Socially-Aware Navigation: Action Discrimination to Select Appropriate Behavior

Santosh Balajee Banisetty † and **Meera Sebastian** ‡ and **David Feil-Seifer** ∗
Computer Science & Engineering
University of Nevada, Reno
1664 N.Virginia Street, Reno
Nevada 89557-0171
Email: santoshbanisetty@nevada.unr.edu †, meerasebastian@nevada.unr.edu ‡ and dave@cse.unr.edu ∗

Abstract

In this paper, we study if modeling can help discriminate actions which in turn can be used to select an appropriate behavior for a mobile robot. For human-human interaction, a significant social and communicative information can be derived from interpersonal distance between two or more people. If Human-Robot Interaction reflects this human-human interaction property, then interpersonal distance between a human and a robot contains similar social and communicative information. An effective robot's actions, including actions associated with interpersonal distance, must be suitable for a given social circumstance. Studying interpersonal distance between a robot and a human is very important for assistive robots. We use autonomously detected features to develop such an interpersonal model using Gaussian Mixture Model (GMM) and demonstrate that such a learned model can discriminate different human actions. The proposed approach can be used in a socially-aware planner to weight trajectories and select actions that are socially appropriate for a given social situation.

Introduction

In the near future, socially assistive robotics (SAR) will help people in real-world environments. These robots have to navigate from one point to another in public places where socially appropriate behavior is very important for a good Human-Robot Interaction (HRI). In order for robots to operate in homes and workplaces, it is essential for such a robot to navigate in a socially appropriate way. Failure to do so could be deleterious for long-term acceptance of a robot.

Significant social communication can be derived from interpersonal distance between two or more people. Similarly, HRI research has demonstrated that the interpersonal distance between a human and a robot contains similar social and communicative information as in human-human interaction. For a robot to be integrated into real-world environments, its actions, including actions associated with interpersonal distance, must be suitable for the given social circumstance. Hence, studying interpersonal distance between a robot and a human is very important for robots in the real-world.

The paper classifies the features that enable socially-aware navigation into three main categories namely comfort, naturalness and sociability. Our main contributions in this paper is an approach to discriminate various human-human interactions related to navigation and predict the occurrence of an event before it is complete. We lay out a plan for both objectively and subjectively evaluating the performance of a system utilizing this discrimination technique.

Copyright © 2016, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

Background

An ethnographic study (Mutlu and Forlizzi 2008) showed that inappropriate navigation behavior caused users to not adopt the robot for long-term use. One of the informants from the study stated:

"*Well, it almost ran me over... I wasn't scared... I was just mad... I've already been clipped by it. It does hurt.*"

These kind of problems arise when a robot treats humans as another dynamic object while navigating in an environment. Robots should treat humans as social beings and should respect their social space. Our goal is to aid acceptance of assistive robots by improving its navigation behavior. Socially-aware navigation can be improved by considering social information along with goal and plan information when executing navigation behavior.

Problems such as these has made socially-aware navigation (SAN) an active area of research (Feil-Seifer and Matarić 2011), (Kruse et al. 2013), (Mead and Matarić 2016). Autonomous robots deployed in human environments like public places communicated primitive intent in a very primitive and explicit social manner (Burgard et al. 1999). Butler and Agah (Butler and Agah 2001) found that for approaching a human, a velocity of 1 m/s made subjects uncomfortable, while 0.5 m/s was acceptable. Kirby modeled the socially appropriate behavior of passing a person by maintaining the right side of the hallway using a cost grid based framework (Kirby, Simmons, and Forlizzi 2009). Saulnier (Saulnier, Sharlin, and Greenberg 2010) studied how various types of non-verbal cues in the robot body language can a person notice in a natural way. Taking into account, visibility and safety criteria, Sisbot (Sisbot et al. 2007), (Sisbot et al. 2006) implemented a Human-Aware Manipulation Planner (HAMP) using a visibility and safety grid based approach. Other research conducted by J. Rios-Martinez (Rios-Martinez, Spalanzani, and Laugier 2015) presents important concepts pertaining to social conventions from both sociology and robotics perspective.

