Human-Robot Co-Learning for Fluent Collaborations

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ABSTRACT

A team develops competency by progressive mutual adaptation and learning, a process we call co-learning. In human teams, partners naturally adapt to each other and learn while collaborating. This is not self-evident in human-robot teams. There is a need for methods and models for describing and enabling co-learning in human-robot partnerships. The presented project aims to study human-robot co-learning as a process that stimulates fluent collaborations. First, it is studied how interactions develop in a context where a human and a robot both have to implicitly adapt to each other and have to learn a task to improve the collaboration and performance. The observed interaction patterns and learning outcomes will be used to (1) investigate how to design learning interactions that support human-robot teams to sustain implicitly learned behavior over time and context, and (2) to develop a mental model of the learning human partner, to investigate whether this supports the robot in its own learning as well as in adapting effectively to the human partner.

CCS CONCEPTS

• **Human-centered computing → Human-computer interaction(HCI)**; *Human-computer interaction(HCI)*; **Collaborative interaction**; *User studies.*

KEYWORDS

human-robot collaboration, co-learning, interaction patterns, co-adaptation, human-agent teaming

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1 INTRODUCTION

When people collaborate in teams, they have to become familiar with each other and learn through interactions how to coordinate their actions to achieve fluent collaboration and effective team performance. This process is called co-learning, a mutual learning process that usually takes place in an implicit as well as explicit manner. While humans tend do this naturally, it is a key research and development challenge for long-term human-robot collaboration: How to involve social robots in a continuing human-robot co-learning process for advanced team performance?

Co-learning is a continuous process, shaping the behavior of the team over time [16]. We define co-learning as two alternating iterative processes: (1) partners monitor each other and adapt their behavior accordingly. This adaptation can be done deliberately but often occurs implicitly and unconsciously. After that, (2) partners communicate about these adaptations and give each other feedback, thereby consolidating the learned behavior. Especially this second process of making explicit what has been learned helps to sustain the behavioral adaptations over time and across contexts.

Many studies on human-robot collaboration and mutual adaptivity focus on short term interactions. We believe that it is necessary to also include the longitudinal aspect when studying co-learning. The presented research project studies co-learning in human-agent partnerships in the context of safety-critical situations, where sustaining the learned behavior in the robot as well as the human is especially important. Two initial experiments on tension-based leader-follower negotiations and observation-based work strategy harmonization addressed the following research question: What patterns of successful human-robot collaborative adaptation can be identified in a given task? The patterns identified in these experiments will be used to study the consecutive research questions: (1) How to apply interaction patterns that make team partners explicitly aware of learned behaviors, so that the behaviors can be sustained over time and contexts? (2) How can a dynamic team model, that takes into account the naturally occurring changes in interaction patterns, support the robot in its learning process? It will be investigated how the combination of interaction patterns and a dynamic team model support co-learning and effective human-robot team performance.

2 BACKGROUND

Creating collaborations between robots and humans in mixed human-robot teams has been widely studied within the HRI community (human-robot collaboration or HRC [1, 4, 15]), as well as the AI community (human-agent teaming or HAT [2, 6, 9]). Understanding how to achieve fluent collaboration between humans and robots is still a challenge, but there is general agreement that adaptivity is necessary in order for a robot or agent to be considered a team partner [7, 8]. Several researchers have emphasized the importance of learning from, with and about each other in creating successful human-robot collaborations (e.g. [11, 16]). Experimental studies

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mostly focus on making the agent or robot adaptive to the human, using different kinds of information about the human (e.g. [3, 5, 13, 17]). Some studies have investigated how a human adapts and learns in situations in which they collaborate with an intelligent agent, but these studies mostly focus on the performance of the human and their resulting behavior (e.g. [10–12, 18]). In addition, most of the empirical studies investigate adaptation within a relatively short amount of time, thus concentrating on ad hoc adaptations. We believe that the field of co-learning in human-robot teams needs models of how human-agent learning develops, as well as insights into methods that enable this process.

3 IDENTIFYING PATTERNS OF COLLABORATIVE ADAPTATION

We conducted experiments to understand how different human-robot interaction patterns influence and enable co-learning. We looked at two types of implicit team behavior adaptations: switching between leader-follower behaviors via tangible interaction, and attuning work strategies via observations of robot behaviors.

