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Challenges in Collaborative Scheduling of Human-Robot Teams

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Abstract

We study the scheduling of human-robot teams where the human and robotic agents share decision-making authority over scheduling decisions. Our goal is to design AI scheduling techniques that account for how people make decisions under different control schema.

Introduction

There is a growing desire to integrate robots to work interdependently with people in traditionally manual manufacturing processes. While robots are not yet capable of performing all of the same tasks as people, robots can improve the efficiency their human teammates by performing non-value-added tasks such as the fetching of parts. However, the real-time choreography of these teams in time and space is a challenging computational problem; scheduling under hard upper- and lower-bound temporal constraints is known to be NP-Hard (Bertsimas and Weismantel 2005)

Researchers and industry practitioners have proposed fully autonomous solutions to the coordination of these teams(Alsever 2011; Bertsimas and Weismantel 2005; Gombolay, Wilcox, and Shah 2013). These solutions work well in domains where people are able to fully encode the domain knowledge for the autonomous system. However, people often make use of implicit knowledge or previous experience, which can be time-consuming to translate for an AI agent. In such cases, the human remains a critical component of the system, providing high level guidance and feedback on the generated plans and schedules (Durfee, Boerkoel Jr., and Sleight 2013; Hamasaki et al. 2004; Zhang et al. 2012; Clare et al. 2012). Significant research effort has been aimed at supporting the human's role through careful design and validation of supervisory control interfaces (Adams 2009; Barnes et al. 2011; Chen, Barnes, and Qu 2010; Cummings, Brzezinski, and Lee 2007; Goodrich et al. 2009; Jones et al. 2002; Hooten, T.Hayes, and Adams 2011). Collaborative human-robot decision-making, in which a human shares decision-making authority with an autonomous robot, is less well studied.

Given full knowledge of the world-state, a robot may potentially outperform a person in planning and scheduling for the team. However, human workers often develop a sense of identity from their role. If decision-making authority over a person's role is taken away from the worker and given to a robotic counterpart, workers may feel devalued and resist the adoption of this technology. To successfully integrate robots into the human workspace, we need to ensure that the technology will improve the productivity of the team and be appreciated by its human operators. In this paper, we summarize recent experiments that inform the mechanism design for shared decision-making in human-robot teams.

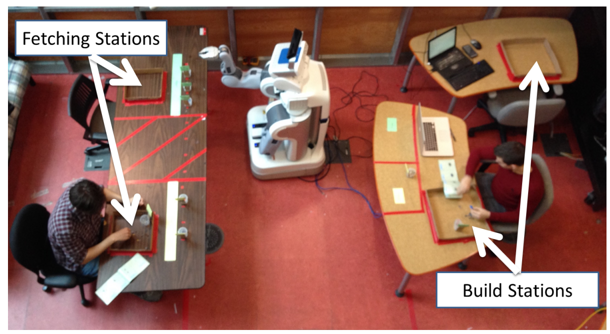

Figure 1: Members of a human-robot team complete a set of fetch and build tasks to complete a Lego kit while negotiating shared resources.

Shared Control of Human-Robot Teams

We recently conducted a human-subject experiment to examine the impact of shared human-robot decision-making on the productivity of the team and human worker satisfaction (Gombolay et al. 2014). Experiment participants worked in teams of three, with one other human teammate and one robot teammate. The goal was to complete a set of fetch and build tasks to assemble a Lego model. The task involved spatial-resource and temporal constraints (Figure 2).

We evaluated three conditions for shared decision-making authority between the human subject and the robotic teammate. In the manual condition, the participant allocated the fetch and build tasks among members of the team. In the semi-autonomous condition, the participant allocated him/herself tasks and the robot allocated the remaining tasks. In the autonomous condition, the robot allocated the tasks to team members. In all conditions, the robot optimized the sequencing of the tasks. We evaluated two hypotheses. First, we hypothesized the team would be more efficient when the robot retained more control over allocation. Second, we hypothesized participants would prefer to retain a role in the decision-making process.

