

# A model of the user's proximity for bayesian inference

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# A Model of the User's Proximity for Bayesian Inference

Elena Torta Eindhoven University of Technology IE & IS - Human Technology Interaction P.O. Box 513, IPO 0.21 Eindhoven, The Netherlands e.torta@tue.nl Raymond H. Cuijpers Eindhoven University of Technology IE & IS - Human Technology Interaction P.O. Box 513, IPO 0.18 Eindhoven, The Netherlands r.h.cuijpers@tue.nl

James F. Juola Eindhoven University of Technology IE & IS - Human Technology Interaction P.O. Box 513, IPO 1.25 Eindhoven, The Netherlands j.juola@tue.nl

# ABSTRACT

Embodied nonverbal cues are fundamental for regulating human-human social interactions. The physical embodiment of robots makes it likely that they will have to exhibit appropriate nonverbal interactive behaviors. In this paper we propose a model of the user's proximity based on a superposition of quasi-Gaussian probability distributions which allows to express findings from HRI trials regarding distances and direction of approach in a human-robot interaction scenario. The way the model is formulated is suitable for well-established Bayesian filtering techniques, and thus the inference of the preferred distance and direction of approach in a human robot interaction scenario can be regarded as a state estimation problem. Results derived from simulations show the effectiveness of the inference process.

# **Categories and Subject Descriptors**

I.2.9 [Artificial Intelligence]: Robotics

# **General Terms**

Algorithms, Human Factors, Design

# Keywords

Cognitive Robotics, User Preferences, Particle Filter

# 1. INTRODUCTION

Navigation issues have been widely studied, and a large number of strategies and systems have been developed for all kinds of environments. Most of these studies focus on reaching a certain goal point in a given environment while avoiding collisions on the way. But when the robot is supposed to live in a domestic environment, sharing the same space with a human being, its navigation trajectories represent nonverbal communication cues that influence the quality of interaction. Therefore we propose a model that aims to describe what the user expects from the robot in terms of approaching distance and direction and a framework that allows combining the model with the robot's perception of the environment trough the formulation of a state estimation problem. The inferred state represents the optimal end point of the robot's navigation trajectory.

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## 2. MODEL FORMULATION

The model is formulated with respect to a reference frame centered on the user's head with the y-axis defined as straight ahead and the x-axis rightwards. The region of approach is defined as a function of the approaching distance  $\rho_0$  and the approaching angle  $\theta_0$  with related tolerances,  $\sigma_{\rho_0}$  and  $\sigma_{\theta_0}$ . The model is expressed by:

$$\Phi_0(\rho,\theta) \sim \exp\left(\frac{(\rho-\rho_0)^2}{\sigma_{\rho_0}^2}\right) \exp\left(\frac{(\theta-\theta_0)^2}{\sigma_{\theta_0}^2}\right).$$
(1)

It is possible to further develop Eq.(1) for representing multiple preferences. Given a set of preferred configurations  $\{\{\rho_0, \sigma_{\rho_0}, \theta_0, \sigma_{\theta_0}\}, ..., \{\rho_k, \sigma_{\rho_k}, \theta_k, \sigma_{\theta_k}\}\}$  multiple preferences are modeled introducing Eq.(1) in a weighted sum:

$$F(\rho,\theta) = \sum_{k=0}^{n} \lambda_k \Phi_k(\rho,\theta), \qquad (2)$$

where the index k represents the particular configuration to be modeled and  $\lambda_k$  is a measurement of the degree of 'desirability' associated to configuration k. The parameters of expression (2) can be derived from already available results of HRI trials. In particular we base their values on the study reported in Dautenhahn et al. [1], which claims that a seated person prefers to be approached from the right side at an angle of 45 (deg sign) or from the left side at -45 (deg sign) with respect to a frontal approach of 0 (deg). The value of the approaching distance is derived from Walters et al. [2]. A graphical visualization of Eq. (2) is reported in Figure 1.

