Human Considerations in the Application of Cognitive Decision Models for HRI

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Abstract. In order for autonomous robots to succeed as useful teammates for humans, it is necessary to examine the lens through which human users view, understand, and predict robotic behavior and abilities. To further study this, we conducted an experiment in which participants viewed video segments of a robot in a task-oriented environment, and were asked to explain what the robot was doing, and would likely do next. Results showed that participants' perceived knowledge of the robot increased with additional exposures over time; however participant responses to open-ended questions about the robot's behavior and functions remained divergent over multiple scenarios. A discussion of the implications of apparent differences in human interpretation and prediction of robotic behavior and functionality is presented.

Keywords: human-robot interaction, mental models, perception of behavior.

1 Introduction

Advances in technology will enable robotic systems with greater intelligence and autonomy. In order for robots and other intelligent systems to succeed as useful teammates for humans, it is necessary to examine the impact of increased decision making capability of robots on individuals that interact with these systems [1]. Humans currently interact with robots in civilian and military contexts. However, in the current settings, the human largely decides the actions that are to be taken by the robot and initiates their execution via teleoperation [2]. In contrast, when robots are able to select and execute actions on their own, the burden falls upon the human to understand and interpret the behaviors and intention of robots. Human understanding of robots is, and will continue to be, further obscured by issues of robot reliability and human perceptions of trust, respectively [3]. In this document, we illustrate the influence of human understanding of robots within a Human-Robot Interaction (HRI) scenario, using results from an exploratory laboratory study in which novice users were tasked with observing, interpreting, and predicting robotic behavior.

While technology aspires to endow robots with mental models, there will also be an increased need for humans to hold an accurate mental model of the robot's mental model (i.e., understanding of the information/means by which robotic systems arrive at decisions and carry out actions). Mental models are the knowledge structures by

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which humans organize information, and provide the mechanisms by which humans can explain system behavior and intention, as well as anticipate future behavior [4]. Variation in the scope and level of detail of mental models occur at the individual level, and the usefulness of a mental model depends on the manner in which it is applied to the situation at-hand. [5]. Therefore, mental models drive HRI [6]. The problem is that the level of sophistication of robot intelligence will likely be irrelevant if a human cannot understand how, what, or why the robot is acting in a certain manner.

Correct, accurate mental models of robots can be actively cultivated, for example, through design and training [7]. However, training is just one way to support accurate user mental models of robots, and it is not a panacea for haphazard design. Instead, multiple stakeholders must participate in the development of a user's mental model [8]. Whether intentional or unplanned, engineers, for example, specifically influence a user's mental model of a robot through their choices regarding physical characteristics [9], communication aspects [10], and robotic movement [11]. However, individuals perceive and react to robots in unique ways [12]. Additionally, humans have a propensity to apply social stereotypes to technological systems [13]. Therefore, the same robot's decision and action may be interpreted differently across users.

Similarly, mental models are naturally evolving systems that develop and change with experience. Through interaction, an individual will continuously modify his or her mental model in order to achieve and effective outcome [8]. This will be of particular importance for cultivating accurate mental models of robots for novice users, without necessitating extensive training. Since novice mental models of robots tend to be inaccurate and overly presumptuous [10], opportunities for interaction and acclimation will be important for fostering mental models that are true and correct representations of system capabilities and limitations.

The purpose of the investigation reported in this paper was to gain a better understanding of the scope and type of knowledge structures that humans, who had limited HRI experience, hold of robotic teammates; and to study the degree to which these knowledge structures can change with exposure to a robotic teammate. In addition, we examined differences in human interpretation of robotic behavior and intention. The results of this study highlight important considerations for the development of decision making capabilities of robotic teammates, especially in terms of designing for ease of human understanding of robotic behavior.

2 Method

This study was part of a larger data collection effort that included an investigation of mental model priming, previously held attitudes towards robots, and different techniques through which mental models might be assessed. For this paper, we specifically sought to examine the following hypothesis:

- *Hypothesis*: Over time, as participants are exposed and acclimated to their robotic partner, they report higher scores on a self-reported perceived mental model measure that pertains to knowledge of their team (self and robot), their task, their equipment, and the interaction between members of their team.

