Establishing Sustained, Supportive Human-Robot Relationships: Building Blocks and Open Challenges

Sarah Strohkorb, Chien-Ming Huang, Aditi Ramachandran, and Brian Scassellati
Department of Computer Science, Yale University
{sarah.strohkorb, chien-ming.huang, aditi.ramachandran, brian.scassellati}@yale.edu

Abstract

As social robots become common alongside humans to support a variety of tasks in daily interactions, their establishment of sustained, supportive relationships with humans is essential to their success in reaching intended outcomes. In this paper, we discuss three building blocks—*socially intuitive interaction*, *personalized interaction experience*, and *long-term interaction*—that facilitate the formation of such human-robot relationships, as well as related open challenges.

Introduction

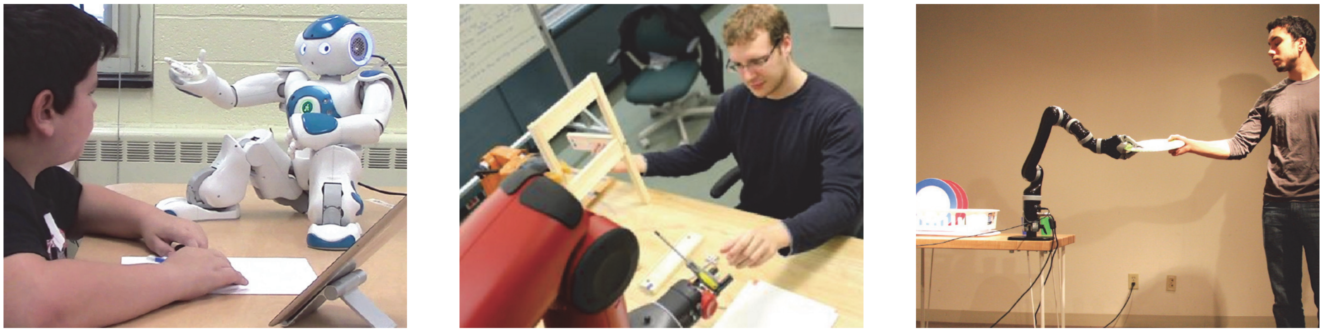
Social robots are increasingly common in schools to support learning goals, in workplaces to augment productivity, and in homes to improve quality of life. The fulfillment of their objectives in these environments are strongly dependent on the quality of the sustained, supportive relationship robots are able to construct with their human users. With well established relationships, robots could better understand user need in an interaction, build necessary trust, and achieve seamless coordination with their users. While there have been studies exploring the rich space of human-robot relationships, how robots might establish sustained, supportive relationships with humans remains computationally challenging and requires further research.

In the domain of education, social robots are becoming increasingly useful as tutoring agents. Because the resources required to provide human tutoring on an individual level are extremely demanding, social robots can be leveraged as tutors in various educational settings (Figure 1a). Researchers have shown that the physical presence of robots can benefit learners in a variety of ways, such as providing social support (Saerbeck et al. 2010), and increasing cognitive learning gains (Leyzberg et al. 2012). Additionally, social robots interacting with students have the capability to provide personalized tutoring interactions for individuals by monitoring the state of the student and providing feedback specific to the student. Robot tutors can assess many relevant characteristics of a student, such as knowledge level, type of learner, or affective state and use this information to tailor aspects of the tutoring interaction. Personalized feedback during a learning interaction often includes the robot's social behavior or the robot's type of help on the task at hand. Though progress has been made in integrating robots into learning environments, these interactions will become more effective as we continue to study and strive to understand what key aspects of the learner should be adapted to by the robot, as well as what salient aspects of a robot tutoring interaction are crucial to long-term learning.

In the workplace, robots are starting to work not only in isolated assembly lines or warehouses, but alongside humans in closer proximity than ever before (Figure 1b). In automobile assembly lines, robots work alongside humans, handing them tools when needed and preforming repetitive tasks requiring high precision. In collaborative manufacturing contexts, humans can guide robot arms to show them how to complete specific tasks. Researchers have been developing algorithms to aid robots in determining task hierarchies (Hayes and Scassellati 2014), learning tasks from humans (Thomaz and Breazeal 2008), and choosing what information to communicate and when to communicate it (Unhelkar and Shah 2016). Although robots have made great strides to improve efficiency and productivity in the workplace, further research is necessary to fully integrate coworker robots into manufacturing workplaces. Robots can continue to improve their interactions with humans through the use of nonverbal social signals, which can be quickly understood without the need for a visual error message, as well as further adaptation to human intent and action, making human-robot collaboration in close proximity more fluid and intuitive.

