Modelling and testing proxemic behaviour for humanoid robots

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MODELLING AND TESTING PROXEMIC BEHAVIOUR FOR HUMANOID ROBOTS

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Humanoid robots that share the same space with humans need to be socially acceptable and effective as they interact with people. In this paper we focus our attention on the definition of a behaviour-based robotic architecture that (1) allows the robot to navigate safely in a cluttered and dynamically changing domestic environment and (2) encodes embodied non-verbal interactions: the robot respects the users personal space by choosing the appropriate distance and direction of approach. The model of the personal space is derived from human-robot interaction tests, and it is described in a convenient mathematical form. The robot's target location is dynamically inferred through the solution of a Bayesian filtering problem. The validation of the overall behavioural architecture shows that the robot is able to exhibit appropriate proxemic behaviour.

Keywords: Behaviour based robotics; Proxemics; User models; Social robotics; Context awareness; Particle Filter.

1. Introduction

It is widely acknowledged that the effectiveness of social robots depends on how well they can interact with the environment and how well they can establish forms of communication with people.¹ Embodied non-verbal interactions, such as approach, touch, and avoidance behaviours, are fundamental to regulating human-human social interactions, and they are likely to play a similar role in human-robot interaction.² The word proxemics indicates the study of mutual positioning of people as they interact and was first introduced by Hall.³ Extensive research has been conducted in the social science domain to model people's proxemic behaviour and to assess how their mutual positions influence the quality of interaction (see Hall³ and more recently Lambert⁴). General results show that relative behaviour and

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positioning is influenced by the task to be accomplished and the degree of familiarity that exists between the different actors.^{5,6,7} As a consequence of humanoid robots' physical embodiment, their positions and postures represent a non-verbal communication cue that influences the quality of interaction with people. Being too close might induce discomfort in the person, while being too far might not persuade the user to start interacting. In the majority of robotic navigation frameworks, emphasis is given to the precise definition of collision-free navigation trajectories to allow the robot to reach a given target point. Little attention has been given to the description of the target itself. But when the robot is supposed to address a human being, the definition of such a location is dependent on what the human expects from the robot in terms of distance and direction of approach. The selection of an appropriate location of approach determines how the user will perceive the overall robot's proxemic behaviour, thus it influences the quality of interaction. It is necessary to derive quantitative models of what users expect in terms of distance and direction of approach from an autonomous humanoid robot that can be easily embedded in already existing navigation frameworks with the purpose of dynamically defining the robot's target point. Therefore we present interdisciplinary work that addresses navigation issues related to the robot's proxemic behaviour presenting methodologies and results that lie in the psychological and technological domain. For doing so, we derive a new model of personal space (PS) upon which we identify a region of approach that lies within the boundaries of comfortable distances. The model is derived by means of a psychophysical experiment and is then embedded in a well-established navigation framework. The work tackles several aspects of the design of a robotics navigation architecture, from gathering users requirements to the definition of a navigation algorithm and the application of probabilistic techniques to obtain the target point location. In Section 2 we describe work related to the definition of robots proxemic behaviours. In Section 3 we define a general robotics navigation architecture which is able to move the robot safely about a cluttered and unknown environment. In Section 4 we derive a personal space (PS) model, whose parameters are obtained from a psychophysical experiment. Using the model of personal space we derive the expression of the region of approach which describes comfortable location for the robot to approach a person. In Section 5 we apply the particle filter technique considering as input the region of approach based on the model of personal space for dynamically deriving the robot's target location. We show that the particle filter can dynamically infer the robot's target location allowing it to approach the person comfortably from a convenient direction. In Section 6 we validate the navigation architecture and the PS model from a technical and user's acceptance perspective. The technical validation shows that the overall navigation architecture is able to move the robot safely in a cluttered environment, approaching the user in a comfortable way. The user's acceptance validation shows that the inclusion of the PS model and the region of approach within the navigation architecture improves user evaluations of the robot's proxemic behaviour.

2. Related Work

Even though Human Robot Interaction (HRI) is a very young research field, attempts to introduce social norms in establishing mutual distances between mobile robots and human beings have been attempted by several authors. Sisbot et al.⁸ introduce a human aware motion planning that, besides guaranteeing the generation of safe trajectories, allows the robot to reason about the accessibility, the visual field and the preferences of its human partner. Robot's trajectories are in this case generated at the level of global path planning. Takayama and Pantofaru⁹ present an experiment which explores the factors that influence proxemic behavior around robots. People could either approach the robot or were approached by it. They evaluated how personal experience and gender modify the shape of the personal space in the presence of robots. However, the results of the user study were not directly implemented in robotic navigation systems. Brooks and Arkin¹⁰ proposed a behavior-based control architecture for a humanoid robot that takes into account non-verbal communication cues, in particular human-robot proxemics. They introduced a proportional factor for mapping human-human interpersonal distances to human-robot interpersonal distances in the case of the humanoid robot QRIO. The proportional factor was not derived by means of a human-robot interaction test but by considering the technical characteristics of the robot QRIO. Nakauchi and Simmons¹¹ developed a control algorithm that allows a robot to stand in line using a model of personal space derived from observation of people standing in line. We argue that the physical embodiment of robots is most likely a proportional factor when it comes to introducing human-human interpersonal distances within robotic navigation algorithms. Dautenhahn et al.² conducted a user study to assess people's preferences of a robot's approaching direction. The study found that people have preferences for rightwards direction and perceive a frontal approach as uncomfortable. The study was performed by using a machine-looking robot which was comparable in size with a human being. Yamaoka et al.¹² presents a model for controlling the robot's position while it presents information about an object to a user. The model takes into account the user's position as well as the object position. Meisner et al.¹³ present work that addresses robotics control architecture for user-following task that causes no distress to humans. Pacchierotti and Christensen¹⁴ define the robot's proxemic behavior in an avoidance scenario based on human-human proxemic distances derived from the work of Hall³ and Lambert.⁴ Robot trajectories are also in this work generated at the level of global path planning. Walters et al.¹⁵ describe an empirical framework for determining the physical proxemic distance between a person and a robot, the data are determined as a result of several HRI trials. Mumm and Mutlu⁷ presented work that addresses the influence of robot's gazing behaviour on human-robot mutual distancing.

