# A Bayesian model for approaching a human

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## ABSTRACT
With the growing need for elder care, research is focusing on robotic assistance at home. Thus, robots must navigate in cluttered, domestic, indoor environments with the purpose of interacting with a person. Here we present a behaviour based navigation model enhanced with a low level decision making process that allows the robot to approach a human in such an environment. The model has been tested on simulation and the first results show the effectiveness of the Bayesian decision making process.

## Keywords
Behaviour based navigation, Bayesian filtering, decision making.

## INTRODUCTION
With the growing need for elder care, research is focusing on robotic assistance at home. The goal is to develop socially interactive robots that "live" in people's homes and coexists with humans in their daily life (Althaus, Ishiguro, Kanda, Miyashita, & Christensen, 2004). Thus the movements of the mobile platform are a fundamental issue to be addressed. Furthermore navigation needs to be robust in order to cope with dynamically changing environments and with information coming from different sources.

## NAVIGATION MODEL
The navigation model is derived from the work by Althaus et al. (2004) and Soares, Bicho, Machado and Erlhagen (2007) and its formal background is based on the theory of nonlinear dynamical systems (Schöner, Dose, & Engels, 1995). A behavior emerges from the time evolution of a behavioral variable that is chosen to be the robot heading direction. Multiple behaviors are aggragated by means of a weighted sum and their coordination is realized by shaping the value of the weights.

We have defined four elementary behaviors whose descriptions are:

*Avoid obstacles*: generates a repulsive force that is dependent on the detected distance between the robot and the obstacle and on the angular location of the obstacle respect to the robot.

*Avoid personal space*: generates a circular shaped repulsive force around the human. The repulsion strenght is locally attenuated by the weighting function to permit the robot to approach the human. This behavior is in competition with the behavior to approach the human.

*Approach a human*: generates an attractive force that steeres the robot to be at a specified target location with respect to the human.

*Allign to the human*: generates an attractive force that steeres the robot heading direction to allow the robot to face the human.

The defined behaviors have been tested in a Matlab simulation environment and the results showed that the robot is able to reach the human with the proper alignment while avoiding obstacles and respecting the human's personal space. An example of the robot trajectory can be seen in Figure 1. The robot turns to approach the human in a straight line, but when the sensors detect an obstacle (black rectangle) the robot circumnavigates the obstacle through dynamic updating of its heading direction. After that, the robot turns to face the human.

## PERCEPTION MODEL
The robot target location is determined by the human's pose in the home environment. This information is, in our case, provided externally by the smart home environment.

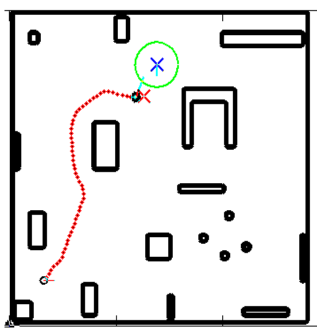

**Figure 1: Diagram showing the trajectory (dots) of the robot (small circle) approaching the human (cross). The personal space (big circle) and selected target position (cross external to the small circle) are also indicated.**

The information on the human's location may still coincide with an obstacle. So, to make the system robust, we enhanced the navigation model with a low level decision making process. In other words, we gave the robot the freedom to choose where to position itself according to its own perception of the environment. The problem is formulated as a Bayesian filtering problem and it is solved numerically by means of a particle filter. The problem consists of estimating the state of a dynamical system from noisy sensor measurements. In our case the dynamical system is composed of the human, the robot and the smart home environment. The state to be estimated is the optimal target position [ $x_t$ , $y_t$ ] of the robot with respect to the human .

The posterior probability of the system state is first initialized according to the *a priori* knowledge about the direction and the distance from which the human likes to be addressed (Dautenhahn et al., 2006). Figure 2

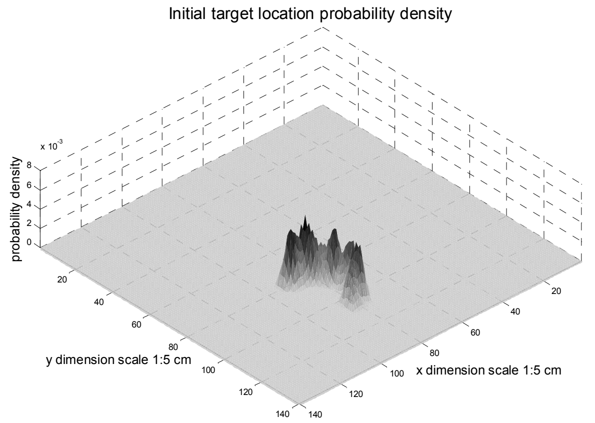


**Figure 2: Initial probability density of robot's destination for a human located at [90 100]. The initial target location is determined by the maximum probability.**

shows how the initial belief is distributed around the human that is located at [90 100]. The target location is chosen to be the point in the space with the highest probability (distribution peak).

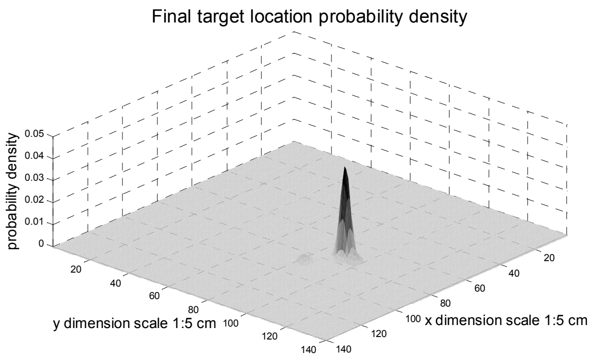


**Figure 3: Final probability density of the robot's destination for a human located at [90 100]. The robot has sensed the environment and updated the probability accordingly. The narrowness of the peak indicates the certainty of the robot about its destination.**

While the robot is approaching the human, the posterior probability is updated according to the robot's sensor measurements and a new position for the target location may be selected.

Figure 3 shows the final probability distribution after the robot has sensed the environment around the human. The comparison between Figure 2 and Figure 3 shows how the belief evolves from the initial broad distribution to the narrow final distribution. The distribution width indicates the robot's uncertainty about which destination is best to use. This evolution is due to the fact that the robot has sensed the environment around the human and the environmental context has constrained the best location to approach the human to a small region (location of the space with the probability peak in Figure 3) .

## CONCLUSION

We built a Bayesian model for approaching a human by modelling the human as an attracting target with a repelling personal space. We dynamically updated the robot's approach direction and location using its own perception model. The simulation results show that the perception model increases the system's robustness against erroneous information and constitutes a framework for low level decision making in robot navigation.

## ACKNOWLEDGMENTS

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