

Approaching a Person in a Socially Acceptable Manner Using a Fast Marching planner

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Abstract. In real world scenarios for mobile robots, socially acceptable navigation is a key component to interact naturally with other persons. On the one hand this enables a robot to behave more human-like, and on the other hand it increases the acceptance of the user towards the robot as an interaction partner. As part of this research field, we present in this paper a strategy of approaching a person in a socially acceptable manner. Therefore, we use the theory of "personal space" and present a method of modeling this space to enable a mobile robot to approach a person from the front. We use a standard Dynamic Window Approach to control the robot motion and, since the personal space model could not be used directly, a Fast Marching planner is used to plan an optimal path to approach the person. Additionally, we give a proof of concept with first preliminary experiments.

Keywords: Social acceptable navigation, approaching strategy, fast marching method, dynamic window approach

1 Introduction

In recent years, mobile robotics are developing towards fields of applications with direct interaction with persons. There are several prototypical systems that aim to help elderly people to improve cognitive abilities [1], to assist care givers in hospitals [2, 3], be an intelligent video-conferencing system [4], guide people in supermarkets and home improvement stores [6, 5] or simply improve the well-being by providing an easy-to-use communication platform. All these scenarios have to consider persons, interacting with the robot system. Psychologists and gerontologists showed in the 90s that technical devices are treated and observed as "social beings", for example cars, television and computers [7]. A robot system is recognized as a social being and has to behave like one. One important part of the robots behavior is the socially acceptable navigation. Navigation commonly includes tasks like mapping, motion control, obstacle avoidance, localization and path planning. Social acceptable navigation focuses on these tasks by keeping in mind that humans are within the operation area of the robot, and that an extra treatment of these humans is needed. The European Ambient Assisted

Living (AAL) association supports robotic projects to enable robotic technologies inside home environments. One of these projects is the ALIAS (Adaptable Ambient LIVING ASsistant) project, we are contributing to. It has the goal of developing a mobile robot system to "interact with elderly users, monitor and provide cognitive assistance in daily life, and promote social inclusion by creating connections to people and events in the wider world" [8].

1.1 The ALIAS robot and the navigation system

The ALIAS project provides a variety of services, like auto-collecting and searching the web for specific events (concerts, sports events, news) that correspond to the users profile, a calendar function to remind the user on specific events, and, most important, a service to communicate by e-mail, social networks and voice- or video telephone, particularly adapted to the needs of the target group. All these tasks are provided by a mobile robot system (see Fig. 1).

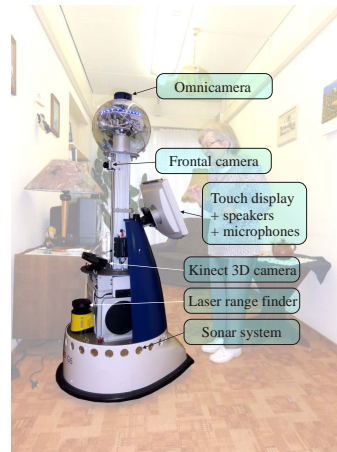


Fig. 1. The ALIAS robot, a SCITOS G5 platform from MetraLabs GmbH, with cameras, Kinect[®] 3D sensor and laser range finder. It interacts with the user by touch-display and speech output.

The benefit of a mobile system is the capability to move: the robot can be requested by the user and should autonomously drive to the user and approach him/her. In the home environment there are already some challenges that make navigation difficult, like narrow spaces, cluttered rooms and resting positions of the user, which are hard to detect. Navigation has to be smooth and exact, therefore our motion controlling system is based on the Dynamic Window Approach [9]. Based on this approach, we present here how to approach a person with known upper body pose while considering the "personal space" of the interaction partner. This provides a more natural, polite and unobtrusive approaching behavior of the robot. The personal space itself is not appropriate to

use directly inside the DWA, so we need to apply a planning strategy to find an optimal approaching behavior.

