Bi-cultural Investigation of Collisions in Social Navigation

Xuesu Xiao[1], **Ross Mead**[2], **Reuth Mirsky**[3]
[1]Department of Computer Science, George Mason University, Virginia, USA
[2] Semio Inc., California, USA
[3] Department of Computer Science, Bar Ilan University, Israel
xiao@gmu.edu, mead@semio.ai, mirskyr@cs.biu.ac.il

Abstract

Imagine a service robot developed in the United States (US) being deployed in a public space in Israel. Due to the cultural differences, the robot from a "contact-averse" culture (i.e., the US) might find it difficult to find its way when navigating the crowd, as people from a "contact-tolerant" culture (i.e., Israel)—where a subtle touch between strangers is not uncommon—will always move closer to the robot than it would expect; conversely, an "Israeli" robot may be found too aggressive in US social spaces. Currently, these cultural differences hinder the ability to plug-and-play social robots in different cultures due to the requirement of extensive extra engineering effort. This paper presents a comparison of the results from an existing study conducted in the US with the same study design that was deployed in Israel. This comparison shows the clear, identifiable criteria that a socially aware robot will need to consider when navigating a new culture. More generally, the results from this paper offer a first step to identifying the cultural differences in social robot navigation so we can structure solutions to be compatible with these cultures and with novel ones, with minimum adaptation.

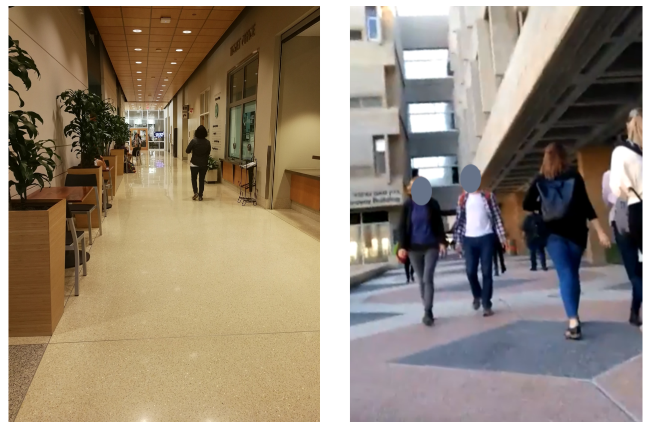

Figure 1: The two hallway-like environments in which the experiments were conducted. The left image shows the US environment and the right shows the Israel environment.

Introduction

We are entering a "golden era of robot adoption" (Gurdus 2021), as technological advances are enabling global market shifts from industrial robots designed to optimize the *quantity* of products for an organization (e.g., a business) to service robots designed to optimize the *quality* of services for an individual (i.e., a person). Unfortunately, this potential has been hindered by poor experiences and acceptance by the people in the target domains. To perform their tasks, service robots must operate in proximity to humans, including those whom the robot is directly serving as well as anyone else the robot indirectly encounters during the process. These robots are often mobile and rely on dynamic path-planning algorithms to autonomously navigate to their desired destination. Traditional robot navigation techniques often break down, as calculated robot trajectories violate social norms influenced by culture, causing the general public's resistance against the adoption of these mobile robot technologies in human-inhabited public spaces (The Seattle Times 2022; Bloomberg 2107; Haaretz 2022; Cities Today 2021).

Socially aware robot navigation has started to address this issue by differentiating between objects and humans within the environment, evaluating not just the *objective* safety of robots and objects, but also the *subjective* experiences of co-present humans during path planning and motion execution. However, as these human-centered navigation strategies garner success in one environment, they subsequently struggle in others, failing to capture micro- and macro-cultural differences expressed as social norms within small groups (e.g., families and workplaces) and large groups (e.g., communities and countries), respectively. For example, one of these norms is tolerance to contact between strangers: a service robot developed for a contact-averse culture (e.g., the US) being deployed in a contact-tolerant culture (e.g., Israel) might find it difficult to find its way around, as crowds in the contact-tolerant culture will always move closer to the robot than it would expect; conversely, a mobile robot designed for a contact-tolerant culture might be found too aggressive in a contact-averse culture (Hall 1966).

