Journal of Science, Computing and Engineering Research (JSCER)
Volume-3, Issue- 2, Mar - April 2022.
DOI: https://doi.org/10.46379/jscer.2022.030202

Human Interaction with Robots through Verbal Communication

C.Vauki

Assistant Professor, Sri Adi Chunchanagiri Women's College, Cumbum, Tamil Nadu, India,

Article Information

Received	:	February 15 2022
Revised	:	March 10 2022
Accepted	:	March 25 2022
Published	:	April 12 2022

Corresponding Author:

Author Name: C. Vasuki
Email: vasukimathavan06@gmail.com

Abstract— In this paper is an overview of human–robot interaction (HRI) through verbal communication. Fundamentally, HRI problems represent breakdowns in communication, where poor information exchange between human and robots leads to faltering, wrong mental representation, poorly balanced trust, incomplete situational awareness, etc. Verbal communication in robotics is a significant increasing field in both the industrial and research side. The aim of verbal communication in robotics is to reach a natural human-like interaction with robots.

Keywords: Human Robot Interaction (HRI), R2-D2, Mixed-observabiliyt, Markov decision process model (MOMDP.

Citation: C.Vauki." Human Interaction with Robots through Verbal Communication", Journal of Science, Computing and Engineering Research, 3(2), 240-243, 2022.

I. INTRODUCTION

Robots are going to increasingly useful thing in our day to day life, entering our homes, our working places, hospitals, and schools. Since humans need to communicate with robots, and because we are regular to communicating with other people, the same way communicate with the humans might also apply to robots. The people often respond socially to computers in ways similar to how they would interact socially with other people. Therefore, the need to develop a robot that can behave socially has pushed researchers to incorporate a form of communication similar to what humans use in the design, such as the non-verbal communication as well as the verbal one.

Although the role of non-verbal behaviors is of clear importance, verbal communication has played a primary role in human-human interaction. Indeed, the voice is one of the most powerful tool that mankind uses to convey their emotions. The language allows the people to convey their meaningful messages in written or spoken words. Therefore, developing people using natural language to interact it for entertainment to create great interest. Moreover, spoken natural language interaction has some more advantages compared to non-verbal language. It makes human-robot communication natural, accurate and efficient and allowing for the possibility of the robot to cooperate, to be trained from non-expert humans, and to efficiently behave in a social environment.

II. ROBOTICS

Robotics is the intersection of science, engineering and technology that produces machines, called robots, that substitute for human actions. Pop culture has always been fascinated with robots. R2-D2. Optimus Prime. WALL-E. These over-exaggerated, humanoid concepts of robots usually seem like a caricature of the real thing...or are they more forward thinking than we realize? Robots are gaining intellectual and mechanical capabilities that don't put the possibility of a R2-D2-like machine out of reach in the future

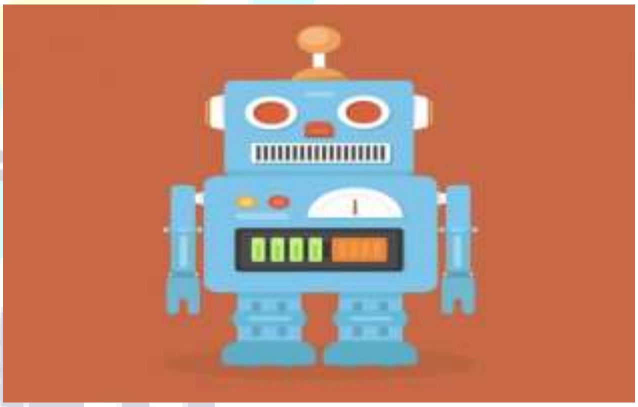

Figure 1: Robot

III. VERBAL COMMUNICATION

Verbal communications are written and oral communication.Oral communication encompasses various activities such as talking, laughing or listening. We often navigate different emotional situations through oral forms of communication. We also have written communication that includes script, alphabets, acronyms, logos and graphics. To interpret written messages, everyone involved must understand the code (e.g., the language). This is different from verbal or spoken communication.