Prediction of human motion is gaining interest in the field of SAN because interpersonal movement is seen as a type of body language. It is beneficial for a robot to have an understanding of what other people are intending to do so that it can plan appropriately. We will achieve this prediction by discriminating between several models of human behaviors given detailed social factors.

Geometric reasoning based prediction

Hanheide (Hanheide, Peters, and Bellotto 2012) adopted a Qualitative Trajectory Calculus (QTC) as the formal foundation for the analysis and representation of human-robot Joint Spatial Behavior (JSB). A collision avoidance method was proposed (Ohki, Nagatani, and Yoshida 2010) that estimates the motions and personal spaces. The method calculates the future position of each obstacle from its past motion. Althoff (Althoff et al. 2012) used Monte Carlo sampling to estimate the collision probabilities. A motion planning method for mobile robots was proposed by Tadokoro (Tadokoro et al. 1995) that coexist and cooperate with human being to avoid collision. The motion predictor used a stochastic process model to predict the human motion. Kushleyev (Kushleyev and Likhachev 2009) used a time-bounded lattice that merges together short-term planning in time with long-term planning without time to develop a path planning algorithm that tracks and predicts the trajectories of moving objects. The approaches all model the motion properties of people as moving obstacles, without considering their intention.

Machine learning based prediction

Ziebart (Ziebart et al. 2009) used a variant of Markov decision processes (MDP) to generate a feature-based model to predict pedestrians motion. Chung (Chung and Huang 2010) presented a spatial behavior cognition model (SBCM) using pedestrian ego-graph (PEG) to efficiently predict pedestrians' trajectories. Chung (Chung and Huang 2012) followed the framework of Spatial Behavior Cognition Model (SBCM) and proposed that this model can be easily extended to different kinds of behavior understanding by representing spatial effects in the feature space. A more high-level prediction based on previous experiences was given by Hansen (Hansen et al. 2009), who showed an approach to determine if a person intends to interact with the robot based on people trajectories and the results demonstrate that the robotic system can adopt to different behaviors and is able to learn navigation based on previous experiences. By analyzing the observed trajectories using SVM, Satake (Satake et al. 2009) developed a model for a robot to approach a human taking into consideration the personal and social spaces proposed by Hall (Hall 1966). (Mead and Matarić 2016) presents work based on data-driven probabilistic models approach of a computational framework of proxemics on how social signals like speech and gesture are produced by a human and how they are perceived by a machine (robot). The results show that interaction potential significantly increases with the proposed model.

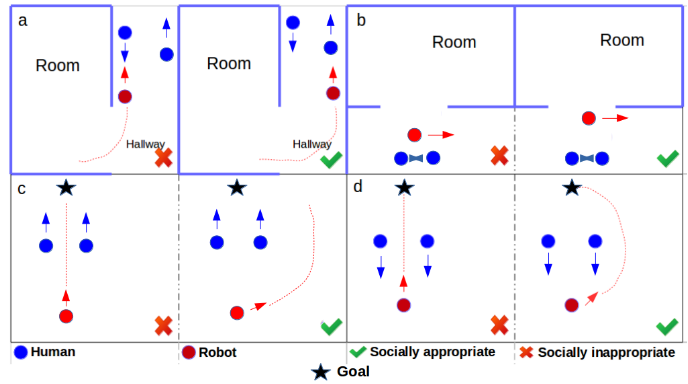

Figure 1: Some examples of socially appropriate/inappropriate navigation scenarios. a) People passing in a hallway, b) People meeting in a hallway, c) people walking towards a goal and d) people walking away from a goal.

One drawback with the above research works related to socially-aware navigation is that most of them deal with only one person interacting with the robot. We propose a learning model that will learn from data that consists of navigation data of more than one person and will be able to deal with social issues related to navigation involving multiple humans in a more natural way. This model should consider interpersonal motion features of agents executing interrelated motions. Our approach utilizes models of human human interactions to achieve the goal of friendly human robot interactions which aid the long-term adoption of robots in public environments.

Approach

Prior work (Feil-Seifer and others 2012) presented and validated an approach to using spatial models of distance-based features on fully implemented robot systems. In this paper we are extending the findings from our previous work by creating a more robust and sophisticated model using more features and that can discriminate between a set of possible 2-agent social actions in real-time.