3. Navigation Framework

Navigation is a necessary capability for mobile robots to move around in their surroundings. This issue is a widely studied research topic and a large number of strategies and systems have been developed for a variety of environments. Most of these studies focus on reaching a target point while avoiding collisions on the way.¹⁶ We propose a behaviour-based navigation architecture which defines the robot's overall behaviour independently of the map, in which each individual behaviour solves a navigational subtask. The navigation algorithm follows the dynamical systems approach to mobile robot navigation that was first introduced by Schöner, Dose and Engels¹⁷ and Bicho¹⁸, and it is based on the theory of non-linear dynamical systems. A behaviour can be described by means of a behavioural variable that, in our work, is chosen to be the robot's heading direction, $\phi(t)$, and by the temporal evolution of it. The evolution is controlled by a non-linear dynamical equation that can be generally expressed as:

$$\omega = \frac{d\phi(t)}{dt} = F(\phi(t)), \quad (1)$$

where $F(t)$ defines how the value of the behavioural variable $\phi(t)$ changes over time.^{19,18} Multiple behaviours are aggregated by means of a weighted sum:

$$\frac{d\phi(t)}{dt} = \sum_{i=1}^m w_i f_i(\phi(t)) + d, \quad (2)$$

where m represents the number of behaviours that are needed for the robot to accomplish its task. The term $f_i(\phi(t))$ represents the force produced by the i^{th} behaviour and w_i represents the weight associated to the i^{th} behaviour. The term d represents a stochastic term that is added to guarantee escape from repellers generated by bifurcation in the vector field.²⁰ Attractor and repeller functions, $f_i(\phi(t))$, are modelled with opposite signs. We identify three basic behaviours whose coordination brings the robot from a generic location in the environment to a target location. The process of reaching a target point is represented by an attractor dynamic whose expression is :

$$f_1(t) = -\sin(\phi(t) - \psi_{tar}(t)), \quad (3)$$

where the term $(\phi(t) - \psi_{tar}(t))$ accounts for the angular location of the target with respect to the robot at time t . The attractor dynamic acts to decrease the difference between $\phi(t)$ and ψ_{tar} ; a graphical representation of those angles is visible in Fig. 1. The ability to obtain collision-free trajectories is encoded by a repulsive dynamic whose mathematical expression is given by:

$$f_2 = \underbrace{\exp\left(-\frac{(\phi(t) - \psi_{obs}(t))^2}{2\sigma_{obs}^2}\right)}_{\text{term A}} \underbrace{(\phi(t) - \psi_{obs}(t)) \exp\left(-\frac{d_{obs}(t)}{\beta_2}\right)}_{\text{term B}}. \quad (4)$$

It generates a force which decays exponentially with the detected distance between the robot and the obstacle through the term B and on the angular location of the obstacle with respect to the robot through the term A . The detected distance between the robot and the obstacle at time t is represented by the term $d_{obs}(t)$, while the direction of the obstacle with respect to the robot at time t is encoded in the term $(\phi(t) - \psi_{obs}(t))$. The coefficients β_2 and σ_{obs} determine the range at which the repulsion strength acts. In order to obtain collision-free trajectories, the weight w_2 associated to the repulsion force is greater than the weight w_1 associated to the attractor force represented in Eq. (3). The repulsion force acts to increase the terms $(\phi(t) - \psi_{obs}(t))$ and $d_{obs}(t)$. A graphical visualization of $\psi_{obs}(t)$ is visible in Fig. 1. When the robot is close to its target point, its trajectory should be adapted such that the robot is able to assume the desired final orientation. The alignment behaviour that acts on $\phi(t)$ to reduce the angular distance between the robot's actual orientation and the desired final orientation, ϕ_{final} , is modelled by an attractor dynamic:

