Exploring the Effect of Communication Patterns and Transparency on Performance in a Human-Robot Team

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Human-robot interaction requires communication, however what form this communication should take to facilitate effective team performance is still undetermined. One notion is that effective human-agent communications can be achieved by combining transparent information-sharing techniques with specific communication patterns. This study examines how transparency and a robot's communication patterns interact to affect human performance in a human-robot teaming task. Participants' performance in a target identification task was affected by the robot's communication pattern. Participants missed identifying more targets when they worked with a bidirectionally communicating robot than when they were working with a unidirectionally communicating one. Furthermore, working with a bidirectionally communicating robot led to fewer correct identifications than working with a unidirectionally communicating robot, but only when the robot provided less transparency information. The implications these findings have for future robot interface designs are discussed.

INTRODUCTION

Future robotic systems are expected to transition from a tool-based interaction paradigm to a more teamwork-oriented paradigm (Ososky, Sanders, Jentsch, Hancock, & Chen, 2014; Phillips, Ososky, Grove, & Jentsch, 2011). In the field of military robotics, this change in robot capability, and subsequent human-robot interaction pattern, anticipates dynamic, complex battlefields (David & Nielsen, 2016; U.S. Army, 2017). By taking advantage of the synergy between human experience and robotic precision, human-robot teams can jointly address the challenges of these complex environments (Chen & Barnes, 2014). Approaches centered around mixed-initiative interaction and increased autonomous capabilities are anticipated to better address future challenges than existing approaches to human-robot interaction (Lyons & Havig, 2014; U.S. Army, 2017). These more complex robots, unlike teleoperated robots, have decision-making capabilities independent of a human operator, so these robots have the ability to act in ways surprising to their human counterparts (Chen, Haas, & Barnes, 2007; Stubbs, Wettergreen, & Hinds, 2007; Sycara & Sukthankar, 2006). In order to prevent this surprise, robots can convey information about their inner workings, giving their human counterparts the knowledge to accurately predict the robot's future actions (Chen et al., 2014; Phillips et al., 2011; Sycara & Sukthankar, 2006). However, the information that best achieves this objective, and how it should be conveyed, is yet undetermined.

Robots need to provide information that allows humans to build and maintain a mental model of the robots' relevant internal processes, without interfering with the humans' thought processes (Maass, 1983; Morrow & Fiore, 2012). Maintaining the humans' awareness of the robots' actions, as well as the underlying reasons for these actions, becomes increasingly important as the robots' autonomy increases. (Allen, Guinn, & Horvtz, 1999; Chen et al., 2018; David & Nielsen, 2016). As robots gain capabilities previously exclusive to humans, research into human teamwork becomes more relevant to the exploration of human-robot teamwork. Combining research from human-human communications with research from human-robot interaction provides an approach to determining the information human-robot teams need to complete shared tasks and how to convey that information.

Transparency

Transparency research focuses on the information that a human needs, when working with an automated system, to understand what the system is doing, why it is doing it, and (potentially) be able to predict what the likely near-term outcome of these actions will be. Transparency is an emergent property that results from the interaction between a human and a system—e.g. a robot (Chen et al., 2014; Ososky et al., 2014). As a result of that interaction, the human has a sufficient understanding of the system in order to accomplish their goals (Karsenty & Botherel, 2005; Maass, 1983). The information that facilitates this understanding is specific to the individual human, the specific robot, and the context in which they find themselves, so frameworks have been developed in order to define what that information should be (Chen et al., 2014; Karsenty & Botherel, 2005; Lyons, 2013).

The Situation awareness-based Agent Transparency (SAT) model is one such framework, using the process by which humans comprehend their environment to inform the selection of data that robots need to convey to their human counterparts to facilitate a transparent interaction (Chen et al., 2014). As such, the SAT model uses the three level structure established by Endsley's (1995) Situation Awareness (SA) model to define the information that a robot should provide to support the human's understanding of the robot. The first SAT level refers to the robot's actions, plans, and knowledge of the environment; the second SAT level refers to the underlying rationale behind the robot's actions; the third SAT level refers to the robot's projected outcomes of these actions and uncertainties within those predictions (Chen et al., 2014).

