User Experience of Unconventional AIs for Big 2

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ABSTRACT

Recent research into artificial intelligence (AI) in games has found that AIs have learned to use unconventional strategies that humans would not expect to be effective. Recent poker AIs, for example, deliberately use to their advantage certain poker plays that humans would deem unwise or useless [1]; AIs are becoming "smarter" at game strategy than humans themselves through these unconventional strategies [2] [3]. At the same time, researchers also aim to create AIs that are more humanlike, exhibiting emotion and personality [4]. Thus, these recent AI developments raise the question of how unconventional strategies might affect user experience of a computer game. I intend to explore this idea by investigating how unconventional strategies like randomization might affect user experience of an AI's personality and opponent difficulty for the card game "Big 2." The results of this study may have implications for our understanding of good strategy and could improve a wide variety of computer game AIs by offering alternative decision-making algorithms that better user experience. I propose to study this by programming a 2-player "Big 2" computer game with four different AI versions, each with different decision-making algorithms, employing play testers to play each version through Mechanical Turk, and gathering user experience feedback.

I. INTRODUCTION

Artificial intelligence (AI) entails any program that models human intelligence in a machine [5]. Though AI has a wide variety of applications in computer science, this paper will focus in particular on the use of AIs in computer tabletop games. Over the years, researchers have continuously strived to make game AIs more humanlike, implementing emotions and personality traits into AI behavior in order to make computer-controlled opponents feel more like real humans and thus make games more satisfying [4] [6]. Recently, however, AIs have been able to invent brilliant strategies that humans would not have expected to be effective [1] [2] [3] [7], suggesting that unconventional strategies may actually be smarter. However, little research has been done focusing on these unconventional methods and what effects they might have on user experience, since AIs are using these strategies to become more intelligent than humans rather than more humanlike. Thus, I want to investigate how different AI algorithms affect user experience of the card game Big 2 by creating several versions of the AI, each programmed with unique and sometimes unconventional strategies such as randomization, and then comparing their user experience results.

II. BACKGROUND

Programmers have thoroughly researched making AIs more humanlike and resulting user satisfaction. In 2008, Delgado-Mata and Ibanez-Martinez [4] programmed a simple set of personality traits (such as impulsiveness or caution) into an AI for Uberpong. By having the AI deliberately deviate from mathematically perfect, predictable behavior, these researchers created an AI that made believable human decisions and mistakes. As a result, though players had described the original AI as unnatural and even "dumb," people were surprised by the new AI's evident personality and seemingly deliberate humanlike choices [4].

While AI humanness has been a progressing subject of much current research, other researchers have chosen to focus on making AIs more intelligent opponents. Many recent AI developments have used deep learning and employed concepts like counterfactual reasoning to develop strategies [1] [2] [3] [7]. In several cases, these AIs have learned to use unconventional strategies to become superhumanly intelligent players, choosing methods that humans would not have considered effective. In 2015, a Texas Hold'em poker AI named Claudico used an unexpected poker play to its advantage [1]. Most human experts generally frown upon "limping" as a weak move virtually equivalent to forfeiting a hand. However, Claudico chose to limp 10% of its hands and actually profited from them [1].

There are many similar examples of AIs learning to use unexpected methods and becoming more intelligent players. DeepMind's AI AlphaGo Zero recently became the new world champion of Go [2] [7]. AlphaGo Zero started out with no knowledge of human strategy; after playing itself for 40 days, it formulated its own strategies, some of which no human had used before [7]. AlphaGo Zero is powerful because it is not constrained by human knowledge [2], and thus shows that AIs can actually be more intelligent when not limited by the knowledge of human experts. Similarly, Louis Lafair created an AI for his board game Pathwayz that learned strategies by playing itself [3]. PathwayzAI was surprisingly aggressive early on in the game, blocking its opponents' future moves by placing its pieces in unconventional spaces [3].

