Social Navigation - Identifying Robot Navigation Patterns in a Path Crossing Scenario

Christina Lichtenthäler[1], Annika Peters[2], Sascha Griffiths[3], Alexandra Kirsch[4]

[1] Institute for Advanced Study, Technische Universität München, Garching, Germany
[2] Applied Informatics Group, Bielefeld University, Bielefeld, Germany
[3] Robotics and Embedded Systems, Technische Universität München, Garching, Germany
[4] Department of Computer Science, Tübingen University, Tübingen, Germany

Abstract. The work at hand addresses the question: What kind of navigation behavior do humans expect from a robot in a path crossing scenario? To this end, we developed the "Inverse Oz of Wizard" study design where participants steered a robot in a scenario in which an instructed person is crossing the robot's path. We investigated two aspects of robot behavior: (1) what are the expected actions? and (2) can we determine the expected action by considering the spatial relationship? The overall navigation strategy, that was performed the most, was driving straight towards the goal and either stop when the person and the robot came close or drive on towards the goal and pass the path of the person. Furthermore, we found that the spatial relationship is significantly correlated with the performed action and we can precisely predict the expected action by using a Support Vector Machine.

Keywords: social navigation, human-robot interaction, spatial relationship

1 Introduction

Robots will increasingly become part of the habitats and work spaces of humans. Wherever they are located, in the factories as co-workers, in nursing homes or hospitals as care assistants, as guides in a supermarket, or as household-robots, one crucial behavior, which they have all in common, is navigation. A robot has to navigate through spaces where humans live and as Althaus et al. [1] already stated *"The quality of the movements influences strongly the perceived intelligence of the robotic system."*. The way a robot moves affects not only the perceived intelligence, also the perceived safety, comfort and legibility and other factors regarding social acceptance [7, 17]. Therefore, one goal in human-robot interaction is to develop methods in order to make robot behavior and in particular navigation socially acceptable [16, 8, 22].

In the literature several social navigation methods have been proposed. One common approach is to model social conventions (e. g. proxemics [10], keeping to the right side in a corridor,...) and norms by using cost functions or potential fields [14, 25, 21]. For example Kirby et al. proposed a navigation method which models social conventions and the constraint to pass a person on the right as well as task conventions like

[0] This work has partially been founded by the the Clusters of Excellence "Cognitive Interaction Technology" CITEC (EXC 277) and "Cognition for Technical Systems" CoTeSys (EXC 142). We would like to express special thanks to the Social Motor Learning Lab of the Neurocognition and Action Group (Prof.Dr. Thomas Schack) at Bielefeld University and to William Marshall Land and Bernhard Brüning for assisting the authors with the VICON system.

time and path length constraints. They use a classical A* path planner equipped with cost functions modeling social and task conventions. Also Tranberg et al. [25] use a proxemics model. Contrary to Kirby et al. they use a potential field instead of cost functions. Another cost function navigation method is proposed by Sisbot et al. [21]. They model not only spacial rules but also other social norms based on their findings in former studies like safety rules, preferred approach directions or visibility constraints.

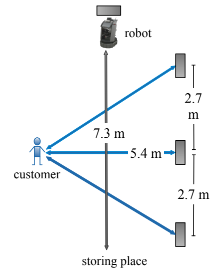
Another approach is to follow the assumption that robot behavior is socially acceptable if the robot shows similar behavior to humans [26, 15]. One of the first methods is proposed by Yoda et al. [26], based on the findings of a human-human experiment they developed an algorithm imitating human passing behavior. Also Kruse et al. [15] developed a Human-Aware Navigation by modeling the findings of a human-human path crossing experiment [3] into a cost function model. However, physical capabilities of robots differ very much from humans' (in particular those of wheeled robots). Therefore, imitating human behavior becomes difficult. Furthermore we showed in former experiments [17] that the legibility and perceived safety of the Human-Aware Navigation method [15] is rather low. In addition, it is not clearly known if humans expect robots to move in a different manner to humans. Is there something like a robot-like behavior that humans expect from robots? A large body of research is dedicated to investigate several aspects of robot navigation [4, 20, 12, 7]. For example Butler et al [4] analyzed the influence of different factors like speed, distance and design on robot motion patterns (frontal approach, passing by, non-interactive navigation). They evaluated how the navigation is perceived by humans regarding the level of comfort. Pacchierotti et al. [20] also tested the conditions speed, and distances in a passing by situation. Proxemics [10] are also widely studied in human-robot interaction [24, 19]. In a controlled experiment Dautenhahn et al. [7] identified preferable robot approaching motions by testing different strategies. The aforementioned research presents controlled experiments testing how motion is perceived regarding different conditions like speed, distance and orientation. However, what is only rarely investigated is what humans expect from a robot, especially when the robot has different capabilities than humans. One study towards expected robot motion patterns is presented by Huettenrauch et al. [12]. In order to identify spatial behavior patterns they investigated the spatial behavior (distances according to Hall [10] and orientation according to Kendon [13]) of a human towards a robot during a "Home Tour" study.

