Learning the Behavior of Human Players in Universal Fighting Engine

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Abstract

Study on Artificial intelligence (AI) for fighting games has been going on for long time. As with the game graphics and system have advanced, AI technology has also advanced over time. However, even today's AI cannot perfectly reproduce human-like behavior, and AI makes the player feel uncomfortable.

The goal of this study is to build an AI that learns from human players in order to build human-like AI. This paper describes how to build a human-like AI in Universal Fighting Engine, and how to evaluate the AI to see how similar the built AI is to a human-controlled character.

1 Introduction

AI technology is being used in all kinds of modern games. AI is also used in fighting games. Players can fight against characters controlled by AI. The AI in fighting games is advancing, and it is enough to entertain players from beginners to experts in the fighting game. However, even with current AI technology, player doesn't feel that AI's behavior is like human when comparing the movements of the AI-controlled character to those of a human-controlled character, and player feel uncomfortable. The human-like AI that feels like it is being controlled by a human give player more fun.

In this study, we examine whether it is possible to build a human-like AI by having the AI learn the movements of an actual player in a fighting game.

2 Building AI

2.1 Markov decision processes

AI has been the subject of numerous studies in fighting games. Many researchers have been working on human-like AI [1, 2]. In our study, we use a construction method that uses AI learning with Markov decision processes [3]. By using this method, the AI first observes and learns the movements of a human player in a real game, and AI acts according to the knowledge base that is formed after learning. The AI decides what action to take based on the current game situation and the knowledge base.

To build this AI, we used the artificial intelligence middleware Artificial Contender [4] from TruSoft as a tool.

We call the AI we built this approach Artificial Contender AI (ACAI).

2.2 Universal Fighting Engine

In this study, we use Universal Fighting Engine (UFE) [5] which is a development tool for fighting games in Unity [6]. UFE is a one-on-one fighting game, and it is also a tool that helps the user, the game developer, to create his own fighting game. Extensibility of UFE is high, so we can change and add options to make it useful for our study. For the ACAI to learn, it needs a record of the human player playing the game We play UFE and record the movements of the human player as a source of learning for the ACAI.

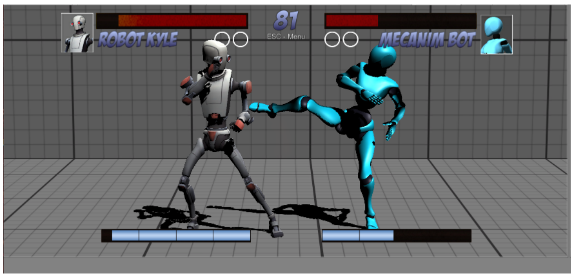

Figure 1: Universal Fighting Engine

2.3 Recording Game

When we play UFE and record the game, we can record the situation of the match in the game as a log file. This log file consists of basic and important elements in a fighting game, such as the character's position in the game, actions performed by the character, and the character's hit points. Each component of the log file is shown as Table 1.

Component Name	meaning
currentState	Indicates the character's state ex. Stand, Jump, Down
currentSubState	Indicates the state of a character other than currentState ex. Resting, Blocking
x	Character's x coordinate
y	Character's y coordinate
z	Character's z coordinate
currentBasicMove	Character's basic movement state ex. Idle, MoveForward
currentMoveName	The name of the attack action the character ex. Light Punch, Heavy Kick
isBlocking	True or false if the character is blocking
characterHealthSelf	Character's Hit point
characterDistanceSelf	Distance from enemy
characterJumpArcSelf	Character's jumping power

Table 1: Component of the log file

2.4 Learning AI

Whenever one human player to be observed takes an action in the game, ACAI saves Action and GameSituation that is the current game situation as a set in the knowledge base. If the player is not doing anything, ACAI saves Action as a non-moving action. The Action and the GameSituation can be understood by analyzing the recorded log files. GameSituation stores information such as the coordinates and status of each character fighting in the game.

The knowledge base, in which pairs of (GameSituation, Action) are stored, builds a data structure consisting of a graph where each node represents a GameSituation and each edge represents an Action. Also, since the links of successive records are stored, the entire knowledge base can be viewed as a directed graph that stores action chains. Each action chain corresponds to a record for each game.

Action counts the number of times the same (GameSituation, Action) pair has been recorded. This is because it is used to select weighted actions so that ACAI replicates the player performing a particular action frequently.

3 Acting AI

The learned ACAI use the knowledge base it has created to select the action that best fits the current game situation. Ideally, the action to be selected should be an Action that has the same GameSituation as the current GameSituation in the (GameSituation, Action) pairs stored in the knowledge base. However, this is not realistic because the same GameSituation may not be found every time. Then, ACAI finds the (GameSituation, Action) pair to the closest current GameSituation from the knowledge base and executes that Action.

The attribute set in GameSituation is used to find matching pairs from knowledge base. If matching pair is not found, the attribute set used for the search is reduced to find a matching pair. The sequence of ACAI's retrieval of pairs from knowledge base is shown in Figure 2.