2 State of the art

Psychologists investigated the human-to-human interaction in public areas very carefully since the 70s of the last century. One of the foundations and most important publications is the work of Hall [10], who first introduced the concept of different spaces around a human being to support different modes of interaction. There is a space for non-interaction, public interaction, interactions with friends and also an intimate space for interaction with very close relatives.

zone	interval	example situation
close intimate	0.0m - 0.15m	lover or close friend touching
intimate zone	0.15m - 0.45m	lover or close friend talking
personal zone	0.45m - 1.2m	conversation between friends
social zone	1.2m - 3.6m	conversation to non-friend
public zone	from 3.6m	no private interaction

Table 1. Psychological definition of the personal space. This space consists of 5 zones, each supporting different activities and different communication intentions.

By formulating the theory that interaction is also coupled to spatial configurations between interaction partners, many investigations on this matter have taken place, and it could be shown that the configuration depends on many aspects like cultural background, age, sex, social status and person’s character [11–13]. But is the personal space a valid description for human robot interaction? As Reeves and Nass [7] showed, complex technical devices are indeed seen as social beings and treated as such. So, we can assume that a robot with a person-like appearance is treated like a person. Additional proof is given by exhaustive experiments done within the COGNIRON project, where wizard of oz methods showed that a spatial configuration between robots and humans exists [14] and that this configuration also changes depending of the task of interaction (e.g. talking, handing over an object)[15], or such constraints like sex or experience with robots [16]. However, non of these works tried to autonomously approach a person in a socially acceptable manner. But the wizard of oz experiments could find out useful spatial parameters to autonomously approach a person. Despite the thorough psychological background work, only few publications exist that describe an actual autonomous approaching behavior. Often a simple control policy is used, where a fuzzy controller [17], a PID controller [18, 19], or a similar technique is used to keep the robot at a certain distance to the person. The used distance thresholds or fuzzy-rules are always hand-crafted and set by the designer without sufficient psychological justification. Some can only approach a person from the front [18], since face detection is needed, and some simply do not consider the upper body orientation of the person and approach the person from any direction [17]. There are only a few works, more aware of

the concept of personal space, which use this space to approach a person or drive around a person without intruding the person’s personal zone. For example Pacchierotti [21] uses an elliptical region around a tracked person in a corridor to signal avoidance towards the person by changing the robot’s driving lane in a corridor at an early stage of approaching, where collision avoidance would not have suggested such a driving behavior. The distance of the lane changing was tuned by hand and the distance threshold for driving by was determined by evaluating a questionnaire. A hand-made approaching scenario was also presented by Hoeller [23], where different approaching regions were defined, each with a different priority. At least one of these regions had to be free from obstacles and the region with the highest priority was the current target region. Hoeller uses expanding random trees[23] to plan the next motion step in an optimal fashion. The work of Svenstrup and Andersen [22] models the personal space explicitly and without the need of any thresholds, so they could create a dense representation of the personal space and approach a person by using a potential field method. Although their results do not consider any obstacles and could get stuck in local minima, they were the first with an actual mathematical model of the personal space. Other authors do not consider the personal space, but also have the need to approach a walking person from the front to catch customer attention [20]. The trajectory of the person is predicted, and a point on that trajectory is chosen as the goal, to give the robot enough time to turn towards that person and approach her from the front.

2.1 The Dynamic window approach

To move a robot, there must be decisions taken which action to be executed as next. Here, two parts are important. First, the robot has to know to which position it has to drive, and second, which trajectory it has to drive to reach a good position. As mentioned before, we use the Dynamic Window Approach [9] for motion planning and therefor can only support physical plausible paths towards the target. We can assume two things when decide upon the next action. First, we can measure the robots position and speed, and second we know the current obstacle situation. The Dynamic Window Approach’s key idea is to select a rectangular region of rotation- and translation speeds around the current rotation- and translation speed, and decide which next speed pair is the best by evaluating different so called objectives. Each objective focuses on one aspect of navigation like avoiding obstacles, heading towards the target, drive at a certain speed and so on. The window’s outer bounds are only based on physical constraints, like the robot’s acceleration capabilities and maximum allowed speeds. The voting values of the objectives are summed up weighted, and the minimum vote of the current speed window is chosen to be the next valid action. Our goal is to design an objective for the DWA, which uses a personal space model to approach a person. The model of the personal space is described in the next section. After that section we show, how to include the model into the DWA.