2.1 Measures

Mental Model Survey. This survey contained a series of questions regarding the degree to which participants had perceived knowledge of the task, team, team interaction, and equipment that was shared between the participant and a robotic entity. These questions were generated to be representative of the four types of mental models shared in teams as proposed by Mathieu and colleagues [14]. As such, the Mental Model Survey contained four subscales which included perceived knowledge of task, perceived knowledge of team, perceived knowledge of team interaction, and perceived knowledge of equipment. Participants utilized a 7-point Likert-type scale to indicate their responses to each item. Higher scores represented higher self-assessments of perceived knowledge of the item in question. Example items include, “The robot has knowledge of likely outcomes of this task” and “I understand this technology.”

Free-Response Items. Participants were asked to respond to several free-response items intended to gain a better understanding of differences in mental model interpretation of a simulated robotic teammate. Free-response questions were intended to probe participant mental models for their ability to explain system behavior, describe system functioning, and predict system actions. Example free-response items included “How would the robot signal to the Soldier that it has spotted something?,” “If the robot did find something, what action(s) would it take next?,” “What was the meaning of the gesture made by the robot at the end of the video?,” “How would the robot signal that it has spotted something?,” and “What would the robot do next?”

2.2 Participants

Fifty-one undergraduate students from a large southeastern university participated in this study. Participants’ ages ranged from 18-31 years (M = 20.09 years, SD = 2.88). Participants were recruited through the university’s research participation system and were offered credit in return for their participation.

2.3 Simulation Environment

Participants observed a series of video clips captured from the RIVET (Robotic Interactive Visualization & Exploitation Technology) computerized simulation, developed by General Dynamics Robotic Systems (GDRS). RIVET was built upon the Torque game engine, features a world editor, and contains a number of pre-configured environments, character models, and vehicles. The RIVET software allows multiple players to enter into a virtual environment and operate a variety of simulated unmanned ground and aquatic platforms. Additionally, the simulation environment can be networked with hardware in the loop (HITL) to evaluate sensor algorithms and software code.

Videos were created using a two-player, man-behind-the-curtain configuration. It was important to capture video clips from the perspective of an observer, rather than from the viewpoint of the robot. The player-observer viewpoint was intended to simulate that of a Soldier working with an autonomous robot in an urban environment. Another player controlled the actions of a robot (a Talon-type robot, in this investigation) who executed a series of navigation and inspection and reconnaissance tasks, either alone or in the presence of civilians. Video was captured using a COTS product, Fraps, which captures video from a specified computer desktop window. The average length of each video clip was one minute.

2.4 Procedure

After reviewing informed consent documents, participants completed a demographic questionnaire that contained general biographical information including familiarity with and attitudes towards computers, robots, and video games. However, these measures were a part of another study component that is not reported here.

After these preliminary activities, participants were provided a training presentation that presented the over-arching narrative for the videos they would be viewing, and familiarized the participant with the robot they were about to see. After viewing the training, participants completed the Mental Model Survey.

Participants then watched a series of 12 videos, broken up into two blocks. Each video depicted a human–robot team in which the robot was autonomously performing a series of inspection or reconnaissance-like tasks in an urban environment. For example, one video clip was presented with the introduction, "the robot was instructed to search the surrounding area for explosive materials." For each video, the actions of the robot were congruent with the narrative (i.e., it did not inexplicably crash into a wall). Participants, however, were asked to interpret the individual motions and gestures made by the robot in the free-response survey.

Block order was counter-balanced between participants; videos within each block were randomized across all participants. The videos in each block differed in whether or not civilians were present while the robot was working. For each of the 12 videos (six in each block), participants were asked to carefully pay attention to the video, and then completed three open-ended, short-answer questions concerning their understanding of the robot, including what it was doing, (functionally) how it completed the work, and what it might do next. A smaller subset of these questions consisted of situational awareness items, designed to identify a participant's engagement (or lack thereof). After each block, participants again completed the Mental Model Survey. Finally, participants were debriefed and thanked for their time.

