A new Strategy based on an Adaptive Spatial Density Function for Social Robot Navigation in Human-Populated Environments

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Abstract. With robots shifting towards human-populated environment, robot navigation is challenging because there are a lot of factors to take into account, such as social rules or the human intentions. While traditional robot navigation algorithms treat all sensor readings, including humans, as objects to be avoided, now it is important to provide robots with the capability to behave in a *socially acceptable* manner.
This work presents a new strategy for social robot navigation based on an adaptive spatial density function to efficiently cluster groups of people according to its pattern of arrangement. The proposed function defines regions where navigation is either discouraged or forbidden. The navigation architecture combines the Probabilistic Road Map and the Rapidly-exploring Random Tree path planners and an adaptation of the elastic band algorithm to include the social behaviour. Numerous trials in real and simulated environments were carried out, which demonstrate the performance of the clustering algorithm and the social navigation architecture.

Keywords: Social robot navigation, aware-navigation

1 Introduction

In the not too distant future, it is expected that social robots will be helpful in everyday life. These robots will perform typical tasks in human-populated environments, such as offices, hospitals, homes or museums. In these environments where people are constantly present, the robot should behave in both a human and robot-friendly manner during its movement, exhibiting appropriate responses.

The term *social navigation* in robotics has been introduced in the last years as a way to relate robot navigation in human environments to human-robot interaction. Developing socially accepted robots has ever been one of the prevalent topics of robotics. A social robot should be able to plan different socially

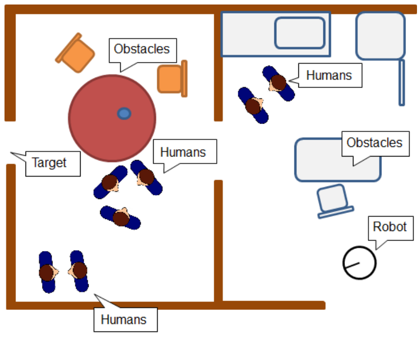


Fig. 1: Example scenario to explain the method described in this paper. The robot is operating in a human-populated environment. It has to choose the best route and navigate without causing discomfort to any human present.

accepted routes during an interaction with humans and also to exhibit proactive social behaviours during the navigation [1] (*e.g.*, to wittily enter and exit from a conversation or to gracefully approach people). In this respect, research on social robot navigation has followed different goals and calls for inquiries (e.g., can the robot make noise now? Can the robot move behind people? How fast can the robot move without disturbing people's sense of safety? Can the robot navigate in front of someone?). In most of the cases, the answers to these questions act as constraints on the paths, turning them *anthropomorphic paths* [3].

In a previous work of the authors [4], a proposal for a social path planner was described, which included a model of social navigation. This paper focuses on a path-planning strategy where it is assumed that humans don't want to interact with the robot. In this work, a new mathematical model built upon the use of an adaptive density function in order to efficiently cluster the individuals is described. The main contribution is the clustering algorithm, which **analyses the environment and then clusters the individuals into groups according to social interactions between them**. This adaptive spatial density function models personal space around group of people, which prevents the emotional discomfort humans may feel when approached closer than they like. The concept of this personal space is related to the term *Proxemics*, which defines spaces that humans mutually respects during an interaction. Next, the system adapts the navigation architecture for including the personal spaces, where navigation is either discouraged or forbidden. 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. The robot has to choose the best path and navigate without causing discomfort to any human present.

This paper is organized as follows: in Section 2 a review of similar works in the literature is described. The adaptive spatial density function for social mapping is presented in detail in Section 4. Next, the social navigation method is described in Section 5, and validated by a group of experiments on real and simulated environments, the results of which are shown in Section 6. Finally, Section 7 concludes with a discussion of the results and future research directions.

2 Related works

Classically, robots working in human environments have used navigation algorithms where all obstacles are considered in the same way, including people. Social robots must consider people as a special entity, and not like a common obstacle. Thus, they must evaluate the person's level of comfort with respect to the route of the robot, among other behaviour.

Social navigation has been extensively studied in the last decade and several methods have been proposed from then (an interesting review is presented in [5]). Different works, such as [6,7,8], have shown that the same proxemic zones that exists in human-human interaction can also be applied to human-robot interaction scenarios. The main idea is to create acceptable behaviours for robots during their navigation. Therefore, the number of works that have incorporated this notion of personal space model in the path planning step has increased in the last years [5].