3 Model of the personal space

As described in section 2, the model of the personal space is the key component to approach a person. Similar to the work of Dautenhahn [14], we also want the robot to approach a person from the front, but with a slight aberration from the direct front, since most user perceive such a behavior more comfortable. For this purpose, obviously we need the position and viewing direction of the person to calculate the configuration of the personal space model. The space configuration should enable the robot to drive around the person in a comfortable distance and turn towards the person when a "front position" is reached. Like in [22], we model the personal space with a sum of Gaussians. The space relative to the persons upper body direction is separated into two regions: a front-region, which is considered to be within $\pm 45^\circ$ around the persons upper direction, and a back-region, which is the rest (see fig. 2).

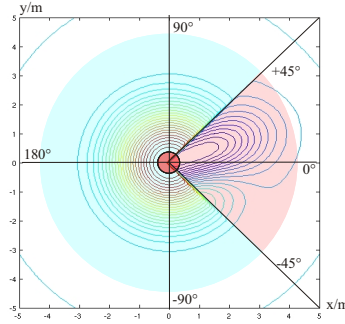


Fig. 2. Two regions of our personal space model. The front region is within an $\pm 45^\circ$ interval (in red). The back region is the rest (in blue). Note, that the regions are not limited in radial extension, like it is done in the illustration.

In both areas we define a distance function to keep the robot out of the user's personal zone but within his/her social zone while approaching the person. The function is defined relative to the persons upper body direction.

$$a(x, y) = \frac{\alpha}{2\pi\sigma_1} \cdot e^{-\frac{x^2+y^2}{\sigma_1^2}} - \frac{\beta}{2\pi\sigma_2} \cdot e^{-\frac{x^2+y^2}{\sigma_2^2}} \quad (1)$$

The variables $\alpha, \beta, \sigma_1, \sigma_2$ describe a classical Difference of Gaussians function and are set in our case (see Fig. 2) to $\alpha = 0.6, \beta = 0.3, \sigma_1 = 2m, \sigma_2 = \sqrt{7}m$ to form a minimum cost region in a distance of 3.5 meters around the person. The front region is treated additionally with an "intrusion function" $i(x, y)$. This is also a Gaussian function and is simply added to $a(x, y)$.

$$i(x, y) = \frac{\gamma}{2\pi\sqrt{|\Sigma|}} \cdot e^{-\mathbf{x}^T \Sigma^{-1} \mathbf{x}} \quad (2)$$

$$\Sigma = \begin{bmatrix} \sigma_x^2 & 0.0 \\ 0.0 & \sigma_y^2 \end{bmatrix} \cdot \begin{bmatrix} \cos(\phi) & -\sin(\phi) \\ \sin(\phi) & \cos(\phi) \end{bmatrix}$$

Here the variables σ_x and σ_y define an elliptical region, that is rotated towards the needed approaching direction ϕ , as seen from the persons perspective. The vector \mathbf{x} is simply a column vector $(x, y)^T$. The variables are set to $\gamma = -0.5$, $\sigma_x^2 = 2.9$ and $\sigma_y^2 = 1.1$. Only ϕ and σ_x need to be set at runtime to regulate the approaching distance and direction. All other parameters are constant and are chosen to reflect the properties of the personal space definition in [10]. So, the final definition of the personal space $p(x, y)$ relatively to the person coordinates $x = 0, y = 0$ and upper body pose towards the x-axis is defined as follows:

$$p(x, y) = \begin{cases} a(x, y) & , \text{ if } \langle x, y \rangle \text{ in back-region} \\ a(x, y) + i(x, y) & , \text{ if } \langle x, y \rangle \text{ in front-region} \end{cases} \quad (3)$$

To compute the personal space in the real world application each point $(\hat{x}, \hat{y})^T$ has to be transformed to the person-centered coordinate system $(x, y)^T$ presented here.

3.1 Planning with Fast Marching and the Dynamic Window Approach

Up to that point, we have shown how the personal space can be computed, if the upper body pose of a person is known. We also stated, that this space is used within the DWA. The basic idea of the DWA is to decide in a local situation, which next action is optimal. The local driving command is only valid for a certain Δt , than the next window configuration is evaluated. If the Dynamic Window uses the personal space directly, it is possible to predict for every speed pair V_{rot}, V_{trans} the trajectory within the interval Δt and simply evaluate the value of the personal space at this point, the robot has reached at that time. This is shown in Fig. 3. The minimal value leads to the most supported driving decision. By using the personal space directly, multiple driving decision lead to the same minimal value and a single local optimum can not be guaranteed.