In order to find out what kind of behavior humans expect from a robot, and in particular a robot with non-humanlike physical capabilities we let naive participants steer the robot in a path crossing task. The study design of the work at hand is a new kind of the classical "Wizard of Oz" [9], which we call "Inverse Oz of Wizard" following the categorization proposed by Steinfeld et al. [23]. According to the "Oz of Wizard" design described by Steinfeld et al. [23], where the human is simulated, the robot behavior is real, and the robot behavior is evaluated using robot centered metrics we designed our "Inverse Oz of Wizard". We "simulate" the human by instructing a confederate with very strict behavioral rules. The robot behavior is controlled by the participant in order to capture the participants' expectations and the resulting robot behavior is evaluated, by analyzing the captured motions.

In order to perform a structured analysis of the observed robot behavior and particularly with regard to the development of a navigation method we have to formalize

(a) BIRON

(b) Laboratory



(c) Study Setup

Fig. 1. Used robot and design of the study

the term ”robot behavior”. Usually behavior is defined as the range of **actions** done by organisms, or artificial entities, which is the **response** of the organism, or artificial entity to various **stimuli**. Or as Arkin shortly states in his book, *”behavior is a reaction to a stimulus”* [2]. Based on this common definition and according to Arkin’s behavior-based robotics theory we formalize robot behavior as an **action *a*** performed by a robot, which is **caused** by a **stimulus *s*** , i.e. it exist a function f so that $f(s) \mapsto a$. In our navigation scenario possible actions can be driving, stopping or driving a curve and the spatial relationship is a stimulus.

Research Questions We want to identify expected robot navigation behavior in a human-robot path crossing scenario. Therefore, we want to answer three questions with the study at hand. First we want to identify the preferred actions a, second we want to identify the stimulus s. We expect that the stimulus for an action in a human-robot path crossing situation lies in the spatial relationship of human and robot, third we hypothesize that it is possible to predict the expected action, based on the spatial relationship. i.e. a function f exist so that $f(s) \mapsto a$.

2 Method

In order to answer the aforementioned questions we implemented a within-subject study using our ”Inverse Oz of Wizard” study design.

2.1 Participants

We recruited 46 participants with an average age of 28 years - thereof 26 women and 20 men. 89% of the participants had rarely or no contact to robots and 11% had regular contact to robots.

2.2 Technical Setup

Robot The platform used in this study was the BIRON (BIelefeld Robotic CompanIoN) robot (see Fig. 1(a)). BIRON has an overall size of approximately 0.5m (w) x 0.6m (d) x 1.3m (h). Besides two wheels, BIRON has two rear casters for balance and is constructed with a differential drive (2 degrees of freedom: translation and rotation).

Robot Remote-Control We used a wireless keyboard to steer the robot. The commands of how to steer the robot were marked on the keyboard with arrows. Five keys corresponded to the five ways of moving the robot: straight forward, rotate around its own axis in a clockwise direction, in an anti-clockwise direction, drive and turn left or right in an arc. The robot only moved by holding down the particular key and the robot stopped by releasing the key. These motions map the actual movement abilities of the robot BIRON. Thus, the actions we investigate in this scenario are drive, stop, curve, and rotate. There was no possibility to accelerate the robot as it was driving at its full speed of 0.7m/s.