Models of appropriate social behavior are learned from logged data of human-human interaction. We collected a training set of 24 recordings for each scenario (people passing in a hallway, people meeting in the hallway, people walking together towards a goal and people walking together away from a goal) recorded from a floor-level 30m laser scanner. We identify people and relevant aspects in the environment (in this case, the location of hallways) and use relative distances as features of the model. This model was then used to classify a social action as one of the trained models.

Given the fact that humans learn social conventions along many years of social interactions, while robots will not have the same time frame to learn. We collect a good amount of human-human navigation data to construct a model using Gaussian Mixture Model. This model will be used to calculate an appropriateness score for a given social situation during the robot's interaction with humans. Based on the appropriateness score, the modified trajectory planner drives the robot towards its goal in a socially appropriate manner which will be discussed in a later section.

Figure 1 shows various scenarios of socially appropriate/inappropriate navigation behaviors of robots. (Scenario A). hallway situation where navigating on the right is socially appropriate (US), in Asian countries like India walking on the left is appropriate. (Scenario B). When two or more people are interacting (meeting), their personal space is larger than usual so, moving close to them is inappropriate and the robot should leave more room in this situation. (Scenario C and D). A robot should not pass between two humans thereby interrupting their conversation. It should instead choose to navigate around them or ask permission to move between them. Few other such situation are: giving precedence to humans is appropriate in situations like entering a room. The robot should maintain a distance from people not to just avoid collision but also to prevent discomfort from an invasion of personal space but close enough to maintain a social communication. The concept of personal space around a person that humans mutually respect called *proxemics* was proposed by Edward T. Hall (Hall 1966). In each of these scenarios, the socially optimal path is not the optimal path for a traditional navigation planner, which finds the shortest path toward a goal that avoids all obstacles.

We extracted a 9-dimensional feature vector of interpersonal distances and environmental information: v=$\langle t,d^r_{p1},d^r_{p2},d^r_L,d^r_R,d^{p1}_L,d^{p1}_R,d^{p2}_L,d^{p2}_R,d_{p1-p2}, \quad d_{p1L-p2L}\rangle$ where t denotes the normalized time, d^r_{p1} denotes the distance between a goal and person 1, d^r_{p2} denotes the distance between a goal and person 2, d^r_L denotes the distance between a goal and the left of the hallway, d^r_R denotes the distance between a goal and the right of the hallway, d^{p1}_L denotes the distance between person 1 and the left of the hallway, d^{p1}_R denotes the distance between person 1 and the right of the hallway, d^{p2}_L denotes the distance between person 2 and the left of the hallway, d^{p2}_R denotes the distance between person 2 and the right of the hallway, d_{p1-p2} denotes the inter person distance between person 1 and person 2, $d_{p1L-p2L}$ denotes the difference between person 1 hallway left and person 2 hallway left. The example appropriate movements were then modeled using expectation maximization to create a Gaussian Mixture Model (GMM) (McLachlan and Peel 2004) in MATLAB. The people, hallways, and the feature vector were calculated from data recorded from a floor-level laser scanner. The laser scanner was used to detect humans and hallways in the environment (see Figure 3). Hallways were detected from the laser data by using Hough Transforms to find parallel straight lines. People were found and tracked using laser scanner with the *leg_detector people_msgs* ROS packages (Pantofaru). Figure 4 shows all the scenarios in which the data were collected.The developed system was demonstrated using the PR2 to evaluate the resultant navigation behavior. One such GMM plot is shown in Figure 2.

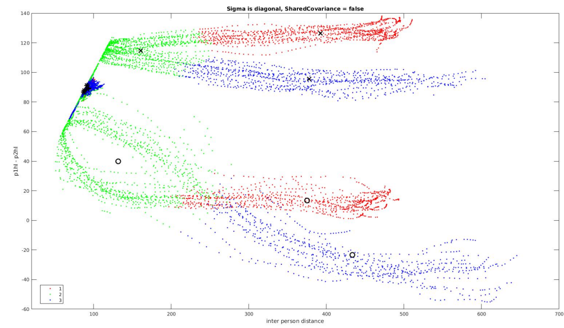

Figure 2: Plot showing the GMM fit to the data, inter person distance vs p1 hallway left - p2 hallway left.