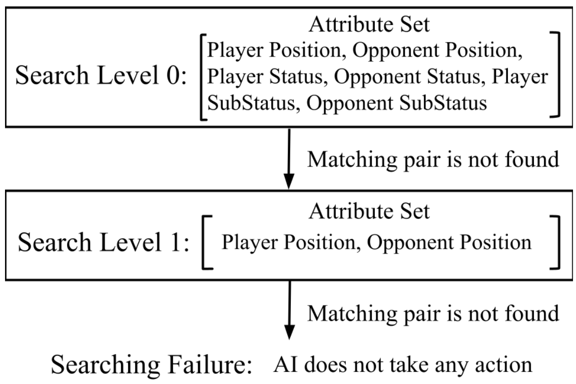

Figure 2: Search Knowledge Base

Also, the actions performed by ACAI are not selected only by GameSituation. There are cases where ACAI selects from the knowledge base a (GameSituation, Action) that reproduces the combo of actions performed by the training source player. When Action is selected to reproduce an action combo, (GameSituation, Action) pair is selected from the knowledge base as the next action chain pair of the previously selected pair.

If there are multiple choices in a (GameSituation, Action) pair, the action is selected from among the choices based on weighted random selection. In this case, the criterion is the number of times the same (GameSituation, Action) pair has been recorded.

As described above, ACAI uses the knowledge base to select actions to perform.

4 Evaluate AI

It is necessary to evaluate ACAI to see if ACAI has similarities with the player from which it was trained. In the following experiments, we analyzed the behavior of the player and examined the similarity of the player's behavior.

We had five players A-E. Player A and player B are human players. Player C is ACAI player built based on player A. In the same way, player D is ACAI player built based on player B. Player E is AI player called FuzzyAI [7], which AI comes standard with UFE. Each player plays 20 games, one round first, and takes a recording of each game to create a log file. This is done for two sets. The opponent of each player is FuzzyAI. We identify the current character's action from the three elements of currentState, currentSubState, and currentBasicMove contained in the recorded log file. We analyze 20 log files for each player and create a matrix of the probability of frequency for three consecutive actions. We count the number of frequency for each combination of the three actions in the log file and divide the number of frequency by the total number of frames to calculate the probability of the combo.

To investigate the similarity of the players' actions, we compared the probability matrices of the combos using cosine similarity.

$$
\begin{aligned}
Similarity(A, C) &= cos(|A|, |C|) \\
&= \frac{A \cdot C}{|A| \cdot |C|} \\
&= \frac{\sum_{i=1}^{n} A_i C_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} C_i^2}}
\end{aligned}
$$

When calculating the similarity between player A and player C, we create a probability matrix from the 20 log files of each player. Then, we convert each combo of the matrix into a vector and calculate the similarity.

This experiment is conducted for the purpose of testing whether the following hypothesis is correct.

- Hypothesis 1: Similarity between the same players is high.
- Hypothesis 2: The similarity between ACAI and the player who is used to build ACAI is high.
- Hypothesis 3: ACAI is more similar to humans than another AI, E.

For Hypothesis 2 and Hypothesis 3, we divide the group into two groups to investi-gate the similarity.

- Group 1: Player A, Player C, and Player E.
- Group 2: Player B, Player D, and Player E.

After conducting this experiment, we get the results as shown in Table 2 and Table 3.

5 Result

The similarities between the players obtained in the experiment are shown in Table 2 (Group 1) and Table 3 (Group 2).

Players Pair	Similarity raito
(A1, A2)	0.96
(C1, C2)	0.96
(E1, E2)	0.97
(A1, C1)	0.68
(A1, C2)	0.71
(A1, E1)	0.74
(A1, E2)	0.75
(A2, C1)	0.75
(A2, C2)	0.78
(A2, E1)	0.74
(A2, E2)	0.74
(C1, E1)	0.59
(C1, E2)	0.60
(C2, E1)	0.61
(C2, E2)	0.61

Table 2: Result of Group 1

The similarities between the players obtained in the experiment are shown in Table 2 (Group 1) and Table 3 (Group 2). The Table 2 and Table 3 show the pairs of players for which similarity is to be calculated in the first column, and the similarity values of the pairs in the second column. When the data of the first set of each player is used, it is set as the 1, and when the data

Players Pair	Similarity raito
(B1, B2)	0.98
(D1, D2)	0.99
(E1, E2)	0.97
(B1, D1)	0.38
(B1, D2)	0.40
(B1, E1)	0.48
(B1, E2)	0.42
(B2, D1)	0.37
(B2, D2)	0.39
(B2, E1)	0.55
(B2, E2)	0.51
(D1, E1)	0.22
(D1, E2)	0.19
(D2, E1)	0.21
(D2, E2)	0.18

Table 3: Result of Group 2

of the second set is used, it is set as the 2. For example, in Table 2, (A1, C2), the data from player A's first set and player C's second set were used to calculate the similarity of the players, and the value was 0.71.