In addition to educational settings and workplaces, robots are envisioned and developed to assist people with daily activities in homes (Cakmak and Takayama 2013). As the demographic structure of our society becomes more constrictive (a typical trend in developed countries), robots could provide assistance to people with decreased physical or sensory capabilities to support independent living and help family members with domestic chores (Figure 1c). For instance, robots have been demonstrated to help with human users to unload dishes from a drying rack (Huang, Cakmak, and Mutlu 2015). While holding the promise in supporting domestic tasks, how robots might be adopted by everyday users and integrated into their daily routines need further explorations. We believe that the ability to build sustained, supportive relationships with human users is essential for robots to be successfully adopted by everyday people.

To fully reach their potential in providing lasting bene-



(a) Educational support (b) Collaborative manufacturing (c) Household service

Figure 1: Social robots capable of establishing and maintaining supportive relationships with humans hold great promise in providing educational support, aiding in collaborative manufacturing, and offering household services.

fits to humans in daily environments, such as schools, workplaces, and homes, robots must develop supportive relationships with users. In this paper, we highlight the importance of sustained, supportive human-robot relationships and discuss building blocks of and open problems to the realization of such human-robot relationships for positive interaction outcomes.

Towards Sustained, Supportive Relationships

In this section, we discuss three building blocks—*socially intuitive interaction*, *personalized interaction experience*, and *long-term interaction*—that are fundamental to the establishment of sustained, supportive human-robot relationships. We briefly review prior research in these three areas and discuss open problems that require future research in order to achieve intended supportive relationships between humans and robots.

Socially Intuitive Interaction

A key ingredient to establishing sustained, supportive relationships between humans and robots is the capacity of engaging in *socially intuitive interactions*. Socially intuitive interactions can be characterized by two processes—expression and interpretation—from a robot's point of view. *Expression* concerns how robots might communicate their internal states (e.g., attention, intention, and affect) to humans. Being able to communicate internal states effectively helps human partners to adjust and coordinate their actions during interactions. *Interpretation* concerns how robots can understand their human partners' internal states via observed behaviors in order to act accordingly. In the following paragraphs, we describe our prior research exploring how socially intuitive interactions might be realized in the processes of expression and interpretation and discuss how such interactions might help establish human-robot relationships.

Expression — Prior research has explored how robots might draw from a repertoire of behaviors to communicate effectively with people (Huang and Mutlu 2013). In particular, it was shown that human-inspired robot gaze could be used as a goal-directed means to communicate a robot's current attention and to redirect people's attention to task-relevant places during human-robot interactions to create cognitive and task benefits. This research demonstrated that social behaviors, such as gaze cues, are effective channels to express the internal state of a robot and that robots could leverage people's inclination to read behavioral expressions to communicate with users in a socially intuitive manner.

Interpretation — In addition to expressing internal states via social behaviors, prior research has also studied how robots can understand and interpret observed human behaviors to react accordingly during an interaction. In an investigation of how to achieve fluid action coordination in a human-robot team, a robot system was developed to infer the human partner's action and task progress based on real-time user poses from a Kinect sensor (Huang, Cakmak, and Mutlu 2015). Based on behavioral inferences, the robot adaptively employed human-inspired coordination strategies in collaborating with the human partner in a joint task in which the robot helped the human to unload dishes from a drying rack (Figure 1c). It was shown that the ability to adapt to the user based on appropriate interpretation of observed user behaviors was critical in enhancing user experience while maintaining team performance in human-robot teamwork. This research highlighted the importance of interpretation of observed human behavior in creating quality interactions.

Although prior research has explored how the processes of expression and interpretation might be realized to enable socially intuitive interactions between humans and robots, further research is needed to study how these two processes might be jointly realized and employed to create personalized interaction experience, as well as how robots can express and interpret behavioral subtleties in natural human environments.