$$f_3(t) = -\exp(-d_t(t)) \sin(\phi(t) - \phi_{final}), \quad (5)$$

The term $(\phi(t) - \phi_{final})$ represents the difference between the robot's orientation at time t and the requested final orientation. A graphical representation of ϕ_{final} is visible in Fig. 1. The alignment behaviour becomes particularly relevant when the robot has a humanoid shape, because the front and back are clearly recognizable. The attractor dynamic of the alignment behaviour is undesirable when the robot is far from the target point. This can be clearly seen in the situation reported in Fig. 1 in which the target attractor dynamic would steer the robot towards the left while the alignment dynamic would steer the robot towards the right. This consideration is modelled by the term $\exp(-d_t(t))$ of Eq. (5) that decreases the attractor dynamic of the behaviour exponentially with the distance from the target, $d_t(t)$. The aforementioned behaviours do not modify the robot's forward speed. The latter should be low when the robot is near obstacles or when the angular distance between the robot and the target is large. These considerations are taken into account in the following expression of the forward velocity:

$$v_{for} = \min \left(\exp \left(-\frac{1}{d_{obs}(t) + \varepsilon} \right), \exp(-|\phi(t) - \phi_{final}(t)|) \right) \cdot v_{max}, \quad (6)$$

where ε is a term added to avoid a division by zero and v_{max} is the maximum robot's forward speed. The forward velocity v_{for} decreases exponentially with the decrease of the distance to the obstacle through the term $\exp \left(-\frac{1}{d_{obs}(t) + \varepsilon} \right)$ or with the angular distance between the robot's actual heading angle and the desired target final orientation through the term $\exp(-|\phi(t) - \phi_{final}(t)|)$. A similar navigation architecture has been adopted in several studies.^{18,21,16,19,20} In all these works, emphasis has been given to the precise definition of the behaviours to allow the robot to generate collision-free trajectories in a cluttered environment. Here we

Fig. 1. Graphical representation of the robot, the target and an obstacle. The angles $\phi(t)$, ψ_{tar} , ϕ_{final} and ψ_{obs} are reported with respect to a global reference frame. The desired robot's final orientation is represented as target orientation.

focus on the definition of the target itself, because the selection of an appropriate location of approach determines how the user will perceive the overall robot's proxemic behaviour, thus it influences the quality of interaction. We do so by deriving quantitative models of what users expect in terms of distance and direction of approach from an autonomous humanoid robot and we include the model in the navigation architecture using it for dynamically defining the robot's target point.

4. User Study

Personal Space is the zone around people which is used for interaction with family and friends or for highly organized interaction such as waiting in line.^{14,3} Such a model, in human-human interaction has been widely studied, but few data are available in human-robot interaction (HRI) contexts. In order to gain insight into the shape of the user's personal space in a HRI context, a psychophysical experiment was carried out in a controlled laboratory set-up. The first aim of the trial was to determine the boundaries of the personal space in a communication scenario and the optimal distance for conveying information. Furthermore we want to obtain the analytical expression of the relationships between direction of approach and distance of approach such that these results can be inserted into mobile robot's navigation frameworks. The second aim was to determine if subjects had different preferences for approaching directions and if some directions are perceived to be more comfortable than others.

4.1. Method

The user study was carried out in laboratory set-up that simulates a living room. During the experiment the robot NAO (Aldebaran Robotics, France), see Fig. 2(b), approaches the subject for conveying information. The robot was placed on the starting point by an operator and was driven under direct remote control to approach the subjects following a straight line. Five starting points were defined with respect to a right-handed reference frame with the y-axis aligned to the subject's shoulders and the x-axis pointing straight ahead. The starting points, in polar coordinates, were defined as $\{(4m, -70^\circ), (4m, -35^\circ), (4m, 0^\circ), (4m, 35^\circ), (4m, 70^\circ)\}$. The overall study's set up can be seen in Fig. 2(a). The operator was seated in the control room next to the living room. Subjects were instructed that the robot could approach them from one of the five different directions. Their task was to stop the robot by pressing a button. The desired moment to stop the robot was task dependent. Three tasks were assigned to the subjects:

- Task A (Optimal): The robot should be stopped when it arrives at the best location for having a comfortable communication.
- Task B (Close): The robot should be stopped when it arrives at the closest location for having a comfortable communication.
- Task C (Far): The robot should be stopped as soon as it arrives at a location which is close enough for having a comfortable communication.

A graphical representation of the experiment set up is visible in Fig. 2(a). Subjects were instructed to keep their shoulders against the back of the chair in order to have consistent measurements. A trial consisted of the robot approaching the subject from one of the five directions and the subject stopping the robot at the convenient moment according to the assigned tasks. After every trial, the distance between the robot and the person was recorded via a ceiling-mounted camera. Subjects were also requested to evaluate the direction at which the robot approached them by answering a questionnaire. The latter consisted of a question with a 5-point Likert scale that ranged from Very Bad to Very Good. Each task (A,B,C) had to be performed three times by each subject for every direction. Therefore the user study used a 3 (task) x 5 (direction) design, with three replication trials in each factorial combination yielding a total of 45 trials per participant.

4.1.1. Subject Sample Sets

A total of 9 participants took part in the user study, 7 males and 2 females. The mean age of subjects was 24.4 years (range: 16- 51). All subjects were right-handed. The subjects had a technical background but were not familiar with robotics research. All subjects were naive with respect to the details of the experiment.

