Understanding Human-AI Teaming Dynamics through Gaming Environments

Qiao Zhang

School of Interactive Computing, College of Computing, Georgia Institute of Technology
Technology Square Research Building, 85 5th St NW, Atlanta, GA 30332
qzhang490@gatech.edu

Abstract

With the goal of better understanding Human-machine Teaming (HMT) dynamics and how team competencies that are transportable across contexts can lead to different teaming behaviors and team performances, I propose a series of three studies to explore communication, coordination and adaptation in HMT paradigms. I implement and integrate multiple AI agents and use collaborative games as testing environments to evaluate teaming effects. My work can provide findings to two higher level research questions that are widely studied in HMT: 1) the bidirectional behaviors that human and AI agents may develop when working as a team and, 2) how different types of AI agents can impact the teaming efficiency in human-AI teaming. Besides, my work can also contribute to Human-Computer Interaction and Game AI scholarship with insights into teaming dynamics in Human-AI teaming.

Introduction

Humans and machines have established collaboration for several decades and have achieved success in multiple domains such like healthcare, education, military operations and video games (Stowers et al. 2021). While recent advancement in Machine Learning and Artificial Intelligence have demonstrated AI agents' proficiency in outperforming human experts in a number of tasks, including playing games (Harpstead et al. 2023; Perez-Liebana et al. 2016). Studies show that AI agents still generally lack the ability to recognize their teammates' knowledge and behaviors, as well as responding to new situations where such information should they arise (Johnson and Vera 2019).

In earlier stages of introducing human-machine teams, psychologists and engineers have explored the use of machines to augment and improve human task performance (Fitts et al. 1951; Dekker and Woods 2002), as well as using machines to automate redundant and repetitive tasks (Autor 2015) with the goal of improving the overall Human-machine Teaming (HMT) performance (Dekker and Woods 2002). The discussion of HMT gradually shifted from "machines as tools" to "machines as teammates" (Phillips et al. 2011) since machines are becoming socially important as technology advances (Katz 2017).

My work fits in the higher-level goal of ARL STRONG (Strengthening Teamwork for Robust Operations in Novel Groups) Cycle 3 [1] ambition of developing novel and human-guided Machine Learning capabilities that can facilitate AI agents to learn from situated interactions with their human teammates in futuristic Human-AI teaming scenarios. My dissertation proposal focuses on team competencies that are transportable across contexts (Salas, Reyes, and McDaniel 2018). I am going to use three games as environments to understand how communication, coordination and adaptation are leveraged in different teaming dynamics, teaming compositions and teaming roles. I want to study the bidirectional interact behaviors between human and their AI teammates to better understand trustworthiness, and teaming efficiency in multiple human-AI teams. I also want to explore how different types of AI agents can impact the teaming efficiency.

Related Works

My current work in AI agent development and integration depends on previous and recent work conducted by collaborators. I am implementing a few agents within the Apprentice Learner (AL) Architecture (Maclellan et al. 2016) to adapt different gaming environments. The AL architecture learns from demonstrations and feedback and generalize them into skill knowledge that can be used to solve problems (MacLellan and Koedinger 2022). I am also implementing the Verbal Apprentice Learner (VAL) agent (Lawley and MacLellan 2023), which is built around the Hierarchical Task Network (HTN) (Sacerdoti 1990). Current AI agent development on interactive construction and modification of HTN is rooted in the Natural Training Interaction (NTI) framework (MacLellan et al. 2018). I have implemented multiple AI agents and adapted them to the games I used as testbeds.

Research Objectives

Previous studies pointed out that people may perpetuate misconceptions and oversimplification of AI's roles in human society by comparing human/AI capabilities and limitations, which limit the potential use cases of AI (Metcalfe et al.

[1] MacLellan, C.; Harpstead, E.; Austerweil, J.; Stowers, K. 2021. Human-Guided ML for Futuristic Human-Machine Teaming (STRONG Cycle 3 proposal)

2021). Effective HMT is built upon the success of complex and bidirectional interactions between human and machine agents, and between these agents and their environment (Stowers et al. 2017). Recent work in team science and I/O psychology emphasized three team competencies (Salas, Reyes, and McDaniel 2018), namely communication, coordination and adaptation, which are all transportable across context (Borrego et al. 2013).

I propose a series of three user studies using games as environments to understand the bidirectional interaction behaviors between human and their AI teammates. My research will bridge the gaps in machine competencies for HMT and provide insights into exploring the generalizability of AI capabilities based on contextual learning and adaptation. I want to investigate the following three research questions in my dissertation proposal:

- **RQ1** Is it possible to use human-AI teaming to adapt and improve human learning and strategic decision making?
- **RQ2** How will a human-AI team react to increasingly difficult tasks when the human interacts with different types of AI agent to collaboratively accomplish tasks?
- **RQ3** How can different team dynamics and team compositions affect the team performance?

