Perceived Social Intelligence as Evaluation of Socially Navigation

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ABSTRACT

As Human-Robot Interaction becomes more sophisticated, measuring the performance of a social robot is crucial to gauging the effectiveness of its behavior. However, social behavior does not necessarily have strict performance metrics that other autonomous behavior can have. Indeed, when considering robot navigation, a socially-appropriate action may be one that is sub-optimal, resulting in longer paths, longer times to get to a goal. Instead, we can rely on subjective assessments of the robot's social performance by a participant in a robot interaction or by a bystander. In this paper, we use the newly-validated Perceived Social Intelligence (PSI) scale to examine the perception of non-humanoid robots in non-verbal social scenarios. We show that there are significant differences between the perceived social intelligence of robots exhibiting SAN behavior compared to one using a traditional navigation planner in scenarios such as *waiting in a queue* and *group behavior*.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **User studies**; **Empirical studies in interaction design**.

KEYWORDS

metrics, socially-aware navigation, social intelligence

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1 INTRODUCTION

Robots can employ navigation behavior that considers social factors (such as personal space) in addition to common performance metrics (e.g., goal distance or path deviation) in order to improve how it is perceived by those around it. This consideration of social information is called Socially-Aware Navigation (SAN). Typically, social navigation behavior is evaluated using performance metrics that don't completely consider how people perceive the behavior of the robot. It can be hard to evaluate the SAN behavior as many actions that a robot can take to be more socially conscious would make the robot perform worse (more time to get to a goal, a longer path) than traditional navigation planners. Since such social behavior is for the benefit of the people around the robot, it is important to assess how we as humans perceive the robot from a social context.

Measuring the resultant performance of the robot system is a key challenge. Robot navigation behavior can typically be evaluated using objective performance metrics, such as time taken to goal, smoothness of movement, deviation from planned paths, efficiency, etc. [9, 16, 22]. However, socially-appropriate behavior often results in lower performance on these metrics in order to act in a socially-appropriate manner. Therefore, instruments to measure the social performance of a robot's actions is required. One way to comparatively evaluate SAN behavior is to assess the social intelligence of the robot. Social intelligence is defined as the ability to successfully interact or communicate with others to accomplish goals [10] and to navigate social environments [4].

When evaluating a robot, several metrics already exist for examining how a robot's behavior affects its perception. Commonly-used survey instruments examine either positive [6] or negative [18] feelings about a robot. However, some of these scales do not drive at a concept that is demonstrated by socially-aware behavior, social intelligence. Our perceptions of robots with SAN are measured imprecisely by the current survey instruments used in HRI research. Common constructs, such as *Intelligence* may refer to many aspects of intelligence, not merely social intelligence. We evaluate whether a newly-validated Perceived Social Intelligence (PSI) instrument [4] can be utilized to differentiate bystander responses to SAN behavior when compared to a traditional navigation planner.

In this paper, we extend prior work on socially-aware navigation planning [3] by measuring how people perceive the social intelligence of a robot as it navigates in multiple scenarios. We provide a quantitative understanding of how the social intelligence of robots is perceived with SAN compared to a traditional model of navigation. Assessing the perceived social intelligence of robots with SAN improves their applications in the real-world and how they interact/navigate around humans in a variety of social settings.

2 BACKGROUND

As social beings, we have a common understanding of what behaviors are appropriate for shared human-human interactions. If a robot can abide by these boundaries, it could give the impression that it knows the rules well enough to respect them. The adoption of socially assistive robots can suffer if the robots do not follow social norms that people value [17]. One open question for socially-aware navigation is, "*How do we evaluate social mapping/navigation*

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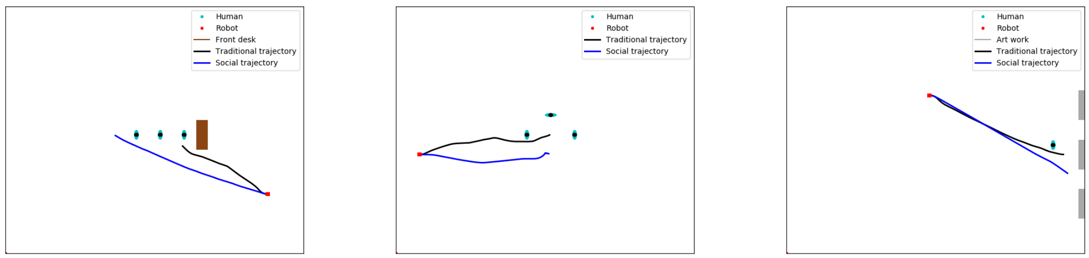

Figure 1: Trajectory for social and traditional models of navigation: *Left:* the waiting in a queue, showing a line forming in front of a desk; *Center:* joining a group; *Right:* joining a human observing art as indicated by the black and blue lines

techniques?" [7]. Using data reflecting this mutual understanding from human-human interaction to shape human-robot interactions (HRI) may help robots account for social norms. In this section, we will describe the principles of socially-aware navigation, evaluation of interpersonal robot navigation, and the role of social intelligence in the evaluation of human-robot interaction.

