Monte-Carlo Tree Search for Implementation of Dynamic Difficulty Adjustment Fighting Game AIs Having Believable Behaviors

Makoto Ishihara
Graduate School of Information Science and Engineering
Ritsumeikan University
Shiga, Japan
is0153nx@ed.ritsumei.ac.jp

Suguru Ito
Graduate School of Information Science and Engineering
Ritsumeikan University
Shiga, Japan
is0202iv@ed.ritsumei.ac.jp

Ryota Ishii
Graduate School of Information Science and Engineering
Ritsumeikan University
Shiga, Japan
is0245ve@ed.ritsumei.ac.jp

Tomohiro Harada
College of Information Science and Engineering
Ritsumeikan University
Shiga, Japan
harada@ci.ritsumei.ac.jp

Ruck Thawonmas
College of Information Science and Engineering
Ritsumeikan University
Shiga, Japan
ruck@is.ritsumei.ac.jp

***Abstract*—In this paper, we propose a Monte-Carlo Tree Search (MCTS) fighting game AI capable of dynamic difficulty adjustment while maintaining believable behaviors. This work targets beginner-level and intermediate-level players. In order to improve players' skill while at the same time entertaining them, AIs are needed that can evenly fight against their opponent beginner and intermediate players, and such AIs are called dynamic difficulty adjustment (DDA) AIs. In addition, in order not to impair the players' playing motivation due to the AI's unnatural actions such as intentionally taking damage with no resistance, DDA methods considering restraint of its unnatural actions are needed. In this paper, for an MCTS-based AI previously proposed by the authors' group, we introduce a new evaluation term on action believability, to the AIs evaluation function, that focuses on the amount of damage to the opponent. In addition, we introduce a parameter that dynamically changes its value according to the current game situation in order to balance this new term with the existing one, focusing on adjusting the AI's skill equal to that of the player, in the evaluation function. Our results from the conducted experiment using FightingICE, a fighting game platform used in a game AI competition at CIG since 2014, show that the proposed DDA-AI can dynamically adjust its strength to its opponent human players, especially intermediate players, while restraining its unnatural actions throughout the game.**

***Index Terms*—Monte-Carlo tree search, dynamic difficulty adjustment, fighting game AI, believable, FightingICE**

I. Introduction

Fighting games are real-time games in which a character controlled by a human player or a game AI has to defeat their opponent using various attacks and evasion. In this work, AI is defined as a computer program that controls a character in a game. There are two types of matches in fighting games: Player VS Player (PvP), where two human players fight against each other, and Player VS Computer (PvC), where a human player fights against an AI-controlled character. An AI in PvC usually acts as the opponent for the human player who plays alone, sometimes as a sparring partner. In this work, we focus on PvC and target beginner and intermediate human players in fighting games.

One of the main features of beginner and intermediate players is that they do not fully know the game information such as character operations, available actions and fighting styles or tactics. They are often defeated by players who fully know about the game and by AIs that are too strong compared with them. This may cause beginner and intermediate players to lose the motivation to play the game, in the middle of improvement of their skill, and quit it. To prevent this, AIs are needed that can entertain beginner and intermediate players, while such players are still improving their playing skills.

Previously, the authors' group proposed a Monte-Carlo Tree Search (MCTS) fighting game AI called "Entertaining AI" (eAI) [1] whose goal is to entertain human players. This AI can evenly fight against its opponent players by dynamically adjusting its strength according to their playing skill, called dynamic difficulty adjustment (DDA). Namely, eAI will conduct an action according to the current game situation: when eAI is losing, it will conduct a strong action, otherwise, eAI will conduct a weak action. From the experimental results, eAI could entertain its opponent human players by evenly fighting against them. However, we observed that eAI often conducted unnatural actions such as repeating no-hit attacks and repeating step back even though the distance between the characters is far away. In order not to impair players' playing motivation due to AIs' unnatural actions such as those by eAI mentioned above, DDA methods able to restrain its unnatural actions are