Fig. 2. Graphical representation of the experiment set-up. The participant was seated on a chair and was approached by the robot NAO (b) from five different directions. The different starting points and the straight trajectories are indicated in (a). The reference frame is also visible in the figure indicated by the coloured arrows.

4.1.2. Procedure

Before the experiment took place, each participant received a sheet with task instructions. In each trial, subjects were presented with the task they had to perform. After each trial, the participant had to indicate on a questionnaire how well they evaluated the robot's approaching direction. When the 45 trials were conducted, the experiment was over.

4.2. Results

The relationship that defines the distance as function of the direction of approach for task A (optimal distance), task B (closest distance), and task C (furthest distance), can be approximated via a second order polynomial. It turns out that for task A and B only the zeroth and second order coefficients are significant and for task C only the zeroth order term. The goodness of approximation for the three tasks has been verified with an ANOVA test with only the significant parameters. The results are summarized in Table 1 and a graphical representation is visible in Fig. 3. The user study also allowed to evaluate how subjects perceived the direction of approach. To clearly identify the difference between comfortable directions and uncomfortable directions, negative numbers were associated with negative items of the Likert scale and *vice versa*. These values are: Very Bad (-2), Bad (-1), Neutral (0), Good (1) and Very Good (2). The mean value of users' rating was computed per direction of approach per task and the results are displayed in Fig. 4. It is straightforward to notice that there is a substantial difference between the central directions of approach ($\pm 35^\circ, 0^\circ$) and the more oblique directions ($\pm 70^\circ$) and that more oblique directions are in general perceived as uncomfortable while the frontal

Table 1. Summary of the parameters of the approximating curves that relate distance and direction of approach for the three tasks of the user study. The parameters for evaluating the goodness of approximation are also reported.

Pol. ID	Pol. order	ANOVA	Pol. Coefficients		
			ζ_2	ζ_1	ζ_0
ρ_A	2	F= 5.31, p=0.006	-16.04	—	194.76
ρ_B	2	F=4.929, p=0.009	-11.82	—	133.60
ρ_C	0	—	—	—	269.19

Note: The general expression of the approximating polynomial is $\rho = \zeta_2\theta^2 + \zeta_1\theta + \zeta_0$. The results of the ANOVA test are not reported for ρ_C since it expresses a constant relation but the standard error associated to it is ± 3.23 ($N = 125$).

Fig. 3. Association between direction of approach and associated distance for the three tasks (A,B,C) in a conveying information scenario. The mean and the standard deviation associated to the 5 approaching directions of the user study are also reported.

directions are in general perceived as comfortable. If we look at more oblique directions, we might notice a difference between preferences associated to the right and to the left, which is not statistically significant, but in accordance with the results of the study reported in Dautenhan et al.². We derive a mathematical relationship between the direction of approach and the preference related to that direction associating at each point of the Likert scale positive numbers, between 0 (Very Bad) and 1 (Very Good). The relationship can be approximated via a second-order polynomial for each task. The goodness of approximation for the three tasks has been verified with an ANOVA test and the results are summarized in Table 2. We can see that the approximating curve models the difference of preference between leftwards and rightwards directions by associating a non-null term to the coefficient κ_1 of the polynomial ν_A which is associated to the optimal task. A graphical visualization of the approximating polynomial is visible in Fig. 5.

Fig. 4. Bar chart representation of the mean value of subjects' evaluation per approaching direction per task with associated 95% confidence interval. Negative values are representative of negative judgements whereas positive values represent positive judgements.

Table 2. Summary of the parameters of the approximating curves that relate directions of approach to the user's evaluation of them for the three tasks of the user study. The parameters for evaluating the goodness of approximation are also present.

Pol. ID	Pol. order	ANOVA	Pol. Coefficients		
			κ_2	κ_1	κ_0
ν_A	2	F=27.74, $p < 0.001$	-0.21	-0.051	0.79
ν_B	2	F=12.67, $p < 0.001$	-0.14	0	0.73
ν_C	2	F=32.49, $p < 0.001$	-0.21	0	0.79

Note: The general expression of the approximating polynomial is $\nu = \kappa_2\theta^2 + \kappa_1\theta + \kappa_0$.

4.3. Region of Approach

The data reported in Table 1 and 2 allow the definition of a region of approach centred at the optimal distance, Task A, that lies within the boundaries defined by the results for Task B (closest distance) and Task C (farthest distance). The

Fig. 5. Preference value as function of the direction of approach. The polynomial approximation, the mean value and the standard deviation of the users' preferences for each direction of approach are reported for each task.

