# Socially Acceptable Robot Navigation over Groups of People

Araceli Vega-Magro[1], Luis Manso[1], Pablo Bustos[1], Pedro Núñez[1] and Douglas G. Macharet[2]

*Abstract*— **Considering the widespread use of mobile robots in different parts of society, it is important to provide them with the capability to behave in a *socially acceptable* manner. Therefore, a research topic of great importance recently has been the study of Human-Robot Interaction. Autonomous navigation is a fundamental task in Robotics, and several different strategies that produce paths that are either length or time optimized can be found in the literature. However, considering the recent use of mobile robots in a more social context, the use of such classical techniques is restricted. Therefore, in this article we present a social navigation approach considering environments with groups of people. The proposal uses a density function to efficiently represent groups of people, and modify the navigation architecture in order to include the social behaviour of the robot during its motion. This architecture is based on the combined use of the Probabilistic Road Mapping (PRM) and the Rapidly-exploring Random Tree (RRT) path planners and an adaptation of the *elastic band* algorithm. Experimental evaluation was carried out in different simulated environments, providing insight on the performance of the proposed technique, which surpasses classical techniques with no proxemics awareness in terms of social impact.**

## I. Introduction

It is expected that the use of mobile robots in different parts of society will be commonplace in the near future. This change from controlled environments (e.g., factories) to unconstrained environments where people are constantly present (e.g., homes, public places, working environments) will require robots to behave in *socially acceptable* ways.

Therefore, a research topic of great importance recently has been the study of Human-Robot Interaction (HRI). This area is responsible for studying the different aspects inherent to the interactions between humans and robots, allowing the development of techniques that let the use of these as transparent as possible.

The interaction between humans and robots can be divided into two basic situations, namely (i) the case where the robot must perform a task whilst reducing the possible social impact, and (ii) the case where the task involves interacting directly with a person. Either way, there are some nonverbal social rules implied that must be respected, especially those related to personal space of individuals, rules which are studied in *proxemics* [1].

*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), MEC project PHBP14/00083 and by CAPES-DGPU 7523/14-9.

[1]Authors are with Robotics and Artificial Lab, RoboLab, University of Extremadura, 10003 Cáceres, Spain. pnuntru@unex.es

[2]D. G. Macharet is with the Computer Vision and Robotics Laboratory, Department of Computer Science, Universidade Federal de Minas Gerais, Belo Horizonte, Brazil. doug@dcc.ufmg.br

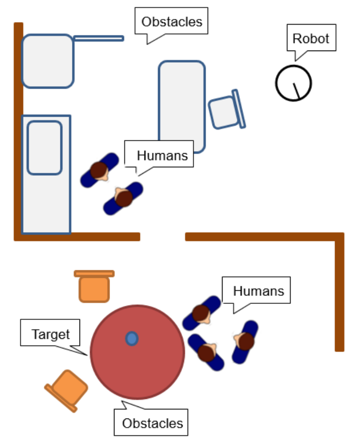



Fig. 1: The robot has to choose the best route and navigate from the kitchen to the living-room by using its social rules.

In the last years, the term *social navigation* in robotics has been introduced as a way to relate the robot navigation in social contexts and human-robot interaction. New generations of social robots should be able to generate different socially accepted routes during an interaction with humans and also exhibit proactive social behaviours during the navigation [2] (*e.g.*, to gracefully approach people, or to wittily enter and exit from a conversation). Figure 1 illustrates the problem to solve: the robot located in the kitchen has to choose the best route and navigate from its current pose to the living-room (target) along a complex environment with people.

This need for socially acceptable behaviour crosses many domains and calls for inquiries (e.g., can I make noise now? How fast can I move without disturbing people's sense of safety? Can I navigate in front of someone? Can I move behind her?), the answers to which act as constraints on the paths, turning them *anthropomorphic paths* [3].