Motion Capturing System To capture the movements of the robot and the interacting person we used a VICON motion capturing system (`www.vicon.com`). We recorded additional video data with an HD camera.

2.3 Study Design

Cover Story In order to make the scenario realistic all participants were told the same cover story about a grocery store that uses a robot (BIRON) to refill the shelves with goods from the storing place. The participants were asked to navigate the robot from the storing place to a shelf (see Fig. 1(c)) by steering the robot with the wireless keyboard. Furthermore, they were told that the robot might encounter customers in the store.

Setup According to the grocery store cover story we built up a store scenario with four shelves and a storing place (see Fig. 1(b),1(c)) in a laboratory which measures approximately $133m^2$. Three shelves were placed at the wall on the right side of the storing place with a distance of 2.7 m between them (see Fig. 1(c)). One shelf was placed 7.3 m opposite to the storing place (see Fig. 1(c)). The robot, steered by the participant, had the task to bring items from the storing place to the opposite shelve (see Fig. 1(c)). One experimenter took the role of a *customer*. The *customer* had the task to walk from a fixed point (see Fig. 1(c)) randomly to one of the three shelves at the wall and put an item into his/her basket. In addition to the three randomized aims the *customer* walked randomly in three different walking velocities slow (0.6 to 0.8m/s), normal (1.2 to 1.5m/s), and fast (1.9 to 2.1m/s). The *customer* had to walk straight and maintain the velocity even if the robot would crash into them. To avoid eye contact with the participant the *customers* wore sunglasses. Due to the arrangement of the shelves the robot and the customer coincidentally met each other in $45°$ and $90°$ angles (see Fig. 1(c)). Thus, the setup was designed to create completely random and unforeseeable crossing events.

Procedure First the participants were welcomed and the cover story (see Section 2.3) was explained. In order to familiarize the participants with the setup and with steering the robot BIRON the participants received an introduction to the robot BIRON and an extensive practice of how to steer the robot. Only after the participants managed to drive around obstacles and felt capable of steering the robot, the study began. The participants were told to carry 15 items (only one item at a time) from the storing place to the opposite shelf (see Fig. 1(c)) and then go back to the storing place. Therefore the robot moves 30 times (two times per item) straight through the room. The *customer* crosses the robots path randomly as described in Section 2.3. The movements of the robot and the *customer* were captured by a motion capture system and a video camera (see Section 2.2). Once the participant completed the task he/she were debriefed about the purposes of the study and discussed the study with the experimenters. Demographical data were recorded within the debriefing.

3 Results

We carried out the data analysis in two steps. First we identified robot actions in the video data by observing its motions (drive, stop, curve, rotate). After that we analyzed the spatial relationships of robot and *customer* using the motion capturing data in order to identify the stimulus for a specific action. We only consider crossing situations for our analysis. A crossing situation is defined as a situation where 1) the paths of both, BIRON and the *customer*, will cross and 2) both are located before reaching the crossing point (see Figure 2(b)).

3.1 Video Data

By analyzing the video data we identified four different navigation patterns performed by the robot in crossing situations (see also [18]):

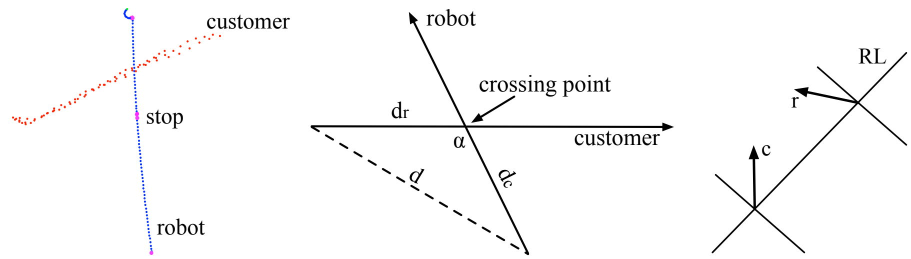
1. stopping before the crossing point (76.7%)
2. driving straightforward and passing behind or in front of the *customer* (18%)
3. driving a curve (3.7%)
4. collision with the *customer* (1.6%) (only shown by two participants)