When a robot plans the best path in human-populated environments, it must address situations such as not passing between two people talking or avoid getting out of the field of view of the people. A broad survey and discussion regarding the social concepts of proxemics theory applied in the context of human-aware autonomous navigation is presented in [9]. There are many works in the literature with different approaches to this problem [10,11,12,13]. The model of these forbidden areas for robot navigation is not permanent, as several authors has pointed out, and can vary accordingly to different aspects, such as previously experience with the robot [14], or functional noise of the robot [15].

In most human-populated scenarios, people is in conversation forming groups. In this situations, path planners must take into account this new *combined entity*, instead of a single personal space. 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 [16,17] or the O-Space [9] formalization, which states that people often group themselves in some spatial formation with a shared space between them. In this respect, this paper focuses on an adaptive spatial density function for clustering groups of people in different formations, which defines the shared space according to distances and relative angles between humans. Fig. 2 illustrates the most frequent Kendon's formations or arrangements: N-shape, Vis-a-vis, V-shape, L-shape, C-shape and side-by-side. Besides, the O-space defined in [9] is also shown in the figure. All of them have been taken into account in the function described in this paper.

The work proposed in this paper defines a mathematical model based upon the use of an asymmetric Gaussian function [1] to model the personal space of an individual. Then, the algorithm uses a modified version of the density function

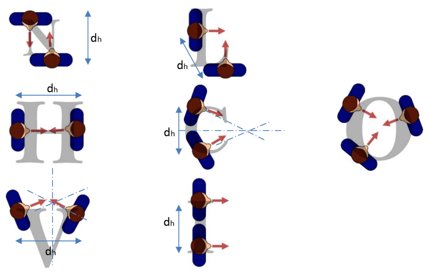


Fig. 2: Taxonomies of arrangements for a two-person formation defined in [16] and three-person formation defined in [9]. In the figure, d_h is the distance between humans during conversation. The method proposed in this paper adapts the social space according to the arrangement.

presented in [18] in order to efficiently analyse the environment and cluster groups of people according to its pattern of arrangement. Next, this model is incorporated on the navigation architecture presented in [19], allowing the robot to navigate in a more social manner among humans.

3 System overview

To plan the best social path in human-populated scenarios, the following strategy is proposed in this paper: i) human detection and representation; ii) clustering of people into groups according to its social interactions; and iii) including these personal spaces in the path planners algorithms. Thus, the methodology described in this paper is divided into two fundamental steps:

- *Individuals representation and clustering*: based upon the use of a Gaussian-based representation for personal space, a global density function to separate individuals into groups accordingly to its pattern of arrangement is defined.
- *Socially acceptable navigation*: the social navigation architecture uses the well-known Probabilistic Road Mapping (PRM) [20] and Rapidly-exploring Random Tree (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 next sections describe with details the social navigation framework.

4 Adaptive Spatial Density Function for Robot Navigation

4.1 Personal space modelling

Let $S \in \mathbb{R}^2$ be the space of the Global Map. An individual i is represented by its pose (position and orientation), $\mathbf{h_i} = [x_i\ y_i\ \theta_i]^T$, being $[x_i\ y_i]^T \in S$

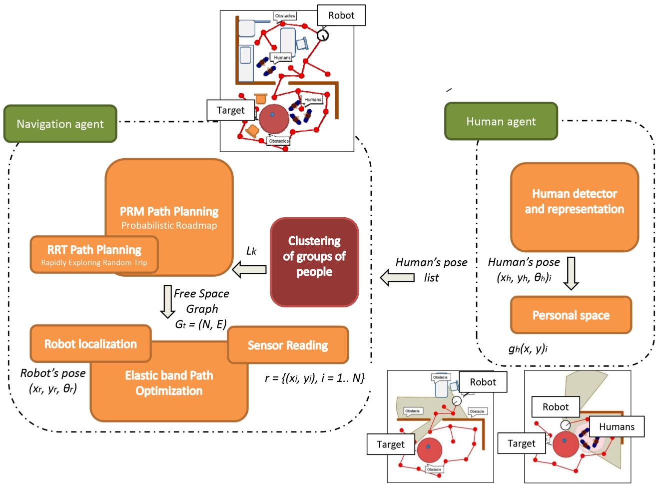


Fig. 3: Overview of the social navigation framework

and $\theta_i \in [0, 2\pi]$. An asymmetric 2-dimensional Gaussian function is used for modelling the personal space [1]. This function 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

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

where the coefficients k_1, k_2 and k_3 are used to take into account the orientation θ_i, and are defined by the relations

$$k_1(\theta_i) = \frac{cos(\theta_i)^2}{2\sigma^2} + \frac{sin(\theta_i)^2}{2\sigma_s^2}$$
$$k_2(\theta_i) = \frac{sin(2\theta_i)}{4\sigma^2} - \frac{sin(2\theta_i)}{4\sigma_s^2}$$
$$k_3(\theta_i) = \frac{sin(\theta_i)^2}{2\sigma^2} + \frac{cos(\theta_i)^2}{2\sigma_s^2}$$

where σ_s is the variance to the sides ($\theta_i \pm \pi/2$ direction) and σ represents the variance along the θ_i direction (σ_h) or the variance to the rear (σ_r) [1]. Figure 4 illustrates an axample of the personal space model.