The embodiment of these cultural differences is often informed by "proxemics", which is the study of human *psychophysical* perceptions and *psychological* preferences with respect to the *physical* space around them (Hall 1966; Mead,

	Gaze Direction				Walk Alignment			
	US		Israel		US		Israel	
Conflict Type	Congruent	Incongruent	Congruent	Incongruent	Left	Right	Left	Right
Partial	25%	45%	8%	19%	45%	28%	50%	40%
Full	0	3%	23%	54%	1%	3%	35%	40%
No Conflict	75%	52%	69%	27%	54%	69%	15%	20%
Total Interactions	60	85	52	48	72	73	48	52

Table 1: Summary of the Interactions in the Trials in the US and in Israel.

Atrash, and Matarić 2012; Mead, Atrash, and Matarić 2013). Proxemic behavior is a dynamic process governed by the desired sensory experiences (e.g., visual, auditory, kinesthetic, tactile, etc.) of individuals in the environment (Hall 1963; Mead 2015; Mead and Matarić 2016), *the parameters for which largely vary by culture* (Hall 1966); however, formal cultural parameterizations and representations have been under-explored within socially aware robot navigation. To the best of our knowledge, no existing singular model of social robot navigation work has taken into consideration cultural differences and has been tested in more than one culture. To address this gap, we propose a preliminary investigation of *cultural influence on collision avoidance*. We present a *replication* of a social navigation study from the US that we re-conducted in a new country/culture (Israel) with different navigational norms than in the original study, and we discuss the findings from these trials. The results of this study help us quantify the effect of different proxemic models between the two cultures, by showing that in the US the number of full-contact collisions was much lower than in Israel, and that the norm of right-alignment to avoid collision is more apparent in the US compared to Israel. These results encourage us to continue and explore culturally adaptive social navigation algorithms and evaluation metrics, where we will use these identified parameters as controllable variables of a culturally-aware social navigation algorithm.

Related Work

We focus on work that goes beyond simply treating humans as dynamic, non-reactive obstacles (Burgard et al. 1999; Thrun et al. 2000). Researchers have modeled the uncertainty of human movements (Joseph et al. 2011; Bennewitz et al. 2005; Shiomi et al. 2014; Unhelkar et al. 2015) or prescribed social norms for navigating agents (Knepper and Rus 2012; Sisbot et al. 2007; Luber et al. 2010), and then devised navigation planners that can take such uncertainty into account for or abide by such selected rules. These models are based on human's behavior features, such as proxemics (Hall 1966; Goffman 2008; Hayduk 1981; Kirby, Simmons, and Forlizzi 2009; Takayama, Dooley, and Ju 2011; Torta, Cuijpers, and Juola 2013; Mead and Matarić 2016,?), intentions (Dragan, Lee, and Srinivasa 2013; Kruse et al. 2012; Szafir, Mutlu, and Fong 2015; Mavrogiannis, Thomason, and Knepper 2018; Hart et al. 2020), and social formations and spaces (Vázquez et al. 2015; Vroon et al. 2015; Fiore et al. 2013; Shiomi et al. 2014; Van den Berg, Lin, and Manocha 2008). More recently, machine learning approaches have been leveraged to learn representations or costmaps to implicitly capture the models and features mentioned above (Kim and Pineau 2016; Kretzschmar et al. 2016; Vasquez, Okal, and Arras 2014; Ziebart et al. 2009), to learn the parameterization of navigation planners (Liang et al. 2021; Xiao et al. 2020), or even to learn an end-to-end navigation policy that maps directly from raw or pre-processed perceptions of the humans in the scene to motor commands that drive the robot (Chen et al. 2017b,a; Everett, Chen, and How 2018). However, these existing approaches to social robot navigation suffer from drawbacks at least in two aspects: (1) most of these social robot navigation approaches have not been deployed in the wild for an extended period of time and their social compliance has not been properly benchmarked; and (2) most existing approaches have only considered either hand-crafted rules or collected navigation data rooted in one single culture. When facing a new culture, it is unclear how the existing system would behave and how much effort is required to enable adaptation (e.g., having to recreate all the models, social norms, and representations for that culture or recollecting another navigation dataset in that culture). These two drawbacks largely limit the wide adoption of autonomous mobile service robots in the wild and in different cultures around the globe, which is supported by the findings of cultural differences from our human ecological field study.