IV. PLANNING WITH VERBAL COMMUNICATION

To compute the robot actions, the developers formulate and learn from data a mixed-observability Markov decision process (MOMDP) model. The model allows the robot to reason about the human internal state, in particular, about how willing the human teammate is to follow a robot task action, a robot verbal command, or a robot state-conveying action, and to optimally choose to take a task action Or issue a communication action. We conducted an online human subject's experiment featuring a table-carrying task and compared results between three instantiations of our formalism. The experiment had three conditions:

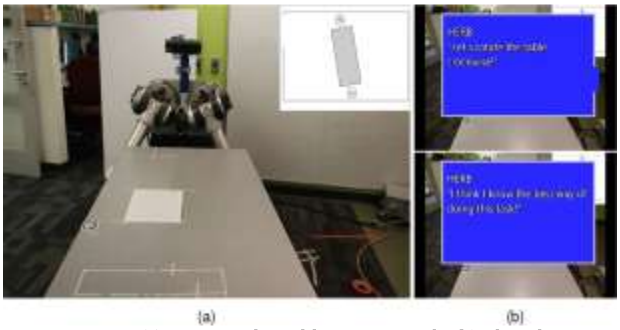

Figure 2. (a) Human-robot table-carrying task. (b) The robot issues a verbal command. (c) The robot issues astate-conveying action.

In the first condition the robot combined task actions with verbal utterances, in the second it combined task actions with the state-conveying action "I think I know the best way of doing the task," and in the third it executed the policy computed using the formalism from previous work that considers only non-verbal task actions, i.e., rotating the table in the table-carrying example. We then compared the number of users that adapted to the robot in the three conditions, and we assessed the users' trust in the robot. Results show that adding verbal commands to the robot decision making is the most effective form of interaction: 100% of participants changed their strategy toward a new, optimal goal demonstrated by the robot in the first condition. However, only 60% of participants in the third condition adapted to the robot. Trust ratings tended to be comparable between the two conditions. Interestingly, in the second condition state-conveying actions did not have a similar positive effect, since participants questioned whether the robot was truthful, as shown in their open-ended responses.

In a follow-up study, the developers added a new condition, where the robot combined task actions with a state-conveying action that was more informative, i.e., "I need to be able to see the door with my forward-facing camera." In this condition, participants were significantly more likely to adapt to the robot. These results indicate that when designing interactions in human-robot collaborative a task, issuing a verbal command where the robot prompts the human teammate to take a specific action appears to be the most effective way of communicating objectives, while retaining user trust in the robot. Communicating information about the robot's internal state should be done judiciously, since the observed behaviors appear to be sensitive to the level of detail of the information provided.

V. VERBAL COMMUNICATION WITHIN HUMANS:

Human Communication is a distributed process that depends on a circuit of brain regions, especially frontal and temporal cortical regions. Broca area, located in the ventral frontal lobe on the inferior frontal gyrus (IFG), is considered essential in the motor control of speech. Areas anterior and surrounding Broca area are involved in semantic processing, comprehension, and auditory working memory Yet, we have no idea how neurons in the ventral frontal lobe function to transform sounds into utterances, or how they initiate responses to heard words. These neural mechanisms which underlie communication are of great importance and may help us understand the causes of neurological disorders which affect communication including speech impairments and autism spectrum disorders.

Although human communication abilities far surpass those of other animal species, there are many features of communication that humans and animals have in common. By investigating the neural mechanisms of communication processes in animals, we can uncover the neural mechanisms and specializations for communication processes in our own brains. Neuroanatomical and neurophysiologic studies of the frontal lobe have allowed us to make great gains utilizing rhesus macaques, which, like humans, are also anthropoid primates. Over the past 50 years evidence has emerged that demonstrates similarities in the organization of macaque and human neocortex. This is especially important in the study of the frontal lobe since only primates have a developed frontal lobe, with Old World Monkeys exhibiting a well-developed prefrontal cortex compared to their New World primate relatives and nonprimate mammals.