Future robots are anticipated to independently generate plans, act on those plans, and contribute to goals shared with their human counterparts (Aha, Molineaux, & Klenk, 2011; David & Nielsen, 2016; U.S. Army, 2017). This increased independence, coupled with the complexity of future battlefields, calls for a collaborative human-robot interaction (Chen & Barnes, 2014; Johnson et al., 2014). A collaborative approach requires a bidirectional pattern of transparency, as the robot has an independent model of the environment which includes its human counterpart and their intentions (Bradshaw, Dignum, Jonker, & Sierhuis, 2012; Chen et al., 2018). This study explores how bidirectional transparency and how it influences human performance.

Communication

In the context of a human-robot team, human-robot interaction can be decomposed into four communication patterns: human-push, where humans provide information to a robot; human-pull, where a human solicits information from a robot; robot-push, where a robot provides information to a human; and robot-pull, where a robot solicits information from a human (Kaupp, Makarenko, & Durrant-Whyte, 2010). These patterns can be used to create a unidirectional flow of information, where information is transferred from a source to a receiver, or a bidirectional flow, where information is exchanged (Kaupp et al., 2010; Marko, 1973). An exchange of information allows for disambiguation and the building of shared knowledge, which mimics how humans build shared knowledge in a team (Héder, 2014; Salas, Shuffler, Thayer, Bedwell, & Lazzara, 2015; Sycara & Sukthankar, 2006).

Human communication can serve as a useful model on which human-robot communication can be compared (Chen et al., 2018; Morrow & Fiore, 2012; Sycara & Sukthankar, 2006). In human teams, communication is a reciprocal process by which team members create and maintain a shared understanding of the shared task that must be performed and of the team members that must perform that task (DeChurch & Mesmer-Magnus, 2010; Salas et al., 2015). Communication in teams, however, has a cost in terms of time and cognitive resources (MacMillan, Entin, & Serfaty, 2004). A bidirectional flow of information amongst human teams has a higher communication overhead than a unidirectional information push. Given robots' processing power and rapid latencies, the overhead in human-robot communication would center primarily on humans (Chen & Barnes, 2014). The current study focuses on the humans' communication overhead in human-robot communication.

Current Study

In the current study, participants were asked to work with a simulated robot in conducting a cordon-and-search-type task. The participants' primary task was to monitor an open area and identify potentially threatening targets while the robot searched a building. The robot and participant communicated via a computer interface. Given the importance of understanding one's teammate, whether human or robot, in pursuing shared goals, the current study explored transparency and communication in human-robot teams. Specifically, the cost of both bidirectional transparency and bidirectional communication on participants' performance in a target identification task was examined. If humans—when interfacing with automated systems—try to pay attention to multiple tasks simultaneously, their divided attention may result in reduced performance, so it was hypothesized that participants would exhibit performance decrements when using interfaces that supported bidirectional transparency, but would not exhibit performance decrements when using interfaces that supported unidirectional transparency (Derryberry & Reed, 2002; Wickens, 2002). Similarly, it was expected that bidirectional communication would yield performance decrements as a result of communication overhead, while participants using interfaces that communicated unidirectionally would not.

METHOD

Experiment Design

The study was a 2 (communication pattern) x 2 (transparency) within-subjects design. The communication patterns were: *unidirectional* communication, where the robot pushed information to the human participant; and *bidirectional* communication, where the robot both pushed information to the human participant and pulled information about the human's reasoning. The transparency conditions were: *agent transparency* which displayed information about the robot's decision-making process using an at-a-glance, icon-based module; and *team transparency,* which displayed both the agent transparency information and a second module describing the robot's understanding of the human's decision-making process. Participants completed four scenarios (counterbalanced), each corresponding to a different factor configuration.

Participants

Forty individuals (13 men, 27 women, M_{age} = 21.13, SD = 3.95), from the Central Florida area, participated in this study for monetary compensation. Participants had neither prior military experience nor prior experience with cordon-and-search-like tasks.