In [4], a proposal for a social path planner is described, which includes a model of social navigation. In this work it is presented a new mathematical model built upon the use of a density function in order to efficiently analyse the environment and cluster the individuals into groups according to their distances to other individuals. Next, the system adapts the navigation architecture for including regions where navigation is either discouraged or forbidden, considering the previously defined clusters. Finally, this paper validates the presented methodology with experiments on different simulated scenarios considering situations which are representative of common problems that might arise when navigating on human-populated environments.

The remainder of this paper is organized as follows: in Section II a review of the literature is presented. Our methodology is presented in detail in Section III and validated by a group of experiments on a simulated environment, the results of which are shown in Section IV. Finally, Section V concludes with a discussion of the results and future research directions.

## II. Related Work

Generally, classical motion planning methods dealing with an autonomous navigation consider all obstacles in the environment the same way, including people. However, this approach may not be the best solution, since it is important to consider people as a special entity, for example considering the person's level of comfort with respect to the path of the robot.

Social navigation started being extensively studied in the last years and several methods have been proposed from then. Works like [5], [6], [7] have shown that the same proxemic zones that exists in human-human interaction can also be applied to human-robot interaction scenarios. Therefore, an increasing number of works have incorporated this notion of personal space model in the path planning step in order to create acceptable behaviours for robots during their navigation.

A path that explicitly takes into account the human presence in the environment must address situations such as not passing between two people talking or avoid getting out of the field of view of the people, with the possibility of scaring them unnecessarily. Many works can be found in the literature with different approaches to this problem [8], [9], [10], [11]. However, this model is not permanent, and can vary accordingly to different aspects, such as previously experience with the robot [12], or functional noise of the robot [13].

In most real-world scenarios, humans in the environment are interacting with each other. In this case, during their deliberation phase, motion planners must take into account this new *combined entity*, instead of single individuals. The problem of identifying and correctly represent groups of people in the environment is a challenge in itself. Most works dealing with groups of people are build upon the F-formation system [14] formalization, which states that people often group themselves in some spatial formation with a shared space between them. Fig. 2 illustrates some of the Kendon's F-formation arrangements.

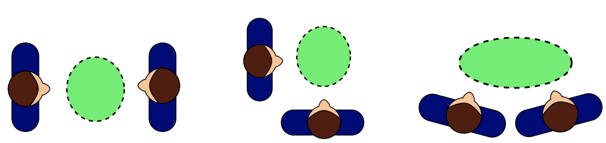



Fig. 2: Kendon's F-formation arrangements. (a) *Vis-a-vis* arrangement; (b) *L*-arrangement; (b) *side-by-side* arrangement.

In [15] it is presented an unified theoretical formalization for different classes of subproblems related to social path planning. Next, considering an extension of the classical F-formation system for more then two individuals, it is proposed a technique to solve problems such as human-aware navigation and how to engage groups of people. In [16] it is proposed a framework that can model context-dependent human spatial interactions, encoded in the form of a social map. The 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.

A broad survey and discussion regarding the social concepts of proxemics theory applied in the context of human-aware autonomous navigation is presented in [17].

This paper proposes a mathematical model based upon the use of a modified two-dimensional Gaussian function [2] to model the personal space of an individual and the use of a density function [18] in order to efficiently analyse the environment and cluster the individuals into groups according to their distances to other individuals. Next, this model is incorporated on the navigation architecture presented in [19], allowing the robot to navigate in a more social manner among humans.

## III. Methodology

The methodology is divided into two fundamental steps: (i) individuals clustering, and (ii) socially acceptable navigation. In the first step, based upon the use of a Gaussian-based representation for personal space, a global density function to separate individuals into groups accordingly to their distances to each other is defined. Next, the social navigation architecture uses the well-known PRM [20] and RRT [21] planners, in conjunction with a modified version of the *elastic band* algorithm for path optimization [19]. An overview of the proposed approach is described in the Figure 3. The rest of the section describes with details the proposed method.