2.1 Social Navigation

Socially-aware navigation planners can accommodate for a person's space without invading it [2]. Prior work has extended this concept to include not just personal space but also group geometry, social goals to exhibit social behavior when navigating in scenarios such as *hallways*, *art galleries*, *joining a group of people*, and *waiting in line* [3]. Another work utilized examples of human-human interactions to score potential navigation trajectories for social appropriateness [23]. Inverse reinforcement learning (IRL)-based SAN uses human demonstrations of socially appropriate navigation [14] to learn socially-aware trajectories. Althoff *et al.* [1] presented a probabilistic framework for reasoning about the safety of trajectories generated by robots in a dynamic environment with uncertain data about the moving objects in the environment.

2.2 Evaluation of Social Navigation

Ramirez *et al.* [22] used trajectory difference metric (TDM) which is a modified Mean Square Error (MSE), evaluates every point of SAN trajectory to the closest point in the trajectory of HHI. For model-based methods, the probability that a trajectory confined to a particular interaction from HHI can be a great metric to determine if the robot is confined to a particular social norm [23]. Other objective performance metrics can include the number of times the robot was able to generate a collision-free social path, time taken to reach a goal, efficiency of the trajectory, efficiency of the algorithms [9] and number of proxemic intrusions [20] can be used. Obaid *et al.* [19] has asked subjective questions about the robot's behavior in a survey instrument such as the Negative Attitudes towards Robots Scale (NARS) [18] and the Godspeed Questionnaire Series (GQS) [6] that are widely used and standardized in the HRI community. Similarly, a perspective from a bystander outside the direct human-robot interaction can rate the robot's behavior. This can occur by presenting unaltered video and having a person rate the robot's behavior or Heider & Simmel-style videos [12] that 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 [8].

2.3 Considering Social Intelligence

Understanding how humans perceive a robot's social intelligence may be crucial to HRI research. When people interact, they orient themselves in a direction and distance that feels most comfortable for them. Research on human space has helped us understand how a robot invading different "zones" of space influences a human's perception of the robot [11]. Counting the number of proxemic intrusions might not validate a social planner as proxemics' theory is complicated and depends on demographic factors such as gender, cultural differences. Validation methods like comparing robot trajectories to that of human-generated trajectories are not always unique as there are uncontrolled factors like the skills of humans operating the robot. Well-validated HRI surveys such as the Negative Attitudes towards Robots Scale (NARS) [18] and the Godspeed Questionnaire Series (GQS) [6] are not evaluating a robot's social intelligence rather than general intelligence.

Navigation systems are becoming more natural (human-like) and less robot-like, giving the impression that a robot may be "thinking about" or "acknowledging" human presence when these robots have no cognition similar to humans, therefore, expanding upon the idea that humans are influenced in basic areas of comfort, naturalness, and sociability when exposed to human-robot interactions [15]. A person's perception of a robot's social intelligence ability may indicate a robot's performance on social tasks [4, 5]. As social navigation techniques are continuously improving, integrating into more advanced roles in human environments, we must understand how people react and perceive these robots' social intelligence.

3 METHODS

We want to experimentally validate that socially-aware navigation behavior will be observable to a bystander, and whether social intelligence is usable to discriminate between socially-appropriate and socially-inappropriate navigation behavior absent any other social cues. We designed an experiment that will examine how bystanders' perception of social intelligence changes given different navigation behavior. This paper's experimental design uses videos showing robot trajectories generated by our SAN planner [3] showing a human-robot interaction using animated agents. Recent work details the real-world validation and technical details of the optimization-based SAN planner [3].

Our goal in this work was to create experimental scenarios where participants were able to observe the interactions of humans and robots and quantitatively compare their behavior, which is complicated for several reasons. It can be challenging to create a controlled experiment for interpersonal interaction. A person interacting with a robot can behave in ways the robot does not expect. It is not easy to create a natural environment that also controls the necessary experimental variables. Finally, it can be difficult for someone participating in interaction to note their contemporaneous feelings about interaction as it is happening. We developed an experiment where a bystander observes overhead views of robots and humans interacting and rate the resultant robot behavior. Here, we outline the scenarios we chose where the participant could be a bystander to the human-robot interaction, which allowed participants to perceive the robot's social intelligence based on the interaction provided (socially-aware vs. traditional navigation).

