Socially Acceptable Behaviour for Robots Approaching Humans using an Adaptable Personal Space

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Keywords: Social Robotics, Service Robotics, Human Robot Interaction, Personal Space, Acceptability.

Abstract: In this paper a new adaptable model of the personal space is proposed. This model takes into account the position of a persons hands aiming to facilitate interactions with the human while maintaining an appropriate social distance during the approach. This personal space model has been used as a cost function in the path planning algorithm Transition-based Rapidly exploring Random Trees. It allows users to influence the robot's generated approach at the planning stage by varying their body and hand positions. Results from an online survey, where participants were shown different simulated approach behaviours, indicate that the model performs well when it comes to distance regulation and how close the robot comes during the approach. An interesting discovery from the survey is that the maintenance of eye contact, i.e. the robot keeping oriented towards the person during the approach, was positively associated with both the closeness of the robot during movement and judging the intentions of the robot for unaware users.

1 INTRODUCTION

As personal care robots become more commonplace and people start sharing their environment with such robots, certain expectations for the robot's behaviour arise. For example, the robot should try to follow similar social conventions to the ones that humans are conforming to. Few path planners create paths that resemble human-like motion behaviour or are subject to the same rules and constraints. Therefore, adapting navigation strategies to conform to social conventions and be as non-obtrusive as possible is important for improving the perception and acceptance of personal care robots.

This paper investigates how social conventions, tendencies and expectations can be modelled and used as cost functions for a path planning algorithm. In particular, it proposes a new adaptable model of the personal space, which describes distance regulations between individuals, and uses this model for planning approach trajectories. It builds on the concept of proxemics, see Figure 1, a term and field of study coined by Hall (1966) and in particular the idea of the personal space. Each space or region emanating from the person relates to the comfortable distance that a certain type of social interaction should take place (Hall, 1966). In this paper the definition of the personal space model is extended to depend on the position of a persons hands, such that it allows for intrusions into the personal space based on hand position. The hypothesis is that an adaptable personal space will allow a path planning algorithm to create approach strategies that can be tailored to the individual's preferences. The robot used for this research is the Care-O-Bot (Graf et al., 2009), a service robot with an omnidirectional mobile base with laser range scanners, a 7-DOF manipulator with gripper, a tray and a sensor head with a stereo camera and a Kinect-like depth sensor. Figure 2 shows the robot interacting with a person using its tray and manipulator.

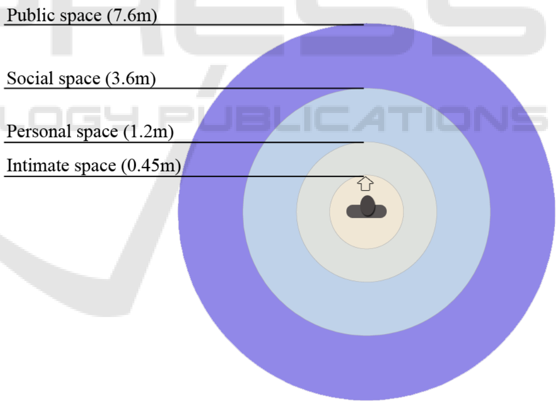

Figure 1: Spaces associated with a person.

Jeppesen K., Bodenhagen L. and KrÃijger N.
Socially Acceptable Behaviour for Robots Approaching Humans using an Adaptable Personal Space.
DOI: 10.5220/0006193801160121
In *Proceedings of the 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2017)*, pages 116-121
ISBN: 978-989-758-229-5

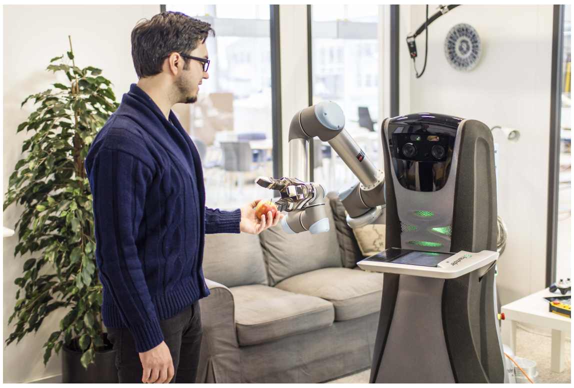

Figure 2: The Care-O-Bot, a personal care robot.