3 Results

3.1 Mental Model Development

A one-way, repeated measures ANOVA was conducted to compare self-reported perceived knowledge of their robotic partner across three periods of time. The mental model measure was administered: immediately following training, after viewing the first block of videos depicting the robotic teammate, and after viewing the second block of videos depicting the robotic teammate. There was a significant main effect for time, Wilks' Lambda = 0.696, $F(1, 51) = 10.936$, $p < .0005$, multivariate partial eta squared = .304. A post hoc analysis with Bonferroni correction was conducted to determine whether a significant difference in reported knowledge of the robotic teammate was present each time perceived knowledge was measured, or if significant differences were present only at specific measurement opportunities. The test for simple effects revealed that there was a statistically significant increase in self-reported, perceived knowledge of the robotic teammate after viewing the second block of videos depicting the robotic teammate in the task environment (M =21.67, SD = 3.52), $t(51) = 4.37$, $p <.0005$. In addition, there was a statistically significant increase in self-reported, perceived knowledge of the robotic teammate between when the participants received the training (M = 20.42, SD = 3.08) and after viewing the second block of videos depicting the robotic teammate in the task environment (M=21.67, SD = 3.52), $t(51) = 3.20$, $p = .002$ (see Table 1).

Table 1. Table of post hoc contrasts, means, and standard deviations

Contrast	Repeated Measure	Mean	Standard Deviation	Sig.
Pair 1	MMS post training MMS post video block 1	20.42 20.57	3.08 3.12	.703
Pair 2	MMS post video block1 MMS post video block 2	20.57 21.67	3.12 3.52	.000*
Pair 3	MMS post training MMS post video block 2	20.42 21.67	3.08 3.52	.002*

Note: MMS = Mental Model Survey.

*Statistically significant at $p < .017$. P value adjusted for Bonferroni correction.

3.2 Interpretation and Prediction of Robot Behavior

A qualitative analysis was conducted to examine apparent differences in perceived knowledge of a robotic teammate as indicated by the free-response items. An independent rater was used to look for thematic similarities across all participants for each of the free response items. Results could not confirm a specific hypothesis. However, the analysis did reveal that participants had thematically different understanding of robotic behavior. For example, in response to the item that asks, "What was the meaning of the gesture the robot made at the end of the video?," 14 of the participants made a thematic response that the gesture was intended to indicate that the area being searched was safe/no dangerous material had been found. Ten of the participants had a thematic response that indicated the opposite; the gesture made by the robot was an indication to the Soldier that the area was unsafe/that hazardous materials had been found. Nine participants provided responses that indicated that they were unsure of meaning of the gesture or that the gesture was related to indicating something else like finding an object (without specific reference to safety) or the robot had finished its task. A sample of additional questions and corresponding thematic results are reported in Table 2.

Table 2. Sample of interpretations and predictions of the robot's behavior and functions

Video description	Free-response question: Thematic category	Characteristic responses
A suspicious object was reported in an alley near the market place. The robot was instructed to located the item and report back to the Soldier.		
	How would the robot signal to the Soldier that it has spotted something?	
	Arm movement	"Robot will raise arm."
	Light	"Robot will turn on light indicating something has been found."
	Sound	"Robot will produce a noise."
	Electronic report	"Robot will message through radio."
The robot was instructed to perform a routine inspection of the marketplace booths before civilians arrive, then report back to the Soldier.		
	What was the meaning of the gesture the robot made at the end of the video?*(*Note to reader: up and down movement of manipulator arm)	
	Safe	"Robot was nodding that the way was clear."
	Unsafe	"Robot was nodding that something dangerous had been found."
	Neutral (Item found)	"It was reporting that something was identified."
	Unsure	"I do not know what the gesture meant."
The robot is instructed to perform a thorough investigation of a burnt out car for traces of explosive material to determine the cause of the damage.		
	Describe the equipment the robot uses to detect explosive materials.	
	Arm	"Robot can use arm to touch and maneuver objects."
	Camera on arm	"Robot has a camera on the top of its arm to look for explosives."
	Sensor equipment	"The robot has a chemical scanner on its top of its body."
	Unsure	"I am unsure how the robot would do this."
The robot is tasked with navigating to and inspecting barrels for explosive materials in an alley of a small village. After inspecting the barrels the Robot must return to the Soldier and await further orders.		
	At what distance is the robot able to detect explosive materials?	
	Close	"Probably close, like 3-5 feet away."
	Far	"A far enough distance to be away from a blast."
	Unsure	"I don't really know."