The robot used Tercio, a fast, near-optimal scheduling algorithm, to perform task allocation and scheduling (Gombolay, Wilcox, and Shah 2013). The algorithm divides the scheduling process into task allocation and sequencing subroutines. The algorithm iterates between the subroutines, solving for the optimal task allocation and then finding a corresponding task sequence. If the schedule does not satisfy deadlines for completion time, a second task allocation is selected and the corresponding task sequence is produced. The process terminates once a user-defined makespan is achieved. The output of the algorithm is encoded as a flexible, dispatchable scheduling policy (Tsamardinos, Muscettola, and Morris 1998).

Results

We found statistically significant evidence that giving human subjects more control authority over task allocation negatively influenced team fluency ($p < 0.02$) and the desire of the subject to work with the robot again ($p < 0.001$). We also found evidence of a complex relationship between human/robot decision-making authority and human preferences over task allocation; people sought looser couplings between human and robot work when they did not retain primary decision-making authority. Specifically, participants with full control over task allocation more frequently chose to rely on their teammates to complete pre-requisite tasks. For example, participants more frequently assigned a team member to fetch the parts that the participant needed to complete his or her build task. In contrast, participants more frequently isolated their work when they retained only partial control, by chosing to fetch parts for their own build tasks.

In *post-hoc* analysis conducted since (Gombolay, Wilcox, and Shah 2013), we have also found inequities in work sharing as a function of decision-making authority. Repeated-measure analysis of variances demonstrated significant differences in the amount of work allocated to the human participant as a function of the level of control $F(2, 46) = 5.3$, $p = 0.0085$. Specifically, the participant allocated statistically significantly more work to him or herself in both the manual ($M = 401$, $SD = 112$), $t(23) = 2.37$, $p = 0.003$, and semi-autonomous conditions ($M = 399$, $SD = 81.4$), $t(23) = 2.37$, $p = 0.01$, as compared to the amount of work the robot chose to allocate to the participant in the autonomous condition ($M = 352$, $SD = 60.6$). The explanation for these results remains an open question and is the subject of ongoing experimentation. For example, particpants may lack trust in the abilities of their teammates, may be acting altruistically in taking on disproportionate work, or may be trying to ensure an important role for themselves on the team.

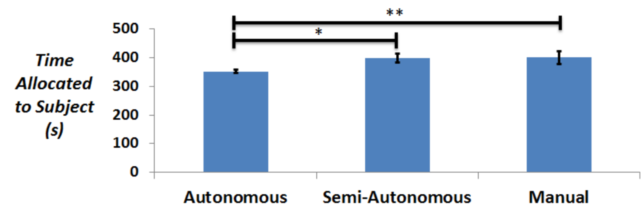

Figure 2: Subjects allocate more work to themselves when they have control over which tasks they will perform.

Human-in-the-Loop System Design Guidance

These results provide some initial guidance for the successful introduction of semi-autonomous robots into human teams, and open many questions. First, providing human teammate subjects more decision-making authority over robot behavior is not sufficient to improve worker satisfaction, and may in fact degrade team performance. Also, team fluency does appear to positively correlate with willingness to collaborate with robotic technology. Finally, the human preference to decouple human and robotic work appears to negatively affect team performance.

We have follow-on studies underway to fully characterize this last phenomenon and test mitigation strategies, since many applications require people to retain partial decision-making authority. Human must often act as safe-guards, and compensate for the fact that is impractical to encode full knowledge of the task and environment into an AI agent. Our initial results indicate that care must be taken in designing the mechansism for sharing decision-making authority. Human operators may make fundamentally different decisions based on how much decision-making authority they are given.