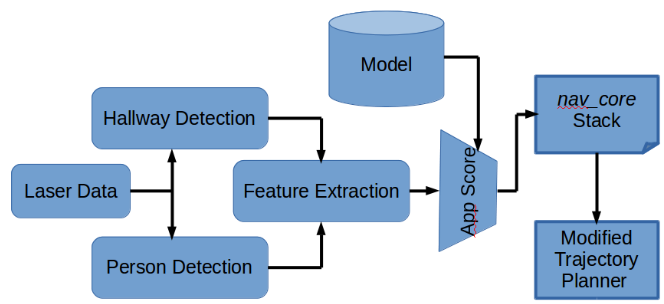

Figure 3: Block diagram explaining the overview of our approach

Results

We used 20 of the 24 recordings as training set for each scenario, we used the remaining 4 recordings as a test set for each scenario to test the model and the results of accuracy of the GMM model in all four scenarios are shown in table 1. The training set of S1, S2, S3 and S4 consists of 3804, 3765, 4062, 3986 samples respectively and the test set consists of 898, 743, 751, 822 samples respectively.

- S1: Two people passing each other in a hallway
- S2: Two people meeting in a hallway
- S3: Two people walking towards a goal
- S4: Two people walking away from a goal
- D1: Passing data
- D2: Meeting data
- D3: Towards a goal data
- D4: From a goal data

Table 1 shows that the proposed model was able distinguish between people passing each other, people meeting, people walking towards a goal location and people walking away from a goal location. The probability density function (pdf) of the data was much higher in the respective model when compared with pdf of the data in other models. In other models, the pdf is either 0 or very small.