Perceived Social Intelligence (PSI) measures can be administered as a long-form (80 items) or short-form (20 items) questionnaire, or users can select relevant items as per their needs [5]. To measure social intelligence, we use the PSI short form. This short-form consists of 20 statements having to do with measuring the robot's social intelligence. It would make sense that if observers relate social-awareness in the navigation to social intelligence, the following hypothesis will be supported:

Hypothesis: Participants who observe a socially-aware navigation planner will perceive the robot as more socially intelligent than one that is utilizing a traditional navigation planner.

3.1 Experiment Design

To test the above hypothesis, we asked participants to view videos of simulated robot movements near humans and environmental features relevant to the navigation task. These videos were renderings of the robot and person's positions on a white background (see Figure 1). The figures are rendered as outlines of people or robots, thus simplifying the scene for the viewer. This overhead view also removed considerations of interaction features, like facial expressions or gestures, thus controlling only movement effects. We asked participants to rate the robot's movement for each video for their perception of social intelligence (PSI).

There were three simulation scenarios for each navigation category: Socially-Aware navigation and Traditional navigation. This between-subjects design allowed participants to be randomly assigned to one of these two categories. The experiment was distributed through the online Qualtrics survey platform and participants were given the PSI short form [4] immediately after watching each video. At the beginning of the survey, we asked participants for their age, gender, and career/field of study. The next sections describe the simulated scenarios the participants viewed.

3.1.1 Waiting in a Queue. In the waiting in a queue scenario, the simulated robot demonstrates socially-aware navigation by joining the queue behind the last person in that queue (see Figure 1). In the traditional navigation scenario, the robot cuts to the front of the queue, cutting off those already in the line.

3.1.2 Joining a Group. In this scenario, the simulated robot with socially-aware navigation joins in the group by completing the "O" formation [13] (see Figure 1). Interacting groups typically form O-formations, participants of the group tend to conform to it, and others tend to respect it. The simulated robot approaches the simulated person closest to the outside before joining the group. The traditional navigation robot joins in the group by cutting into the group's center, getting close to the other humans, and not accounting for a group setting's social norms.

3.1.3 Art Gallery. In this scenario, the robot with socially-aware navigation approaches the human and oriented itself to the side of the "art" or item on the wall so as to "present" to the human (see Figure 1). However, the robot with the traditional navigational planner crossed the human's personal space orienting itself in front of the human and in front of the "art" or item on the wall.

3.2 Participants

We recruited 70 participants (25 Female, 43 Male, 1 Agenderflux, and 1 Non-Binary). The age range was from 18-65 with a mean of 28. One participant was omitted from the data set due to the failure of answering all questions in the Group scenario PSI rating. Each participant was randomly assigned to one of the two interaction conditions, socially-aware navigation, or traditional navigation.

4 RESULTS

A Shapiro-Wilk test was used in R [21] to determine data normality. Two out of the three conditions were normally distributed; therefore, an ANOVA was run for the normally distributed conditions (Queue and Group). A Kruskal-Wallis test was used for the non-normally distributed data for the Art scenario.

After conducting an ANOVA on the Queue scenario, there was a statistically significant difference between PSI ratings of robots with socially-aware navigation compared to traditional navigation ($F(1,67) = 10.32$, $p<0.01$). Figure 2 shows the significant difference between the socially-aware (SAN) and traditional (TRA) navigation groups for PSI ratings. Robots with SAN were rated significantly higher on the PSI compared to the traditional navigation.

An ANOVA showed a statistically significant difference between PSI ratings in the Group scenario. Robots with socially-aware navigation were rated as significantly more intelligent on the PSI than robots who demonstrated the traditional navigation ($F(1,67) = 12.46$, $p<0.001$). Figure 2 shows the significant difference in PSI ratings for the SAN and TRA groups.

There was no statistical significance after conducting a Kruskal-Wallis on the Art scenario. The PSI of a robot with SAN was rated similarly to a robot's ratings with the traditional model of navigation (Chi-squared= 0.35, $p>0.05$). Figure 2 shows the similarities between PSI ratings for the SAN and TRA navigational groups.