Once the personal space for each human in the environment is calculated, it is used as the input of a global density function that clusters the individuals, as the next section explains.

4.2 People clustering

According to [16], for two people in conversation and depending of the kind of scenario, *e.g.*, spaces open, spaces that are semi-open and spaces where there is

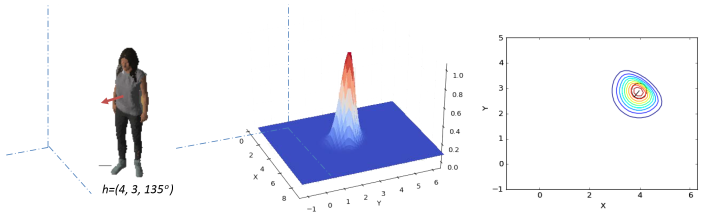


Fig. 4: Contour map personal space of a single individual as modelled by Equation (1). The person is posed at $\mathbf{h} = [3.0m\ 4.0m\ 245^o]^T$.

no pedestrian movement, six arrangements are the most frequent. These typical formations were shown in Fig. 2. In conversation of more than two people, typical formations are defined as O-spaces [9]. Then, 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.

Let $g_{h_i}(\mathbf{p})$ be the personal space function for each individual i in the set of all P of all people in S. The Global Density Space Function $G_d(\mathbf{p})$ is defined as:

$$G_d(x, y) = \sum_{i \in P} g_{h_i}(x, y). \tag{2}$$

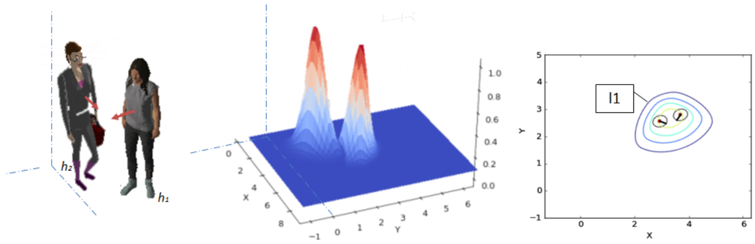
Once the association is performed and the value of $G_d(\mathbf{p})$ is calculated, the next stage is to separate people in groups. The method described in this paper discriminates the group contour to which each individual belongs, so it can define regions of forbidden navigation. This is accomplished by using a modified version of the method described in Viera's work [18], which is employed for grouping points in a cloud of points to categorize them as to whether they belong to the same object.

In order to group individuals into clusters, the method chooses the Ω_d and Ω_θ parameters as the *smallest euclidean distance and the smallest difference of angles between two people* $\mathbf{h_i}(\mathbf{x}, \mathbf{y}, \theta), \mathbf{h_j}(\mathbf{x}, \mathbf{y}, \theta) \in P$ *such that those two are neighbours*. These values are given by the insights of proxemics. If $\mathbf{h_i}(\mathbf{x}, \mathbf{y}), \mathbf{h_j}(\mathbf{x}, \mathbf{y})$ are neighbours, then $\|\mathbf{h_i}(\mathbf{x}, \mathbf{y}), \mathbf{h_j}(\mathbf{x}, \mathbf{y})\| \le \Omega_d$ and $\|\mathbf{h_i}(\theta), \mathbf{h_j}(\theta)\| \le \Omega_\theta$ and the density contribution δ between them is

$$\delta = g_{h_i}(\mathbf{h_j}). \tag{3}$$

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

$$\phi = 1 + k\delta, \tag{4}$$



(a) (b)

Fig. 5: (a) shows a group of two people in points $\mathbf{q_1} = [4m, 3m]^T$ and $\mathbf{q_2} = [3m, 1.28m]^T$, with orientations $\theta_1 = 245^o$ and $\theta_2 = 335^o$ respectively. Both two gaussians are also drawn. (b) shows the result of applying the clustering algorithm to these groups with $\phi = 1.0$.