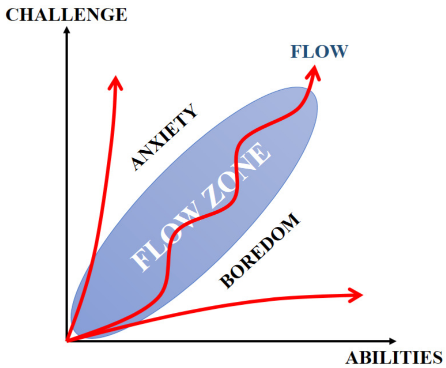

Fig. 1. Game flow [4]

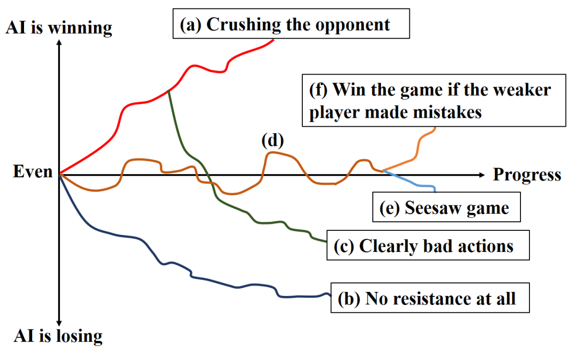

Fig. 2. Game flow in fighting games

needed [2].

In this paper, we propose an MCTS fighting game AI capable of dynamic difficulty adjustment while maintaining believable behaviors. This work targets beginner-level and intermediate-level players. We use eAI as a based AI and we introduce a new evaluation term on action believability, to the AI's evaluation function, that focuses on the amount of damage to the opponent. In addition, we introduce a parameter that dynamically changes its value according to the current game situation in order to balance this new term with the existing term in the evaluation function. We verify the performance of our proposed DDA-AI by a subjective experiment using FightingICE, a fighting game platform used in a game AI competition at CIG since 2014 [3].

II. Game Flow

Chen [4] mentioned the required elements by which players can enjoy playing games and how to design games to satisfy players using game flow (Fig. 1). In Fig. 1, the x-axis represents players' skill of the game and the y-axis represents the game difficulty. This figure indicates that players can enjoy playing the game if their skill and the game difficulty fall in "FLOW ZONE". That is, adjusting the game difficulty according to players' skill is needed. This can be said not only for game design, but also game AIs.

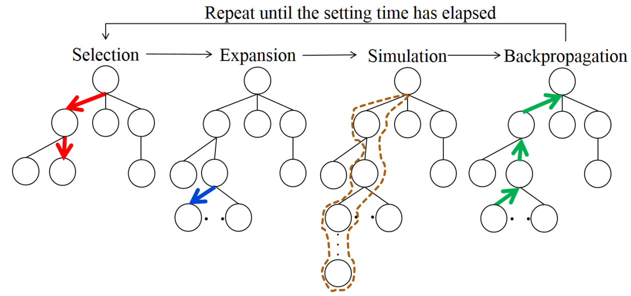

Fig. 3. An overview of MCTS

Ikeda and Viennot [2] mentioned the required elements according to which players can enjoy playing games and how to design them in terms of AIs in Go. They said using the aforementioned game flow that AIs are needed that can adjust their strength according to the opponent players' skill to evenly fight against or lose with a little difference in winning ratio. Fig. 2 shows the game flow applied to fighting game AIs by us with reference to the aforementioned work by Ikeda and Viennot. In Fig. 2, players cannot enjoy playing the game if the opponent AI crushes them (a) or loses with no resistance at all (b). Additionally, performing clearly unnatural actions only to balance the game (c) also impairs players' enjoyment. AIs should evenly fight against its opponent without unnatural actions (d), and finally, AIs might lose to its opponent with a little difference (e), or win if the opponent made some mistakes (f). That is, DDA-AIs capable of restraining its unnatural actions are needed.