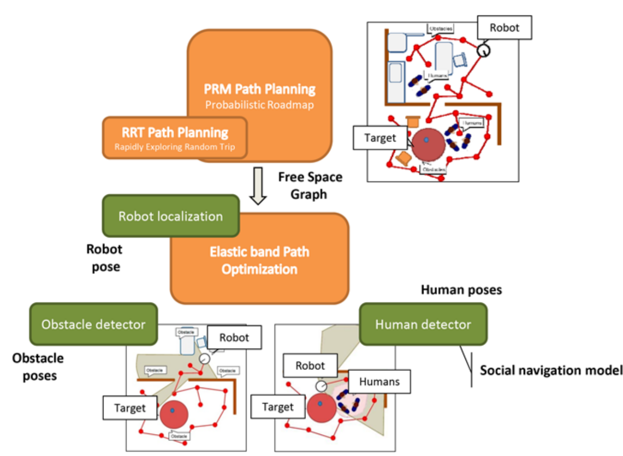



Fig. 3: Overview of the social navigation framework.

### A. Personal Space

Let $S \in \mathbb{R}^2$ be the space of the Global Map. An individual $i$ is represented by its position $\mathbf{q_i} = [x_i \ y_i]^T$ in $S$ and it orientation $\theta_i \in [0, 2\pi]$. The personal space is modelled by a asymmetric 2-dimensional Gaussian function [2], which associates the distance between a point $\mathbf{p} = [x \ y]^T \in S$ and the person's position with a real value $g_i \in [0, 1]$. The expression for the Gaussian function is

$$g_i(x, y) = exp(-(a(x-x_i)^2+b(x-x_i)(y-y_i)+c(y-y_i)^2)), \quad (1)$$

where the coefficients $a, b$ and $c$ are used to take into account the orientation $\theta_i$, and are defined by the relations

$$a(\theta_i) = \frac{cos(\theta_i)^2}{2\sigma^2} + \frac{sin(\theta_i)^2}{2\sigma_s^2},$$

$$b(\theta_i) = \frac{sin(2\theta_i)}{4\sigma^2} - \frac{sin(2\theta_i)}{4\sigma_s^2},$$

$$c(\theta_i) = \frac{sin(\theta_i)^2}{2\sigma^2} + \frac{cos(\theta_i)^2}{2\sigma_s^2},$$

where $\sigma_s$ is the variance to the sides ($\theta_i \pm \pi/2$ direction) and $\sigma$ represents the variance along the $\theta_i$ direction ($\sigma_h$) or the variance to the rear ($\sigma_r$) [2]. Figure 4 illustrates the personal space model.

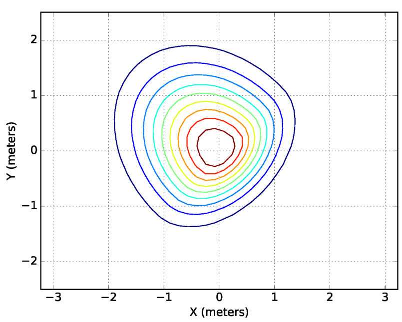



Fig. 4: Contour map personal space of a single individual as modelled by Equation (1). The person is posed at $\mathbf{q} = [0 \ 0 \ 3\pi/4]^T$.

The decision to use Gaussian functions to modelling personal spaces is very useful, since it allows for many established techniques to be used in this context. In our case, it will be used as the input of a global density function that clusters the individuals, as the next section explains.

### B. Individuals Clustering

When considering groups of humans, it is needed to define how to associate the various personal spaces of each individual. In this paper, this association is accomplished by performing a Gaussian Mixture. We sum the personal space function $g_i(\mathbf{p})$ for each individual $i$ in the set of all $P$ of all people in $S$ and arrive at a Global Space function $G(\mathbf{p})$. The proposal defines the Global Space Function:

$$G(x, y) = \sum_{i \in P} g_i(x, y). \quad (2)$$

Having performed the association and calculated the value of $G(\mathbf{p})$, the next step is to separate the individuals in groups. The method described in this paper discriminate the group contour to which each individual belongs, so it can define regions of forbidden navigation. This is accomplished by using the method described in [18].

This method was originally employed for grouping points in a point cloud to categorize them as to whether they belong to the same object. In essence, this method takes advantage of the property that, if for each point in a point cloud we associate a Gaussian function centered around it, then the closer two or more points are, the larger the sum of their respective Gaussian will be. This same line of reasoning can be used to group people into clusters which a robot can use to reason about space.