proposed expression of the Region of Approach (RA) is given by:

$$RA = \{\mathbf{x} \in \mathbb{R}^2 : l(\mathbf{x}) \geq 0.1\} \quad (7)$$

where

$$\mathbf{x} = (\rho, \theta)$$

$$l(\mathbf{x}) = l(\rho, \theta) = \nu_A(\theta) \exp\left(-\frac{(\rho - \rho_A(\theta))^2}{\sigma_{\rho_A}^2}\right), \quad (8)$$

where ρ represents the distance and θ represents the angular distance from the user. Considering a right-handed reference frame centred on the users head with the y-axis aligned to the users shoulders and the x-axis pointing straight ahead, Eq.(7) allows definition of a region of space that associates at each point in the reference frame a likeability value, $l(\mathbf{x})$. This term is dependent on the distance and direction of approach and that expresses how comfortable that location is for the user in a scenario in which the user sees the robot approaching for conveying information. The value of acceptability is directly dependent on the direction of approach through the evaluation of the term $\nu_A(\theta)$, see Table 2, and on the approaching distance through the evaluation of the term $\rho_A(\theta)$, see Table 1. As we can see from Fig. 5, RA is not symmetrical due to the presence of the polynomial $\nu_A(\theta)$ in Eq.(7). As already introduced, this is a consequence of the non-symmetrical preferences configuration gathered during the user study (see Fig.4). The decision of modelling the preference on the distance through the use of a Gaussian function is a consequence of the observation that the data regarding the distance of approach are normally distributed in all directions. The standard deviation σ_{ρ_A} represents the variability associated to the recorded distances of task A (optimal) and it is equal to 34.13 cm. A graphical visualization of Eq. (7) is visible in Fig. 6.

Fig. 6. Contour graph of the Region of Approach (RA). Each point of the space expressed with respect to the user's reference frame is assigned a value, $l(\theta, \rho)$, derived from the evaluation of Eq. (7). Such a value is representative of the subjects' rating of that point in an approaching scenario.

5. Dynamic Target Selection

This section links the results of the user study with the dynamic definition of the target location for the navigation framework which was introduced in Section 3. Preliminary results of the work presented were first introduced in Torta et al. ²²

5.1. Target Representation and Navigation

The region of approach defined in Eq. (7) can be regarded as a measure of how the user evaluates the surrounding space from a proxemic HRI perspective. In particular, it encodes what the user expects in terms of distance and direction of approach in a scenario in which the robot approaches for conveying information. At first glance one might locate the target at a point that leads to the maximum of the users' evaluation. Unfortunately there are situations in which this simple approach produces undesirable and unintelligent robotic proxemic behaviours. This happens when reaching the target point makes the robot cross the user's visual field or when the target point defined by the maximum of the Region of Approach (RA) is unreachable due to the presence of obstructions. Such situations underlie the need for adapting the *a-priori* model to the particular circumstances that the robot is facing. It is therefore necessary to insert the Region of Approach (RA) defined in Eq. (7) into a dynamical framework that locates the target not only according to the RA but also to the perception that the robot has of the environment. The problem of estimating the direction and the distance of approach in a scenario in which the robot is supposed to convey information to a human can be solved through state estimation algorithms. We notice that the region of approach introduced in Eq. (7) is suitable for Bayesian inference with the objective of deriving the best robot position, proximate to the user, given the knowledge of user's preferences and the robot's perception of the environment. State estimation using Bayesian filters such as Kalman Filter (KF), Extended Kalman Filter (EKF), Unscented Kalman

Filter (UKF) and Particle Filter (PF) has been widely used in robotics, primarily for SLAM algorithms or localization algorithms (see Thrun et al.²³, Gustafsson²⁴ and Arulampalam et al.²⁵ for an overview). The state to be estimated is usually the robot's pose in the environment or both the robot and the human pose with respect to it (see Pineau²⁶, Thrun et al.²³, Bellotto and Hu²⁷ and Gonzalez et al.²⁸). While KF, EKF and UKF propagate Gaussian distributions representative of the posterior, PF propagates multimodal distributions.²⁴ The latter property of the PF is appealing when formulating the problem of inferring the best location of the robot in the user's proximity space, because this can be represented by a multimodal distribution as already described in Section 4.3 and represented in Fig. 6. Therefore we formulate the problem of estimating the direction and distance of approach in a scenario in which the robot is supposed to convey information to a human as a Bayesian filtering problem, and we solve it by means of a particle filter.

5.2. Problem formulation

The general Bayesian filtering problem consists of computing the posterior distribution $p(\mathbf{x}_t | \mathbf{y}_{1:t})$, at time t , of the hidden state $\mathbf{x}_t$ of a dynamical system given observations $\mathbf{y}_t$ and control inputs $\mathbf{u}_t$.²³ The posterior distribution is also called the belief of the state $Bel(\mathbf{x}_t)$ and its expression is given by:

$$Bel(\mathbf{x}_t) = p(\mathbf{x}_{0:t} | \mathbf{y}_{1:t}) = \frac{1}{\eta} p(\mathbf{y}_t | \mathbf{x}_t) \int p(\mathbf{x}_t | \mathbf{x}_{t-1}, \mathbf{u}_{t-1}) Bel(\mathbf{x}_{t-1}) d\mathbf{x}_{t-1}, \quad (9)$$

where η is a normalizing factor. With respect to the problem that we are addressing, the dynamical system is composed by the user, the robot and the environment in which the interaction takes place. We suppose that the system state is described with respect to a right handed reference frame centred on the user's head with the x-axis pointing straight ahead and the y-axis leftwards. The system state $\mathbf{x}_t$, represents the most "desirable" robot's target location with respect to the user in terms of approaching distance and direction. Its mathematical expression is given by:

$$\mathbf{x}_t = \begin{pmatrix} \rho_t \\ \theta_t \\ \phi'_{final} \end{pmatrix}, \quad (10)$$

where ρ_t and θ_t represent the distance and the angular location of the most desirable robot's target point and ϕ'_{final} its orientation. Since the robot final pose should allow the robot to face the user and since the target orientation is expressed with respect to the user reference frame, the term ϕ'_{final} is a function of the target angular location and can be expressed as:

$$\phi'_{final} = \theta_t + \pi \quad (11)$$

Fig. 7. Graphical representation of the robot and the user. ϕ_{user} , θ_u , and ρ_u are represented with respect to the robot's reference frame. The terms θ_t, ρ_t and the target orientation are represented with respect to the user's reference frame.