III. Existing Methods for MCTS-Based DDA

In this section, we describe two DDA-AIs using MCTS. These AIs are used for comparison with our proposed AI.

A. *Entertaining AI*

Entertaining AI (eAI) was an MCTS-based DDA-AI proposed by our group [1]. This DDA method combines MCTS, Roulette Selection, and Rule-Based. In this section, we mainly explain MCTS, but we point out here that Roulette Selection, where the frequency of each action actually played by the opponent human player is used in simulation of his/her actions, is deployed in all of the AIs evaluated in this work. For more details about the other methods, please see Ishihara *et al.* [5].

Fig. 3 shows an overview of MCTS applied to fighting games. This MCTS is based on an open loop approach [6]. In this figure, the root node has the current game information which consists of both characters' Hit-Points (HPs), energies, positions, ongoing actions and the remaining time of the game. Each node except the root node represents an action. In this MCTS, an action spans from its input to its end, at which the next action becomes executable. An edge simply represents the connection between a parent node and its child node. When a parent node's action has finished, the next action will be one of its child nodes. In summary, the game tree using this MCTS represents the execution order of the AI's actions.

eAI repeats the four steps in Fig. 3 within a time budget of T_{max}. After the time budget is depleted, eAI selects the most visited direct child node (action) from the root node as the next action. The rest of this subsection explains each step of MCTS.

1) Selection: The child nodes with the highest Upper Confidence Bounds ($UCB1$) value [7] are selected from the root node until a leaf node is reached. The formula of $UCB1$ is:

$$UCB1_i = \overline{X}_i + C\sqrt{\frac{2\ln N}{N_i}}, \quad (1)$$

where N_i is the number of times node (action) i was visited, N is the sum of N_i for node i and its sibling nodes and C is a constant. $\overline{X_i}$ is the average evaluation of node i represented by the following formula:

$$\overline{X}_i = \frac{1}{N_i}\sum_{j=1}^{N_i} eval_j, \quad (2)$$

where $eval_j$ is the reward value gained in the jth simulation and is defined as:

$$eval_j = 1 - \tanh\frac{\left|afterHP_j^{my} - afterHP_j^{opp}\right|}{Scale}, \quad (3)$$

where $afterHP_j^{my}$ and $afterHP_j^{opp}$ stand for HP of the AI and the opponent after the jth simulation, respectively, and $Scale$ is a constant. As the HP difference between the AI and the opponent after the simulation is closer to 0, $eval_j$ will obtain an evaluation value closer to 1. Thereby, strong actions are highly evaluated when the AI is losing; otherwise, weak actions.

eAI selects the nodes with the highest $UCB1'_i$ value (using $\overline{X}_i$ value normalized by using formula (4)) from the root node until a leaf node is reached.

$$\overline{X}'_i = \frac{\overline{X}_i - \overline{X}_{min}}{\overline{X}_{max} - \overline{X}_{min}} \quad (4)$$

In this formula, $\overline{X}_{max}$, $\overline{X}_{min}$ stand for the maximum and minimum $\overline{X_i}$ in all nodes at the same tree depth.

2) Expansion: After a leaf node is reached in the $Selection$ part, if the number of times the leaf node is explored exceeds a threshold N_{max} and the depth of the tree is lower than a threshold D_{max}, all possible child nodes are created at once from the leaf node.

3) Simulation: A simulation is carried out for T_{sim} seconds, sequentially using all actions in the path from the root node to the current leaf node for the AI, and actions selected by Roulette Selection (see [5]) for the opponent. If the number of actions of the AI or the opponent used in the simulation is less than a given number, five in our previous work, randomly selected actions will be used after all actions of the AI or the opponent have been conducted. The variable $eval_j$ is then calculated using formula (2).