We are currently developing new AI scheduling techniques that utilize a humans in-the-loop while countering the natural bias created by separating the human from full control over the system. The design of our technique will be informed by human-subject experiments that characterize the biases created by giving human supervisors various levels of decision-making authority. We will leverage statistical and machine learning approaches to model the decision-making strategies of human operators as a function of decision-making authority and offer corrective guidance to the human operator to counter the bias. We hypothesize that this new system will produce measurable improvements in human-robot team planning and scheduling, as compared to methods to that do not mitigate human bias.

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References

Adams, J. A. 2009. Multiple robot-single human interaction: effects on perceived workload and performance. *Behavior* *and Information Technology* 28(2):183–298.

Alsever, J. 2011. Robot workers take over warehouses. *CNN Money*. http://money.cnn.com/2011/11/09/smallbusiness/kiva_robots/.

Barnes, M. J.; Chen, J. Y.; Jentsch, F.; and Redden, E. S. 2011. Designing effective soldier-robot teams in complex environments: training, interfaces, and individual differences. In *Proceedinggs of the International Conference on Engineering Psychology and Cognitive Ergonomics (EPCE)*, 484–493. Springer.

Bertsimas, D., and Weismantel, R. 2005. *Optimization over Integers*. Belmont: Dynamic Ideas.

Chen, J. Y.; Barnes, M. J.; and Qu, Z. 2010. Roboleader: an agent for supervisory control of mobile robots. In *Proceedings of the International Conference on Human-Robot Interaction (HRI)*.

Clare, A. S.; Cummings, M. M. L.; How, J. P.; Whitten, A. K.; and Toupet, O. 2012. Operator objective function guidance for a real-time unmanned vehicle scheduling algorithm. 9:161–173.

Cummings, M. M. L.; Brzezinski, A. S.; and Lee, J. D. 2007. Operator performance and intelligent aiding in unmanned aerial vehicle scheduling. *IEEE Intelligent Systems* 22(2):52–59.

Durfee, E. H.; Boerkoel Jr., J. C.; and Sleight, J. 2013. Using hybrid scheduling for the semi-autonomous formation of expert teams. *Future Generation Computer Systems*.

Gombolay, M. C.; Gutierrez, R. A.; Sturla, G. F.; and Shah, J. A. 2014. Decision-making authority, team efficiency and human worker satisfaction in mixed human-robot teams. In *Proceedings of the Robots: Science and Systems (RSS)*.

Gombolay, M. C.; Wilcox, R. J.; and Shah, J. A. 2013. Fast scheduling of multi-robot teams with temporospatial constrints. In *Proceedings of the Robots: Science and Systems (RSS)*.

Goodrich, M. A.; Morse, B. S.; Engh, C.; Cooper, J. L.; and Adams, J. A. 2009. Towards using UAVs in wilderness search and rescue: Lessons from field trials. *Interaction Studies, Special Issue on Robots in the Wild: Exploring Human-Robot Interaction in Naturalistic Environments* 10(3):453–478.

Hamasaki, M.; Takeda, H.; Ohmukai, I.; and Ichise, R. 2004. Scheduling support system for academic conferences based on interpersonal networks. In *Proceedings of ACM Hypertext*.

Hooten, E. R.; T.Hayes, S.; and Adams, J. A. 2011. A comparison of communicative modes for map-based tasking. In *IEEE Internation Conference on Systems, Man, and Cybernetics*.

Jones, H. L.; Rock, S. M.; Burns, D.; and Morris, S. 2002. Autonomous robots in SWAT applications: Research, design, and operations challenges. *AUVSI*.

Tsamardinos, I.; Muscettola, N.; and Morris, P. 1998. Fast transformation of temporal plans for efficient execution. In *Proceedings of the Association for the Advancement of Artificial Intelligence (AAAI)*.

Zhang, H.; Law, E.; Miller, R.; Gajos, K.; Parkes, D.; and Horvitz, E. 2012. Human computation tasks with global constraints. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, 217–226. New York, NY, USA: ACM.