PAI, AlphaGoZero, and Claudico suggest that there may be innovative strategies that humans would consider unconventional but that may actually perform better. At the same time, since these AIs have become "superhuman" [3], their strategies may no longer produce humanlike opponents that make believable choices. Studying these unexpected strategies thus leads us to reconsider the constraints of human expectations on our understanding of strategy.

Currently, however, there has not been much research into the pattern of unconventional strategies in AIs. Creators of AIs like Claudico and PAI have been concerned with AI learning capabilities [1] [3] rather than the relationship between innovative AI strategies and perceived humanness. Thus, there remains the question of how user experience is related to unconventional strategies. For example, surprising an opponent with an unideal but unanticipated move might be strategic for an AI, but would affect the human user's perception of the AI. Further exploring the applications and effects of these unconventional strategies has implications for improving a broad spectrum of games, beyond poker and Go, as well as for other real-world applications like security [8].

Big 2 is a 2-4 player card shedding game where the objective is to get rid of all of one's cards the fastest by putting down various poker-based card combinations [9]. It is a suitable game for testing these ideas because it is relatively simple but requires strategy. Current experts have described several approaches to Big 2 [9]: For example, playing high combinations early on can help a player maintain control of the game because the winner of a hand determines the next round's combination type. At the same time, letting others play their high cards first will draw out opponents' hands. However, waiting too long might give opponents the chance to win in the meantime. Given these clearly opposing strategy approaches, implementing several different AIs with both traditional and nontraditional strategies can reveal insights about the relationship between unconventional strategy and human perception of AIs [9].

Thus, I intend to explore the question, "How do unconventional decision-making algorithms in an AI for Big 2 affect user experience of the AI's personality and its difficulty as an opponent?"

III. METHODS

I will begin by creating a computer program for two-player Big 2, where one player will be an AI and one will be a human play tester. Limiting the game to two players eliminates the confounding actions of other human players and makes evaluating the AI's strategy more straightforward. To develop the Big 2 program, I will use object-oriented programming to implement the game's players, objects, rules, and mechanics in code. I will then program four versions of an AI to play the game. The first AI will use the established strategies and choosing patterns detailed by Big 2 experts. The others will be implemented with unconventional decision-making algorithms: one will always choose the weakest card combination, saving high cards for the end. Another will always choose the strongest card combination, getting ahead early on. The last AI will randomly pick a valid card combination to play. Once the game has been programmed, I will develop a web application with appropriate supplemental visuals (such as pictures of cards) so that all users can play on an identical interface. I expect that developing the game and AIs will take roughly three weeks to create and debug, working 20 hours per week.

To test user experience, I plan to use Amazon Mechanical Turk (MTurk), a website that employs thousands of workers worldwide to test AI programs quickly and affordably. I will have at least 60 people to each play against 2 different Big 2 AIs so that each of the four AIs will have been tested at least 30 times, providing sufficient data to have statistical significance. To gather user experience feedback, I will devise a set of specific questions to ask each player, including questions like "Which game felt more like you were playing against another human?" or "On a scale of 1 to 5, how satisfying was your opponent?" Since MTurk provides such a large and convenient base of on-demand workers, I expect play testing to take roughly a week.

Once I have gathered feedback and win/loss data for all four versions of the Big 2 AI, I will be able to compare each version's user experience and difficulty. I hope to be able to identify which AI was the most difficult to beat and compare how its user experience feedback compared to the others, and from there draw out implications for algorithms of AI in games in general.

IV. EXPECTED RESULTS

At the end of this study, I will have produced a Big 2 computer game with four different AI versions, and will produce a paper that can be published in the ACM Digital Library. Depending on the results of the user feedback, my paper may include conclusions about alternative algorithms that could be implemented into AIs to improve game difficulty or user experience.