4) Backpropagation: $eval_j$ obtained from the simulation part is backpropagated from the leaf node to the root node. The $UCB1$ value of each node along the path is updated as well.

B. True Proactive Outcome-Sensitive Action Selection

True Proactive Outcome-Sensitive Action Selection (TPOSAS) is one of the MCTS-based DDA-AIs with believability proposed by Demediuk *et al.* [8]. TPOSAS also uses the same $UCB1$ formula (1). However, TPOSAS evaluates nodes using the following formula:

$$node.score = -\left(|h_s| - I_h\right)^+, \quad (5)$$

where h_s is the HP difference between the AI and the opponent, I_h defines the interval within which all HP differences can be neglected, and $(\cdot)^+$ indicates the ramp function, i.e., a function behaving like the identity function for positive numbers and returning 0 for negative numbers.

In this formula, the evaluations of all actions having h_s less than I_h will be 0; otherwise, will be negative. Therefore, all nodes (actions) with h_s less than I_h are more visited. Because there exist multiple actions that have the highest evaluation value of zero, unnatural behaviors like repeating the same action can be avoided.

In our experiment, I_h is set to 10% of the maximum player health as in the work by Demediuk *et al.* [8].

C. Problems

As we mentioned in Section I, eAI could entertain its opponent human players by evenly fighting against them. However, we could observe that eAI often conducted unnatural actions such as repeating no-hit attacks and repeating step back even though the distance between both characters is far away, especially in the game situation where the HP difference is around zero. In that situation, the evaluations of actions which do not give damage to the opponent and at the same time receive no damage such as moving actions will be higher than other actions. From this, one can readily see that eAI tends to select such unnatural actions in the above situation.

Demediuk *et al.* conducted the experiments where TPOSAS fought against human players and other AIs that were submitted to the Fighting Game AI Competition (FTGAIC)[1] to verify the method's effectiveness. From these experimental results, TPOSAS could dynamically adjust its strength according to its opponents' skill. However, although they mentioned about its believability, the authors did not quantitatively evaluate this factor. Also, they only used the HP difference at the end of the game as the evaluation criterion of DDA, and did not evaluate whether the AI can dynamically adjust its strength throughout the game.

IV. Proposed Method

In this section, we define what is believability in fighting games and explain our new DDA method considering fighting-game believable behaviors.

[1]http://www.ice.ci.ritsumei.ac.jp/~ftgaic/index.htm

A. Definition of Believable Behaviors in Fighting Games

As mentioned in Section I, the main purpose of fighting games is to defeat the opponent using various attacks and evasion. For that purpose, in this work, believable behaviors are defined as the aggressive behaviors aimed to defeat the opponent such as hitting attacks to the opponent properly. Conversely, unnatural behaviors are defined as those behaviors contrary to the main purpose mentioned above such as no-hit attacks (described in Section III-C), although it could be argued that such non-aggressive actions are also performed to a certain extent by some human players to taunt their opponents.

B. Evaluation Function with Believability

The new evaluation function taking into account believability is defined as follows:

$$eval_j = (1-\alpha)\,B_j + \alpha E_j, \tag{6}$$

where E_j is for difficulty adjustment defined using the same formula as formula (3). B_j about the AI's aggressiveness (believability) represented by the following formula:

$$B_j = \tanh \frac{beforeHP_j^{opp} - afterHP_j^{opp}}{Scale}, \tag{7}$$

where $beforeHP_j^{opp}$ and $afterHP_j^{opp}$ stand for HP of the opponent before and after the jth simulation, respectively, and $Scale$ is a constant. If the AI gives a high amount of damage to the opponent, B_j will obtain a high evaluation value. Therefore, this term makes the evaluations of aggressive actions aimed at defeating the opponent higher than non-aggressive ones.