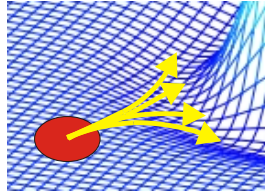


Fig. 3. No distinct speed decision is possible, when the personal space model is used directly. Here, several actions can lead toward the same minimal value.

3.2 Fast Marching and the cost function

To avoid situations, where no distinct decision is possible, path planning methods are used to create continuous decreasing functions to get to the optimum by

gradient descents. An excellent planning technique is the Fast Marching method [24], which origins from the level set methods of single wave fronts and is applied to path planning. The core idea is to code space as a physical medium, where waves can travel with different speeds. For example in obstacles the speed is nearly zero, while in free space the speed can be any feasible speed. By propagating a wave front from the target to the robot, a function of the traveling time of the wave for every point in space is constructed. The benefit is, that also fuzzy values, that are not obstacles or free space, can be considered in this simulation and deform the initial circular waveform. So all we have to do, is to transform the personal space into a physical "speed-space". We know the minimum of $p(x, y)$ and use p_{min} to create a function that is non-negative. High values of the personal space symbolize bad places to drive to, while low values should be preferred. So we define the speed function $v(x, y)$ as follows:

$$v(x, y) = 1 / (p(x, y) + p_{min} + \epsilon) \quad (4)$$

The variable ϵ is used to prevent an infinite speed at the minimum point.

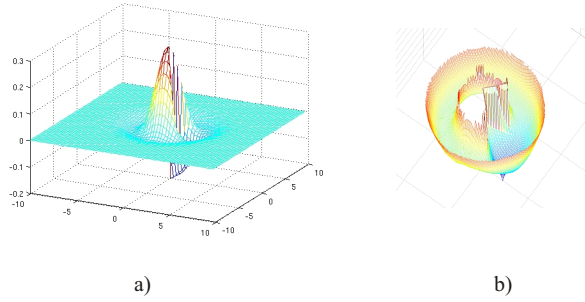


Fig. 4. From personal space to the planning function. The personal space function in a) is transformed to create the continuously decreasing planning function b).

3.3 Extracting the target region

To navigate with the Dynamic Window, we use local occupancy maps to represent the surrounding obstacle situation around the robot. In this grid representation, we also have to rasterize the personal space values $p(\acute{x}, \acute{y})$ to merge the costs of the personal space with the costs of obstacles to create an optimal path. Each planning algorithm has to know the target, to which state the system has to drive to. Since we have a rasterized personal space, we are able to easily extract the minimum value $p_{min}(\acute{x}, \acute{y})$. The planning algorithm has to know the target, to which state the robot has to drive to. This target is the origin of the wave and each point (\acute{x}, \acute{y}) with $p(\acute{x}, \acute{y}) < p_{min} + \epsilon$ belongs to the target region. Planning is complete when the traveling wave front hits the cell of the current robot position, and now the values of the traveling function can be used directly

by the dynamic window to apply a gradient descent. When the robot reaches a small region around the target region the approaching task is done.

4 Experiments

A problem on approaching a person is the estimation of the person’s position and the associated measurement noise. We plan to detect the upper body pose by fusing two standard tracker methods, namely the leg-pair detector of [25] by using the laser range scanner and the OpenNI full body pose tracker by using the Kinect. To test the stability and robustness of the approach, we investigated three scenarios, two in narrow spaces and one in a large room of our lab. We use a simulator to avoid the problems of person detection and to control the (simulated) measurement noise of the person’s and robot’s pose. We could also proof in first test, that the approach is running well on the real robot, but here you have to face the challenging task of upper body pose estimation. To investigate the stability of the approaching behavior on a wider range of positions or sensor noise, the position of the person and the robot was chosen randomly to approach in a circle around a marked position. The robot and the person should face towards a given direction each. For each of the three locations, we define two person positions with different viewing angles and performed ten runs for each position. So we have a set of six trials with a sum of 60 single runs. The variance of the final robot position and the person’s position are shown in table 2.