The three research questions each correlate to and set the theme of a project I am currently working on, and planning to launch a series of user studies in the near future. I will present the work-in-progress experimental design and up-to-date results in the following sections.

Research Methodologies

Study 1: Using an Intelligent Tutoring System To Evaluate Human-AI Teaming Behaviors and Adaptations in Gomoku

AI systems such like AlphaGo (Silver et al. 2016), AlphaGo Zero (Silver et al. 2017), and AlphaZero (Silver et al. 2018) have all demonstrated their competency over expert human players. However, little research has looked into possibly apply those algorithms in intelligent tutoring systems and apply human-AI teaming for educational purposes. To bridge this gap, I designed and developed a Gomoku tutor (Zhang and MacLellan 2022) using an open-source implementation of the AlphaZero algorithm that was designed specifically for Gomoku (Song 2019). I designed three study conditions by providing different types of feedback (immediate feedback, delayed feedback, outcome feedback) to the participants during the training phase, where they are going to play with an expert Gomoku model that has been trained on a A40 GPU for approximately three weeks. Participants will do a pretest that consists of 20 test items, a 20 minutes of training, a posttest consists of the same test items and are asked to complete a survey in the end to receive payment. Each participant is going to receive the test items during pretest and posttest in random order.

From the perspective of ensuring effective human-AI teaming, where people and AI interact interdependently and adjust based on each other's response with respect to a common goal (Demir et al. 2018), tutoring can also be viewed as a type of teaming since the tutor and the tutee are working towards the same goal. Therefore, I want to understand if different types of feedback provided by the intelligent tutoring system can lead to different learning outcomes, thus different human-AI teaming behaviors and adaptations. I have launched a pilot study on Amazon Mechanical Turk, collected preliminary data and conducted quantitative and qualitative analysis. Moving forward, I plan to launch another study and recruit participants from the Georgia Tech community for in-person participation.

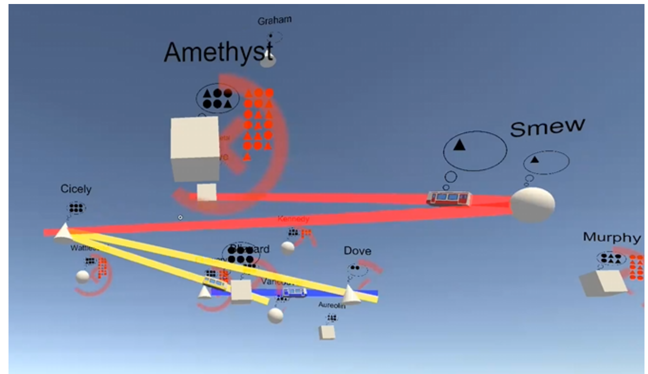

Figure 1: A snapshot of game play in Unity. The 3D shapes with shades represent the stations and the 2D shapes in the bubble represent the destination of the passengers. A train is allocated on each line. The red circle around each station indicates how soon the station will get crowded and time out.

Study 2: Understanding Human-AI Teaming Roles and Communication in Space Transit – A Path Planning 3D VR Game

Inspired by the strategy simulation game Mini Metro [2], where players design subway maps for a growing city and transport passengers, I collaborate with researchers and game developers at University of California San Diego to implement a few AI agents in a 3D VR game called *Space Transit* (designed and developed by UCSD team). Building the game in 3D/VR leads to more possibilities to manipulate the cognitive load and perceptual load. As a result, the original game of Mini Metro can then be adapted into a multi-modal version, enabling a multiplayer mode to explore the communication, coordination and adaptation between human player(s) and AI agent(s).

I have mainly worked on agent development and integration for this project. I implemented the VAL agent (Lawley and MacLellan 2023) with Space Transit by defining primitive actions and have reached a stage where a human player can use step-to-step prompts to instruct the AI agent to perform actions. I plan to further integrate the VAL agent with the Space Transit environment and reach a state where the agent can suggest a few possible actions but the human player will make the final decision. In addition, I am also interested in exploring the evaluation metrics when defining

[2]https://dinopoloclub.com/games/mini-metro/

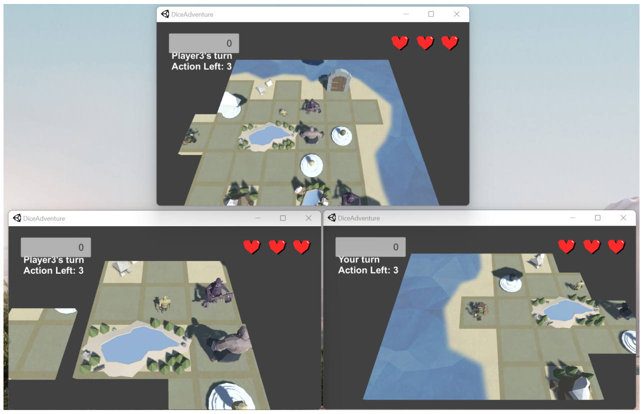

Figure 2: A screenshot of three players instances playing *Dice Adventure*. The dwarf (lower left) has the least view, the giant (upper window) has the most view, and the human (lower right) has a scope of view in between.

an effective human-AI team. I want to launch a user experiment and study how human and AI agent can collaboratively make strategic decisions through verbal communication.

