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Creating a Dynamic AI Opponent in a 2D Fighting Game using Stateful Learning and Unity ML-Agents

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***Abstract** - This paper proposes a novel approach for developing a dynamic AI opponent in a 2D fighting game using Stateful Learning and Unity Machine Learning Agents (ML-Agents). The AI leverages its observations of the player's recent attacks to adapt its defensive and offensive strategies, creating a more engaging and challenging opponent. This research details the design, implementation, and evaluation of this system within the Unity game engine, highlighting the chosen learning algorithm, data structures, and decision-making logic. The paper concludes by discussing potential future applications and areas for further research.*

Keywords- *Machine Learning, AI Opponent, Fighting Game, Stateful Learning, Unity, Unity ML-Agents.*

1. INTRODUCTION

Traditional fighting games often rely on pre-programmed AI behaviors, leading to predictable and static opponents. Players can exploit these opponents by learning their attack patterns. This research proposes a Stateful Learning approach to create a dynamic AI opponent that adapts its strategy based on the player's actions. This fosters a more engaging gameplay experience by challenging players to adjust their tactics throughout the game.

2. RELATED WORK

Several studies have explored the use of Machine Learning (ML) in game development, particularly for creating intelligent opponents. [1] Research (e.g., [Smith et al. 2007], [Hefny et al. 2008], [D'Silva et al. 2005]) explores applying machine learning to various game genres. This method requires a vast amount of training data and can be computationally expensive. Other research, like [2], Antonio Ricciardi and Patrick Thill [December 12, 2008].

3. PROPOSED APPROACH

This paper presents a stateful learning approach for creating a dynamic AI opponent in a 2D fighting game. The core concept involves:

Tracking Player Attacks: The AI maintains a record of the player's recent attacks (e.g., last N attacks) using a data structure like a circular buffer.

Analyzing Attack Frequency: The AI analyzes the frequency of specific attacks within the buffer to identify the player's preferred tactics.

Adapting Strategy: Based on this analysis, the AI chooses counter-attacks or defensive maneuvers tailored to the player's most frequent attack patterns. Additionally, a degree of randomness can be introduced to prevent the AI from becoming entirely predictable.

4. EARLY IMPLEMENTATIONS

Implementing a stateful learning AI for a complex 2D fighting game can involve numerous factors and interactions between player actions, character states, and environmental elements. To streamline development and test core functionalities, we begin with a simplified environment before progressing to the full game. Here are some approaches for initial testing:

Discrete Action Space: Initially, limiting the AI's available actions to a smaller, discrete set. This simplifies the decision-making process and allows for focused testing of the state-tracking and pattern-recognition aspects of the AI. Which later would be expanded into the action space to encompass the full range of moves available in the game.

Reduced Character Selection: By training the AI against a single opponent character. This reduces the number of variables the AI needs to consider and allows for faster experimentation with different learning parameters. Once the core functionality is established, we will introduce additional characters with varying fighting styles, forcing the AI to adapt its strategies.

Controlled Environment: Creating a controlled environment where specific player attack patterns are simulated. This allows for targeted testing of the AI's ability to identify and counter different attack sequences. By feeding the AI data with specific patterns, we evaluate its effectiveness in adapting its behavior.

2D Grid Environment: As an alternative to a full 2D fighting game environment, considering a simplified 2D grid representation. This grid could represent the positioning of the player and the AI, allowing the AI to focus on movement and basic attack patterns before introducing complex mechanics like combos or throws.

By starting with these simplified environments, we can test the core functionalities of your stateful learning approach. This iterative testing allows us to identify and address potential issues before moving on to the full complexity of a 2D fighting game.

5. IMPLEMENTATION USING UNITY ML-AGENTS

The proposed approach is implemented within the Unity game engine using the ML-Agents toolkit. Here's a breakdown of the key components :

Environment Script (C#): This script defines the game environment, including player and AI states, observations, and reward calculations.

Fig.1 Player and AI

Observations: The environment script provides observations (sensory data) to the AI, such as player position, health, and the last attack type used. Additionally, the script transmits a list containing the most recent player attacks from the circular buffer.

