Investigating Kinect-based Fighting Game AIs That Encourage Their Players to Use Various Skills

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***Abstract*—This paper investigates AIs that increase their players' amount of exercise by encouraging the usage of various skills in fighting game FightingICE, recently used in a number of game AI competitions. Our research aim is to develop such AIs for promoting players' health with fighting games that use Kinect as the input interface. In our experiment, two types of AIs are used as the opponent against a human player. One of the AIs is based on the k-nearest neighbor algorithm and fuzzy control, and the other is based on UCT, a variation of Monte-Carlo Tree Search. Our results show that the players, participating in the experiment, use more different skills, thus demonstrating higher action entropy, when playing the game against the UCT AI.**

Keywords—Kinect; fighting games; games for health; UCT; k-nearest neighbor algorithm; fuzzy control; FightingICE;

I. INTRODUCTION

AI in fighting games is one of the most important factors for entertaining players. Recently, it has become a popular research field. For example, in previous work by Moriyama et al [1], an AI was proposed that focuses on combos for a fighting game and can adapt to its players, allowing them to enjoy the game even when playing it alone.

Research on promoting players' health by the use of Kinect has gained a lot of attention [2]. By controlling a character using Kinect as the input interface, the player can play a fighting game while exercising, which promotes his or her own health. In a Kinect-based fighting game, every in-game skill corresponds to a specific movement of the player. The player has to perform a number of movements in front of the Kinect camera in order to activate various skills in the game, and such variety of movements increases the player's amount of exercise. Therefore, to promote the player's health, an AI that encourages the usage of various skills is desirable.

In this work[1], we investigate AIs that increase players' amount of exercise by encouraging their usage of various skills in FightingICE[2], a fighting game that has been recently used in a number of game AI competitions. We aim at developing AIs for promoting players' health with fighting games that use Kinect as the input interface. In our experiment, we use two types of AIs as the opponent against a human player. One of the AIs is based on the k-nearest neighbor algorithm (k-NN) and fuzzy control, and the other is based on UCT, a variation of Monte-Carlo Tree Search.

II. AI ALGORITHMS

A. k-NN and fuzzy control

The first AI, JerryMizunoAI (JMAI) proposed by Chu and Thawonmas [3], of the two AIs in this work has applied a combination of k-NN and fuzzy control. First, JMAI will determine whether there is enough opponent's action data for action prediction using fuzzy control. If there is enough such data, JMAI will predict the opponent's action using k-NN and perform the most advantageous action against the predicted action. Otherwise, JMAI will use fuzzy rules to determine the next action and perform it.

B. UCT

The second AI in this work uses UCT proposed by Kocsis and Szepesvari [4]. In UCT, the UCB value of each child node is calculated by (1), and the child node with the highest UCB value is selected. After arriving at a leaf node, if its number of visits exceeds a pre-defined threshold and the depth of the tree has not reached the upper limit, UCT will create all possible direct child nodes from it; otherwise, UCT will evaluate it using random simulations whose initial state is this node.

$$UCB = \overline{X_i} + C\sqrt{2\ln(N_i^p)/N_i} \tag{1}$$

In this AI, called UCTAI, $\overline{X_i}$ is the evaluation value of node i that is the average value of the amount of the opponent character's hit-point changes subtracted by the amount of that of the player character, C is the balance parameter, N_i^p is the total number of times the parent node of node i has been visited, and N_i is the total number of times node i has been visited. In our experiment, the threshold, maximum tree depth and C were set to 10, 2 and 3, respectively. These parameters were chosen experimentally. UCTAI will execute UCT for 19ms, limited by execution speed, and select the most visited direct child node, from the root, as the next action.

