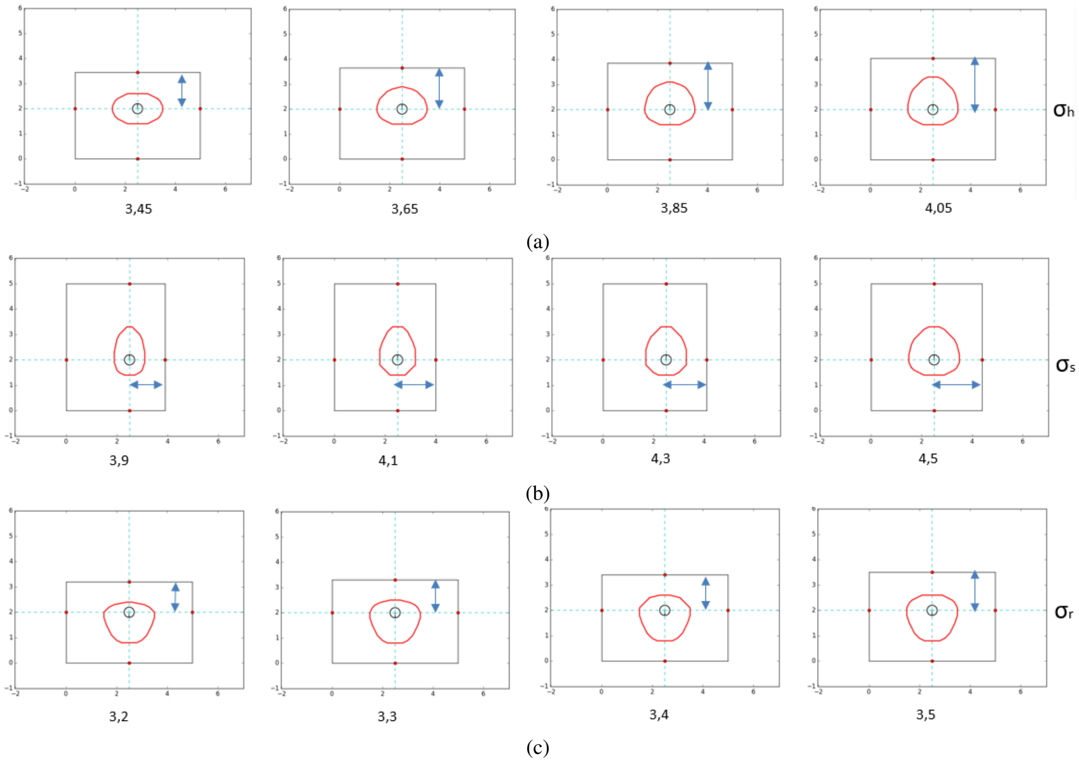


Fig. 6: Four different tests were conducted for each σ_h, σ_s and σ_r. Tests consist of varying the distance from human to the corresponding wall. Distances (in meters) are drawn in the figure.

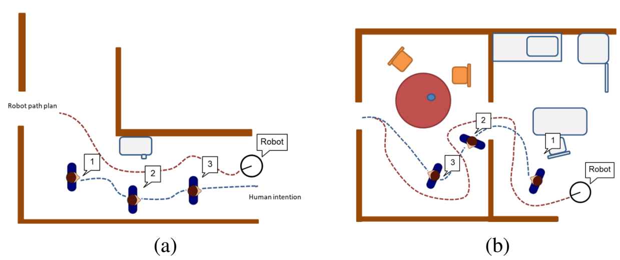


Fig. 7: Two use cases are used in this validation: a) a person who crosses the robot in a corridor; and b) a companion robot moving around an apartment.

References

[1] P. Papadakis, P. Rives, and A. Spalanzani, "Adaptive spacing in human-robot interactions," in *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on*. IEEE, 2014, pp. 2627–2632.

[2] E. T. Hall, *The Hidden Dimension: Man's Use of Space in Public and Private.* The Bodley Head Ltd, 1966.

[3] A. Vega, L. Manso, D. Macharet, P. Bustos, and P. Núñez, " A new Strategy based on an Adaptive Spatial Density Function for Social Robot Navigation in Human-Populated Environments." in *Proceedings of REACTS workshop at the International Conference on Computer Analysis and Patterns*, 2017.

[4] A. Vega, L. J. Manso, P. Bustos, P. Núñez, and D. G. Macharet, "Socially acceptable robot navigation over groups of people," in *IEEE Conference on Robot and Human Interactive Communication, RO-MAN2017*, Portugal, 2017.

[5] T. Kruse, A. K. Pandey, R. Alami, and A. Kirsch, "Human-aware robot navigation: A survey," *Robotics and Autonomous Systems*, vol. 61, no. 12, pp. 1726–1743, 2013.

[6] J. Rios-Martinez, A. Spalanzani, and C. Laugier, "From proxemics theory to socially-aware navigation: A survey," *International Journal of Social Robotics*, vol. 7, no. 2, pp. 137–153, 2015.

[7] K. Charalampous, I. Kostavelis, and A. Gasteratos, "Recent trends in social aware robot navigation: A survey," *Robotics and Autonomous Systems*, vol. 93, pp. 85–104, 2017.

[8] ——, "Robot navigation in large-scale social maps: An action recognition approach," *Expert Systems with Applications*, vol. 66, pp. 261–273, 2016.

[9] J. Mumm and B. Mutlu, "Human-robot proxemics: physical and psychological distancing in human-robot interaction," pp. 331–338, 2011.

[10] M. L. Walters, M. A. Oskoei, D. S. Syrdal, and K. Dautenhahn, "A long-term human-robot proxemic study," in *RO-MAN, 2011 IEEE*. IEEE, 2011, pp. 137–142.

[11] R. Mead and M. J. Mataric, "A probabilistic framework for autonomous proxemic control in situated and mobile human-robot interaction," pp. 193–194, 2012.

[12] P. Papadakis, A. Spalanzani, and C. Laugier, "Social mapping of human-populated environments by implicit function learning," in *Intelligent robots and systems (IROS), 2013 IEEE/RSJ international conference on*. IEEE, 2013, pp. 1701–1706.

[13] R. Mead and M. J. Matarić, "Perceptual models of human-robot proxemics," in *Experimental Robotics*. Springer, 2016, pp. 261–276.

[14] I. Kostavelis, A. Kargakos, D. Giakoumis, and D. Tzovaras, "Robot's workspace enhancement with dynamic human presence for socially-aware navigation," in *International Conference on Computer Vision Systems*. Springer, 2017, pp. 279–288.

[15] R. Kirby, *Social robot navigation*. Carnegie Mellon University, 2010.

[16] L. V. Calderita, *Seep State Representation: a Unified Internal Representation for the Robotics Cognitive Architecture CORTEX*. University of Extremadura, 2015.

[17] A. Kendon, *Conducting interaction: Patterns of behavior in focused encounters*. CUP Archive, 1990, vol. 7.