Thus, investigation of communication-related ventral prefrontal cortex in Old World primates, with their phylogenetic proximity to humans and elaborate cognitive abilities, will help us understand the neural basis of our own frontal lobe communication regions. In addition it will aid in defining the cellular basis of communication disorders.

VI. VERBAL COMMUNICATION WITHIN HUMAN-ROBOT

Verbal communication in human-robot teams has been shown to affect collaboration, as well as People's perception of the robot Robot dialog systems have mostly supported human initiated or robot-initiated communication in the form of requests. An important challenge for generating legible verbal commands has been symbol grounding which is described as the ability of the robot to map a symbol to a physical object in the world. Tellex et al. presented a model for inferring plans from natural language commands; inverting the model enables a robot to recover from failures, by communicating the need for help to a human partner using natural language Khan et al proposed a method for generating theminimal sufficient explanation that explains the policy of a Markov decision process, and Wang et al proposed generating explanations about the robot's confidence on its own beliefs. Recent work by Hayes and Shah has generalized the generation of explanations of the robot policies to a variety of robot controllers. Of particular relevance is previous work in the autonomous driving domain. Messages that conveyed "how" information, such as "the car is braking," led to poor driving performance, whereas messages containing "why" information, such as "There is an obstacle ahead," were preferred and improved performance. Contrary to the driving domain, in our setting the human cannot verify the truthfulness of the robot "why" action.

Additionally, unlike driving, in physical human-robot collaboration setting there is not a clearly right action that the robot should take, which brings the human to a state of uncertainty and disagreement with the robot. In agreement with Koo et al. our results show the importance of finding the right away to explain robot behavior to human teammates. Our work is also relevant to the work by Clair and Mataric. The authors explored communication in a shared-location collaborative task, using three different types of verbal feedback: Self-narrative (e.g., “I’ll take care of X”), role-allocative (e.g., “you handle X”), and empathetic (e.g., “Oh no” or “Great”). They showed that feedback improves both objective and subjective metrics of team performance. In fact, the robot’s verbal commands (“Let’s rotate the table clockwise”) and state-conveying actions (“I think I know the best way of doing the task”) of our work resemble the role-allocative and self-narrative feedback.

Additionally, Oudah et al integrated verbal feedback about past actions and future plans into a learning algorithm, resulting in improved human-robot team performance in two game scenarios. Contrary to existing work, our formalism enables the robot to reason about the effects of various types of verbal communication on the future actions of different human collaborators, based on their internal state. The human internal state captures inter-individual variability. Integrating it as a latent variable in a partially observable stochastic process allows the robot to infer online the internal state of a new human collaborator and decide when it is optimal to give feedback, as well as which type of feedback to give.

VII. CONCLUSION

In this work, we proposed formalism for combining verbal communication with actions toward task completion, to enable a human teammate to adapt to its robot counterpart in a collaborative task. We identified two types of verbal communication: verbal commands, where the robot explained to the human how it wanted to do a task, and state-conveying actions, where the robot informed the human why it chose to act in a specific way. In human subject’s experiments, we compared the effectiveness of each communication type with a robot policy that considered only non-verbal task actions.

REFERENCES

[1]. Altbach, P. G., and de Wit, H. (2019). Too much academic research is being published. Int. Higher Edu. 59, 2–3. doi:10.6017/ihe.2019.96.10767

[2]. Arun, R., Suresh, V., Veni Madhavan, C. E., and Narasimha Murthy, M. N. (2010). “On finding the natural number of topics with latent dirichlet allocation: some observations,” in Pacific-Asia conference on knowledge discovery and data mining. Berlin, Heidelberg: Springer, 391–402.