The action rotate was never performed in a crossing situation and driving a curve was mostly performed by a participant in his/her first trials. The overall navigation strategy, which we can conclude from our observation, was driving straight towards the goal (shelve or storage place) and either stop when both, the *customer* and the robot, came close to the crossing point, or otherwise drive on towards the goal and pass the path of the *customer* without colliding. This strategy was performed by almost all (44 of 46) participants. We assume that the participants anticipate if a collision will happen or not and either stop or drive on. To conclude, from our video analysis we can derive that the actions drive and stop are the preferable actions and we can assume that the stimulus lies in the spatial relationship.

3.2 Motion Data

Spatial Feature Calculation The raw data from the motion capturing system contains the position of robot r and *customer* c (see Fig. 2(a)) captured with a frame rate of 150Hz. In order to describe the spatial relationship between robot and *customer* we calculated the following spatial features using Matlab (see also Figure 2(b)):

- QTC_c according to Hanheide et al. [11] to determine a crossing situation
- distance between *customer* and robot d
- distance between *customer* and the crossing point d_c
- distance between robot and the crossing point d_r
- angle robot-*customer* α
- velocity *customer* v



(a) Path of customer and robot with identified stopping point

(b) Distance features

(c) QTC_c double cross (reproduced from [11])

Fig. 2. Spatial features of a crossing situation

Calculating QTC_c Features: QTC_c is a compact representation of spatial relations between two moving objects. It represents the relative motion, with respect to the reference line RL that connects them, as shown in Fig. 2(c) We calculated the QTC_c according to Hanheide et al. [11] as follows:

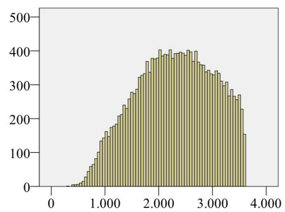
(1) movement of the robot r with respect to the *customer* c:
 - 1 : r is moving towards c
 +1 : r is moving away from c
(2) movement of c with respect to r
 same as (1), but with r and c swapped
(3) movement of r with respect to RL:
 -1: r is moving to the left-hand side of RL
 0 : r is moving along RL or not moving at all
 +1 : r is moving to the right-hand side of RL
(4) movement of c with respect to RL
 same as (3), but with r substituted by c

Therefore, a crossing situation is given when: (1)= -1, (2)= -1, (3) = -1·(4) or (3)=(4)=0.

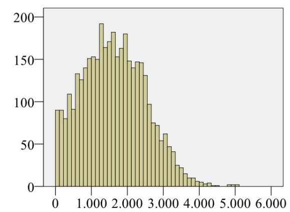
Calculating Spatial Features: For the purpose of reducing the amount of data we calculated one feature vector for every 15 frames. Thus, we get 15 feature vectors for one second of recorded data. Additionally, to the aforementioned spatial features we determined the action a (drive, stop, curve, rotate) the robot is performing (see Fig. 2(a)). Thus, we transformed position data points into action related spatial feature vectors containing the action a, distance between customer and robot d, distance between *customer* and the crossing point d_c, distance between robot and the crossing point d_r, angle robot-*customer* α, velocity *customer* v, and the QTC_c values.

$$(a, d, d_c, d_r, \alpha, v, QTC_c)$$

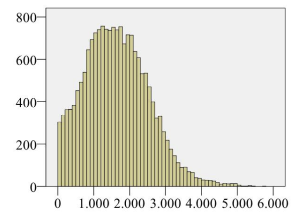
In order to concentrate only on the main strategy we excluded all feature vectors with curve and rotate actions. We identified the crossing situations by using the QTC_c [11] information and excluded all non-crossing situations. We also excluded all feature vectors where the robot is outside of the *customer's* social space ($d > 3.6m$) [10]. Note