Study 3: Exploring the Coordination Outcomes of Different Human-AI Teaming Compositions in Dice Adventure

I work with researchers and game developers at Carnegie Mellon University, who designed and developed *Dice Adventure* (Harpstead et al. 2023), a turn-based dungeon crawling adventure game, in which players take on the roles of a dwarf, a giant and a human to coordinate together and navigate through maze-like dungeons to reach goals. Each role is designed to have unique and asymmetric abilities that can address different challenges in the game.

I have also worked on agent development and integration for this project. In addition to implementing the VAL agent (Lawley and MacLellan 2023) with the *Dice Adventure* environment, I am also implementing a few agents developed under the Apprentice Learner Architecture (Maclellan et al. 2016) to control a character and mimic human behaviors. Moving forward, I want to conduct a user study with four types of team compositions and study if there are any specific patterns that can be detected with human and AI playing different roles. The four types of teaming compositions can be described as : 1) all human team; 2) all AI team; 3) two human one AI team; and 4) one human two AI team. With alternative character allocations in 2) and 3), there will be 8 groups in total. I am interested in designing a single-blind experiment where all 7 human-involved teams are not clear about the identity (human or AI) of their teammates.

Results to Date

For Study 1 (Gomoku environment), pilot study results show that people who received feedback (either immediate or delayed) during the training overall performed better in testing than people who only received outcome feedback. Moreover, people who received immediate feedback showed higher learning efficiency than people who received delayed feedback.

Study 2 and Study 3 are in earlier stages comparing to Study 1. I am working on agent development, implementation and integration to get to a stage where preliminary user studies can be conducted. For Study 2 (Space Transit environment), the VAL agent can only break down tasks and execute actions as instructed. For example, the agent's capability is limited to recognizing the components in the game and performing the exact action it is instructed (e.g. create a line between station A and station B). The current version of the VAL agent is able to break down higher level of actions into pre-defined primitives actions and construct a tree to store the path. I am implementing basic algorithms that can support the agent to provide a selection of choices (e.g. listing the closest station to a single station, simulating the number of passengers that can be transported, etc).

For Study 3 (Dice Adventure environment), I have worked closely with the game development team and provided insights through multiple demo sessions and play tests. I am working on implementing primitive actions of the characters and getting to a stage where three AI agents can be connected and play the game.

Contribution and Future Works

My dissertation proposal is built on current work in team science, intelligent tutoring systems, conversational agents and speculative game design. I start from building context-dependent AI agents by integrating and adapting current agents that are originally designed for other tasks. My work can contribute to the broader body of knowledge in Human-AI teaming, Game AI, Human-Computer Interaction and Machine Learning. I aim to understand the necessity and uniqueness of human and AI roles in human-AI teaming scenarios. Future scholars can build on this work to raise awareness of design thinking in human-AI teaming structures.

Upon launching the three studies I previously introduced, I aim to collaborate with neuroscientists, system scientists, and game developers to further study how trustworthiness can possibly affect the team performance of human-AI teams as human and AI agents work on collaborative tasks.

Acknowledgements

This work was funded in part by the ARL STRONG programs (award #W911NF2120101 and #W911NF2120126). The views, opinions and/or findings expressed are those of the author and should not be interpreted as representing the official views or policies of these funding agencies. I would like to thank Dr. Erik Harpstead and Dr. Christopher J. MacLellan for providing feedback on early stage experimental design and writing. I would also like to thank Dr. Erik Harpstead and his team at Carnegie Mellon University as well as Dr. Ying Choon Wu and her team at University of California San Diego for game design and development.

References

Autor, D. H. 2015. Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives*, 29(3): 3–30.

Borrego, M.; Karlin, J.; McNair, L. D.; and Beddoes, K. 2013. Team effectiveness theory from industrial and organizational psychology applied to engineering student project teams: A research review. *Journal of Engineering Education*, 102(4): 472–512.

Dekker, S. W.; and Woods, D. D. 2002. MABA-MABA or abracadabra? Progress on human–automation co-ordination. *Cognition, Technology & Work*, 4: 240–244.