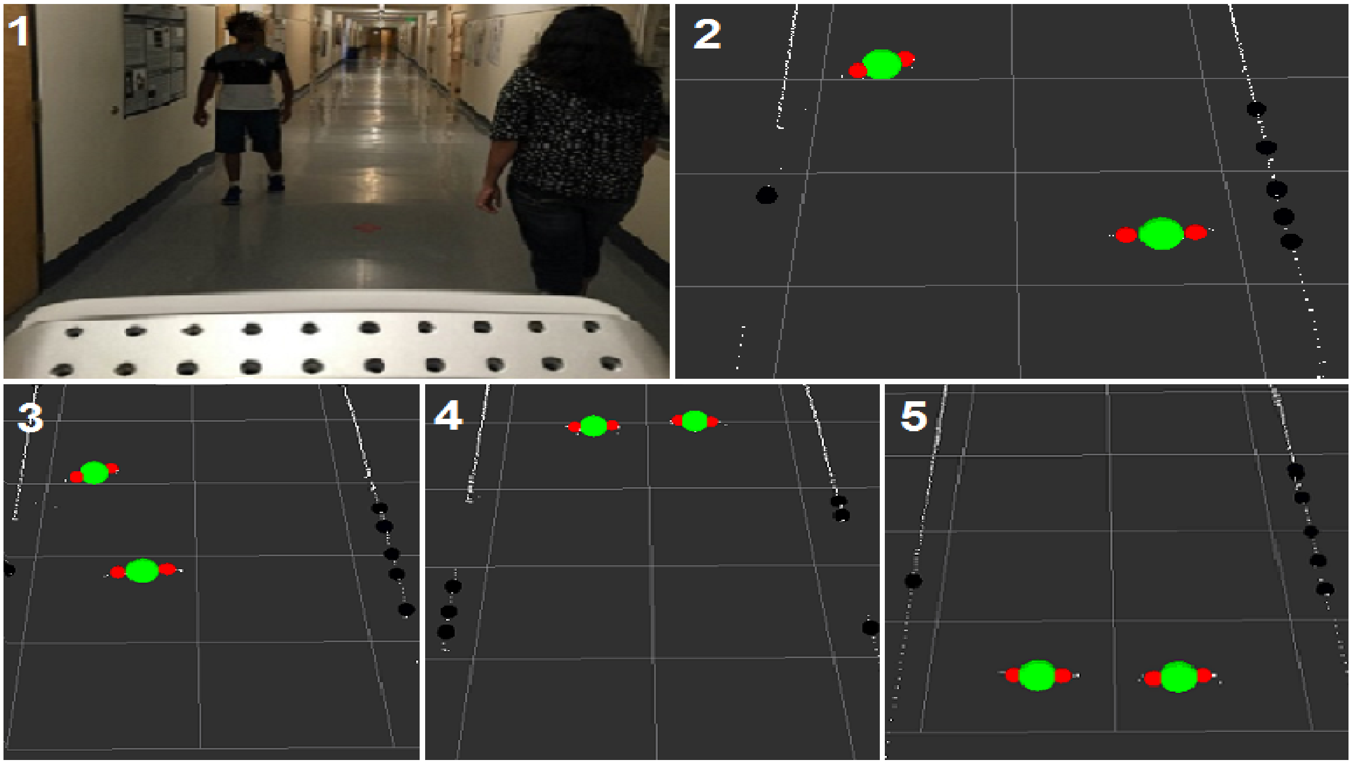

Figure 4: 1. Shows the real picture of PR2 watching people. 2,3,4,5 shows the RVIZ screen capture of PR2 tracking people in all the four scenarios, Passing, Meeting, Walking towards a goal and Walking away from a goal respectively.

*	S1	S2	S3	S4
D1	100.00	0.00	0.00	0.00
D2	0.00	100.00	0.00	0.00
D3	0.00	0.00	91.61	8.39
D4	0.00	0.00	12.77	87.22

Table 1: Table showing accuracy (in percentage) of the GMM in all the four scenarios.

Future Work and Discussion

Socially-Aware Planner

We have previously developed a socially-aware navigation planner that utilized a single model of social behavior. The socially-appropriate behavior comes from a modification of *nav_core* package of Robot Operating System (ROS) (Quigley et al. 2009). The modified trajectory planner (socially-aware planner) uses the social model discussed above to weight candidate trajectories and give greater precedence to socially appropriate trajectories over the most efficient, shortest path etc. resulting in social appropriate navigation for a given social situation. We were also able to use the proposed models to predict an event before it is complete. The prediction time is less than 0.3t which leaves enough time for the socially-aware planner to plan and execute its actions that are appropriate to a social situation.

Our current technical work is to modify this planner to utilize several models and discriminate between those models autonomously depending on the social situation as described in this paper. Figure 3 shows the block diagram of the system under implementation. Future work will evaluate the performance of such a system for purely social goals (e.g., maintaining social distance with an interaction partner) and for environmental goals (e.g., move to a particular place while being accompanied by a person). The rest of this section will detail a proposed evaluation plan.

Evaluation Plan

After bridging socially-aware navigation model and socially-aware planner, we will evaluate the entire system by conducting in-person and observer experiments.

The in-person experiments will be a 2x2 between-participants study with two factors, interaction partner and navigation type. The interaction partner factor will have two levels, human partner and robot partner. The navigation type factor will have two levels, traditional navigation behavior and Socially-Aware Navigation behavior. We will recruit 40 participants. Participants will be asked to interact with a partner (human or robot) for the developed navigation tasks. After the session, the participants will be asked to rate the robot (and its behavior). Participants will answer a pre-questionnaire which includes demographic questions. After the experiment session, participants will be asked to answer a post-questionnaire which includes questions related to the goals of Socially-Aware Navigation (Comfort, Naturalness, Sociability) as described by T. Kruse (Kruse et al. 2013) and the Godspeed questionnaire (Bartneck et al. 2009).

In the observer experiments, participants will watch an unaltered video (from side-view or overhead angles) and rate the robot's behavior. An alternative approach, which can be used to control for a viewer's perception of a robot in these tasks, is to use Heider & Simmel-style videos (Heider and Simmel 1944) that preserve the spatial relationships of the agents performing navigation actions, but conceal whether those agents are humans, robots, or neither. Observers can then rate agents' behavior for several subjective factors related to the spatial behavior communicated by their movement (Feil-Seifer and others 2012). The intent is to have the participants observe only the spatial relationships between the agents without picking up any social cues that might be observed with a more realistic representation.