Experimental Design

In our human ecological field study, we investigated the extent to which social navigation interactions in shared spaces may be affected in different cultures by violating underlying social norms; for example, head pose and gaze are predictive of navigation trajectory (Patla, Adkin, and Ballard 1999; Unhelkar et al. 2015) and right-alignment is a default behavior for collision avoidance considering traffic rules. The first study was performed in a campus hallway at *Anonymized University* in the US, as part of a paper that was published on the implication of gaze direction on pedestrians (Hart et al. 2020). We extended this study with a second run, by looking at a circumscribed sidewalk at *Anonymized University* in Israel. Both locations become crowded during class changes.

In this study, research confederates walk in crowded areas, and when reaching a frontal approach with a pedestrian they have to shift either to the left or to the right to pass the pedestrian without a collision. The distance at which this shift occurred was set to be around $1m$ from the pedestrian, which is estimated to be the distance at which pedestrians will feel an intrusion into their personal space. In each country, the chosen confederates are native to the underlying culture and navigational social norms, such as acceptable passing distances and personal spaces. Moreover, for each interaction, the confederates chose to either look congruently with their movement direction, or the opposite way.

If the confederate and the pedestrian encounter problems walking around each other or nearly collide, the interaction is annotated as a "conflict". Conflicts are further divided into "full" (in which the two parties *gently* bump into each other) vs. "partial" (in which they brush against each other or abruptly shift to the left or right to pass after coming into conflict).

Two sets of conditions are evaluated in this study:

1. **Gaze Direction** was used to evaluate the influence of the confederate's gaze direction on the decision of the pedestrian to shift their movement direction in advance of a potential collision.
2. **Walk Alignment** was used to evaluate the influence of the direction the confederate shifted to on the decision of the pedestrian to move or not.

Results

In total, 245 interactions were recorded in these experiments, 145 in the US and 100 in Israel. Table 1 summarizes the results from these two experiments: on the left is the **Gaze Direction** experiment, and on the right is the **Walk Alignment** experiment. As seen in this table, there are significantly more *full* conflicts and much fewer *partial* conflicts in Israel than in the US, regardless of whether the confederates signal about their goal direction using their gaze. The high number of *full* collisions (i.e., the interaction between the confederate and the pedestrian is more likely to involve physical contact) suggests that the navigation culture in Israel is less contact-averse, a factor to consider for social robot navigation.

For the second part of the evaluation, the table shows on the right the number of *partial* and *full* collisions split by whether the confederate passes the pedestrians from the left or from the right. The number of collisions is significantly higher when the confederates turn left in the US, but there is no significant difference to either side in Israel. This result implies that while right-alignment is a default behavior for collision avoidance in the US, it is not the case in Israel, making it an additional factor to consider when designing a socially compliant mobile robot. The results of these two sets of experiments show that the US and Israel cultures use different social norms regarding collision avoidance in a crowded space.

Conclusion

In this paper, we present a study design for the evaluation of collision avoidance strategies across cultures with different navigational norms. We examined a study that originally took place in the US, and re-conducted it in Israel. As such, this new study covers two cultures: the US and Israel. We show the different behaviors of pedestrians in these countries under varying interaction modes: with a distracting gaze, and with an unconventional alignment. We observed that in Israel, full-contact collisions were more common, and left-alignment was less confusing than in the US. These results encourage us to continue and pursue additional comparisons of social navigation across cultures, such as bypassing and person following. Moreover, we expect that the results of this study will inform us in the design of new social robot navigation algorithms that will be culturally adaptive.

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