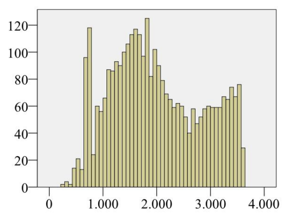
(a) d for action = drive
$Mdn = 2.32m$



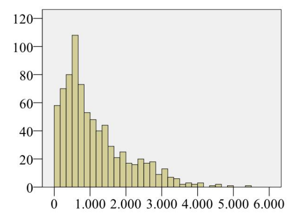
(b) d_c for action = drive
$Mdn = 1.58m$



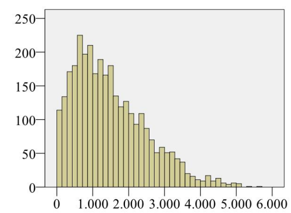
(c) d_r for action = drive
$Mdn = 1.59m$



(d) d for action = stop
$Mdn = 1.85m$



(e) d_c for action = stop
$Mdn = 0.85m$



(f) d_r for action = stop
$Mdn = 1.29m$

Fig. 3. Histograms of the distance values for action = {stop, drive} measured in mm

that we have far more than one feature vector per crossing situation, because different to the video analysis, where we were only counting the reaction for a crossing situation, we now consider every data point of a crossing situation. Furthermore, due to the fact that the robot drives before it stops we have more feature vectors for the action drive than for the action stop.

Statistical Data Analysis The aim of the statistical data analysis, which was performed with SPSS, was to find support for our hypothesis: ”can we predict the action based on the spatial features”.

First of all we show the distributions for the distance values (d, d_c, d_r) in Fig. 3.2. The histograms in Figure 3.2 show, that there is a trend for greater distances for the drive action and that most of the participants stop the robot within a distance of approximately 0.7 m to the crossing point whereby the *customer* has a distance of approximately 0.67 m to the crossing point.

By performing inferential statistic tests, we found support for our hypothesis that the spatial features are correlated with the action. Due to the dichotomous action variable we calculated the point-biserial correlation coefficients. The action of the robot was significantly related to the distance between *customer* and robot d, $r_{pb} = .149$, $p < .01$, to the distance between *customer* and the crossing point d_c, $r_{pb} = .200$, $p < .01$, to the distance between robot and the crossing point d_r, $r_{pb} = .063$, $p < .01$, to the angle robot- *customer* α, $r_{pb} = .027$, $p < .01$, and to the *customer's* velocity v, $r_{pb} = .054$, $p < .01$.

As a next step to support our hypothesis that we can predict the action based on the spatial features, we performed a logistic regression on the normalized spatial feature values. Results are shown in Table 1. Only the angle has no significant influence on the classification model ($B = .06, p = .396$). All other variables have a significant influence and the model is able to predict 86.7 % of the actions correctly. Additionally

Table 1. Results of the logistic regression, performed with SPSS

Value	B (SE)	Lower	Odds Ratio^a	Upper
distance d	-1.023** (.086)	.304	.359	.425
velocity v	-.515** (.037)	.556	.598	.643
angle α	.060 (.71)	.924	1.062	1.221
distance robot d_r	.648** (.081)	1.630	1.912	2.243
distance customer d_c	-.255** (.071)	.674	.775	.892
constant	-2.131 (.059)		.119	

** $p < 0.001$, ^{a}95% CI for Odds Ratio

Model Statistics

$R^2 = .15$ (Cox & Snell), .25 (Nagelkerke)
$\chi^2(8) = 106.097, p < 0.001$ (Hosmer & Lemeshow)
accuracy 86.7% (goodness-of-fit)

to the logistic regression we trained a Support Vector Machine SVM with a RBF Kernel [6] in order to show that we can precisely predict the expected action based on the spatial features. The results of a ten-fold-cross-validation, performed with LibSVM [5] are shown in Table 2. The very good prediction results also support our hypothesis.