2 RELATED WORK

The field of robotics research that focuses on human-robot interaction and collaboration is one of the more recent and interdisciplinary areas.

Rios-Martinez et al. (2015) discuss a domain called Social Signal Processing. They estimate that over 60% of communication between two people come from nonverbal communication, i.e. body language and social cues. It discusses the connection between social cues (e.g. hand gestures and posture) and social signals (e.g. emotion, personality, status) and the importance of this connection in future research of human-robot interactions. The survey also looks at proxemics and various spaces such as common models of the personal space, which are mostly static and non-adaptable. Interaction spaces, related to groups of people, affordance or activity and spaces related to objects are discussed and it is apparent that modelling these spaces efficiently is important for socially acceptable robot navigation. The possibility of a dynamic personal space model is briefly mentioned, and in our paper the concept of an adaptable personal space is explored.

Dautenhahn et al. (2006) carried out human-robot interaction trials to determine the preferred approach direction and other defining characteristics of a robot approach. Results based on a live trial showed that the most preferred direction was to the right or left hand side of the person and the least preferred direction was from the front. The approaches were also rated in terms of practicality (seen in relation to the trial environment) and comfort, and the frontal approach was again the least preferred or lowest rated. In our work we found the same trend of people preferring non-frontal or direct approaches when it comes to judging the closeness of the robot. The paper also discusses the idea of combining *safety*, *visibility* and *hidden zone* criteria that together seek to model the cost map of an environment. The cost is modelled based on e.g. whether the person can get the robot into his field of view by moving just his eyes or if he needs to turn his head. The cost function also tries to penalize the robot for making surprising appearances, such as when coming from a hidden zone that the person cannot see and into the persons field of view. Instead, the robot should seek to enter the persons field of view at a comfortable distance so there is enough time for the person to react and be aware of the robot. In our work we use a cost function which is based on the position of a persons body and hands. We also vary the orientation of the robot so the robot either looks in the direction of travel or tries to maintain a sort of eye-contact by looking at the person.

Kirby et al. (2009) implement a navigation framework where human social conventions such as personal space and tending to one side of hallways are represented as constraints on a robot's navigation. The following constraints were identified as important for social behaviour in hallway situations; *Minimize travelled distance*, *obstacle avoidance*, *person avoidance* with personal space and passing on the right hand side, *default velocity* where the robot tries to keep a constant velocity and *inertia* where the robot should try to keep moving straight as much as possible. Each of these constraints are weighted and combined linearly and used as the objective function in a modified A^* planner. The method was successful in generating paths that resemble human-like behaviour when moving down a hallway; passing oncoming traffic on the right and cutting across the hallway based on how far oncoming traffic is. In our work we utilize a sampling based method for path planning. Our cost function is also based on a personal space model, but our model is adaptable instead of constant.

Woods et al. (2006) investigate differences, between live and video based trials, in responses and preferences for different characteristics of robot approaches. Participants, both in the live and video based trials, were questioned about their preferred approach direction, stopping distance and approach speed. There were a high levels of correspondence (85% resp. 87%) for the least preferred approach direction (frontal) and the ratings of the robot's speed. Moderate to high (60-80%) agreement was found between video and live trials for most preferred approach direction and the robot's stopping distance from the subject. Almost all subjects (93%) preferred the live trials over the videos. These results are interesting, since in our paper we utilize videos of simulated approaches and online questionnaires for evaluation. This evaluation method is a lot faster, allows for more experimentation and does not have the same

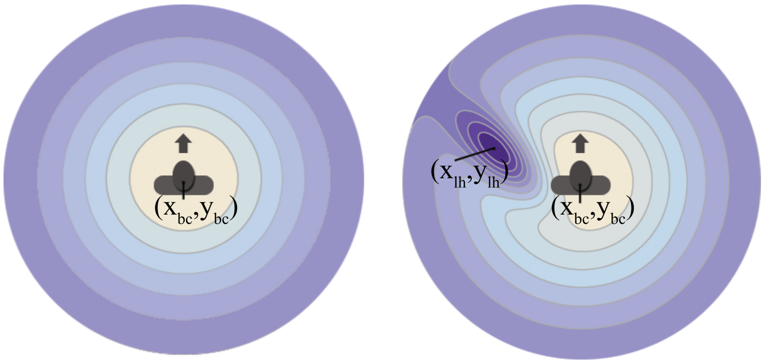

Figure 3: **Left**: Non-adaptable model. **Right**: Proposed adaptable model. (x_{bc}, y_{bc}) and (x_{lh}, y_{lh}) are coordinates for the body center and left hand respectively. White corresponds to high values, purple to low values.

safety requirements as live trials, which are time consuming to set up and carry out.