3.1 Tension-based Leader-Follower Negotiations

The first study involved an embodied human-robot collaborative navigation task, using a Wizard of Oz robot on a leash [19]. As capabilities of a human and a robot are often complementary, deciding who needs to lead and who needs to follow at each moment in a collaboration is not trivial. In order for a human-robot team to learn what interactions between them are productive for achieving the team's goal the partners need to try out different mutual behavioral adaptations to initiate or accommodate leadership shifts. In the experiment, participants performed a physical navigation task with the robot on a leash (see Figure 1), during which they were continuously confronted with seemingly conflicting intentions of the robot. Participants were instructed to find a good strategy by finding a balance between taking the lead and following the robot. Feedback factors from the task (e.g. getting closer to the goal) and from the robot partner (e.g. the robot pulling the leash) triggered humans to reconsider when to lead and when to follow. Participants developed diverse strategies of leading and following, such as gradually handing over the lead to the robot, or exploring a leading strategy but moving to a more following strategy.

3.2 Observation-based Work Strategy Harmonization

For the second experiment, an urban-search-and-rescue inspired virtual task and virtual robot were designed. Within this environment, participants had to clear away rocks to save a victim, together with the virtual robot (see Figure 1). The robot was programmed to select from three rule-based behaviors in each phase of the task using the options framework in reinforcement learning [14]. Over the course of several rounds of performing the task, participants were instructed to develop strategies for saving the victim in a safe and efficient manner. The learning algorithm enabled the robot to also learn a strategy that supported the team in achieving its objective.

Preliminary results show that when participants were focused on their own strategy or not behaving consistently, the robot would be unable to learn a working strategy. On the other hand, when participants adapted their strategy to avoid the robot making mistakes, the robot was able to not only learn an effective strategy, but also to choose the strategy that fit best with the participant's strategy.

Figure 1: Left: A participant with the robot on a leash for the leader-follower experiment. Right: The USAR task used in the work strategy harmonization experiment.

4 FUTURE STEPS

Using the insights obtained, we will research two directions: how to develop a dynamic team model that takes into account the changing nature of the interaction patterns and supports the robot in co-learning, as well as how interaction patterns can support the team members to become explicitly aware of implicitly learned behaviors. This explicit awareness should ultimately lead to sustaining the learned behavior over time and context.

When co-learning in a collaborative task, there is not necessarily one best strategy, and learning does not necessarily have an endpoint. The strategies that team members apply will evolve due to changes in the environment and the partners themselves. We believe that it is necessary for both team partners to take the possible changes in their partner into account while learning themselves. The dynamic team model will therefore model changing knowledge of the team members about each other and the task over the course of the collaboration. Additionally, we will model the different adaptive interaction patterns identified in the experiments from behavior, such that they can be recognized and communicated about. We will investigate whether such a model can be used to help the robot successfully adapt to its human partner.

Key in co-learning is the process of becoming aware of implicitly learned interaction patterns. We will design new interaction patterns that support this process, for example through explanations or feedback between the team partners. These communications can in turn be used to update the dynamic team model, such that both team members can grow their understanding of the behaviors that are successful in the context of their task.

We envision future experiments to make use of a combination of the found leader-follower negotiation patterns and the work strategy harmonization patterns, in a context where the robot is able to reflect on these through its dynamic team model. From this, we hope to learn how the different elements (implicitly learned behaviors, interaction patterns for feedback and reflection, and the dynamic team model) support and enable sustainable co-learning and effective human-robot team performance.

REFERENCES

[1] Arash Ajoudani, Andrea Zanchettin, Serena Ivaldi, Alin Albu-Schäffer, Kazuhiro Kosuge, and Oussama Khatib. 2018. Progress and Prospects of the Human-Robot Collaboration. *Autonomous Robots* 42, 5 (2018), 957–975. https://doi.org/10.1007/s10514-017-9677-2

[2] Jeffrey M. Bradshaw, Maarten Sierhuis, Alessandro Acquisti, Paul Feltovich, Robert Hoffman, Renia Jeffers, Debbie Prescott, Niranjan Suri, Andrzej Uszok, and Ron Van Hoof. 2003. Adjustable Autonomy and Human-Agent Teamwork in Practice: An Interim Report on Space Applications. In *Agent Autonomy*, Gerhard Weiss, Henry Hexmoor, Cristiano Castelfranchi, and Rino Falcone (Eds.). Vol. 7. Kluwer Academic Press, Boston, MA, 243–280. https://doi.org/10.1007/978-1-4419-9198-0_11

[3] Hendrik Buschmeier and Stefan Kopp. 2013. Co-constructing Grounded Symbols - Feedback and Incremental Adaptation in Human-Agent Dialogue. *KI - Künstliche Intelligenz* 27 (2013), 137–143. https://doi.org/10.1007/s13218-013-0241-8

[4] Judith Bütepage and Danica Kragic. 2017. Human-Robot Collaboration: From Psychology to Social Robotics. *arXiv:1705.10146 [cs]* (May 2017). http://arxiv.org/abs/1705.10146 arXiv: 1705.10146.