The method chooses the $\Omega$ parameter as the *smallest euclidean distance between two people* $\mathbf{p_i}, \mathbf{p_j} \in P$ *such that those two are neighbours*. This value is given by the insights of proxemics. If $\mathbf{p_i}, \mathbf{p_j}$ are neighbours, then $\|\mathbf{p_i}, \mathbf{p_j}\| \leq \Omega$, and the density contribution $\delta$ between them is

$$\delta = g_i(\mathbf{p_j}). \quad (3)$$

Since $g_i(\mathbf{q_i}) = 1$ for each $\mathbf{q_i} \in P$, then if $\mathbf{q_i}$ has $k$ neighbours then $G(\mathbf{q_i}) \geq 1+k\delta$. Therefore, in order to group individuals who have at least $k$ neighbours, the method can adjust a density threshold $h$ given by

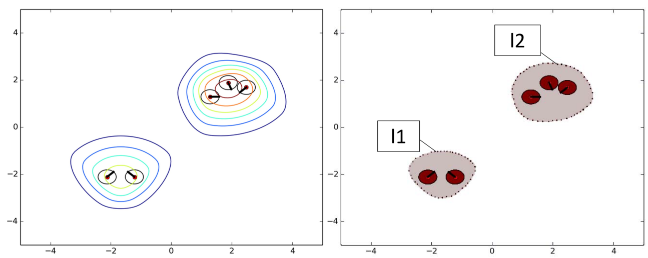
$$h = 1 + k\delta, \quad (4)$$

and it can compare the value of the Global Function for each point in $S$ and determine whether that point belongs to the personal space of a group of individuals. The set of such points is denoted by $J$ and given by the expression

$$J = \{\mathbf{p} \in S \mid G(\mathbf{p}) \geq h\}. \quad (5)$$

By manipulating the value of $h$ either by setting it directly or by manipulating the value of $\delta$, it is able to control how near or far the border of $J$ is in relation to each human in the cluster. In the method described in this paper we have experimentally fixed $h = 1$, so that the border of the forbidden region is not immediately adjacent to an individual. Figure 5b shows the result of applying this procedure to the group shown in Figure 5a. In the Figure Figure 5a, two regions of forbidden navigation have been calculated by the algorithm.

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 $J$. The number of vertices, $m$, is dynamically adjusted by the algorithm, being the Euclidean distance between two consecutive vertices, $d(a_i, a_j)$, less than 10 cm. An example of two polylines generated by the algorithm, $l_1$ and $l_2$, for the Figure 5a are drawn in Figure 5b.




(a) (b)

Fig. 5: (a) shows a group of three people in points $\mathbf{q_1} = [2.48m, 1.67m]^T, \mathbf{q_2} = [1.28m, 1.28m]^T, \mathbf{q_3} = [1.88m, 1.88m]^T$, with orientations $\theta_1 = 225°$, $\theta_2 = 0°$, $\theta_3 = 290°$ respectively, and a group of two people at $\mathbf{q_4} = [-1.22m, -2.12m]^T, \mathbf{q_5} = [-2.12m, -2.12m]^T$ with orientations $\theta_4 = 135°$ and $\theta_5 = 45°$. (b) shows the result of applying the clustering algorithm to these groups with $h = 1.0$. Regions of forbidden navigation are shown in red.

### C. Socially Acceptable Navigation

An overview of the social navigation architecture described in this paper was illustrated in the Figure 3. Once the polygonal curves associated to group humans have been calculated, $L_k$, the proposed approach integrates this information in the path planners. First, the global planner traces a navigation plan for a given target $\mathbf{T} \in S$. Then, the local planner modifies the plan according to the obstacles and humans detected by the robot. In the proposed approach, the social navigation architecture is a modified version of the one presented in [19], which consists of the next stages:

*1) PRM-RRT path planners:* First, the PRM planner [20] uses a learnt graph of the free space to search for a path free of obstacles from the robot location to the target. The initial graph is created using a generalized inverse kinematics algorithm, based on the Levenberg-Marquardt method [22]. In case that the graph still had more that one connected region or there was not a direct line of sight from the robot (or the target) to the graph, the RRT planner [21] is used. Thus, the final graph that describes the free space is defined by a set of nodes, $N$, and edges, $E$, $G_t = (N, E)$. In Fig. 6, a descriptive example of this graph is drawn as a set of nodes (red circles) and arcs (red lines). Next, the path is created by first searching the closest point in the graph to the current robot's pose, the closest point in $G_t$ to the target position $T$ and a path through the graph linking both points.