3 ADAPTABLE PERSONAL SPACE MODEL

While a person only physically occupies a portion of the intimate space, see Figure 1, there is a sense of ownership and occupation associated with the personal space. If someone else enters ones personal space and it was neither expected nor allowed, that person will be negatively judged because of the intrusion. Of course, it is not always possible to keep ones personal space free of other people, e.g. in public transport situations. However, a person willingly lets go of personal space privileges when participating in certain activities or entering certain locations. In approach scenarios the robot should try to obey the personal space of the person it is approaching and should only enter when allowed.

In this paper, a new variant of the personal space model, which is meant to be used for approach-based human-robot interaction, is proposed. The main difference between the proposed model and previous variants of the personal space is that it is dependent upon the placement of the hands of the person. Each hand has its own small space with the opposite sign to the space radiating out from the center of the person. This can be viewed as a sort of *intrusion space* where a cavity is created in the personal space to allow the robot to intrude. Figure 3 shows the difference between a common static model (left) and our proposed adaptable model (right) with a cavity to the persons left hand side. In the proposed model the space centered around the left hand allows for intrusion because of the low value of the personal space in that area. Each of the spaces that make up the personal space are modeled by (1).

The center of the Gaussian coincides with the current position of hand $\mathbf{p}_h \in \mathbb{R}^2$ resp. the body center, $\mathbf{p}_{bc} \in \mathbb{R}^2$. The shape of the Gaussian is controlled by the amplitude M_i and the covariance matrix $\mathbf{C}_i$ which depend on which body part is used – for the body a isotropic Gaussian has been used, while an elongated Gaussian, hence having elliptical isocontours, was used for the hands. The cost associated to a position $\mathbf{p}$ in the personal space is determined by the sum of spaces for all body parts, each being modeled by:

$$PS_i(\mathbf{p}) = M_i \, exp\left((\mathbf{p}_i - \mathbf{p})\,\mathbf{C}_i\,(\mathbf{p} - \mathbf{p}_i)^T\right) \qquad (1)$$

with $i \in \{h, bc\}$ indicating the body part. Such that the total cost is:

$$PS_{cost}(\mathbf{p}) = PS_h(\mathbf{p}) + PS_{bc}(\mathbf{p}) \qquad (2)$$

4 PATH PLANNING WITH THE PERSONAL SPACE MODEL

The path planning algorithm Transition-based Rapidly exploring Random Trees (Jaillet et al., 2008) (TRRT) works on the same principles as the well known Rapid Random Trees (LaValle, 2006), but changes the way new configurations are accepted. The transition test, which gives the algorithm its name, accepts a new node based on the costs and distance between the two nodes in the extend step. Negative cost slops are accepted, nodes with costs above a max threshold are rejected and nodes that lead to positive cost slopes are accepted with a low (self-tuning) probability.

The cost of a robot configuration is determined by the value of the personal space at that configuration's coordinates, given by (2) with the proper inputs. Therefore, the negatively valued parts of the personal space, determined by the persons hands, will contain

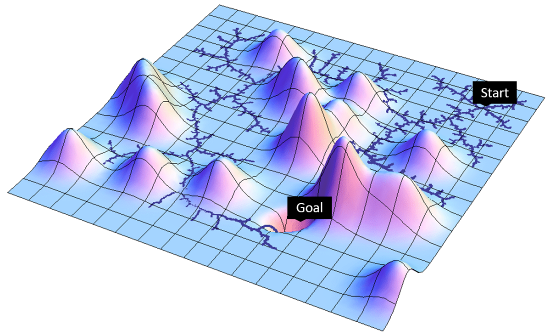

Figure 4: TRRT exploration in an artificial environment with many high cost areas.

the goal configuration or goal region for the path planning and allow for easy exploration due to the associated low cost.