Personalized Interaction Experience

Another critical factor in fostering sustained human-robot relationships is the capability to adapt to individual human users. Each individual has their own set of preferences and needs during social interaction. In order to maintain effective and engaging interactions, robots must be able to perceive these differences and personalize behavior accordingly, rather than provide generic interactions that remain constant across all users.

Below we explore recent research involving personalization and adaptation in human-robot interactions. Leyzberg et al. demonstrated that a social robot employing personalized lessons based on the user's skill level could significantly improve performance during a puzzle solving task when compared to the robot delivering non-personalized lessons (Leyzberg, Spaulding, and Scassellati 2014). Leite et al. developed an adaptive system involving a social robot that employed a reinforcement learning approach to choosing appropriate empathic behaviors that matched the user's preferences during one-on-one interactions with children (Leite et al. 2012b). The algorithm for choosing the robot's empathic responses utilized an affective reward signal from the child that the robot sensed in real-time. Recent research conducted by Baraka and Veloso proposes models that characterize user preferences and a framework for a robot to successfully learn the parameters for each user group (Baraka and Veloso 2015). Their adaptive algorithm is based on a sequence of rewards provided by users during interactions with the robot. They demonstrate the robot's ability to efficiently learn model parameters for each group during a light animation scenario involving a CoBot. Leite et. al. has developed Support Vector Machines models capable of predicting disengagement in children interacting with a social robot both individually and within small groups (Leite et al. 2015). Such an algorithm could be used by a robot to detect disengagement in real-time to catalyze a response to reengage those with whom the robot is interacting.

While recent research has made progress on developing and employing adaptive algorithms for robots to understand users and their needs, there is still much work to be done in this area. Adapting to user preferences across a variety of domains remains a significant challenge for social robots. Robots must be able to fluidly sense needs, preferences, and states of the humans they are interacting with, as well as efficiently select actions that correspond to these differences in order to foster engaging human-robot relationships.

Long-Term Interaction

Perhaps the most important and challenging factor of establishing sustained, supportive human-robot relationships is the long-term interaction component. Robots must be able to interact with users over periods of days, weeks, months, and years in order to make long-lasting influence in any domain.

Some recent studies in human-robot interaction have demonstrated promising results in multiple session studies spanning several weeks. Leite et. al. conducted a five session experiment over five weeks where a iCat robot played chess with third-grade students, responding empathetically to perceived affective states of the participants (Leite et al. 2012a). Overall, participants felt supported by the robot and preferred esteem support as a supportive behavior from the robot. Short et. al. ran a six session experiment over three weeks where a Dragonbot robot interacted with first-grade students individually to instruct them about healthy food choices (Short et al. 2014). Over the six sessions, children maintained a highly positive perception of the robot, and demonstrated increased engagement with the robot. Ramachandran et. al. conducted a four session study over two weeks where a NAO robot tutored fifth grade children in math, where half of the participants received tutoring where the robot tried to adaptively shape the child's help-seeing behaviors and half of the participants received standard tutoring (Ramachandran, Litoiu, and Scassellati 2016). The participants receiving the adaptive shaping of help-seeking behavior robot instruction had significant learning gains from pretest to posttest, where the control group did not. These studies demonstrate that robots can develop a supportive, *sustained* human-robot relationship with human participants where participants had a positive perception of the robot and from which participants experienced learning gains.

There is still much to explore in evaluating the effectiveness of supportive human-robot relationships in long-term interactions. We have not yet fully tested the possibilities of social robots to affect long-term behavioral change ranging from encouraging positive fitness habits to assisting in the development of social skills for children with autism spectrum disorder. In the education domain, in order to demonstrate the quality and scope of social robots as tutors, we have yet to run and test long-term benefits from robot instruction in a variety of domains including reading, history, and science. In the home and workplace environments, we have yet to discover the success of a social robot in reducing the workload of the humans it assists and how a social robot changes the interaction dynamics of its environment. Long-term studies are absolutely necessary as the field of human-robot interaction grows and as social robots continue to make and develop sustained, supportive relationships with humans in our everyday environments.