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

$$J = \{\mathbf{h} \in S \mid G_d(\mathbf{p}) \geq \phi\}. \tag{5}$$

By manipulating the value of ϕ either by setting it directly or by manipulating the value of δ, it is able to control how near or far the border of J is in relation to each human in the cluster. A validation of this parameter ϕ is described in the next section. Figure 5b shows the result of applying this procedure to the group shown in Figure 5a.

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 a fixed threshold d_l.

5 Social navigation based in human-populated environment

5.1 Socially Acceptable Navigation

Once the polygonal curves associated to each group of humans, L_k, has been calculated, 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's sensor. 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, a graph of the free space is created using a generalized inverse kinematics algorithm, based on the Levenberg-Marquardt method. This graph is used by the PRM planner [20] to search for a path free of obstacles from the robot location to the target. 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* For the path optimization, the initial path is 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) $\in S$ locations − called steps − of the robot's configuration space. Then, an internal contraction virtual force is defined to model the tension in a physical elastic band using the following equation:

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

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 is created to push 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.

$$f_r = \begin{Bmatrix} k_r(\rho_0 - \rho(p))\frac{\partial \rho}{\partial p} & p < \rho_0 \\ 0 & p \geq \rho_0 \end{Bmatrix}, \qquad (7)$$

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 $\frac{\partial \rho}{\partial p}$ 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.

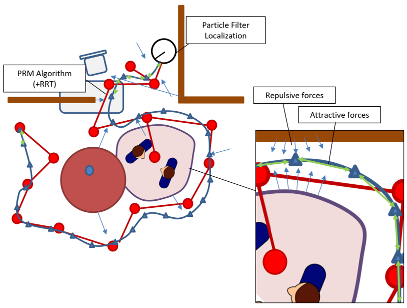


Fig. 6: The final social path is shown as the blue continuous line (△). Besides, the graph G_t provided by path planners (red colour), and the set of forces are drawn.

6 Experimental results

6.1 Validation of the adaptive spatial density function

One of features of the proposed method is the existence of a set of parameters to adjust. These parameters are:

- The Euclidean distance between two consecutive vertices in the polyline, d_l.
- The density threshold ϕ, directly related to the type of formation defined in [16].

The threshold value d_l allows to dynamically adjust the number of vertices of the polyline. A high value of d_l implies that the polyline follows correctly the shape of the forbidden area. On the contrary, a low value of this threshold creates a shape of the forbidden region very different to the reality. In order to choose a correct d_l value, several simulated experiments with different individuals in the scenario were tested. From these experiments, this threshold has been fixed to $d_l = 10cm$.

The threshold ϕ allows to correctly cluster individuals according to their formation during a conversation. The process to approximate this value has consisted on a set of simulated experiments with humans in different formations and distances between them, d_h. Table 1 summarizes the value of ϕ for these formations (*i.e.*, N-shape, Vis-a-vis, V-shape, L-shape, C-shape and Side-by-side). The algorithm proposed in this paper adapts the threshold ϕ according to the formation (red color in Table 1).

6.2 Navigation in real and Simulated scenarios

To validate the performance of the proposed algorithm, real and simulated scenarios were used. The algorithms have been developed in C++, as components

Table 1: Different two-person formations and results of the clustering algorithm in function of the threshold ϕ and the distance between humans d_l.

N-shape		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	N
	150 cm	N
	200 cm	N

Vis-a-vis		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N

V-shape		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	N
	150 cm	N
	200 cm	N

L-shape		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N

C-shape		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N

Side-by-side		
ϕ	Distance	Cluster (Y/N)
0,1	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	Y
0,3	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,5	50 cm	Y
	100 cm	Y
	150 cm	Y
	200 cm	N
0,7	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N
0,9	50 cm	Y
	100 cm	Y
	150 cm	N
	200 cm	N

of the framework RoboComp[1]. The tests in simulated scenarios have been performed on a PC with processor Intel Core i5 2.4GHz with 4Gb of DDR3 RAM and GNU-Linux Ubuntu 16.10. The robot Shelly of RoboLab has been the anthropometric social robot used in the real tests. In order to assess the effectiveness of the proposed navigation approach, the methodology has been evaluated accordingly to the following metrics in both scenarios: (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.