*2) Elastic Band Path Optimization:* The initial path is first transformed into a regularly separated series of way-points, or steps, at a distant closer than the length of the robot. The elastic band path optimization [19] updates the path planned for each step as it is traversed, adapting it to unexpected events, such as obstacles or group of humans described by the list of polylines $L_k$. As illustrated in Figure 6, the path is analysed under the laser range, and two virtual forces are created. Let's define the path $P = p_i \in \mathbb{R}^2$ as an ordered set of (x, y) locations – called steps – of the robot's configuration

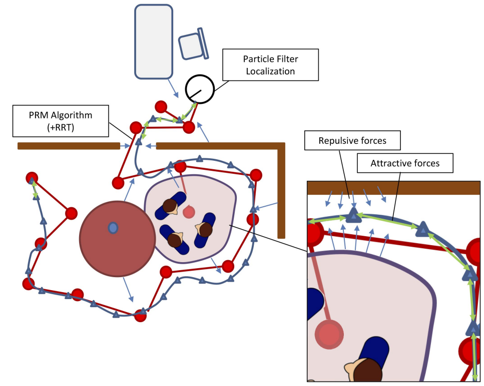



Fig. 6: The final social path is shown as the blue continuous line ($\triangle$). Besides, the graph $G_t$ provided by path planners (red colour), and the set of forces are drawn.

space. Then, an internal contraction virtual force is defined to model the tension in a physical elastic band using the following equation:

$$f_c = k_c \cdot \left( \frac{p_{i-1} - p_i}{\|p_{i-1} - p_i\|} + \frac{p_{i+1} - p}{\|p_{i+1} - p_i\|} \right), \tag{6}$$

where $p_i$ is the position of step $i$ in the path. The physical interpretation is a series of springs connecting the path steps, with $k_c$ as a global contraction gain. These contraction forces are illustrated in green colour in Figure 6.

Also, a repulsive force pushes each step away from the obstacles and humans defined by $L_k$ to increase the clearance of the robot. A function $d(p)$ is defined $\mathbb{R}^2 \times \mathbb{R}^2 \rightarrow \{R^+ \cup 0\}$ that computes the minimum distance of a step $p$ to the nearest obstacle, as perceived by the laser sensor.

$$f_r = \begin{Bmatrix} k_r(d_o - d)\frac{\partial d}{\partial p} & p < p_o \\ 0 & p \geq p_o \end{Bmatrix}, \tag{7}$$

where $k_r$ is a global repulsion gain and do is the maximum distance up to which the force is applied. These repulsion forces are illustrated in blue colour in Figure 6. The Jacobian $\frac{\partial d}{\partial p}$ is approximated using finite differences. The final force is calculated as a linear combination of both, $f = f_c + f_r$, that is continuously applied to each step inside the laser field. This force modify the final path, as is shown in the Figure 6.

## IV. Experiments

To evaluate the performance of the proposed algorithm, a set of simulated scenarios were used. 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. In order to assess the effectiveness of the proposed approach, the methodology has been evaluated accordingly to the following metrics: (i) minimum distance to a human during navigation; (ii) distance travelled; and (iii) navigation time. A comparative study of the proposal with the navigation architecture presented in [19] is also provided.

