Comparing Reinforcement Learning and Finite State Machine Agents in Real Time Strategy Games: Impact on Player Experience

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***Abstract*—abstract**

***Index Terms*—Keywords**

I. Introduction

A. Theme and Topic Rationale

The Theme chosen is Decision-Making AI for Real-Time Strategy (RTS) Games, and will focus on comparing Finite State-Machine (FSMs) AI opponents traditionally used in games, against Machine Learning (ML) opponents, specifically Reinforcement Learning (RL), and their impact on player experience.

Game AI plays a huge role in player experience and immersion, as they provide the challenge and unpredictability that makes games fun and engaging. While extensive research has been conducted on the topic, most have focused more on the pure performance of the RL agent, and/or its impact on player experience, never directly comparing it to traditional FSMs, such as the work done by Grech [1], Berta, et al. [2], and Zhasulanov [3]. This study aims to address the research gap by directly comparing RL Agents to FSMs, and evaluating their impact on player experience, with the goal of identifying if the computational and development cost of implementing RL agents is justified by the improvement in player experience.

B. Positioning and Research Onion

This research addresses the gap in player experience found in the literature, building on the works of [1] and [4] on AlphaStar by providing a better understanding on the role RL agents will play in the future of RTS games. As can be seen in Figure 1, this study will follow a positivist research paradigm, following a deductive and experimental approach, gathering both quantitative and qualitative data to measure player experience.

C. Background to the Research Theme

Game AI has evolved significantly over the years, especially in RTS games. Early RTS titles, such as StarCraft, relied on Finite State Machines (FSMs) for their AI decision-making. These FSM-based approached are deterministic and predictable, which can lead to repetitive and boring gameplay, and allow players to exploit the gameplay patters of the AI. [4]

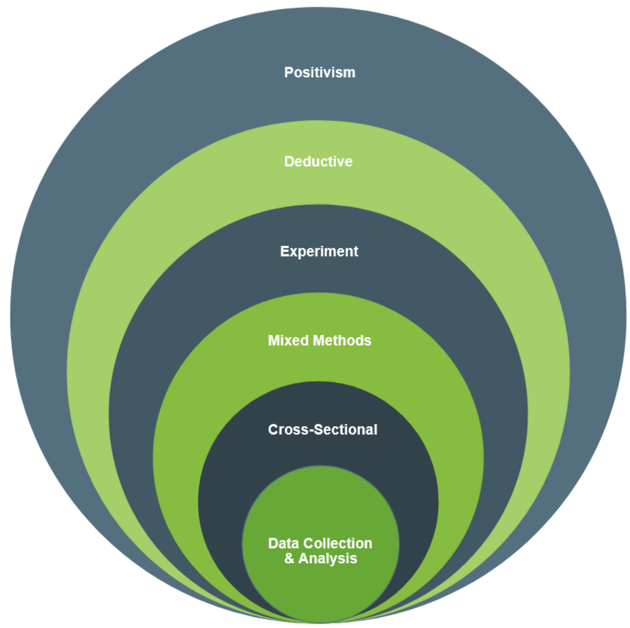

Fig. 1. Research Onion

More recently, RL has emerged as an alternative AI approach, taking advantage of advancements in ML and computer hardware. In games such as AlphaStar [4], RL agents were able to demonstrate adaptive and human-like behaviour, providing a more challenging and engaging experience for players. Another paper that highlights this is the work done by Grech [1], where he created multiple difficulties of AI opponents using RL, and found that players reported higher levels of enjoyment and immersion. A similar study is the one done by [2], where they trained an RL agent to act as an opponent in a fighting game, with the agent being able to adapt to the player's skill level, and provide a more engaging experience, similar to the work done by [4]

Despite all of this, the implementation of RL in commercial games remains limited due to the high computational cost, long training and development times, and added complexity. This further proves the need for research in this area, and in evaluating if the benefits of RL agents in RTS games are worth the cost compared to traditional FSMs.

D. Hypothesis

Players report a higher level of enjoyment and improved experience when playing against RL agents comparted to FSMs in RTS games.

E. Independent & Dependent Variables

Independent variables are variables that are manipulated by the researcher, and are mainly used to influence the dependant variables. Dependant variables are what happen as a result of the independant variables, and are what the researcher is interested in measuring.

The independent variable in this study is the type of AI opponent. The dependant variables, those are player experience, player immersion, and perceived difficulty. Player experience will be measured through surveys and engagement metrics, player immersion will be measured through surveys and validated game design principles, and perceived difficulty will be measured through surveys, player feedback, and engagement metrics.

F. Research Aim

The aim of this study is to evaluate the impact of Reinforcement Learning (RL) and Finite State Machines (FSMs) AI opponents on player experience in Real-Time Strategy (RTS) games, and determine if the extra resources is justified by the improvement in player experience for RL agents.

To be more specific, the study will focus on the following research objectives:

- Compare player-reported enjoyment and engagement levels when playing against RL and FSM AI opponents in RTS games.
- Assess the impact of RL and FSM AI opponents on player immersion in RTS games.
- Determine if the computational and development costs and complexity of RL justify its implementation over FSMs in RTS games.

G. Purpose Statement

This study is important because AI opponents shaoe the core gameplay experience of RTS games. While FSMs remain widely used due to their simplicity, RL-based AI has the potential to revolutionise RTS games by providing adaptive and unpredictable opponents. However, the significant resource demand from developers raise questions if the benefits of RL are worth the investment.

By investigating the difference in player experience between RL and FSM AI, this study will provide valuable insights to game developers, AI designers, and the broader gaming community, helping them in making more informed decisions regarding AI decision-making strategies in RTS game development.

II. Literature Review

Literature review goes here

III. Research Methodology

Research Methodology goes here

IV. Findings

Findings go here

V. Conclusion

Conclusion goes here:

References

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