We also suppose that the robot is able to determine the user's orientation ϕ_{user} with respect to its reference frame. The knowledge of the user orientation allows to compute the terms $\phi - \psi_{tar}$ and $\phi - \phi_{final}$ of the attractor dynamics defined in Eq. (3) and Eq. (5) as:

$$\phi - \psi_{tar} = \theta_t + \phi_{user} \quad (12)$$

$$\phi - \phi_{final} = \theta_t + \phi_{user} + \pi \quad (13)$$

A graphical visualization of the angles is visible in Fig.7. Referring to Eq. (9), the term $\mathbf{y}_t$ represents the measurements available at time t . Here we consider as measurement the user's pose with respect to the robot. Therefore the expression of $\mathbf{y}_t$ is:

$$\mathbf{y}_t = \begin{pmatrix} \rho_u \\ \theta_u \\ \phi_{user} \end{pmatrix}, \quad (14)$$

where ρ_u and θ_u represent the coordinates of the center of the user reference frame with respect to the robot reference frame expressed in polar coordinates and ϕ_{user} represents the user's orientation with respect to the robot's orientation (see Fig.7 for a graphical representation of the measured variables). The term $\mathbf{u}_t$ represents the input coming from the user's state. In principle, the user's state can be representative of a physical condition like sitting down, standing up, lying down or moving or, it can be representative of an emotional condition like loneliness, happiness, fear etc. . Here we consider a constant user state, the user remains seated on his chair.

5.3. Particle Filter

We solve the Bayesian filtering problem reported in Eq.(9) by means of a particle filter. This is a numerical method that approximates the posterior distribution of a dynamical system at time t , $Bel(\mathbf{x}_t)$ introduced in Eq.(9), with a set of particles and their weights, $\{\mathbf{x}_{0:t}^i, w_t^i\}$. The term $\mathbf{x}_{0:t} = \{\mathbf{x}_j, j = 0, \dots, t\}$ is the set of all states up to time t and the weights associated to each particle, w_t^i , are normalized such that $\sum_i w_t^i = 1$.²⁵ The posterior density at time t , given the observations up to time t , $\mathbf{y}_{1:t}$, can be approximated as:

$$Bel(\mathbf{x}_t) = p(\mathbf{x}_{0:t}|\mathbf{y}_{1:t}) \approx \sum_{i=1}^N w_t^i \sigma(\mathbf{x}_{0:t} - \mathbf{x}_{0:t}^i), \quad (15)$$

where σ denotes the Dirac impulse. Using the principle of *importance sampling*^{29,30,25} when assigning the weights w_k^i , it is possible to obtain a recursive approximation of the posterior as:

$$Bel(\mathbf{x}_t) = p(\mathbf{x}_{0:t}|\mathbf{y}_{1:t}) \approx \sum_{i=1}^N w_t^i \sigma(\mathbf{x}_t - \mathbf{x}_t^i). \quad (16)$$

The weight w_t^i , which is proportional to the perception term $p(\mathbf{y}_t|\mathbf{x}_t)$ of Eq.(9), expresses the likelihood that a particle represents a "desirable" approaching distance and direction according to the robot's perception at time t and to the user's expectations regarding distances and directions of approach. Its expression is derived as:

$$w^i = \frac{1}{\rho_{tr}} l(\mathbf{x}_t^i) = \frac{1}{\rho_{tr}} l(\rho_t^i \cos(\theta_t^i), \rho_t^i \sin(\theta_t^i)), \quad (17)$$

where ρ_{tr} represents the distance between the robot and the particle $\mathbf{x}_t^i$ and $l(\mathbf{x}_t^i)$ represents Eq. (8) evaluated at the particle location. It is important to notice that the weight w_t^i is influenced by the target location at time $(t-1)$ through the target attractor dynamic (see Eq. (3)) that acts as to decrease the distance between the robot and the target. Indeed the attractor dynamic tends to decrease the term ρ_{tr} for those particles which are located close by the target point increasing the weight associated to them. The weight is also influenced by the the presence of obstacles through the repulsive dynamic (see Eq.(4)). That dynamic steers the robot away from obstructed locations thus increasing the term ρ_{tr} and decreasing the weight. The measurements of what the user expects from the robot in terms of approaching distance and direction for a the given context (the user is seated on the chair) is encoded in the term $l(\mathbf{x}_t^i)$. This is derived beforehand through the user study that leads to the formulation of the region of approach (see Eq. (7) and Eq. (8)). The product of the terms in Eq. (17) indicates that a particle is positioned in a desirable location if it simultaneously represents a feasible point (thus a low value of ρ_{tr}) and a desirable point in terms of user's preferences (thus a high value of $l(\mathbf{x}_t^i)$). Indeed the conceptual novelty of the particle filter presented here is the

fusion of contextual cues derived from the robot's perception with knowledge derived from psychological experiments. Eq. (17) accounts for contextual cue the distance between the robot and the particle, but the weight expression can be easily extended for taking into account multiple contextual cues; i.e. the user's head pose. The particle filter algorithm is applied to the recursive Bayesian filtering problem and it is reported in pseudo-code in Table 3.²⁵ During implementation, we represented