Main Experiment Insights

Prior work (Feil-Seifer and Matarić 2011) and our current progress as discussed in results session demonstrate that by modeling human navigation behavior, we can achieve Socially-Aware Navigation. Current work demonstrates a hallway behavior which can be expanded for a general navigation in a workplace.

Our hypotheses are as follows:

H1 - Comfort. *People will be comfortable with the robot using Socially-Aware Navigation planner when compared with the traditional navigation planner.*

H2 - Sociability. *People will feel sociable with the robot using Socially-Aware Navigation planner when compared with the traditional navigation planner.*

H3 - Natural. *People think that the robot using Socially-Aware Navigation planner is natural when compared with the traditional navigation planner*

From the in-person experiments, the Likert scale responses of the subjects for the post questionnaire will be analyzed to validate our hypotheses. The post questionnaire will have questions to measure comfort, sociability and naturalness of the robot navigation. The responses from the observer experiments will be used to analyze how the observers are classifying the spatial relationships of the agent's navigation actions using adjectives like avoiding, ignoring etc. The percentage of right and wrong classification of the behaviors will indicate naturalness. Similarly, the video recordings will be used to analyze how the participants reacted to both navigation planners will measure comfort and sociability.

Our hypotheses will be supported if the participants rate the robot 4 or more on the 7-point Likert scale for an appropriate behavior and 3 or less for an inappropriate behavior. This shows that the modified planner will be more acceptable when compared to that of traditional navigational planner.

Conclusion

In this paper, we were able to discriminate between people walking with appropriate/inappropriate hallway behavior, people meeting situations and we were able to identify if two people are walking together as shown in figure 1. As the system can predict what people are doing, it can select its actions appropriately. For example, if the system identifies two people walking together, it will not pass between them provided if there is enough space around them. If not, it will ask permission to pass between them.

By modeling human navigation behavior, we are likely to address all three categories (Comfort, Sociability and Naturalness) identified by T. Kruse (Kruse et al. 2013) and make progress towards a Unified Socially-Aware Navigation planner. Our preliminary results show that by modelling human navigation behavior using a GMM, we can distinguish between various navigation scenarios, including those that have multi-modal distributions instead of a single solution. They key contribution from this paper is the discrimination between several human-human models of navigation behavior to quickly determine which navigation scenario is currently occurring. We plan to collect more data and construct more robust models which can be used by the robot to plan appropriate trajectories, taking into consideration the interacting person's navigation behavior. Once the proposed system is implemented, we will conduct HRI studies as discussed earlier.

Acknowledgment

The authors would like to acknowledge the financial support of this work by Office of Naval Research (ONR) under *Designing Collaborator Robots for Highly-Dynamic Multi-Human, Multi-Robot Teams*, and *DURIP: Humanoid Platforms for Human-Robot Collaboration* grants and University of Nevada, Reno Provost's Office under *Instructional Enhancement Grant: Robotics for Experimentation in the classroom*.

References

Althoff, D.; Kuffner, J. J.; Wollherr, D.; and Buss, M. 2012. Safety assessment of robot trajectories for navigation in uncertain and dynamic environments. *Autonomous Robots* 32(3):285–302.

Bartneck, C.; Kulić, D.; Croft, E.; and Zoghbi, S. 2009. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International journal of social robotics* 1(1):71–81.

Burgard, W.; Cremers, A. B.; Fox, D.; Hähnel, D.; Lakemeyer, G.; Schulz, D.; Steiner, W.; and Thrun, S. 1999. Experiences with an interactive museum tour-guide robot. *Artificial intelligence* 114(1):3–55.

Butler, J. T., and Agah, A. 2001. Psychological effects of behavior patterns of a mobile personal robot. *Autonomous Robots* 10(2):185–202.

Chung, S.-Y., and Huang, H.-P. 2010. A mobile robot that understands pedestrian spatial behaviors. In *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, 5861–5866. IEEE.

Chung, S.-Y., and Huang, H.-P. 2012. Incremental learning of human social behaviors with feature-based spatial effects.

In *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, 2417–2422. IEEE.

Feil-Seifer, D., and Matarić, M. 2011. People-aware navigation for goal-oriented behavior involving a human partner. In *Development and Learning (ICDL), 2011 IEEE International Conference on*, volume 2, 1–6. IEEE.