The real scenario is located at RoboLab facilities, a $65m^2$ apartment with different rooms, such as kitchen, bath or living-room. In this apartment, the same two persons talk in a vis-a-vis formation in different poses, being d_h=1.2m. The robot Shelly navigates in this apartment to several targets[2]. Fig. 7 shows the set-up of the experiment. The individuals are grouped as is shown in Fig. 7a. A frame of the video recorded during the test is shown in Fig. 7b. Fig. 8 describes the different stages of the adaptive spatial density function proposed in this

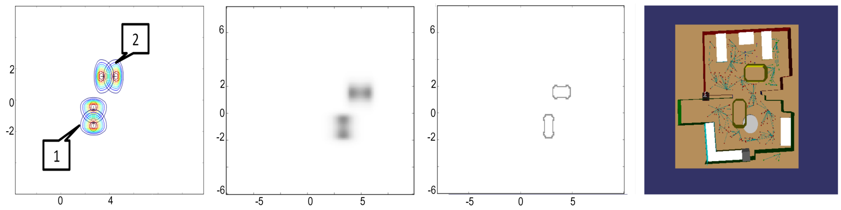
[1] https://github.com/robocomp

[2] A video of the real tests is accessible on https://youtu.be/zdTvhhZ7_uMs

(a) (b)

Fig. 7: a) A representation of the real apartment used in the tests. The robot Shelly must socially navigate between two groups of people in a vis-a-vis formation; b) A frame of the video recorded during the real tests.

paper. In Fig. 8a, the discomfort experienced by the individuals is modelled using different curve lines of each Gaussian. In Fig. 8b is 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 ϕ parameter ($phi = 0.7$). Polilynes associated to each cluster are illustrated in Figs. 8c-8d.



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

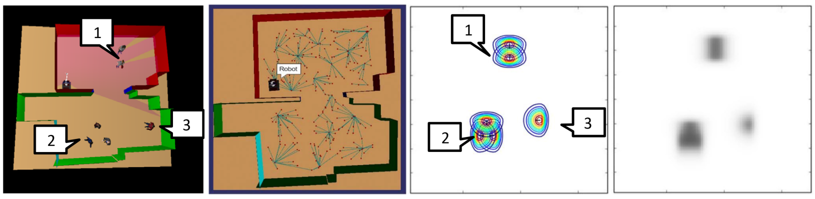
Fig. 8: a) four persons are located in the real apartment in a vis-a-vis formation; b) discomfort areas; c) polylines generated by the algorithm; and d) Polylines are used in the path-planning algorithm to modify the graph of free space.

The simulated scenario is a recreation of this same real apartment with 6 individuals in different formations (see Fig.9a), where the robot navigates between different targets. The original graph of free space is shown in the Fig. 9b. The isocontour maps of the personal space are shown in the Fig. 9c. In the Fig. 9d is drawn the clusters of persons after using the algorithm.

Finally, a comparative study of the proposed navigation methodology and the navigation system without social awareness [19] is included. For the real experiment, the robot had to perform two different paths, navigating in a socially acceptable way. Each path has been repeated 10 times. The mean values of the

Table 2: Navigation results for the real apartment

Social navigation architecture		Haut et al. [19]	
Parameter	Value	Parameter	Value
Travelled distance	8,03m	*Travelled distance*	6.0m
Total time	52s	*Total time*	50s
d_{min} *Person 1*	188cm	d_{min} *Person 1*	26cm
d_{min} *Person 2*	79cm	d_{min} *Person 2*	61cm
Travelled distance	8.64m	*Travelled distance*	6.49m
Total time	59s	*Total time*	52s
d_{min} *Person 1*	167cm	d_{min} *Person 1*	88cm
d_{min} *Person 2*	83cm	d_{min} *Person 2*	32cm



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

Fig. 9: a) 3D visualization of the simulated environment; b) Initial graph generated for the path planners; c) Potential regions of discomfort of the humans is modelled using Mixture of Gaussians; and d) cluster of persons, which define the forbidden regions for navigation.

time used by the robot during its navigation so as its traveled distance are shown on Table 2. The mean values of the minimum distances to each individuals, d_{min}, are also shown in 2. The same information for simulated environment is summarized in Fig. 3. The tests were achieved 10 times in the simulated environment using always the same targets and positioning of objects and people. 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 to 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 travelled.

7 Conclusions

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.

Table 3: Navigation results for the simulated apartment

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

In this article, an adaptive spatial density function for social navigation in human-populated environment is presented. This density function is used to efficiently cluster individuals into groups according to its pattern of arrangement. Besides, a social navigation architecture is presented to execute the navigation considering this social representation. The experiments demonstrate the performance of the approach, so as the improvement of the robot's social behaviour during its motion in human-populated environment. .

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