5 DISCUSSION

The findings largely support the hypothesis that participants will rate a simulated agent higher if exhibiting socially-aware navigation behavior than behavior typical of a traditional planner. The distinct

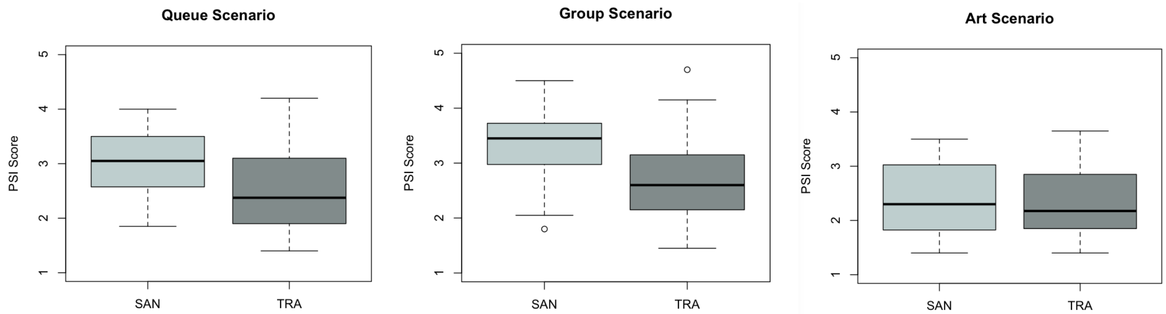

Figure 2: ***Left:*** **PSI ratings for the waiting in a queue scenario (F(1,67)= 10.32, p<0.01). SAN indicates participants viewing the SAN planner, while TRA indicates participants viewing the traditional navigation planner. The black line in the box indicates the median;** ***Center:*** **the group scenario showing the significant difference between PSI ratings for SAN and TRA conditions (F(1,67)= 12.46, p<0.001);** ***Right:*** **the art scenario showing no significance between SAN and TRA (Chi-squared= 0.35, p>0.05).**

differences between social and traditional trajectories for these scenarios closely relate to human-human interaction's acceptable and unacceptable behaviors. These results support the use of the PSI scale to note bystander judgments of a SAN planner's effectiveness.

These effects were observed in the *Queue* and *Group* scenarios. These scenarios utilizes a traditional planner which commits gross social violations (cutting in line, breaking into the center of a group of people in social proximity). The participants clearly viewed these actions as indicative of lower social intelligence.

There was no significance between the robot's perceived social intelligence with socially-aware navigation in the art gallery scenario compared to the traditional model of navigation. We attribute this to the minor difference between the socially-aware planner and the traditional planner in the simulations participants viewed. As we can see from Figure 1, the robot with the traditional model of navigation (indicated in black) approaches the human, getting quite close and orients itself in front of the human, blocking or obstructing their view). In Figure 1, the trajectory for the robot with socially-aware navigation gives the human more space than the traditional model when passing by, but proceeds to get closer to the artwork than the present human. This is a potential dilemma because if a robot (regardless of the type of navigation) proceeds to be closer to an object than the present person, the robot can be perceived as not socially intelligent. Indeed, both robots scored about a 2.2/5 on the PSI scale, indicating low social performance.

An alternative art scenario, where a robot avoiding the *activity zone* between the person viewing the art and the art may be better. The SAN trajectory could be in such a way that the robot avoids the *activity space* [3], but the traditional navigation trajectory navigates in front of the person observing the art (invading *activity space*). This new approach scenario will more distinctly highlight a social violation; it will be similar to the other scenarios where the robot is in the human's view prior to approaching them. It will be more like the queue and group scenarios where the robot approaches from the side and interacts in a face-to-face manner.

5.1 Limitations and Future Work

The PSI scale seems to observe differences in perceived social intelligence when gross social violations occur for bystander interactions, but not minor when social violations occur. The (metaphorical) distance a bystander has from the social scenario could reduce the impact of a minor violation below a threshold captured by the PSI. A participant in an interaction where the robot is interacting with them and commits a minor social violation might then rate the robot as lower on a social intelligence scale.

The population we surveyed is a limitation; the majority of the participants were college-educated or had some higher education, a limitation because robots are likely to be deployed in various work settings that take into account all levels of education. Additional limitations include not acquiring the participants' locations or cultures. Geographical/demographic data like this can influence an experiment, such as this, where the approach behavior is monitored. Western cultures may have different cultural norms and socially accepted behaviors than other countries/cultures. When interpreting cultural differences, this may have some effect.

Future work could apply these simulations to real-life HRI scenarios, allowing participants to interact directly with the robot that either has socially-aware navigation or the traditional model of navigation. It will be interesting to see how PSI ratings remain the same or different when the participant is a real-life bystander.

6 CONCLUSION

We present an experiment meant to isolate social navigation behavior for observation by a bystander. This experiment is meant to validate the use of the perceived social intelligence (PSI) scale for comparing socially-aware navigation behavior. In our experiment, participants rated a robot with SAN as more socially intelligent in scenarios such as waiting in a queue and joining a group. This partially supports the hypothesis that robots with socially-aware navigation would be perceived as more socially intelligent than robots demonstrating the traditional model of navigation and that the PSI can be used to observe this difference.

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