Feil-Seifer, D., et al. 2012. Distance-based computational models for facilitating robot interaction with children. *Journal of Human-Robot Interaction* 1(1).

Hall, E. T. 1966. The hidden dimension .

Hanheide, M.; Peters, A.; and Bellotto, N. 2012. Analysis of human-robot spatial behaviour applying a qualitative trajectory calculus. In *RO-MAN, 2012 IEEE*, 689–694. IEEE.

Hansen, S. T.; Svenstrup, M.; Andersen, H. J.; and Bak, T. 2009. Adaptive human aware navigation based on motion pattern analysis. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, 927–932. IEEE.

Heider, F., and Simmel, M. 1944. An experimental study of apparent behavior. *The American Journal of Psychology* 57(2):243–259.

Kirby, R.; Simmons, R.; and Forlizzi, J. 2009. Companion: A constraint-optimizing method for person-acceptable navigation. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, 607–612. IEEE.

Kruse, T.; Pandey, A. K.; Alami, R.; and Kirsch, A. 2013. Human-aware robot navigation: A survey. *Robotics and Autonomous Systems* 61(12):1726–1743.

Kushleyev, A., and Likhachev, M. 2009. Time-bounded lattice for efficient planning in dynamic environments. In *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*, 1662–1668. IEEE.

McLachlan, G., and Peel, D. 2004. *Finite mixture models*. John Wiley & Sons.

Mead, R., and Matarić, M. J. 2016. Autonomous human–robot proxemics: socially aware navigation based on interaction potential. *Autonomous Robots* 1–13.

Mutlu, B., and Forlizzi, J. 2008. Robots in organizations: the role of workflow, social, and environmental factors in human-robot interaction. In *Human-Robot Interaction (HRI), 2008 3rd ACM/IEEE International Conference on*, 287–294. IEEE.

Ohki, T.; Nagatani, K.; and Yoshida, K. 2010. Collision avoidance method for mobile robot considering motion and personal spaces of evacuees. In *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, 1819–1824. IEEE.

Pantofaru, C. *Leg Detector*.

Quigley, M.; Conley, K.; Gerkey, B.; Faust, J.; Foote, T.; Leibs, J.; Wheeler, R.; and Ng, A. Y. 2009. Ros: an open-source robot operating system. In *ICRA workshop on open source software*, volume 3, 5.

Rios-Martinez, J.; Spalanzani, A.; and Laugier, C. 2015. From proxemics theory to socially-aware navigation: A survey. *International Journal of Social Robotics* 7(2):137–153.

Satake, S.; Kanda, T.; Glas, D. F.; Imai, M.; Ishiguro, H.; and Hagita, N. 2009. How to approach humans?-strategies for social robots to initiate interaction. In *Human-Robot Interaction (HRI), 2009 4th ACM/IEEE International Conference on*, 109–116. IEEE.

Saulnier, P.; Sharlin, E.; and Greenberg, S. 2010. Exploring minimal nonverbal interruption in social hri.

Sisbot, E. A.; Clodic, A.; Marin, L.; Fontmarty, M.; Brethes, L.; and Alami, R. 2006. Implementing a human-aware robot system. In *Robot and Human Interactive Communication, 2006. ROMAN 2006. The 15th IEEE International Symposium on*, 727–732. IEEE.

Sisbot, E. A.; Marin-Urias, L. F.; Alami, R.; and Simeon, T. 2007. A human aware mobile robot motion planner. *Robotics, IEEE Transactions on* 23(5):874–883.

Tadokoro, S.; Hayashi, M.; Manabe, Y.; Nakami, Y.; and Takamori, T. 1995. On motion planning of mobile robots which coexist and cooperate with human. In *Intelligent Robots and Systems 95.'Human Robot Interaction and Cooperative Robots', Proceedings. 1995 IEEE/RSJ International Conference on*, volume 2, 518–523. IEEE.

Ziebart, B. D.; Ratliff, N.; Gallagher, G.; Mertz, C.; Peterson, K.; Bagnell, J. A.; Hebert, M.; Dey, A. K.; and Srinivasa, S. 2009. Planning-based prediction for pedestrians. In *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, 3931–3936. IEEE.