Table 3. Particle filter algorithm in pseudo-code.

Initialization:
Generate N particles $\{x_0^i, w_0^i\}$ $i = 1, \dots, N$ according to Eq.(18)
Iteration:
for $i=1, 2, \dots, N$
Draw $x_t^i \sim q(x_t x_{t-1}^i, z_t)$
Assign the particle a weight, w_k^i , according to the evaluation of Eq.(17)
end for
Calculate total weight: $tw = \sum_i^N w_k^i$
for $i=1, 2, \dots, N$
Normalize: $w_k^i = tw^{-1}w_k^i$
end for
Calculate N_{eff} using Eq.(19)
If $N_{eff} < N_t$
for $i = N + 1, \dots, \frac{3}{2}(N)$
Draw x_t^i according to Eq.(18)
Assign the particle a weight, w_k^i , according to the evaluation of Eq.(17)
end for
Resampling:
Select N particles with replacement, $\{x^i, w^i\}$ for $i = 1, \frac{3}{2}N$ where the probability of taking sample i is w^i
end if

the state space with 300 particles thus, referring to Table 3, $N=300$. The initial particles distribution is generated according to:

$$\begin{cases} \rho_i = \rho_{min} + i\Delta_\rho + \epsilon_\rho, & \text{with } \Delta_\rho = \frac{\rho_{max} - \rho_{min}}{N} \\ \theta_i = \frac{-\pi}{2} + i\Delta_\theta + \epsilon_\theta, & \text{with } \Delta_\theta = \frac{\pi}{N} \end{cases} \quad (18)$$

where ϵ_ρ and ϵ_θ are noise terms drawn from a normal distribution and i is the particles' index and varies between 1 and N . The terms ρ_{max} and ρ_{min} define the spatial limits for representing RA. In our implementation the values of those terms are chosen to be equal to σ_{ρ_A} , which has been introduced in Eq.(7). In order to avoid the phenomenon of particles impoverishment, where after a few iteration only few particles have no negligible weight ²⁵ a resampling step is applied at each iteration of the particle filter if the degeneracy measure approximated as:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (w_k^i)^2} \quad (19)$$

Fig. 8. A screen-shot from the validation trial. The robot NAO starts from 35° with respect to the user. The starting point is identified by the reference frame labelled as "Start". The subject is seated on the chair. The particles are represented by the red arrows while the inferred target location is identified by the reference frame labelled as "target". The video of the validation trials is available at <http://ksera.ieis.tue.nl/medianode/89>.

is less than N_t . We tackle the problem of particles impoverishment by augmenting the vector of particles with $\frac{N}{2}$ new particles randomly drawn from the distribution reported in Eq.(18) at every iteration when the resampling step is executed. During the resampling step, N particles are selected, therefore after an iteration of the particle filter the dimension of the particles vector is always N .

6. Validation

The effectiveness of the navigation algorithm enhanced with the model of the user's personal space and the dynamic target selection was tested in a user trial. The validation set-up was the same as the experiment set-up. The robot approached a seated person for conveying information. The approaching direction could be one of the five directions defined in the user study: $\{-70^\circ, -35^\circ, 0^\circ, 35^\circ, 70^\circ\}$. The robot autonomously determines its target point and therefore its trajectory. The position of the user with respect to the robot reference frame is given externally by a ceiling-mounted camera. A screen-shot from the ceiling-mounted camera during the validation trial can be seen in Fig. 8. The recorded trajectories of the robot and the target location, expressed with respect to the user's reference frame, show that the target location dynamically changes over time due to the dynamic inference process described in Section 5. The recorded trajectories are visible in Fig. 9. The robustness of the algorithm was also tested. The robot was requested to approach a person starting from a frontal position. An obstacle was placed on the initial target location. As soon as the robot modifies its trajectory due to the presence of the detected obstacle, the target location changes allowing the robot to cope with the presence of the obstacle. The recorded trajectories are visible in Fig. 10. The algorithm was subject to a user validation with the purpose of proving that the

Fig. 9. Technical validation of the navigation architecture enhanced with the PS model. The robot can start from five different directions and its trajectory is influenced by the dynamic evolution of the target location. The point where the robot reaches the target is shown with a circle. The region of approach and the PS for an optimal approach is also visible. The video of the trials that generated the robot's trajectories are available at <http://ksera.ieis.tue.nl/medianode/89> .