Experimental System

The simulation was delivered via a commercial desktop computer system, 2 - 22" monitors, standard keyboard, and three-button mouse. The left screen displayed a simulated environment depicting humans and vehicles crossing in front of a building (see Figure 1). Multiple buttons along the bottom of the screen were used to identify different targets.

The right screen displayed an adaptation of the multimodal interface developed for the Robotics Collaborative Technology Alliance (Barber et al., 2015). This screen depicted a camera feed showing the robot's point of view as it searched through the building (upper right corner), communications with the robot, including queries (right side lower), a map of the surrounding area with real-time movements (left side), and the at-a-glance transparency modules (upper left corner), see Figure 2. The at-a-glance modules conveyed information according to the SAT framework and were adapted from previous SAT research (Chen et al., 2014; Selkowitz, Larios, Lakhmani, & Chen, 2017). The queries pertained to the participant's underlying concerns—either the safety of the robot or the pursuit of the mission. Participants answered these queries by using their mouse to click on the relevant answer.

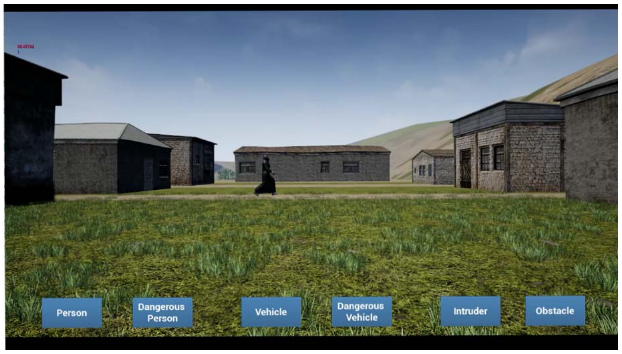

Figure 1. The left screen, in all conditions, displays a simulated environment from the human's point of view. Directly ahead is the building the robot is searching. As traffic crosses the area in between, participants use the buttons along the bottom of the screen to identify the nature of the traffic and its behavior.

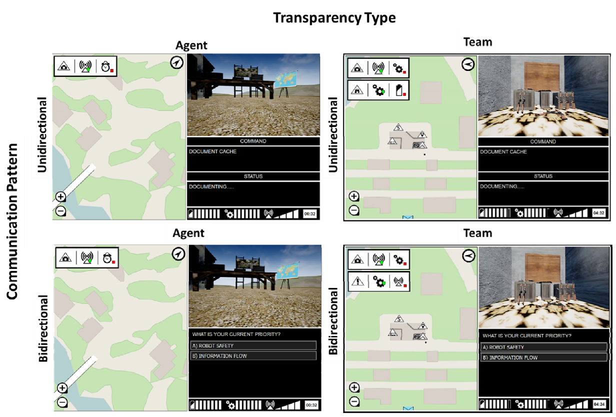

Figure 2. The right screen displays the human-robot interface. Shown above are the four configurations for the different transparency x communication conditions. The labels on the left side and on top of each image denote which condition it represents.

Procedure

Upon arrival, participants signed an informed consent document, and were trained on how to use the interface. Training lasted approximately an hour, and consisted of self-paced PowerPoint slides, several assessments, and mini-exercises for practice. Participants were required to achieve at least 80% proficiency on the assessments to continue.

The experimental session began immediately after the training session and lasted approximately 2 hours. Participants completed four (counterbalanced) scenarios, each corresponding to a different factor configuration, and each lasting approximately 15 minutes. Participants monitored the area in front of a building, identified specific targets when they entered the area, notified the robot when a person approached the building entrance, and communicated with the robot to assist the robot in maintaining its SA of the human. Following completion of all four scenarios, participants were debriefed and dismissed.