Figure 4 shows the TRRT exploring and finding a solution in a cost environment with many high cost areas. The cost of the environment in which the simulated approaches take place in is considered obstacle free, and therefore only influenced by the personal space model.

5 EXPERIMENTS

Recordings of the body and hand position of a real person, using the Microsoft Kinect V2 sensor, were used to obtain the input for the personal space model for the simulation environment. The recorded person was sitting in a chair and stretched his left hand out to indicate where he wants the robot to end up. The simulated person is static throughout the robot approach and is merely there for visualization purposes.

The TRRT algorithm generated a path offline and post-processing steps for smoothing the path were applied. The approach was visualized in the Gazebo simulator using the Care-O-Bot ROS/Gazebo packages. A series of videos was recorded, where the robot approached a sitting man using different trajectories and different orientations along the trajectory. An online survey gathered responses (between 36 and 39 for each question) about agreement with the statements **S1**-**S4** about the robot approaches.

S1: The robot came too close during its movement

S2: The robot stopped too close

S3: The robot's movements were predictable

S4: The robot's intention was clear

The participants rated their agreement on a 5-point Likert-scale between 1 (strongly disagree) and 5 (strongly agree). Participants were not privy to any information about what they were going to be asked

Figure 5: Simulated environment, personal space model and TRRT exploration tree.

or the content of the videos and the order of the videos was randomized.

In the simulation scenario, the robot starts near the kitchen area and moves to the persons left hand side to deliver a beverage. The start and goal location are therefore the same in all the videos, but the robot path and orientation differs. Figure 5 shows the different steps in simulating the approach scenario. Pictured is the kitchen environment, the exploration of possible robot configurations by the TRRT algorithm and a plot of the personal space model (cost function) with a cavity in front of the person to his left hand side. More details about the scenario and simulations can be found in Jeppesen (2015).

The four different approach strategies are visualized in a time-lapse manner in Figure 6(a-d) and are accessible online[1].

6 FINDINGS

The paths that were planned using the personal space model (video 1 and 2) tended to stay farther from the person during the approach and only come close once there was a cavity in the personal space (see Figure 5). Approaches planned without the personal space model (video 3 and 4) would take almost straight line paths to the goal, violating the personal space boundaries.

Participants rated their agreement with statements in a questionnaire on a 5-point Likert-scale. For each statement an ANOVA was conducted to investigate if the usage of the proposed model had a positive effect. The results indicate a positive effect for the