Table 2. Results of the ten-fold-cross-validation of the SVM model performed with LibSVM [5]

accuracy	99.9527%	f-score	0.999764
precision	100%	recall	99.9527%

4 Discussion

The study at hand was conducted to identify expected robot navigation behavior. In the video analysis we found a prominent robot behavior. Driving straight towards the goal and, when a crossing situation occurs, either stop and wait until the customer passes the robot's path or drive on and pass the path of the person before or behind the person. Thus, the expected actions a are $drive$ towards the goal and $stop$. We hypothesized that the stimulus lies in the spatial relationship. Therefore, we used the motion capturing data to identify the stimulus s and calculated several spatial features. We used the QTC_c [11] representation to identify a crossing situation and extended these purely relative representations with distance measures, the crossing angle, and velocity information. We found support for our hypothesis that the spatial relationship is significantly correlated with the action. Furthermore we could show that it is possible to predict the expected action based on our spatial features whereby we found that the distance measures are the most influential values. Additionally, we could show that it is possible to precisely predict the action, by using a Support Vector Machine.

The overall navigation strategy, that we found in our data, is similar to the behavior Basili et al. [3] found in their human-human path crossing experiment. In both studies the participants were going (driving the robot) straight towards the goal and show a collision avoiding strategy by manipulating the speed. In our case by stopping and in their case by decreasing the speed.

However, the findings of the study at hand are significant, but the correlation values are rather low. The reason can be failures in the used equipment, which causes much noise in our data. Sometimes a stop was caused by loosing the connection to the robot or we lost a marker due to occultation. Furthermore, in the study at hand the participants only had a third person view from a fixed point in the room. This fact makes it difficult for the participants to exactly estimate distances, which can also be the reason for the rather low correlation values. Another limitation of the study is the small set of crossing angles and the missing of a frontal approach. Furthermore, the actions are limited. Due to safety reasons we does not provide the option to manipulate the robots' speed.

The aforementioned limitations can be the basis for further investigations of robot navigation behavior. For example, by implementing more controlled experiments, based on our findings, one can avoid the noise and find more precise thresholds for the distance values. Also a first person view by using a camera on the robot can yield more precise results. Furthermore, it could be useful to evaluate the identified robot navigation patterns and test how they are perceived by a human in order to verify our hypothesis that we can find out human expectations about robot behavior by using our "Inverse Oz of Wizard" study design. This can be done by doing it the other way around in a experiment where the behavior of the robot is scripted and the participants are asked to rate the behavior.

5 Conclusion

To sum up, we conducted a study to identify robot behavior patterns in a human robot path crossing scenario. The overall navigation strategy we can conclude from the data is to drive straight towards the goal and only react (stop) to a crossing human when the stimulus based on the spatial relationship predicts to stop, otherwise drive on towards the goal. The expected action can be predicted by using a standard machine learning method like an SVM trained on our dataset. Based on these findings and by using our SVM model, we can develop a social navigation method, that meets human expectations about robot navigation behavior.

References

1. Philipp Althaus, H. Ishiguro, T. Kanda, T. Miyashita, and H.I. Christensen. Navigation for Human-Robot Interaction Tasks. In *IEEE International Conference on Robotics and Automation*, 2004.
2. Ronald C Arkin. *Behavior-Based Robotics*. MIT press, 1998.
3. Patrizia Basili, Murat Sag, Thibault Kruse, Markus Huber, Alexandra Kirsch, and Stefan Glasauer. Strategies of Locomotor Collision Avoidance. *Gait & Posture*, 2012.
4. John Travis Butler and Arvin Agah. Psychological Effects of Behavior Patterns of a Mobile Personal Robot. *Autonomous Robots*, 2001.
5. Chih-Chung Chang and Chih-Jen Lin. LIBSVM: A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems and Technology*, 2, 2011. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.
6. Nello Cristianini and John Shawe-Taylor. *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*. Cambridge university press, 2000.