Two different simulated scenarios have been created. The first one consists of a square environment without objects, with dimensions $8\,\mathrm{m}\times 8\,\mathrm{m}$, and the presence of 6 individuals. These individuals are grouped as is shown in the Fig. 7a. The second experiment has been achieved in a simulated 65 $m^2$ apartment with 6 individuals, which are grouped as is illustrated in the Fig. 7e. The graph $P_t$ generated by the combined PRM-RRT path planner for both two environments are shown in the Figures 7b and 7f, respectively. These graphs define the navigation plan for the robot within the environment, before detecting group of humans in its surrounding.

The contour maps of the personal space of the groups of persons in the environments are shown in the Figs. 7c and 7g. The discomfort experienced by the individuals is modelled using different curve lines of each Gaussian. In the Figs. 7d and 7h are drawn the clusters of persons after using the algorithm proposed in this paper. These clusters describe the forbidden areas for the robot navigation and are related with the $h$ parameter ($h$ = 1.0 in all the tests).

Finally, for illustrative purposes, an example of the possible results given by the proposed methodology and by the navigation system without social awareness [19] is presented in Figs. 8a and 8b. A list of targets has been defined and marked in the figure and, over the same figures, the robot trajectory is drawn. In Fig. 7, red and blue lines are the final paths followed by the robot during its social navigation or without it, respectively. Green lines show the polylines that define the contour of forbidden navigation. These tests were achieved 10 times per simulated environment using always the same targets and positioning of objects and people.

The mean values of the time used by the robot during its navigation in the environment described in Fig. 7a so as its traveled distance are shown on Table I. The mean values of the minimum distances to each individuals, $d_{min}$, are also shown in I. Besides, Table II summarizes these same values for the experiment described in Fig. 7e[1]. From the results of the experiments, it is possible to conclude that the robot successfully navigate in a socially acceptable way avoiding the group of individuals. In particular, $d_{min}$ values using the navigation architecture proposed in this work are higher than the navigation method without social skills. These $d_{min}$ values allows the robot move around the humans without disturbing them. The total time in reach the targets is higher, but it is normal due to the greater distance traveled.

TABLE I: Navigation results for the square environment

| Social navigation architecture | | Haut et al. [19] | |
|---|---|---|---|
| Parameter | Value | Parameter | Value |
| *Travelled distance* | 21.99m | *Travelled distance* | 20.12m |
| *Total time* | 175s | *Total time* | 140s |
| $d_{min}$ *Person 1* | 115cm | $d_{min}$ *Person 1* | 45cm |
| $d_{min}$ *Person 2* | 160cm | $d_{min}$ *Person 2* | 52cm |
| $d_{min}$ *Person 3* | 80cm | $d_{min}$ *Person 3* | 43cm |
| $d_{min}$ *Person 4* | 82cm | $d_{min}$ *Person 4* | 75cm |
| $d_{min}$ *Person 5* | 220cm | $d_{min}$ *Person 5* | 71cm |
| $d_{min}$ *Person 6* | 109cm | $d_{min}$ *Person 6* | 58cm |

TABLE II: Navigation results for the apartment

| Social navigation architecture | | Haut et al. [19] | |
|---|---|---|---|
| Parameter | Value | Parameter | Value |
| *Travelled distance* | 22.3m | *Travelled distance* | 19.94m |
| *Total time* | 230s | *Total time* | 120s |
| $d_{min}$ *Person 1* | 138cm | $d_{min}$ *Person 1* | 50cm |
| $d_{min}$ *Person 2* | 94cm | $d_{min}$ *Person 2* | 43cm |
| $d_{min}$ *Person 3* | 170cm | $d_{min}$ *Person 3* | 62cm |
| $d_{min}$ *Person 4* | 115cm | $d_{min}$ *Person 4* | 16cm |
| $d_{min}$ *Person 5* | 101cm | $d_{min}$ *Person 5* | 47cm |
| $d_{min}$ *Person 6* | 81cm | $d_{min}$ *Person 6* | 48cm |

## V. Conclusion and Future Work

Despite the increasing use of mobile robots in many different areas and applications, the integration of these into a more social context still has a major potential for growth. However, this requires the research and development of techniques that will allow these robots to act in a way that is socially acceptable.