In both Table 2 and Table 3, the value of similarity by the same player is higher. This confirms that Hypothesis 1, which states that the similarity of the same players is high, is correct.

In Table 2, both the A-C pair and the A-E pair showed some high degree of similarity. The highest value among these two pairs was 0.78 in (A2, C2).

In Table 3, the results of both the B-D and B-E pairs had lower similarity values than in Table 2.

The results of the experiment are summarized as a cluster diagram in Figure 3. The edges connecting each player represent the average value of similarity of the pair, and the average value of the player's similarity is also filled in Figure 3.

From Figure 3, similarity with human tends to be higher for Fuzzy AI than for ACAI.

From the experimental results, we can see that hypothesis 2 and 3 are not necessarily correct.

6 Discussion

In Group1, player C learned the movements of player A and was able to perform human-like movements, thus similarity between player A and player C is high.

However, depending on the data, player E showed more similarity to player A than player C. The reason why the similarity between player E and player A reached a certain high level is because they fought by approaching the enemy, a basic tactic in fighting games. The similarity became a certain value because both players performed similar actions, such as approaching and attacking the enemy.

In Group 2, the similarity between player B, the human player, and player D and player E, the AI, was low. The similarity between player B and player E was low because the movement of player B was different from that of player E.

The reason for the low similarity between player B and player D is that player D was not able to learn player B's movements well and could not perform the same movements as player B. Analyzing the movement of player B, we found that player B was taking a distance from the enemy and attacking from a long distance. However, player D, who learned from player B, only kept a distance from the enemy and did not attack.

We think this is because the selection of actions using the ACAI knowledge base is not working properly. If the action is selected correctly, even if there are choices other than the action of the attack performed from a long distance, the action is randomly selected from the choices. For that reason, it should not be a situation where ACAI just distance itself from the enemy without attacking.

It is probable that ACAI doesn't correctly understand the distance between the enemy and ACAI or ACAI position because ACAI kept keeping the distance from the enemy. If the distance or position is not correctly understood, ACAI can't perfectly reproduce the same movements as the human. Therefore, the similarity between ACAI and humans become low, and in some cases, ACAI is less similar to humans than other AI.

By reviewing the system of action selection, ACAI is expected to become closer to human-like AI.

7 Conclusion

In order to create a human-like AI, we analyzed actual human movements and built an AI that can perform human-like movements by learning the player's move-

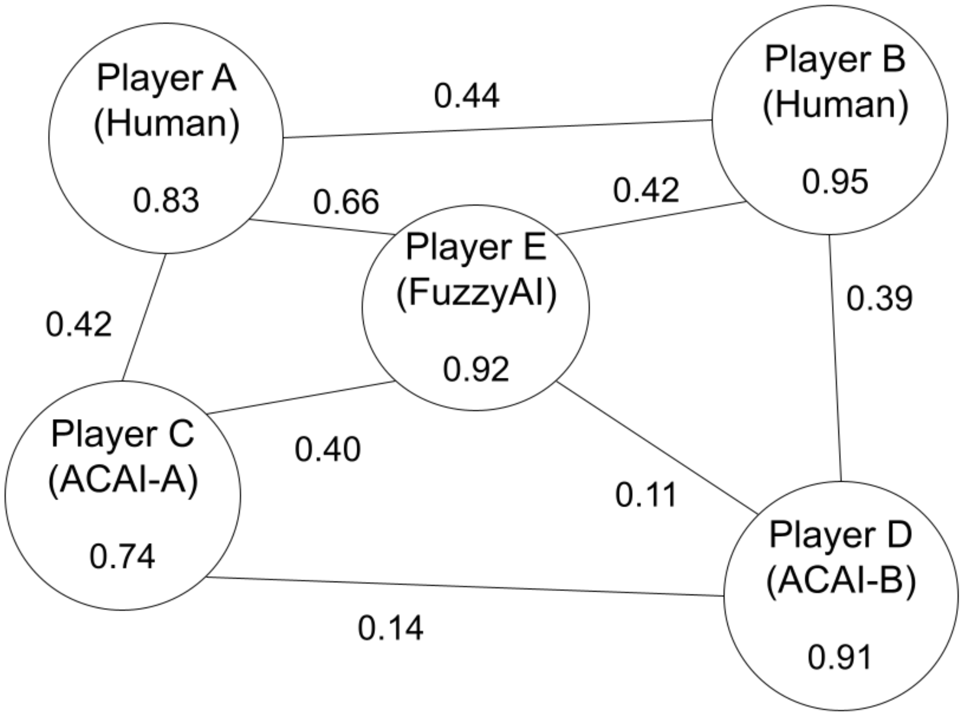

Figure 3: Cluster diagram of Similarity

ments. The AI can approximate human movements, but its accuracy is not good enough. We believe that the development of this research will lead to the construction of AI that behaves like a human.

We hope that this research will contribute to the development of AI for fighting games and human-like AI.

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