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Yuda K., Otomo K., Ito R., Wakana I., Tanji R., Kamei S., Mozgovoy M.

Behavior similarity between human players and built-in AI characters in universal fighting engine

Abstract

In certain game genres, such as one-vs-one fighting games, AI-controlled opponents are expected to behave in a human-like manner to facilitate higher player engagement. To develop a human-like AI decision making system, it is essential to be able to perform proper evaluation, i.e., to be able to test any given opponent for human-likeness. In this paper, we propose a tool for a fighting game environment Universal Fighting Engine, able to analyze game recordings and assess similarity between individual characters by examining their internal states and their actions. We test our tool on a sample of human players and five skill levels of a built-in AI system. Our results show that human players possess certain "human-like" traits that make their play styles distinguishable from a conventional rule-based AI system.

1. Introduction. Computer games can serve as a good platform to try artificial intelligence (AI), because its actions are clearly visualised and easy to understand; moreover, games have well-defined rules to follow. In 2016, when AlphaGo [2] won a professional Go player Lee

Yuda Kaori – Master student, The University of Aizu; e-mail: m5241108@u-aizu.ac.jp, phone: +81-242-37-2664

Otomo Kimitaka – Undergraduate student, The University of Aizu; e-mail: s1250047@u-aizu.ac.jp, phone: +81-242-37-2664

Ito Ryoya – Undergraduate student, The University of Aizu; e-mail: s1260233@u-aizu.ac.jp, phone: +81-242-37-2664

Wakana Ippo – Undergraduate student, The University of Aizu; e-mail: s1260210@u-aizu.ac.jp, phone: +81-242-37-2664

Tanji Riku – Undergraduate student, The University of Aizu; e-mail: s1270139@u-aizu.ac.jp, phone: +81-242-37-2664

Kamei Shota – Undergraduate student, The University of Aizu; e-mail: s1270112@u-aizu.ac.jp, phone: +81-242-37-2664

Mozgovoy Maxim – Associate professor, The University of Aizu; e-mail: mozgovoy@u-aizu.ac.jp, phone: +81-242-37-2664

Sedol, it impressed many people in different industries. AI abilities and potential impacts of this technology were widely discussed afterwards.

The focus of our research is to make a human-like AI system for the game of fighting. Fighting is one of most popular game genres, having numerous hit games in its history, such as Street Fighter, Mortal Kombat or Super Smash Bros. People often enjoy playing with other people as popularity of online games indicates, so developing a human-like AI (in terms of play style) may improve user experience. As a preliminary step of this work, it is necessary to understand what exactly constitutes "human-like behavior" and what kind of features such an AI system have to possess. In this paper we evaluate play styles of various human players and of a generic rule-based AI using an automated scoring algorithm, based on cosine similarity.

2. Universal Fighting Engine. In this study, we use Universal Fighting Engine 2 (UFE) [3], which is a development tool for one-vs-one fighting games in Unity. UFE is highly extensible: for example, we can limit the selection of actions or speed of making decisions for individual characters. It also includes a "Fuzzy AI" for non-player characters (NPC), which is a fine-tunable rule-based AI. It can be set to different difficulty levels by adjusting the parameters corresponding to time between decisions, time between actions, rule compliance, aggressiveness and combo efficiency. We will mainly discuss about differences in human player and Fuzzy AI.

3. Cosine similarity analysis. In order to compare different players' behavior profiles, we have developed a similarity scoring procedure based on a cosine similarity metrics. It operates as follows. We analyze recordings of games where a character of our interest participates, and create its "behavior fingerprint" as an ordered list of probabilities of every possible tuple (A_1, A_2, A_3), representing three consecutive player actions. Each action is uniquely defined with its elements `currentState`, `currentSubstate`, and `currentBasicMove` (see Table 1). Behavior fingerprints can be then compared using cosine similarity [4], yielding a similarity ratio of [0, 1].