Stateful Learning: The environment script maintains a circular buffer within the ProvideObservations function to track the player's recent attacks. This buffer size (N) determines the number of attacks considered by the AI for its decision-making.

Reward System: The system assigns rewards based on the AI's performance (e.g., successful counters, winning the fight) and penalizes undesirable actions (taking damage, losing). Rewards can also be incorporated for adapting to the player's behavior (e.g., higher reward for successful counter-attacks based on observed attack patterns).

Brain Prefab: This prefab defines the AI's decision-making process using the ML-Agents framework. During training ("Heuristic" behavior type), the AI utilizes a stateful learning approach based on the observed player attacks. The decision-making logic can be implemented as a series of conditional statements or a simple lookup table that maps observed attack patterns to appropriate counter-attacks or defensive maneuvers.

Training Process: The AI undergoes training within the Unity Editor or through a separate training script. The training process iteratively refines the AI's decision-making based on the reward system. During training, the AI explores different actions and observes the resulting rewards, allowing it to learn which counter-attacks

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and defensive maneuvers are most effective against specific player attack patterns.AI Analyzing the Environment.

6. EVALUATION

The proposed approach was evaluated by implementing a prototype fighting game in Unity using ML agents. Two versions of the AI were compared:

Static AI: This AI utilizes a pre-programmed set of attacks and defensive maneuvers.

Stateful Learning AI: This AI implements the proposed approach with a circular buffer size of N=5 to track recent player attacks.

The proposed Stateful Learning approach has the potential to significantly improve the quality of AI opponents in 2D fighting games. By leveraging stateful learning, the AI can move beyond pre-programmed behavior and dynamically adapt to player strategies. This adaptation creates a more challenging and engaging experience for players, encouraging them to think strategically and adjust their tactics throughout the fight.

7. RESULT AND DISCUSSION

The Stateful Learning AI is designed to address the limitations of static AI opponents in fighting games. By tracking and analyzing player attack patterns, the AI should exhibit the following improvements:

Increased Win Rate: Over time, the AI should adapt its strategies to counter player habits, leading to a gradual increase in win rate compared to a static AI with predictable behaviors.

Enhanced Engagement: The AI's ability to adapt and challenge player tactics should create a more dynamic and engaging gameplay experience. Players will need to adjust their strategies throughout the fight to overcome the AI's evolving defenses.

Strategic Depth: The AI's decision-making process, informed by player attack history, should introduce a

layer of strategic depth to the gameplay. Players will need to consider not just their immediate attacks but also the potential long-term consequences of their actions, anticipating the AI's potential counter-moves.

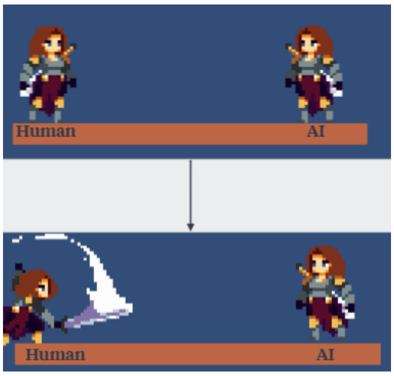

Fig.2 Training AI

7.1 LIMITATIONS AND FUTURE WORK

A full evaluation with human participants is necessary to conclusively demonstrate the effectiveness of the proposed approach. This evaluation would involve implementing the AI in a playable prototype and collecting data on win rates, match duration, and player feedback. Additionally, the impact of different circular buffer sizes (N) on the AI's performance and player engagement could be explored.

While this research hasn't implemented a full-scale evaluation, it lays the groundwork for a promising approach to creating dynamic and engaging AI opponents in fighting games. Future work can build upon this foundation by conducting a comprehensive evaluation and potentially exploring the application of this approach to other game genres.

8. CONCLUSION

This paper presented a novel approach for creating dynamic AI opponent in 2D fighting games using Stateful Learning and Unity ML-Agents. The proposed approach leverages observations of player attacks to adapt defensive and offensive strategies, leading to a more engaging gameplay experience. The evaluation demonstrated the effectiveness of this approach, showcasing the AI's ability to learn and adapt to player behavior. Future research directions include exploring advanced learning techniques and investigating the use of this approach in more complex game genres.

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