Conclusion

As social robots become more common in our everyday environments, their ability to form sustained, supportive human-robot relationships is increasingly important. In this paper, we highlight foundational research and open challenges in the three areas most relevant to the growth of these supportive human-robot relationships: *socially intuitive interaction*, *personalized interaction experience*, and *long-term interaction*. In order for robots to engage in social interactions smoothly, we must further investigate when it is appropriate to express verbal and nonverbal behaviors and how best to interpret the verbal and nonverbal behaviors of humans. To afford personalized interaction experiences, further development of sensing technology and algorithms is needed for robots to obtain a more direct and accurate understanding of the affective and mental states, needs, and preferences of humans. Finally, reliable and robust robot platforms, rich and adaptive interaction content, and a sizable amount of research resources are necessary for the development of long-term human-robot interactions. By addressing these challenges, we, as a research community, will enable robots to firmly establish sustainable, supportive human-robot relationships, facilitating the adoption of social robots into everyday environments for positive outcomes.

Acknowledgements

This work was supported by the National Science Foundation award number 1139078.

References

Baraka, K., and Veloso, M. 2015. Adaptive interaction of persistent robots to user temporal preferences. In *Social Robotics*. Springer. 61–71.

Cakmak, M., and Takayama, L. 2013. Towards a comprehensive chore list for domestic robots. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction*, 93–94. IEEE Press.

Hayes, B., and Scassellati, B. 2014. Discovering task constraints through observation and active learning. In *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems. Chicago, USA, September 14 - 18.* IEEE.

Huang, C.-M., and Mutlu, B. 2013. The repertoire of robot behavior: Enabling robots to achieve interaction goals through social behavior. *Journal of Human-Robot Interaction* 2(2):80–102.

Huang, C.-M.; Cakmak, M.; and Mutlu, B. 2015. Adaptive coordination strategies for human-robot handovers. In *Proceedings of Robotics: Science and Systems*.

Leite, I.; Castellano, G.; Pereira, A.; Martinho, C.; and Paiva, A. 2012a. Long-term interactions with empathic robots: Evaluating perceived support in children. In *Social Robotics*. Springer. 298–307.

Leite, I.; Pereira, A.; Castellano, G.; Mascarenhas, S.; Martinho, C.; and Paiva, A. 2012b. Modelling empathy in social robotic companions. In *Advances in User Modeling*. Springer. 135–147.

Leite, I.; McCoy, M.; Ullman, D.; Salomons, N.; and Scassellati, B. 2015. Comparing models of disengagement in individual and group interactions. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, 99–105. ACM.

Leyzberg, D.; Spaulding, S.; Toneva, M.; and Scassellati, B. 2012. The physical presence of a robot tutor increases cognitive learning gains. In *Proceedings of the 34th Annual Conference of the Cognitive Science Society. Austin, TX: Cognitive Science Society*.

Leyzberg, D.; Spaulding, S.; and Scassellati, B. 2014. Personalizing robot tutors to individuals' learning differences. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, 423–430. ACM.

Ramachandran, A.; Litoiu, A.; and Scassellati, B. 2016. Shaping productive help-seeking behavior during robot-child tutoring interactions. In *Proceedings of the 11th International Conference on Human-Robot Interaction (HRI 2016). ACM/IEEE (to appear)*.

Saerbeck, M.; Schut, T.; Bartneck, C.; and Janse, M. D. 2010. Expressive robots in education: varying the degree of social supportive behavior of a robotic tutor. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1613–1622. ACM.

Short, E.; Swift-Spong, K.; Greczek, J.; Ramachandran, A.; Litoiu, A.; Grigore, E. C.; Feil-Seifer, D.; Shuster, S.; Lee, J. J.; Huang, S.; et al. 2014. How to train your dragonbot: Socially assistive robots for teaching children about nutrition through play. In *Robot and Human Interactive Communication, 2014 RO-MAN: The 23rd IEEE International Symposium on*, 924–929. IEEE.

Thomaz, A. L., and Breazeal, C. 2008. Teachable robots: Understanding human teaching behavior to build more effective robot learners. *Artificial Intelligence* 172(6):716–737.

Unhelkar, V., and Shah, J. 2016. Contact : Deciding to communicate during time-critical collaborative tasks in unknown, deterministic domains. In *Thirtieth AAAI Conference on Artificial Intelligence*.