## **3. STATE INFERENCE**

At a first glance, one might say that a location is desirable when it leads to high value of the preferences model introduced in Eq.(2). Unfortunately this may not be true when locations in the user's proximity are unreachable due to the presence of obstacles. Or, in general, when reaching locations with an high value of Eq.(2) causes the robot to produce trajectories that are judged unintelligent by the user. Therefore we introduce a Bayesian filtering algorithm for adapting the preferences model to the particular circumstances the robot has to face. Since the best location of the robot in the user's proximity can be represented by a multimodal distribution, as described in Eq.(2), we solve the Bayesian filtering problem by means of a particle filter. The problem, at time t, consists of computing the posterior distribution  $(x_t|y_{1:t})$  of the hidden state  $x_t$  of a dynamical

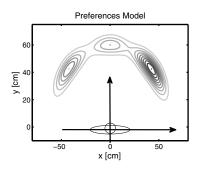


Figure 1: Graphical representation of user's approaching preferences. The right side approach is preferred over the left side approach. A side approach is more desirable than a frontal approach.

system given observations  $y_t$  and control inputs  $u_t$ . The expression of the posterior distribution is given by:

$$Bel(x_t) = \frac{1}{\eta} p(y_t | x_t) \int p(x_t | x_{t-1} u_{t-1}) Bel(x_{t-1}) dx_t.$$
 (3)

The system state  $x_t$  is the most 'desirable' robot final location, with respect to the user, in terms of approaching distance and angle. The term  $y_t$  represents the measurements available at time t and it accounts for the perceptual cues that the robot has about the environment around the user. The term  $u_t$  accounts for the user's movements in the space. The innovation term,  $p(y_t|x_t)$ , expresses the likelihood that a particle represents a 'desirable' approaching distance and direction according to the prior knowledge on user preferences and the robot's perception. The weight  $w^i$  of the  $i^{th}$ particle at time t is generated as:

$$w^i = \frac{1}{d(x_t^r x_t^i)} F(x_t^i). \tag{4}$$

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. Expression (4) counts as contextual cue the particle's proximity to the robot but the weight expression could take into account multiple contextual cues; e.g. the user's head pose. The multiplication of the terms in Eq.(4) indicates that a particle is positioned in a desirable location if it simultaneously represents a feasible point (thus an high value of  $\frac{1}{d(x_1^T x_1^T)}$  and a desirable point in terms of preferences (thus an high value of  $F(x_t^i)$ ). An example of the robot's trajectory during a simulated human-robot interaction scenario can be seen in Figure 2. The evolution of the probability distribution related to the same trial is visible in Figure 3. It shows that the algorithm has preferred to approach the user frontally respect to the right side. This happened because going to the user's right side would have obliged the robot to cross the user's visual field producing an unintelligent trajectory.

# 4. DISCUSSION AND CONCLUSION

We proposed a general model, independent from the precise details of the adopted navigation framework, for expressing findings regarding distances and direction of approach in a human-robot interaction scenario. We also introduced a statistical framework for adapting the model to

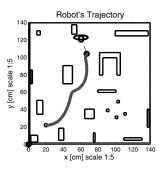


Figure 2: Robot's trajectory in a simulated humanrobot interaction scenario. The robot chooses the appropriate approaching distance and direction according to the time evolution of the probability distribution introduced in Eq. (2).

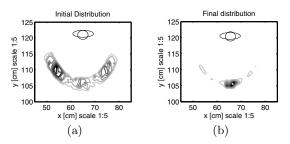


Figure 3: Temporal evolution of the probability distribution from the initial (a) to the final configuration (b). The robot has chosen a frontal approach rather than a right side approach not to cross the user's visual field.

the robot's perception of the environment. The validation of the algorithm by means of simulated trials leaves open the problematic related to the influence of uncertainties related to the pose estimation of the user and the robot on the inference process. Nevertheless, we expect those uncertainties not to cause severe limitations on the inference process due to the probabilistic nature of the model. Future work will address this issue.

## 5. ACKNOWLEDGMENTS

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