[3]. Azeta, J., Bolu, C., Abioye, A. A., and Oyawale, F. A. (2017). A review on humanoid robotics in healthcare. MATEC Web Conf. 153 (5), 02004. doi:10.1051/matecconf/201815302004

[4]. Barakova, E. I., Bajracharya, P., Willemsen, M., Lourens, T., and Huskens, B. (2015). Long-term lego therapy with humanoid robot for children with asd. Expet Syst. 32, 698–709. doi:10.1111/exsy.12098

[5]. Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., and Tanaka, F. (2018). Social robots for education: a review. Sci. Robot. 3, aat5954. doi:10.1126/scirobotics.aat5954

[6]. Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. J. Mach. Learn. Res. 3, 993–1022. doi:10.1162/jmlr.2003.3.4-5.993

[7]. Breazeal, C., Kidd, C. D., Thomaz, A. L., Hoffman, G., and Berlin, M. (2005). “Effects of nonverbal communication on efficiency and robustness in human-robot teamwork,” in IEEE/RSJ international conference on intelligent robots and systems, Sendai, Japan, September–October 2–28, 2005 (Edmonton, AB, Canada: IEEE), 708–713.

[8]. Henny Admoni and Brian Scassellati. 2014. Data-driven model of nonverbal behavior for socially assistive humanrobot interactions. In Proceedings of the 16th International Conference on Multimodal Interaction. ACM, 196–199.

[9]. Stefano Vittorino Albrecht, Jacob William Crandall, and Subramanian Ramamoorthy. 2015. An empirical study on the Practical impact of prior beliefs over policy types. In Proceedings of the Association for the Advancement of Artificial Intelligence (AAAI’15). 1988–1994.

[10]. David W. Eccles and Gershon Tenenbaum. 2004. Why an expert team is more than a team of experts: A socialcognitiveconceptualization of team coordination and communication in sport. J. Sport Exer. Psychol. 26, 4 (2004),542–560. DOI:https://doi.org/10.1123/jsep.26.4.542

[11]. Pamela J. Hinds, Teresa L. Roberts, andHank Jones. 2004. Whose job is it anyway? A study of human-robot interaction in a collaborative task. Hum.-Comput. Interact. 19, 1 (2004), 151–181.

[12]. Stefanos Nikolaidis, Anton Kuznetsov, David Hsu, and Siddharta Srinivasa. 2016. Formalizing human-robot mutual adaptation: A boundedmemorymodel. In Proceedings of the 11th ACM/IEEE International Conference on Human-Robot Interaction. IEEE Press, 75–82.

[13]. NingWang, David V. Pynadath, and Susan G. Hill. 2016. The impact of POMDP-generated explanations on trust and performance in human-robot teams. In Proceedings of the 2016 International Conference on Autonomous Agents and Multiagent System

[14]. Rob Powers and Yoav Shoham. 2005. Learning against opponents with bounded memory. In Proceedings of the International Joint Conferences on Artificial Intelligence (IJCAI’05).

[15]. Jonas Moll and Eva-Lotta Sallnas. 2009. Communicative functions of haptic feedback. In Proceedings of the 4th International Conference on Haptic and Audio Interaction Design. Springer-Verlag Berlin Heidelberg.

[16]. Daniel Monte. 2014. Learning with bounded memory in games. GEB 87 (2014), 204–223.

[17]. Bernard Moulin, Hengameh Irandoust, Micheline Belanger, and Gaelle Desbordes. 2002. Explanation and argumentation capabilities: Toward the creation of more persuasive agents. Artific. Intell. Rev. 17, 3 (2002), 169–222.

[18]. Bilge Mutlu, Takayuki Kanda, Jodi Forlizzi, Jessica Hodgins, and Hiroshi Ishiguro. 2012. Conversational gaze mechanismsfor humanlike robots. ACM Trans. Interac. Intell. Syst. 1, 2 (2012), 12.

[19]. Clifford Nass and Youngme Moon. 2000. Machines and mindlessness: Social responses to computers. J. Soc. Iss. 56, 1 (2000), 81–103.

[20]. Stefanos Nikolaidis, David Hsu, and Siddhartha Srinivasa. 2017. Human-robot mutual adaptation in collaborative tasks: Models and experiments. Int. J. Robot. Res. 36, 5–7 (2017), 618–634.