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2 http://www.ice.ci.ritsumei.ac.jp/~ftgaic/

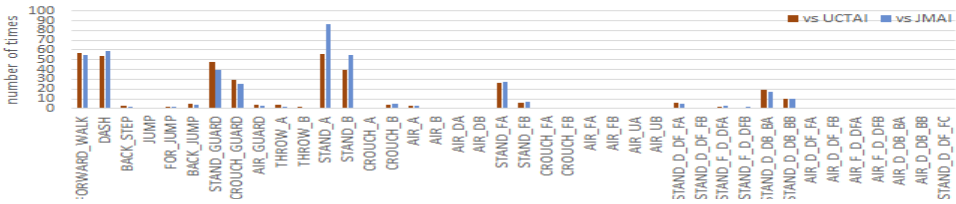

Fig. 1. The average number of times each action was executed by the players against each AI in one game

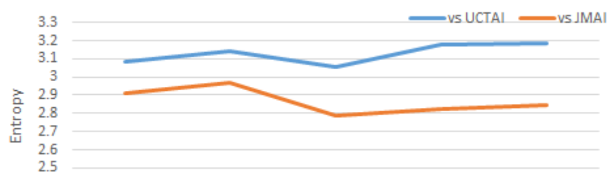

Fig. 2. The average action entropy of the players when fighting against each AI through all games.

III. Experiment and Results

A. Environment

We placed Kinect at 0.9m from the floor and 2.5m away from a player. The game rules in use followed those of the FightingICE competition. In addition, we used the system called P-Tracker [2] to control the player character in FightingICE by using Kinect as the input interface.

B. Methodology

We conducted an experiment with 13 players (11 males and 2 females with the age between 21 and 25). Considering the performance degradation due to their fatigue, we divided the experiment in two days.

1) First Day

The first day was for practicing, on which each player was asked to get accustomed to the Kinect controller. First, he or she was given the written instructions of the controller. After that, we demonstrated one game while explaining to them how to control the character using Kinect. Second, each of them was asked to fight against an idle AI, a dummy opponent, for three games. Finally, they were individually asked to fight against the AI (CloseAI) that uses close attacks only for another three games. The break time between any two consecutive games was set to one minute, as in boxing.

After finishing practicing all players, the average score in the last three games of each player was calculated. After that, we divided them into two groups. This was done such that there was no significant difference in the average scores between the two groups at a significance level of 5%, using the Wilcoxon rank sum test.

2) Second Day

On the second day, we asked the players to fight against JMAI and UCTAI. First, each of them was asked to fight against CloseAI for one game as a warm-up. Second, each player was asked to fight against UCTAI and JMAI alternately for 5 games per each AI. The break time was also set to one minute between two consecutive games.

C. Results

The average number of times each action was executed against each AI in one game is shown in Fig. 1. In this figure, the horizontal axis lists the name of each action; the vertical axis represents the number of times each action was executed, with the red bar against UCTAI and the blue bar against JMAI. From this result, we could see that the participated players used simple skills, e.g., STAND_A (Right Punch) more frequently. In contrast, JUMP or more complex skills, which require more movements, were seldom used.

The average of the player's action entropy when fighting against each AI through all games is shown in Fig. 2. From the result shown in Fig. 2, UCTAI leads to the higher action entropy than JMAI throughout all games, meaning our players used more various skills against UCTAI than against JMAI. In particular, there are significant differences in the 2nd, 3rd and 4th games with 5% significance level using Wilcoxon signed rank test. This indicates that some players discovered that JMAI could not react when it was cornered at the end of the stage and attacked by such a player continuously using STAND_A or STAND_B (Left Punch).

IV. Conclusions and Future Work

This paper investigated AIs whether they can affect players' amount of exercise by encouraging the usage of various skills in fighting game FightingICE. Our experimental results show that the players use more different skills, thus demonstrating higher action entropy, when playing the game against UCTAI. Thereby, the proposed UCTAI promotes the player's health with respect to the amount of exercise through having the player perform different skills. For future work, we will explore the factors that encourage the player to conduct more JUMP or more complex skills, requiring more movements.

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