Person position		Robot final position
Scenario	σ_{pers} in meter/deg	σ_{rob}
1(I)	(0.4, 0.1)	(0.4, 0.1)
1(II)	(0.5, 0.1)	(0.4, 0.1)
2(I)	(0.2, 0.1)	(0.2, 0.2)
2(II)	(0.2, 0.2)	(0.3, 0.2)
3(I)	(0.1, 0.1)	(0.1, 0.1)
3(II)	(0.1, 0.2)	(0.1, 0.1)

Table 2. Variance of the robot’s final pose and variance of the wait position of the person

From the experimental setup we get uncertainties of 0.1 to 0.5 meters in the person’s resting position. The question to be answered in our experiments is, how the variance of the robot’s target position will increase when approaching a person, by knowing the initial variance of the person’s upper body pose. We also want to know, how the trajectories variate on the person’s position noise. To do so, we record the trajectory of the robot and calculate the mean and standard deviation of the final robot position. The results are shown in table 2 and figure 5. The average distance from the person is 0.7 meters, the variance is within the same magnitude as the variance of the person’s pose. So measurement noise is not amplified by this method. Figure 5 shows the path and the mean person position with variance of all six test cases. Scenario 2 shows, how the upper body pose heavily influences the trajectory of the robot. Scenarios 1 and 3 show,

that in narrow spaces the trajectory has to follow the physical restrictions. The personal space has to be intruded, if there is no other chance.

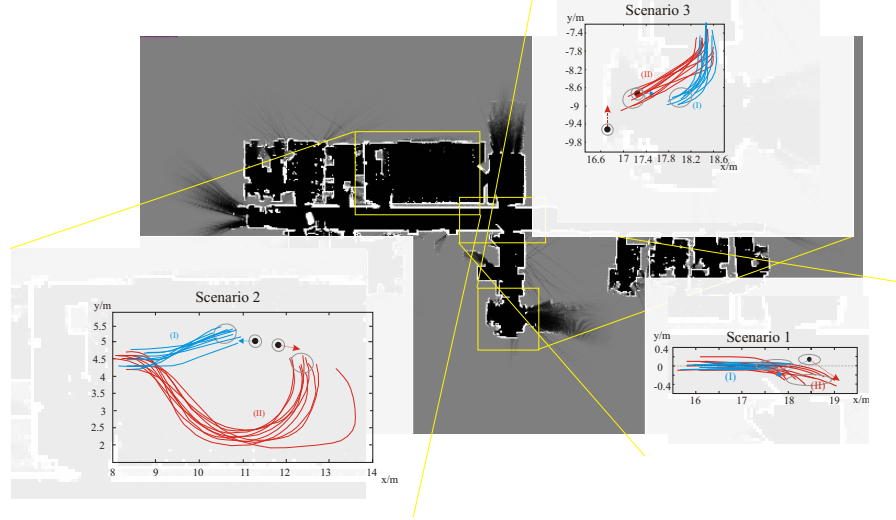


Fig. 5. Resulting trajectories of the three tested scenarios. Per scenario two different poses are evaluated by the user (I and II). The mean positions of the user are shown as black dots, the mean upper body poses as arrows. In each scenario the blue lines denote the robot's trajectories corresponding to the first person setup, while the red lines show trajectories of the second setup. All scenarios show, how the upper body pose influences the approaching trajectory. Scenario 2 also shows, that the social zone is respected if there is room to navigate.

5 Conclusions

In this paper we presented a method, working within the Dynamic Window Approach, to approach a person by considering his/her personal space. We could demonstrate, by using a planning strategy, that a stable and reliable solution could be achieved. Nevertheless the method of extracting the target region could be improved in future work. We also want to include obstacles into the personal space model, to improve planning quality and focus on the task of real time replanning, when the person changes his/her pose while the robot approaches.