Demir, M.; Likens, A. D.; Cooke, N. J.; Amazeen, P. G.; and McNeese, N. J. 2018. Team coordination and effectiveness in human-autonomy teaming. *IEEE Transactions on Human-Machine Systems*, 49(2): 150–159.

Fitts, P. M.; Viteles, M.; Barr, N.; Brimhall, D.; Finch, G.; Gardner, E.; Grether, W.; Kellum, W.; and Stevens, S. 1951. Human engineering for an effective air-navigation and traffic-control system, and appendixes 1 thru 3. *Ohio State Univ Research Foundation Columbus*.

Harpstead, E.; Stowers, K.; Lawley, L.; Zhang, Q.; and Maclellan, C. 2023. Speculative Game Design of Asymmetric Cooperative Games to Study Human-Machine Teaming. In *Proceedings of the 18th International Conference on the Foundations of Digital Games*, 1–4.

Johnson, M.; and Vera, A. 2019. No AI is an island: the case for teaming intelligence. *AI magazine*, 40(1): 16–28.

Katz, J. E. 2017. Do machines become us? In *Machines that become us*, 15–25. Routledge.

Lawley, L.; and MacLellan, C. J. 2023. Interactive Learning of Hierarchical Tasks from Dialog with GPT. *arXiv preprint arXiv:2305.10349*.

MacLellan, C. J.; Harpstead, E.; Marinier III, R. P.; and Koedinger, K. R. 2018. A framework for natural cognitive system training interactions. *Advances in Cognitive Systems*, 6: 1–16.

Maclellan, C. J.; Harpstead, E.; Patel, R.; and Koedinger, K. R. 2016. The Apprentice Learner Architecture: Closing the Loop between Learning Theory and Educational Data. *International Educational Data Mining Society*.

MacLellan, C. J.; and Koedinger, K. R. 2022. Domain-general tutor authoring with apprentice learner models. *International Journal of Artificial Intelligence in Education*, 1–42.

Metcalfe, J. S.; Perelman, B. S.; Boothe, D. L.; and Mcdowell, K. 2021. Systemic Oversimplification Limits the Potential for Human-AI Partnership. *IEEE Access*, 9: 70242–70260.

Perez-Liebana, D.; Samothrakis, S.; Togelius, J.; Schaul, T.; and Lucas, S. 2016. General video game ai: Competition, challenges and opportunities. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 30.

Phillips, E.; Ososky, S.; Grove, J.; and Jentsch, F. 2011. From tools to teammates: Toward the development of appropriate mental models for intelligent robots. In *Proceedings of the human factors and ergonomics society annual meeting*, volume 55, 1491–1495. SAGE Publications Sage CA: Los Angeles, CA.

Sacerdoti, E. D. 1990. The Nonlinear Nature of Plans. *Readings in Planning*, 162–170.

Salas, E.; Reyes, D. L.; and McDaniel, S. H. 2018. The science of teamwork: Progress, reflections, and the road ahead. *American Psychologist*, 73(4): 593.

Silver, D.; Huang, A.; Maddison, C. J.; Guez, A.; Sifre, L.; Van Den Driessche, G.; Schrittwieser, J.; Antonoglou, I.; Panneershelvam, V.; Lanctot, M.; et al. 2016. Mastering the game of Go with deep neural networks and tree search. *nature*, 529(7587): 484–489.

Silver, D.; Hubert, T.; Schrittwieser, J.; Antonoglou, I.; Lai, M.; Guez, A.; Lanctot, M.; Sifre, L.; Kumaran, D.; Graepel, T.; et al. 2018. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science*, 362(6419): 1140–1144.

Silver, D.; Schrittwieser, J.; Simonyan, K.; Antonoglou, I.; Huang, A.; Guez, A.; Hubert, T.; Baker, L.; Lai, M.; Bolton, A.; et al. 2017. Mastering the game of go without human knowledge. *nature*, 550(7676): 354–359.

Song, J. 2019. AlphaZero-Gomoku. https://github.com/junxiaosong/AlphaZero_Gomoku. Accessed: 2023-08-24.

Stowers, K.; Brady, L. L.; MacLellan, C.; Wohleber, R.; and Salas, E. 2021. Improving teamwork competencies in human-machine teams: Perspectives from team science. *Frontiers in Psychology*, 12: 590290.

Stowers, K.; Oglesby, J.; Sonesh, S.; Leyva, K.; Iwig, C.; and Salas, E. 2017. A framework to guide the assessment of human–machine systems. *Human factors*, 59(2): 172–188.

Zhang, Q.; and MacLellan, C. J. 2022. (A) I Will Teach You to Play Gomoku: Exploring the Use of Game AI to Teach People. In *Proceedings of the Ninth ACM Conference on Learning@ Scale*, 263–266.