7. K. Dautenhahn, M. Walters, S. Woods, K.L. Koay, C.L. Nehaniv, A. Sisbot, R. Alami, and T. Siméon. How May I Serve You? A Robot Companion Approaching a Seated Person in a Helping Context. In *ACM SIGCHI/SIGART Conference on Human-Robot Interaction*, 2006.
8. Kerstin Dautenhahn. Methodology and Themes of Human-Robot Interaction: A Growing Research Field. *International Journal of Advanced Robotic Systems*, 2007.
9. Anders Green, Helge Huttenrauch, and K Severinson Eklundh. Applying the Wizard-of-Oz Framework to Cooperative Service Discovery and Configuration. In *IEEE International Workshop on Robot and Human Interactive Communication*, 2004.
10. Edward T. Hall. *The Hidden Dimension*. Anchor Books New York, 1969.
11. Marc Hanheide, Annika Peters, and Nicola Bellotto. Analysis of Human-Robot Spatial Behaviour Applying a Qualitative Trajectory Calculus. In *IEEE International Workshop on Robot and Human Interactive Communication*, 2012.
12. Helge Hüttenrauch, K Severinson Eklundh, Anders Green, and Elin Anna Topp. Investigating Spatial Relationships in Human-Robot Interaction. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006.
13. Adam Kendon. *Conducting Interaction: Patterns of Behavior in Focused Encounters*, volume 7. CUP Archive, 1990.
14. Rachel Kirby, Reid Simmons, and Jodi Forlizzi. COMPANION: A Constraint-Optimizing Method for Person-Acceptable Navigation. In *IEEE International Symposium on Robot and Human Interactive Communication*, 2009.
15. Thibault Kruse, Alexandra Kirsch, E. Akin Sisbot, and Rachid Alami. Dynamic Generation and Execution of Human Aware Navigation Plans. In *International Conference on Autonomous Agents and Multiagent Systems*, 2010.
16. Thibault Kruse, Amit Kumar Pandey, Rachid Alami, and Alexandra Kirsch. Human-Aware Robot Navigation: A Survey. *Robotics and Autonomous Systems*, 2013.
17. Christina Lichtenthäler, Tamara Lorenz, and Alexandra Kirsch. Influence of Legibility on Perceived Safety in a Virtual Human-Robot Path Crossing Task. In *IEEE International Symposium on Robot and Human Interactive Communication*, 2012.
18. Christina Lichtenthäler, Annika Peters, Sascha Griffiths, and Alexandra Kirsch. Be a Robot ! Robot Navigation Patterns in a Path Crossing Scenario. In *Proceedings of the 8th ACM/IEEE International Conference on Human Robot Interaction*, 2013.
19. Jonathan Mumm and Bilge Mutlu. Human-Robot Proxemics: Physical and Psychological Distancing in Human-Robot Interaction. In *ACM/IEEE International Conference on Human-Robot Interaction*, 2011.
20. Elena Pacchierotti, Henrik I Christensen, and Patric Jensfelt. Human-Robot Embodied Interaction in Hallway Settings: a Pilot User Study. In *IEEE International Workshop on Robot and Human Interactive Communication*. IEEE, 2005.
21. Emrah Akin Sisbot, Luis F Marin-Urias, Rachid Alami, and Thierry Simeon. A Human Aware Mobile Robot Motion Planner. *IEEE Transactions on Robotics*, 23, 2007.
22. Aaron Steinfeld, Terrence Fong, David Kaber, Michael Lewis, Jean Scholtz, Alan Schultz, and Michael Goodrich. Common Metrics for Human-Robot Interaction. In *ACM SIGCHI/SIGART Conference on Human-Robot Interaction*, 2006.
23. Aaron Steinfeld, Odest C Jenkins, and Brian Scassellati. The Oz of Wizard: Simulating the Human for Interaction Research. In *ACM/IEEE International Conference on Human-Robot Interaction*, 2009.
24. Leila Takayama and Caroline Pantofaru. Influences on Proxemic Behaviors in Human-Robot Interaction. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009.
25. S Tranberg Hansen, Mikael Svenstrup, Hans Jørgen Andersen, and Thomas Bak. Adaptive Human Aware Navigation Based on Motion Pattern Analysis. In *IEEE International Symposium on Robot and Human Interactive Communication*, 2009.
26. Mitsumasa Yoda and Yasuhito Shiota. The Mobile Robot which Passes a Man. In *IEEE International Workshop on Robot and Human Communication*, 1997.