Investigating the Effectiveness of Different Interaction Modalities for Spatial Human-robot Interaction

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ABSTRACT

With the increasing use of social robots in real environments, one of the areas of research requiring more attention is the study of human-robot interaction (HRI) when a person and robot are moving close to each other. Understanding effective ways to design how a robot should communicate its intention during dynamic movement is based on what people's expectations are and how they interpret different cues from the robot. Building on the existing literature, we tested a range of non-verbal cues such as eye contact, gaze and head nodding as part of the robot's behaviour during close proximate passing. The research aimed to investigate the effects of these cues, as well as their combination with body posture, on the efficiency of passing and the quality of HRI. Our results show that the combination of eye contact and the robot turning sideways is the most effective and appropriate compared to other modalities.

KEYWORDS

human robot interaction modalities; movement intention; gaze; eye contact; nod; body posture

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1 INTRODUCTION

Recent years have witnessed a rapid development in social robots. They have been employed in a variety of fields, such as care, service and education [7, 8, 11]. As more robots are developed for these purposes, we will encounter situations in the future where people need to pass by mobile robots in close proximity. Even though passing each other is a simple task for two humans, this is not always true for a human and a robot. In human-human interaction (HHI), people usually use some social cues to convey their movement intention, although sometimes there can also be confusion regarding which path each will take, especially when passing through narrow spaces. There has been extensive research on the impact of these cues on human-robot communication and robot-to-human handovers [1, 5, 6, 10]. However, it remains unclear whether the effects of these cues can be generalised to other scenarios of HRI. Failure to use effective and appropriate cues can lead to a collision or the robot being perceived negatively. Therefore, it is important to investigate how the robot should express its movement intention and how easy people find to interpret the cues. For this, we conducted an experiment where people had to pass a robot and the robot communicated its intention of moving using six different modalities (2 (stop vs. turn sideways) x 3 (eye contact vs. gaze vs. nod)).

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2 RELATED WORK

In HHI, people adjust their behaviour and react to others based on social and physical cues. Social cues include behavioural cues that include verbal cues (e.g. speech, laughter and other non-speech utterances) and nonverbal cues (e.g. gestures, eye and other movements of the body), physical cues include features of physical appearance or environment) [12]. To facilitate natural HRI, some of these cues are also used in the design of the robot's behaviour as they are likely to be familiar and understandable to humans [3]. Given that verbal cues are not always used when two people pass by each other, we focus on nonverbal cues in our study.

As proposed by [2], the most obvious nonverbal cues are body posture, gestures, head position and movement, and eye contact and gaze. It is important to note the distinction between eye contact and gaze. Gaze can be categorised into mutual gaze, which is also known as "eye contact"; referential gaze: gaze directed at an object or location in space; joint attention: focusing on a common object and gaze aversions: shifts of gaze away from the main direction. Based on initial HHI studies, in our study, we focused on investigating mutual gaze (from now on described as eye contact) and referential gaze (from now on described as gaze). [10] conducted an eye-tracking study on collaborative learning and demonstrated that eye contact helped to increase the quality of collaboration and learning gain. [6] showed that gaze can improve the handover timing and users tend to perceive the robot positively when the robot looking at their faces. [4] stated that people use head nodding to show their acknowledgement and engagement during interactions. Researchers also focus on the design of the robot's nodding to achieve a more natural human-robot dialogue interaction [5].

Given that the time spent in passing can be quite short, if the robot can show its attentiveness and engagement, it may help people to pass by the robot with more confidence so that the efficiency of passing and the experience that people have when they pass by the robot can be improved. Previous studies indicate that the robot’s gaze behaviour is able to attract people’s attention and guide them in a cooperative task, and nodding can be used as a cue of acknowledgement and engagement. We thus developed an experiment in which the robot showed these cues before passing by people.

3 METHODS

We ran a within-subjects experiment, where participants had to walk past a Pepper robot [9] and then go through a door on the other side. This was repeated six times. Each time the robot would use different cues to indicate its moving intention (the order of these cues was randomised). The six conditions are summarised in Table 1.