The coefficient α in formula (6) is dynamically determined by formula (8) based on the current game situation:

$$\alpha = \frac{\tanh\left(\frac{beforeHP_j^{my} - beforeHP_j^{opp}}{Scale}\right) + 1}{2}, \tag{8}$$

where $beforeHP_j^{my}$ and $beforeHP_j^{opp}$ stand for HP of the AI and the opponent, respectively, before the jth simulation, and $Scale$ is a constant. The more the AI is winning against the opponent, the closer α reaches 1. Conversely, the more the AI is losing against the opponent, α becomes closer to 0. Therefore, this coefficient makes it easier for the AI to select actions suitable for difficulty adjustment (E_j) when the AI is winning and select those increasing its aggressiveness (B_j) when the AI is losing. Also, when the HP difference is zero which means the AI is evenly fighting against the opponent, α becomes 0.5. In that situation, the AI selects actions that maintain both difficulty and believability.

In summary, the mechanism of our proposed method is making the AI select actions by considering not only how to adjust its difficulty toward the opponent's skill but also always how to defeat it.

V. Experiments

In this section, we describe the conducted experiments to verify the performance of our proposed DDA-AI (Believable Entertaining AI: BEAI).

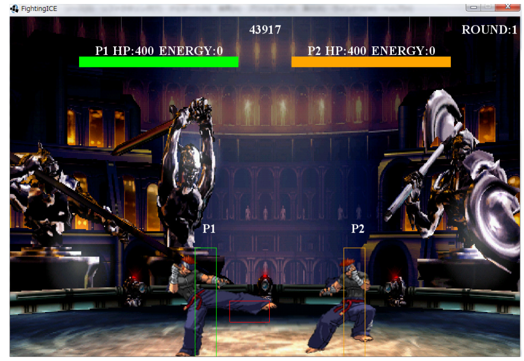

Fig. 4. Screen shot of FightingICE

TABLE I
PARAMETERS USED IN THE EXPERIMENTS

Notation	Meaning	Value
C	Balancing parameter	0.42
N_{max}	Threshold of the number of visits	7
D_{max}	Threshold of the tree depth	3
T_{sim}	The number of simulations	60 frames
T_{max}	Execution time of MCTS	16.5 ms
$Scale$	Scaling parameter	30

A. FightingICE

FightingICE (Fig. 4) is a real-time 2D fighting game platform used in a game AI competition (FTGAIC) at CIG since 2014 [3]. This game has all main elements of fighting games. In addition, it does not use a ROM emulator and has been originally developed from scratch and publicly made available for research purpose (see [10-14] for other recent publications using this platform), so there are no legal issues to be concerned. In FightingICE, one game consists of three 60-second rounds and one frame is set to 1/60 seconds. Each AI has to decide and input an action in one frame. Each character's initial HP is set to HP_{max}, and it will decrease when the character is hit. After 60 seconds or either character's HP is 0, the game will proceed to the next round, and each character's HP will be reset to HP_{max}. The character with the larger remaining HP at the end of the round is the winner.

In our experiments, the value of HP_{max} is set at 400 according to the rule of Standard Track of FTGAIC.

B. Parameters

The parameters used in our experiments are shown in Table I. These parameters were set empirically through pre-experiments.

C. Methods

We conducted subjective experiments to verify whether BEAI can adjust its strength according to the opponents' skill while maintaining its believability. We used 38 subjects (average age: 23.4 ± 2.2) in our experiments. Before starting our experiments, we conducted an informed consent session about our experiments, and subjects' consents were obtained with their signature in a separate informed consent form. In addition, we used eAI and TPOSAS for comparison. Our experiments were conducted for two days; the first day is to measure each subject's skill of fighting games (Exp. 1) while the second day is to have them individually fight against eAI, TPOSAS and BEAI (Exp. 2). The content of Exp. 1 and Exp. 2 is given below.