Table 1. Elements of player actions

Element	Meaning
`currentState`	Indicates characters state (e.g., Stand, Jump, Down)
`currentSubstate`	Indicates additional state modifier of the character (e.g., Resting, Blocking)
`currentBasicMove`	Indicates characters basic movement state (e.g., Idle, MoveForward)

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

4. Experimental Results. We test four human players, Ryoya, Kaori, Ippo, and Riku. In addition, we test an non-player character operated by 5 different skill level of Fuzzy AI. We test 12 different combinations of players. Each game recording consists of 10 matches. Each match takes two rounds of 100 seconds each (unless it ends prematurely with a knockout). We calculate similarity scores for the player pairs and analyze obtained results.

In Figure 1, graph edges show pairs of players participated in our game recordings. Edge labels denote similarity between the player. The minimum similarity detected in our recordings is 0.18, and the maximum similarity is 0.73.

In Figure 2, solid lines show the similarity between Fuzzy AI and a human opponent Ryoya. Dashed lines show the similarity between different levels of Fuzzy AI. While resemblance of Fuzzy AI with Ryoya varies in these recordings, it never achieves scores higher than 0.73. In contrast, the similarity between two Fuzzy AI-based agents is 0.91. . . 0.98 regardless of tunable parameters values.

Figure 3 shows the relationships between four players: Kaori, Ippo, Riku, and Fuzzy-AI (normal difficulty level). It shows 39 possible links for each character out of every combination of game. For example, there are 7 links between Kaori and Ippo, the minimum similarity ratio is 0.57 and the maximum ratio is 0.68.

5. Discussion and Conclusion. We have shown how the behavior of individual players (including those controlled by an AI system) can

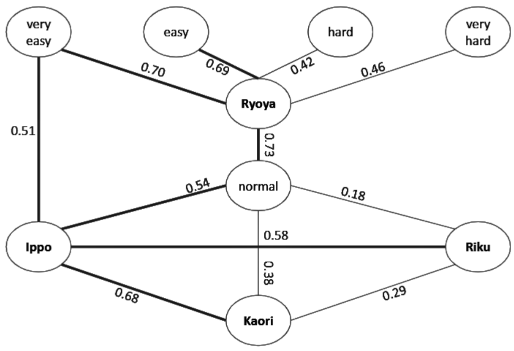

Figure 1. Similarity with match opponent (direct similarity)

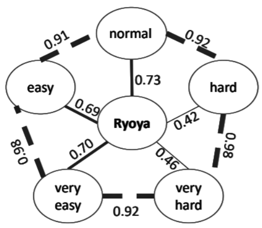

Figure 2. Similarity between Fuzzy AI agents of different skill levels

be evaluated by analyzing their action choice. However, we could not find clear differences between human players and rule-based AI. Still, our observations let us make the following conclusions:

1. A typical rule-based AI system preserves its play style regardless of its difficulty level.
2. People mostly keep their play style even when playing against different opponents.
3. People are diverse, and they are different or similar to other people and/or AI systems, and there is no easy way to tell whether the given player is human or AI.
4. It is possible to compare play styles of the players A and B indirectly by comparing the recordings of matches of A and B against other players.

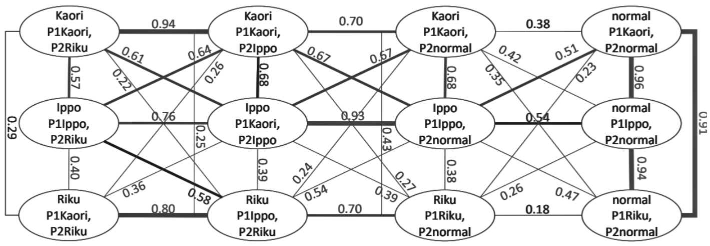

Figure 3. Direct and indirect similarities between the players

It remains unclear whether our inability to separate human players from AI-controlled characters can be explained by the weakness of our method or by objective factors. One of our future goals is to employ a Turing test-like approach to check whether people are able to distinguish human participants from AI players in fighting.

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