RESULTS

Participants had six seconds to identify specific figures and/or their actions by clicking on the buttons at the bottom of the left-hand screen. There were 28 possible correct identifications in each scenario. A correct identification is defined as clicking on the appropriate button when a specific figure either appears on the screen or commits a pre-specified action. An incorrect identification is defined as clicking on an inappropriate button when a figure either appears on the screen or commits a pre-specified action. A miss is defined as not clicking any button when a figure appears on the screen or commits a pre-specified action.

In this study, all data analyses consisted of 2 x 2 repeated measures ANOVAs. There was an interaction between communication pattern and transparency type on number of correct identifications, $F(1, 39) = 3.97$, $p = .05$, $\omega^2 = .06$, as seen in Figure 3. When the interface displayed information about the robot's decision-making process alone (*agent transparency)*, participants identified more targets correctly in the unidirectional communication condition (M = 27.3, SD = 1.11) than in the bidirectional communication condition (M = 26.28, SD = 2.20). When participants received both at-a-glance transparency modules (*team transparency*), however, they responded similarly, regardless of communication pattern (*unidirectional*: M = 26.58, SD = 2.27; *bidirectional* M = 26.70, SD = 1.26).

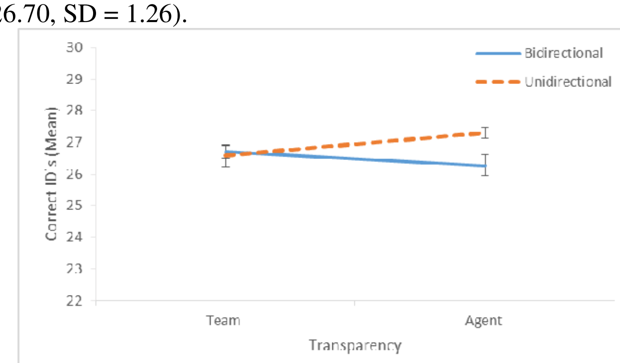

Figure 3. Correct identifications of targets for bidirectional and unidirectional communication pattern conditions. Error bars represent standard error.

Contrary to expectations, there was no difference in participants' correct target identification due to transparency condition alone, $F(1, 39) = 0.52$, $p = .48$. $\omega^2 = .00$. There was a significant difference in participants' correct target identification due to communication pattern, however, $F(1, 39) = 5.55$, $p = .02$, $\omega^2 = .06$. Participants made fewer correct identifications when they were queried by the robot (M = 26.49, SD = 3.07) than when the robot only pushed information (M = 26.94, SD = 2.71).

This difference in correct identifications did not lead to a corresponding difference in incorrect identifications. There was no interaction between transparency and communication pattern on incorrect identifications, $F(1, 39) = 2.94$, $p = .09$, $\omega^2 = .04$, and participants' number of incorrect identifications did not differ based on communication pattern, $F(1, 39) = 2.27$, $p = .14$, $\omega^2 = .02$, or transparency type, $F(1, 39) = 0.02$, $p = .89$, $\omega^2 = .00$.

Overall, participants missed few identifications. There was no interaction due to communication pattern or transparency type on missed identifications, $F(1, 39) = 3.08$, $p = .09$, $\omega^2 = .04$. Contrary to expectations, there was no difference in number of misses due to transparency condition, $F(1, 39) = 1.06$, $p = .39$, $\omega^2 = .00$. There was a difference in number of misses due to communication pattern. When the robot queried participants, they missed more target identifications ($M = 1.15$, $SD = 2.27$) than when the robot only pushed information ($M = 0.84$, $SD = 1.93$), $F(1, 39) = 4.37$, $p = .04$, $\omega^2 = .05$, see Figure 4.

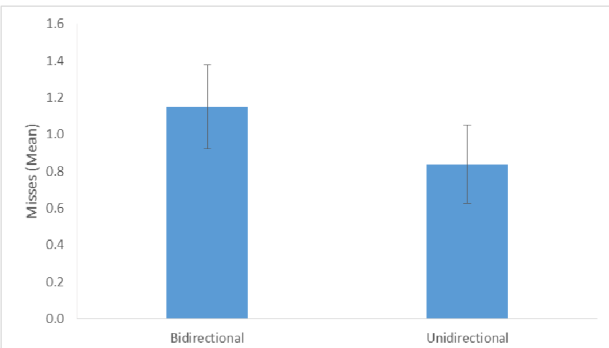

Figure 4. Average missed identifications for bidirectional and unidirectional communication pattern conditions. Error bars represent standard error.