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References

1. Pastor, C. et al: CompanionAble- Affective robotics for assisting elderly people. In: Conf. Proc. Assistive Technology From Adapted Equipment to Inclusive Environments: AAATE 2009, Florence, Italy, pp. 153–258

2. Pollack, M.E. et al: Pearl: A Mobile Robotic Assistant for the Elderly. In: AAAI Workshop on Automation as Eldercare, 2002
3. Weisshardt, F. et al: Making High-Tech Service Robot Platforms Available. In: Joint International Conference of ISR/ROBOTIK2010, 2010, pp.1115–1120
4. Schroeter, Ch. et al: Autonomous Robot Cameraman - Observation Pose Optimization for a Mobile Service Robot in Indoor Living Space. In: ICRA, 2009, pp.424–429
5. H.-M. Gross et al: Toomas: Interactive shopping guide robots in everyday use - final implementation and experiences from long-term field trials, in Proc. IROS, St. Louis, 2009, pp. 2005–2012
6. Kanda, T. et al: ShopBot: A Communication Robot in a Shopping Mall, In: IEEE Transactions on Robotics, vol. 26, Nr. 5, 2010, pp.897–913
7. Reeves, B. and Nass, C.: The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places, Stanford, CSLI Press, 1996
8. Walhoff, F. and Bourginion, E., ALIAS home page, <http://www.aal-alias.eu/content/project-overview>
9. Fox, D. et al: The dynamic window approach to collision avoidance. In: IEEE Robotics and Automation, vol. 4, no. 1, 1997, pp.23–33
10. Hall, E.T.: The hidden dimension, NY, Doubleday, 1966
11. Gillespie, D.L. and Leffler, A.: Theories of nonverbal behaviour: A critical review of proxemics research. In: Journal on Sociological Theory, vol. 1, 1983, pp. 120–154
12. Leffler, A. et al, J.C.: The Effects of Status Differentiation on Nonverbal Behaviour. In: Social Psychology Quarterly, vol. 45, 1982, pp. 153–161
13. Smith, H.W.: Territorial Spacing on a beach revisited: A Cross-National Exploration. In: Social Psychology Quarterly, vol. 44, 1981, pp. 132–137
14. Dautenhahn, K. et al: How may I serve you? A Robot Companion Approaching a Seated Person in a Helping Context. In: Proc. HRI 2006, pp. 172–179
15. Koay, K. et al: Exploratory Study of a Robot Approaching a Person in the Context of Handing Over an Object. In: Proc. Association for the Advancement of Artificial Intelligence Spring Symposia, 2007
16. Takayama, L. and Pantofaru, C.: Influences on Proxemic Behaviours in Human-Robot Interaction In: Proc. IROS 2009, pp. 5495–5502
17. Hu, Ch. and Ma, X. and Dai, X.: Reliable Person Following Approach for Mobile Robot in Indoor Environment. In: Proc. 8th IEEE International Conf. on Machine Learning and Mechatronics, 2009, pp. 1815–1821
18. Chen, Z. and Birchfield, S.T.: Person Following with a Mobile Robot Using Binocular Feature-Based Tracking. In: Proc. IROS 2007, pp. 815–820
19. Ma, X. and Hu, C. and Dai, X. and Qian, K.: Sensor Integration for Person Tracking and Following with Mobile Robot. In: Proc. IROS 2008, pp. 3254–3259
20. Satake, S. et al: How to Approach Humans? - Strategies for Social Robots to Initiate Interaction. In: Proc. HRI 2009, pp. 109–116
21. Pacchierotti, E. et al: Evaluation of Passing Distance for Social Robots. In: Proc. RO-MAN 2006
22. Svenstrup, M. et al: Pose Estimation and Adaptive Robot Behaviour for Human-Robot Interaction. In: Proc. ICRA 2009, pp.3571–3576
23. Hoeller, F. et al: Accompanying Persons with a Mobile Robot using Motion Prediction and Probabilistic Roadmaps. In: Proc. IROS 2007, pp.1260–1265
24. Sethian, J.A.: A Fast Marching Level Set Method for Monotonically Advancing Fronts, In: Proc. Nat. Acad. Sci., vol. 93, no. 4, 1996, pp.1591–1595
25. Arras, K. and Moos, O.M. and Burgard, W.: Using Boosted Features for the Detection of People in 2D Range Data, In: Proc. ICRA 2007, pp. 3402–3407