V. CONCLUSION

Recent research into AIs in games has shown that AIs have devised brilliant strategies that take advantage of unconventional methods human experts would never have considered [1] [3] [4]. This suggests that there is potential for game AIs to be improved by using unconventional or unexpected strategies, but leaves the question of how these strategies affect user experience. Thus, I plan to investigate the use of several unconventional AI decision-making algorithms in the card game Big 2 in order to compare the different AIs' level of difficulty and user experience feedback. This study would have implications for improving games, and could also affect how we understand good strategy in general, which has important applications beyond games in the real world.

VI. REFERENCES

[1] S. Ganzfried, "Reflections on the First Man vs. Machine No-Limit Texas Hold 'em Competition," *ACM SIGecom Exchanges*, vol. 14, no. 2, pp. 2–15, 2016.

[2] L. Greenemeier, "AI versus AI: Self-Taught AlphaGo Zero Vanquishes Its Predecessor," *Scientific American*, 18-Oct-2017. [Online]. Available: https://www.scientificamerican.com/article/ai-versus-ai-self-taught-alphago-zero-vanquishes-its-predecessor/. [Accessed: 14-Oct-2018].

[3] L. Lafair, "Building an AI that Can Beat You at Your Own Game – Towards Data Science," *Towards Data Science*, 14-Mar-2018. [Online]. Available: https://towardsdatascience.com/pathwayz-ai-3c338fb7b33. [Accessed: 14-Oct-2018].

[4] C. Delgado-Mata and J. Ibáñez-Martínez, "AI Opponents with Personality Traits in Überpong," *Proceedings of the 2nd International Conference on INtelligent TEchnologies for interactive enterTAINment*, Jan. 2008.

[5] D. M. West, "What is artificial intelligence?," *brookings.edu*, 18-Oct-2018. [Online]. Available: https://www.brookings.edu/research/what-is-artificial-intelligence. [Accessed: 12-Dec-2018].

[6] M. Waltham and D. Moodley, "An Analysis of Artificial Intelligence Techniques in Multiplayer Online Battle Arena Game Environments," *Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists on - SAICSIT 16*, Sep. 2016

[7] D. Silver, J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai, A. Bolton, Y. Chen, T. Lillicrap, F. Hui, L. Sifre, G. V. D. Driessche, T. Graepel, and D. Hassabis, "Mastering the game of Go without human knowledge," *Nature*, vol. 550, no. 7676, pp. 354–359, 2017.

[8] F. M. D. Fave, Y. Qian, A. X. Jiang, M. Brown, and M. Tambe, "Planning and learning in security games," *ACM SIGecom Exchanges*, vol. 12, no. 1, pp. 38–41, Jun. 2013.

[9] T. K. Meng, R. K. Y. Siong, J. A. K. Yong, and I. L. W. Chiang, "Dai-di Analysis," *Gambiter*.

VII. TIMELINE

- Programming (creating the Big 2 game, 4 versions of an AI player, and web application):
  3 weeks, 20 hours per week
- Play testing (via Amazon Mechanical Turk):
  1 week to allow 60 play testers to each play 2 different versions
- Compiling results and producing paper
  1 week, 10 hours

VIII. BUDGET

I expect that the programming stage will take roughly 3 weeks, working 20 hours per week, because I will need to create a computer game for Big 2, four versions of an AI player, and a web application, all of which will require significant time decoding and testing before it can be released to users. Once the program has been created, the testing phase should take place relatively quickly because MTurk allows convenient access to a broad pool of workers. As mentioned above, I plan to hire at least 60 workers, each to play 2 versions of the game so that each AI can be tested 30 times. The workers should be able to finish 2 rounds of Big 2 and answer a short set of feedback questions in half an hour to an hour, so I think the appropriate amount of monetary compensation is $15 per worker, to be paid through MTurk. In total, this amounts to $900 in remuneration funds.

Time Required:
    3 weeks x 20 hours per week = 60 hours
    (60 + 10) hours x $11.00/hour = $770
Remuneration for Mechanical Turk play testers:
    60 workers x $15 each = $900
TOTAL: $1670