DISCUSSION

While communication pattern did not affect participant performance in the team transparency conditions, it did in the agent transparency conditions. Specifically, answering the robot's queries hampered participants' correct identification of targets, but when there was no query to answer, participants did not exhibit a performance decrement. The additional interface module in the team transparency condition may have added sufficient communication overhead to the participant so that the unidirectionally communicating robot no longer had the advantage over its bidirectional counterpart. This suggests that the addition of another transparency interface module adds to the communication overhead and must be considered when designing for human-robot interaction.

Additionally, a main effect for communication pattern was found. When looking at the bidirectional communication conditions, where the robot both pushed information to and pulled information from the participant, participants correctly identified fewer figures correctly and missed identifying more figures than in the unidirectional communication conditions, when they were only receiving information from the robot. These findings supported the hypothesis that a bidirectional communication pattern would interfere with participants' performance. The issue was not that answering queries made participants worse at correctly identifying targets—given that there was no difference in incorrect identifications—but that answering the query caused participants to identify fewer figures correctly and to miss identifying their targets during the allotted six seconds.

Since the physical act of responding to the robot's queries affected the participants' performance, allowing a human partner to respond to the robot queries verbally may alleviate this issue. According to multiple resource theory, people process information along several dimensions—e.g. visual, auditory (Wickens, 2008). In situations where a human has to perform concurrent tasks, such as in the context of this study, shifting one of those tasks to a different dimension can reduce interference and extend mental limitations (Lakhmani, Abich, Barber, & Chen, 2016; Wickens, 2002). By shifting the response from a button click to a vocal response, participants could be expected to spend less time responding.

Previous research using interface modules based off the SAT model found that providing multiple levels of information proved helpful in decision-making tasks and supervisory-control tasks (Selkowitz, Lakhmani, & Chen, 2017; Stowers et al., 2016). However, the addition of an interface feature describing the robot's understanding of the human's decision-making process did not help participant performance in this task. Contrary to expectations, this additional information did not induce enough of a communication overhead to affect participant performance on its own, but did when the communication pattern was also manipulated. Furthermore, the secondary interface element, seen in the team transparency condition, could have been used to help participants identify the stimuli they saw, but there is no evidence that they used it do so. Essentially, this particular approach to implementing a bidirectional transparency did not influence the number of mistakes participants made (i.e. misses and incorrect identification).

Conclusion

While a robot conveying information about *itself* to a human teammate has been shown to have myriad effects on that team (Chen et al., 2018), the result of a robot conveying its understanding of *their human teammate* to said human is still being explored. This study has shown that bidirectional communication can result in a communication overhead that influences performance and that transparency can affect that effect. The outcome shown here may be specific to the nature of the shared task expressed in this study. In human teams, team members can use their understanding of the situation, task, and the individuals with whom they work to predict what will be needed and act accordingly (Cannon-Bowers, Salas, & Converse, 1993). In this situation, the teammates do not need to explicitly communicate in order to conduct their individual portions of the larger shared task. In the human-robot task, participants used the buttons on the interface to convey their findings to the robot. However, at no point could the human and robot fail at their shared task, regardless of the human's performance. Future studies could introduce elements, such as errors, that would require the correction or the building of a shared consensus or understanding between a human and robot.

Additionally, this study showed that communicating with a robot by making a single binary choice affected human performance in the identification task. However, this form of communication is highly simplistic. If a binary communication choice can cause issues with regard to performance, then a more complex kind of communication—three or more choices, branching communication paths, or more freeform communication—may have a greater negative affect on performance of a shared task. Future studies should examine the effects of more complex communications, as well as comparing how different communication modalities affect performance. In the end, communication is anticipated to be a major part of effective human-robot teamwork and the form that communication will take is still undefined.

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