In this article, a social navigation approach considering environments with groups of people is presented. This paper proposes the use of a global density function to efficiently cluster individuals into groups, therefore facilitating the robot's navigation. Finally, a social navigation architecture is presented to execute the navigation considering this social representation. The experiments demonstrate the effectiveness of the approach, so as the improvement of the robot's social behaviour during its motion in human-populated environment.

Future research directions include the extension of the methodology to deal with dynamic environments (i.e. people moving around) and the interaction between humans and objects in the scene. We also intend to apply the methodology in a real-world scenario, and to study, under realistic conditions, the actual reaction of human subjects regarding to safety and discomfort.

[1]A video of the experiments is accessible on https://youtu.be/qV4QQwl5HOU.

## References


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

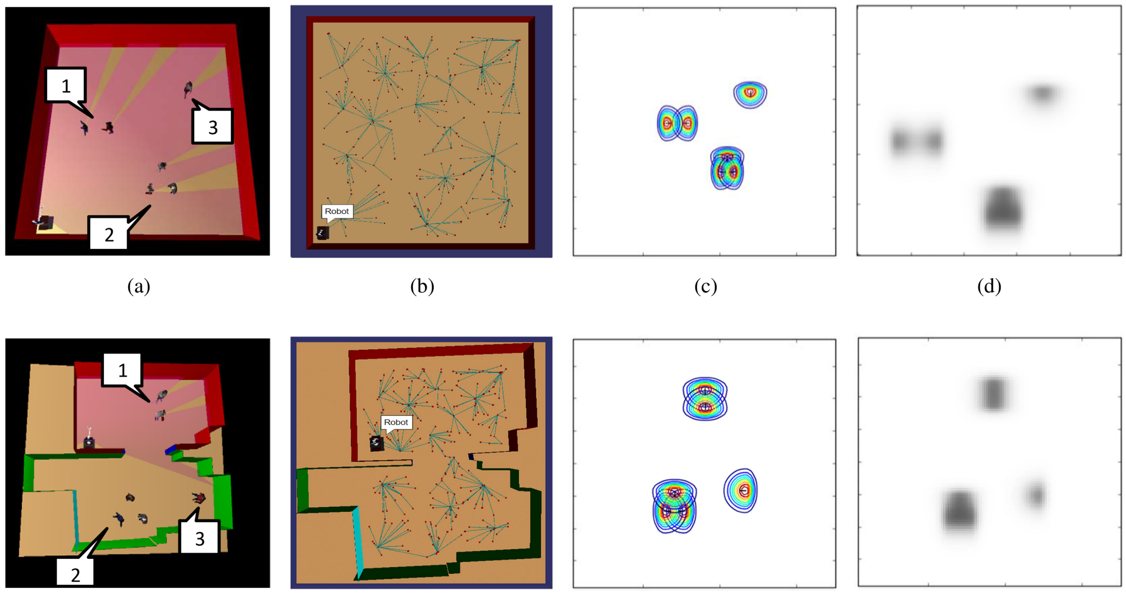
[2] R. Kirby, "Social robot navigation," Ph.D. dissertation, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, May 2010.

[3] L. Scandolo and T. Fraichard, "An anthropomorphic navigation scheme for dynamic scenarios," in *IEEE International Conference on Robotics and Automation (ICRA)*, ser. ICRA '11. Piscataway, NJ, USA: IEEE, 2011, pp. 809 – 814.

[4] P. Núñez, L. Manso, P. Bustos, P. Drews-Jr, and D. Macharet, "A Proposal for the Design of a Semantic Social Path Planner using CORTEX," in *Workshops on Physical Agent*, june 2016, pp. 1–7.

[5] J. Mumm and B. Mutlu, "Human-robot proxemics: physical and psychological distancing in human-robot interaction," in *Proceedings of the 6th international conference on Human-robot interaction (HRI)*. New York, NY, USA: ACM, 2011, pp. 331–338.