Table 1: Experimental conditions

<table>
<tr><th>Behavioural Design</th><th>Description</th></tr>
<tr><td>Stop & Eye contact (SE)</td><td rowspan="2">The robot tracked the participant’s face while moving. Before passing by the participant, the robot stopped/turned sideways and maintained eye contact.</td></tr>
<tr><td>Turn & Eye contact (TE)</td></tr>
<tr><td>Stop & Gaze (SG)</td><td rowspan="2">The robot rotated its head 15 degrees left first then started to move. Before passing by the participant, the robot stopped/turned sideways.</td></tr>
<tr><td>Turn & Gaze (TG)</td></tr>
<tr><td>Stop & Nod (SN)</td><td rowspan="2">The robot nodded first then started to move. Before passing by the participant, the robot stopped/turned sideways and nodded again.</td></tr>
<tr><td>Turn & Nod (TN)</td></tr>
</table>

The experiment was video-recorded to determine the duration of passing the robot for each condition. Three cameras captured the views from the top, front and side (Figure 1). The ground was marked with a 0.5m x 0.5m grid for more precise measurements. To simulate the situation where people have to pass the robot in close proximity, we also put two boards on either side to limit the width of the path to 1.5m. The length of the path was 4.0m. After each trial, participants were asked to answer three short questions and move back to the starting position. The questions were on how comfortable and safe they felt, and how helpful they thought the robot’s cues were. Other measurements included demographics (age, gender, familiarity with Pepper and robotic technologies).

Figure 1: The views captured by three cameras.

4 RESULTS

A total of 22 participants (14 males, 8 females) took part in the experiment. Most participants were from the 18-34 age range and three of them were aged 45 and over. Their average familiarity with robotics technology was 2.86 (*SD* = 1.08) and that of the Pepper robot was 2.09 (*SD* = 0.75) based on a 4-point Likert scale ranging from “Not familiar” to “Very familiar”.

Data from 2 participants were excluded from analysis due to being outliers (8.94 *SDs* and 4.55 *SDs* away from the mean). The average time spent in passing the robot for each condition is presented in Figure 2 (left). Although the results from the two-way ANOVA show that the six modalities were not significantly different (p = 0.72), compared to the conditions where the robot stopped before passing by participants, participants passed the robot more quickly when the robot turned sideways. This difference is best shown between SG and TG. The time spent in passing is lower when the robot made eye contact with participants as opposed to the conditions that involve head nodding.

Results show no significant difference between perceived safety by participants for the six conditions (p = 0.72), nor was there a main effect of the different conditions on the comfort level of participants (p = 0.53), or the helpfulness of these conditions (p = 0.72). Even so, from Figure 2 (right) we found that both perceived comfort and helpfulness were highest for TE. In terms of perceived helpfulness, it is noteworthy that when eye contact and gaze were accompanied by turning sideways, participants reported the robot’s behaviour was more helpful in communicating its intention to move.

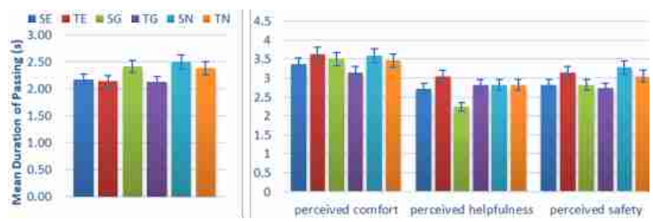

Figure 2: Mean duration of passing for the six different modalities (left); mean scores of each dimension in the follow-up questionnaire of each trial (right), a high value is a positive response.

5 DISCUSSION

This study investigated six different robot behaviour modes using a combination of cues to show its intention to move when passing a human. The results showed that eye contact resulted in the shortest and most efficient passing duration. Additionally, it appears that the robot turning sideways made the passing more effective, especially when it was combined with gaze. Overall TE appears to be the most effective and appropriate modality in communicating movement intention before passing.

Previous studies have demonstrated the effects of eye contact on the improvement of task performance and quality of HRI [6, 10]. The results obtained in our research indicate that such effects also exist in human-robot close encounter. In future work, we will further investigate the effects of these cues on communicating the robot’s intent to move in other spaces and scenarios and whether these effects can be applied to different robot embodiments.

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