[5] Stefan K Ehrlich and Gordon Cheng. 2018. Human-agent co-adaptation using error-related potentials. *Journal of Neural Engineering* 15, 6 (Dec. 2018), 066014. https://doi.org/10.1088/1741-2552/aae069

[6] G. Klein, D. D. Woods, J. M. Bradshaw, R. R. Hoffman, and P. J. Feltovich. 2004. Ten challenges for making automation a "team player" in joint human-agent activity. *IEEE Intelligent Systems* 19, 6 (Nov. 2004), 91–95. https://doi.org/10.1109/MIS.2004.74

[7] Ari Kolbeinsson, Erik Lagerstedt, and Jessica Lindblom. 2019. Foundation for a classification of collaboration levels for human-robot cooperation in manufacturing. *Production & Manufacturing Research* 7, 1 (Jan. 2019), 448–471. https://doi.org/10.1080/21693277.2019.1645628

[8] Matti Krüger, Christiane B. Wiebel, and Heiko Wersing. 2017. From Tools Towards Cooperative Assistants. In *Proceedings of the 5th International Conference on Human Agent Interaction - HAI '17*. ACM Press, Bielefeld, Germany, 287–294. https://doi.org/10.1145/3125739.3125753

[9] Sirui Li, Weixing Sun, and Tim Miller. 2016. Communication in Human-Agent Teams for Tasks with Joint Action. In *Coordination, Organizations, Institutions, and Norms in Agent Systems XI*, Virginia Dignum, Pablo Noriega, Murat Sensoy, and Jaime Simão Sichman (Eds.). Vol. 9628. Springer International Publishing, Cham, 224–241. https://doi.org/10.1007/978-3-319-42691-4_13

[10] Y. Mohammad and Toyoaki Nishida. 2008. Human adaptation to a miniature robot: Precursors of mutual adaptation. In *RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication*. 124–129. https://doi.org/10.1109/ROMAN.2008.4600654

[11] Stefanos Nikolaidis, David Hsu, and Siddhartha S. Srinivasa. 2017. Human-robot mutual adaptation in collaborative tasks: Models and experiments. *I. J. Robotics Res.* 36 (2017), 618–634. https://doi.org/10.1177/0278364917690593

[12] Stefanos Nikolaidis, Yu Xiang Zhu, David Hsu, and Siddhartha Srinivasa. 2017. Human-Robot Mutual Adaptation in Shared Autonomy. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17*. ACM Press, Vienna, Austria, 294–302. https://doi.org/10.1145/2909824.3020252

[13] Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A Neural Network Approach to Context-Sensitive Generation of Conversational Responses. *arXiv:1506.06714 [cs]* (June 2015). http://arxiv.org/abs/1506.06714 arXiv: 1506.06714.

[14] Richard S. Sutton, Doina Precup, and Satinder Singh. 1999. Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning. *Artificial Intelligence* 112, 1-2 (Aug. 1999), 181–211. https://doi.org/10.1016/S0004-3702(99)00052-1

[15] Yeshasvi Tirupachuri, Gabriele Nava, Lorenzo Rapetti, Claudia Latella, Kourosh Darvish, and Daniele Pucci. 2020. Recent Advances in Human-Robot Collaboration Towards Joint Action. *arXiv:2001.00411 [cs]* (Jan. 2020). http://arxiv.org/abs/2001.00411 arXiv: 2001.00411.

[16] Karel van den Bosch, Tjeerd Schoonderwoerd, Romy Blankendaal, and Mark Neerincx. 2019. Six Challenges for Human-AI Co-learning. In *Lecture Notes in Computer Science*, Vol. 11597. 572–589. https://doi.org/10.1007/978-3-030-22341-0_45

[17] S. Yamada and T. Yamaguchi. 2002. Mutual adaptation to mind mapping in human-agent interaction. In *Proceedings. 11th IEEE International Workshop on Robot and Human Interactive Communication*. IEEE, Berlin, Germany, 105–110. https://doi.org/10.1109/ROMAN.2002.1045606

[18] Khaoula Youssef, P. Ravindra S. De Silva, and Michio Okada. 2014. Sociable Dining Table: Incremental Meaning Acquisition Based on Mutual Adaptation Process. In *Social Robotics*, Michael Beetz, Benjamin Johnston, and Mary-Anne Williams (Eds.). Vol. 8755. Springer International Publishing, Cham, 206–216. https://doi.org/10.1007/978-3-319-11973-1_21

[19] E. M. van Zoelen, E. I. Barakova, and M. Rauterberg. 2020. Adaptive Leader-Follower Behavior in Human-Robot Collaboration. In *29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. 1259–1265. https://doi.org/10.1109/RO-MAN47096.2020.9223548 ISSN: 1944-9437.