4 Discussion

The hypothesis was partially supported, as results revealed a significant main effect for time on change in reported knowledge of the robotic teammate. An examination of the simple effects revealed that there was a significant difference in reported mental models between time 1 (immediately post training) and time 3 (following viewing all of the videos). In addition, there was a significant difference in reported knowledge of the robotic teammate between time 2 (after viewing the first block of videos) and time 3 (after viewing the second block of videos). This finding lends support for the importance of experience when forming mental models of robotic teammates.

For example, while participants' reported that their knowledge of the robotic teammate steadily increased over time, the difference between their perceived knowledge post-training (i.e., but before viewing any videos) and after viewing one block of videos was small and non-significant (see Table 1). That is, there was no significant effect for the order in which the two blocks of views were presented. Only after viewing the robotic teammate in both blocks of videos, which presented the teammate performing tasks in two different contexts (i.e., civilians present while the team was working and civilians not present while the robot was working), was there a significant difference in self-reported knowledge of the robotic teammate. This may indicate that familiarizing the human partner to the robot in multiple contexts is important to developing a clear understanding to the robot.

The data suggests that subjective self-assessment of participant mental models increase over time, as participants see the robot performing a wide variety of tasks in different contexts. However, this did not imply that mental models between participants were similar. For example, when asked how a Talon robot might inform a Soldier that it encountered an IED, participant responses varied greatly. Some participants applied anthropomorphic stereotypes and social rules to the robot (e.g., it should wave its arm; it should nod). Differences in the expected method of communication were also observed across participants (e.g., it would produce a noise to inform the Soldier it found something). These expectations were also used to reason about the robot's performance on the task (e.g., I am assuming it checked everything along the path it was instructed to check; the open garage was obvious, it should have looked there), as well as how the robot would act in the future.

5 Conclusion

This research highlights a number of important considerations for the development of high-autonomy, intelligent robots. Specifically, an individual's perceived understanding of a robotic system increases given additional robotic exposures in different contexts. However, it is important to recognize the difference between the richness of understanding and accuracy of understanding. Different individuals may be similarly confident in their knowledge of the robot, but arrive at vastly different conclusions about its function and performance; with each conclusion being an equally valid interpretation of the robot's behavior (e.g., "it signaled that it detected something" vs. "it signaled that it did not detect anything").

Secondly, given a task-oriented human–robot team, the ability of an autonomous robot to complete the task is only part of the overall solution. It is important to consider additional functions such as: How will the robot indicate the task has been completed? How will the user know if the robot cannot complete the task? What should the robot do if it becomes stuck or damaged? What information should the human expect to provide to the robot? And, what information should the human expect to receive from the robot?

Finally, it is safe to assume that individuals, specifically designated to be robot handlers, will receive adequate training to mitigate the effect of potentially ambiguous robot behavior. However, robots will be expected to operate among other team members, bystanders, and even hostile forces for which specialized training will be minimal or non-existent. It is therefore necessary to consider those cases in which the intention of robot behavior should be transparent, opaque, or even deceptive, depending upon the circumstances of the operational environment.

We continue to investigate the role of human understanding within HRI, in order to provide designers useful input for the development of robotic systems that are compatible with the knowledge and understanding of their human counterparts.

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