Fig. 10. Robot's trajectories in cluttered environments. The robot approached a person frontally. A rounded obstacle was placed at the initial target location. When the robot starts to be driven away by the repulsive dynamic, the target location dynamically changes until a feasible location is found. The video of the trials are available at <http://ksera.ieis.tue.nl/medianode/89>. In the video are also shown trajectories in a complex cluttered environment.

inclusion of the personal space model and the dynamic target selection allows the robot to select a target position that is considered comfortable by the user. The validation had the same set-up as the user test. The robot autonomously approached the user for conveying information. Subjects (N=6) were given the same instructions used during the previous user study (see Section 4). After each trial subjects were

Fig. 11. Results of the user validation. The blue bars represent the user's evaluation of the direction of approach in autonomous condition with associated 95% confidence interval. The light blue bars represent the user's evaluation of the different approaching directions, with 95% confidence interval, when the robot moves towards him on a straight line. The comparison between the user's ratings show that when the robot autonomously approaches the user from one of the most oblique directions, it does not proceed on a straight line but changes its trajectory to end up in points considered comfortable by the user.

requested to evaluate the direction of approach. The results show that there is an effective improvement of the user's perception of the robot's trajectory, as can be seen from Fig. 11. When the robot starts from one of the most oblique directions, it does not proceed on a straight line but changes its trajectory to end up in points considered comfortable by the user as it is shown in Fig. 9.

7. Discussion and Conclusion

We presented a behaviour-based navigation architecture that allows the humanoid robot NAO to exhibit appropriate proxemic behaviour when interacting with a person aiming at the completeness of the approach with respect to several aspects of the development of a mobile robot navigation architecture with the purpose of addressing a human being. We started by underling the need for the inclusion of appropriate models related to users' expectations for mobile robots' proxemic behaviour. As a consequence, we conducted a psychophysical experiment for deriving the model of the personal space in an approaching scenario in the case of the humanoid robot NAO. The region of approach was then constructed so as to respect the boundaries of the personal space and to include information regarding user preferences of the approaching direction. The results of the user study reported in Section 4 show that the distance range of the personal space in the case of the robot NAO (indicatively 137 cm - 265 cm, see Table 1) is larger than the distance range of the personal space in human-human interaction context (indicatively 45 cm - 120 cm, see Walters et al.³¹) therefore we argue that the application of human-human interpersonal distances in human-robot interaction should be verified before hand

because the distance range might be significantly different contrary to what is reported in Walters et al. .¹⁵ The results of the user study reported in Fig. 4 seem to suggest that there is a difference between rightwards and leftwards directions that might be due to the homogeneity of the subjects sample set, indeed all participants were right-handed. This is in accordance with the results presented in the study by Dautenhahn et al. .² Therefore future work might explore how the preferences distribution changes in the case of a homogeneous sample set of left-handed subjects and then compare the results for the two groups. We also argue that appropriate models should fit the shape and size of the particular robot being used therefore the parameters of the personal space model derived in Section 4 are valid for the robot NAO, but their validity for other robots needs to be further investigated. Future developments may derive a standard parametric model of the personal space in a HRI scenario considering, as parameters, the robot's height, its appearance and the purpose of the interaction. From our perspective the model of the region of approach represents a novelty both in terms of its derivation as well as for the analytical representation of the experiment's results. Nevertheless we argue that the shape of the personal space as well as the shape of the approaching region might vary depending on the robot's body posture as well as the user state. For the user's state we indicate several possible user conditions both physical (the user can move or be static) as well as emotional. Future work might address issues related to the dynamic definition of the personal space based on the feedback about the user's state. The model of the region of approach is introduced in the reactive navigation algorithm based on the dynamical system approach to mobile robot navigation introduced by Schoener et al.¹⁷ and Bicho.¹⁸ An attempt to use this framework for mobile robot navigation in the presence of human beings has been made by Althaus et al.¹⁶, but the way the robot approached people already engaged in a conversation did not rely on the definition of models of people's personal space. Even though the model has been included in a specific navigation framework, its structure is independent of the precise details of the navigation architecture. On the contrary of Sisbot et al.⁸ and Pacchierotti and Christensen¹⁴, the personal space model is not included in the global path planner thus the definition of the robot's target point is derived real time by means of the particle filter which dynamically infers the optimal distance and direction of approach based on contextual cues and on the approaching model derived from the psychophysical experiment. Therefore this approach is particularly feasible for cluttered and dynamic environments, as can be seen from the last part of the video available at <http://ksera.ieis.tue.nl/medianode/89>. The resulting combination of psychological cues with contextual cues in the design of robotic proxemic behaviour constitutes a conceptual novelty. Future work will consider multiple user states and will include other contextual cues such as the user's head pose or physiological signals such as galvanic skin conductivity. Future work will also extend the system state model to consider the robot's body posture beside the robot's target point. The performance of the overall navigation architecture has been tested from a technical point of view, showing the algorithm is feasible and

robust and works in real time. Also from a user perspective it shows that the inclusion of the approaching model increases the user rating of the robot's direction of approach. In conclusion we presented interdisciplinary work that derives the robot NAO's proxemic behavior based on a new personal space model testing it with user trials.

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22 Elena Torta et al.

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