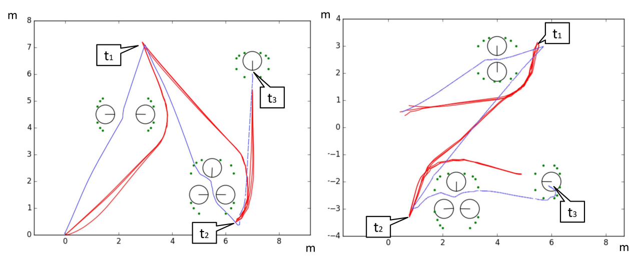
[6] M. Walters, M. Oskoei, D. Syrdal, and K. Dautenhahn, "A long-term Human-Robot Proxemic study," in *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, aug 2011, pp. 137 –142.




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

(e) (f) (g) (h)

Fig. 7: (a, e) 3D visualization of the simulated environment; (b, f) Initial graph generated for the path planners; (c, g) Potential regions of discomfort of the humans is modelled using Mixture of Gaussians; and (d, g, h) cluster of persons, which define the forbidden regions for navigation.




(a) (b)

Fig. 8: (a, b) path followed by the robot in the environment described in the Figures 7a and 7e. Red colour represents three different tests without the robot social behaviour. Blue colour shows the path including the social behaviour. Green lines are the polylines obtained from the algorithm proposed in this paper.

[7] R. Mead and M. J. Mataric, "A probabilistic framework for autonomous proxemic control in situated and mobile human-robot interaction," in *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, ser. HRI '12. New York, NY, USA: ACM, 2012, pp. 193–194.

[8] E. Sisbot, L. Marin-Urias, R. Alami, and T. Simeon, "A Human Aware Mobile Robot Motion Planner," *IEEE Transactions on Robotics*, vol. 23, no. 5, pp. 874–883, oct. 2007.

[9] M. Svenstrup, S. Tranberg, H. Andersen, and T. Bak, "Pose estimation and adaptive robot behaviour for human-robot interaction," in *IEEE International Conference on Robotics and Automation (ICRA)*, may 2009, pp. 3571 –3576.

[10] J. Kessler, C. Schroeter, and H.-M. Gross, "Approaching a person in a socially acceptable manner using a fast marching planner," in *Proceedings of the 4th international conference on Intelligent Robotics and Applications - Volume Part II (ICIRA)*. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 368–377.

[11] T. Kruse, P. Basili, S. Glasauer, and A. Kirsch, "Legible robot navigation in the proximity of moving humans," in *Proceedings of the IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO'12)*, may 2012, pp. 83–88.

[12] L. Takayama and C. Pantofaru, "Influences on proxemic behaviors in human-robot interaction," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, oct. 2009, pp. 5495–5502.

[13] N. van Berkel, "How adjustments to the velocity and functional noise of a robot can enhance the approach experience," in *Proc. of TSConIT*, 2013.

[14] A. Kendon, *Conducting Interaction: Patterns of Behavior in Focused Encounters (Studies in Interactional Sociolinguistics)*. Cambridge University Press, Nov. 1990.

[15] J. Gomez, N. Mavridis, and S. Garrido, "Fast marching solution for the social path planning problem," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, May 2014, pp. 1871–1876.

[16] P. Papadakis, A. Spalanzani, and C. Laugier, "Social mapping of human-populated environments by implicit function learning," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Nov 2013, pp. 1701–1706.

[17] 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.

[18] A. W. Vieira, "Spatial density patterns for efficient change detection in 3d environment for autonomous surveillance robots," in *IEEE Transactions on Automation Science and Engineering*. Piscataway, NJ, USA: IEEE, 2014, pp. 766 – 774.

[19] M. Haut, L. Manso, D. Gallego, M. Paoletti, P. Bustos, and A. Bandera, A. Romero, "A navigation agent for mobile manipulators," in *Proceedings of the Robot 2015: Second Iberian Robotics Conference*, July 2016, pp. 745–756.

[20] E. Olson, J. Leonard, and S. Teller, "Fast iterative alignment of pose graphs with poor initial estimates," in *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, 2006, pp. 2262–2269.

[21] S. M. LaValle, *Planning algorithms*, 2006.

[22] J. J. Moré, *The Levenberg-Marquardt algorithm: Implementation and theory*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1978, pp. 105–116.