[1]https://www.youtube.com/playlist?list=PLKvb2SEOLjc9Wi_ts3GwhRE_7aV7UR_2z

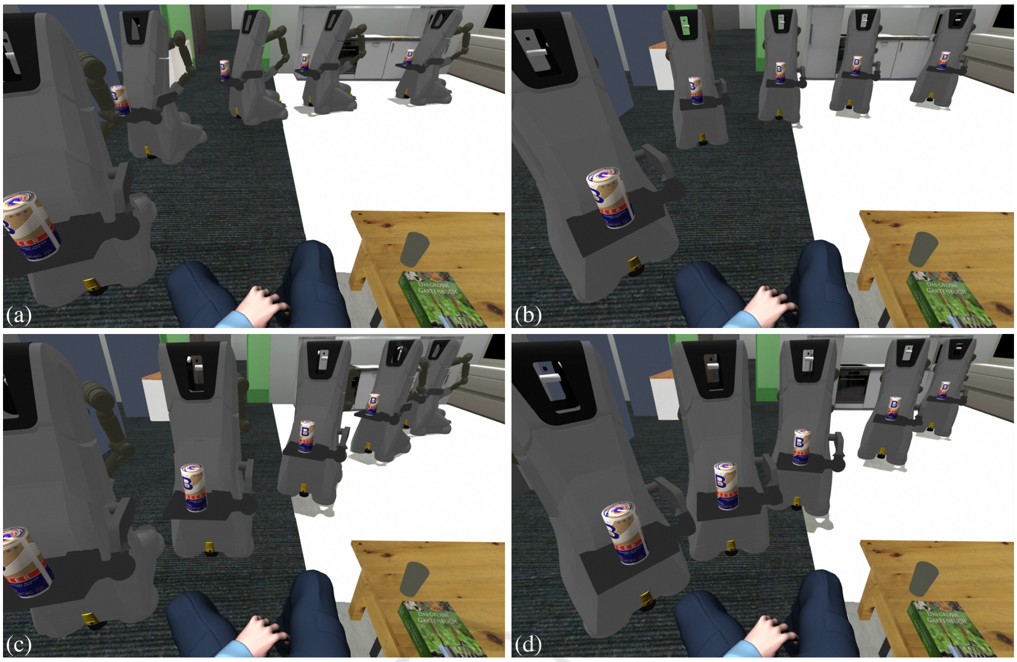

Figure 6: Illustration of the videos. Top row (*a*, *b*): using the adaptable model; bottom row (*c*, *d*): using straight motions; left column (*a*, *c*): facing the in direction of motion; right column (*b*, *d*): facing the subject.

closure, based on the statement “the robot came too close during its movement”, (p=0.061). Interestingly, the intention of the robot was rated to be less clear (p=0.049) when the proposed model is used. This can indicate that the participants might expect additional cues, revealing the robots intention, to be provided by the robot.

The paths planned with the adaptable personal space model (video 1 and 2) rated more positively for the closeness of the robot during the movement, i.e. the participants had stronger disagreement with the statement. The results clearly indicate that video 2 shows the best rated approach. Keep in mind that the difference between video 1 and 2 is that in video 2 the robot keeps looking at the person during the approach, i.e. the simulated eye-contact. The straight-line paths (video 3 and 4) rated higher in terms of predictability of motion, which was expected since it is a simpler motion.

An interesting finding was that similar paths that utilized different robot orientation strategies rated differently. The paths planned with the adaptable personal space model were tested with the robot looking in the direction of travel and with the robot trying to maintain ‘eye-contact’ by facing the user the entire time. The approach with eye-contact (video 2) had significantly better ratings in terms of closeness of the robot compared to video 1 without eye-contact. The difference in rating between video 3 (no eye-contact) and video 4 (eye-contact) is smaller, but supports the trend. The down-side to the strategy of maintaining eye-contact is that it can make the robot’s movement feel less predictable, especially when the robot is not moving in a straight line, because it is easier to guess where the robot is going when the robot faces in the direction of movement.

The comments from the participants provide additional clues on this aspect. One of them (participant 31) argues:

> *“There is a scenario where the robot makes a wide arc whilst keeping the person in its focus – this seems predatory and is alarming.”*

on the other hand participant 38 states:

> *“The first one where it curved around you to your side whilst facing you gave a much more waiterly impression, I liked that one.”*

which indicates that neither of the strategies might fully comply with the behavioral norms that are applied unconsciously. This might be one underlying reason for the results for the different conditions not to differ as much as expected. Furthermore, this leads to the conclusion that a more complex model for the approach behaviour, with the gaze as an active element and taking characteristics of the person, e.g. gender, into account, will improve the robots abilities to optimize the social distance (Mumm and Mutlu, 2011).

7 CONCLUSION

An adaptable personal space model was used as a cost function for a path planning algorithm, TRRT, to plan simulated approaches toward a sitting person. The approaches using the proposed adaptable personal space model were rated more positively than the direct approaches, according to results from an online survey asking if the robot came too close during its movement. Furthermore, approaches where the robot orients itself to look at the person received more positive ratings than approaches where it was oriented in the direction of travel.

Due to the simplistic nature of the simulation environment, the adaptability of the personal space model could not be tested fully. Live trials with the real robot would be the best way to verify the trends that the online survey has revealed, concerning eye-contact and the distance regulation due to the personal space model. The different approaches will likely be rated slightly differently in live trials due to the embodiment and physical presence of the robot, which are an important aspects of human-robot trials. However, our results give good indications that our adaptable personal space model has relevant properties and that gaze contact is rated positively in approach behaviours.

ACKNOWLEDGEMENTS

This work has been supported by the project Patient@Home which is funded as a strategic platform for innovation and research by the Danish Innovation Fond.

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