1) Measurement of fighting games' skill (Exp. 1): The procedure of Exp. 1 is as follows:

1) Explain the experiments and how to operate the character in FightingICE.
2) Ask each participant to fight against a non-action-AI for five minutes as practice.
3) Ask each participant to fight against an MCTS-Based high-performance AI (MctsAi) for one game.
4) Ask each participant to answer a questionnaire.
5) Repeat Steps 3 and 4 two times.

At Step 3, we used a sample AI of FTGAIC proposed by Yoshida *et al.* [9]. The questionnaire used at Step 4 is shown in Table II. This questionnaire was made with reference to previous studies [15] and [16]. We asked the subjects to evaluate each question in a 5-Likert scale (1: Strongly Disagree, 2: Disagree, 3: Neither, 4: Agree, 5: Strongly Agree). The evaluation of each factor is the average of the evaluation values of all questions (two in our case) belonging to each factor.

After finishing Exp. 1, we divided all subjects into three groups (G1, G2 and G3). We then confirmed that there is no significant difference between three groups in terms of both the average HP difference against the MctsAi and the evaluation value of the Challenge factor, using a Kruskal-Wallis test.

2) Fighting against eAI, TPOSAS and BEAI (Exp. 2): The procedure of Exp. 2 is as follows:

1) Explain the experiments and how to operate the character in FightingICE.
2) Ask each participant to fight against a non-action-AI for five minutes as practice.
3) Ask each participant to fight against an AI for one game.
4) Ask each participant to answer a questionnaire.
5) Repeat Step 3 and 4 for all AIs

The questionnaire used in this experiment is the same as the one in Exp. 1, rather than rank-based questionnaires [17] where participants are asked to compare the play session they have just finished with the former one. This is because in our case the time window between the two consecutive play sessions is up to 3 minutes – one game – by which participants might not be able to make precise comparison. The fighting order of each AI was determined according to the Latin-square method as follows:

- G1 eAI→TPOSAS→BEAI
- G2 TPOSAS→BEAI→eAI
- G3 BEAI→eAI→TPOSAS

In Exp. 2, we evaluated each AI's performance using a metric called Average HP Difference Throughout the Game (AHDTG), described in Section VI-D, and the evaluation values of three factors in the questionnaire. Video clips showing typical gameplay by participants against these AIs are available[1].

TABLE II
CONTENT OF QUESTIONNAIRE

Dimension	Index	Content
Positive Affect	1	I felt it content
	2	I felt it enjoyable
Challenge	3	I felt it challenged
	4	I felt it stimulated
Believability	5	The opponent's attack skills were believable
	6	The opponent's dodging skills were believable

TABLE III
SUBJECT GROUPING IN TERMS OF FIGHTING GAME SKILL

Name	Average	Median	# of people
Expert	3 ± 38	4	11
Intermediate	-151 ± 29	-159	12
Beginner	-225 ± 25	-221	15

D. Average HP Difference Throughout the Game

AHDTG is introduced by the authors to evaluate how the AI can dynamically adjust its difficulty according to the opponent throughout the game, defined by the following formula:

$$AHDTG = \frac{\sum_{i=1}^{F_{total}} |HP_i^{my} - HP_i^{opp}|}{F_{total}}, \tag{9}$$

where HP_i^{my} and HP_i^{opp} stand for HP of the AI and the opponent at the frame i, respectively, and F_{total} stands for the total number of frames in this round. If the AI evenly fight against the opponent throughout the round, the value of AHDTG becomes small. This indicates that the smaller the value of AHDTG is, the more the AI can dynamically adjust its difficulty according to the opponent's skill throughout the round.

VI. RESULTS AND DISCUSSIONS

In this section, we show the experimental results and our discussions in terms of AHDTG and each factor of the questionnaire. Note that the symbols $*$ and $**$ used in figures and tables in this section represent a significant difference at 5% and 1%, respectively.

A. Subject grouping

From the result of Exp. 1, we divided subjects into three groups –Expert, Intermediate and Beginner– based on the

[1] http://www.ice.ci.ritsumei.ac.jp/~ruck/dda-cig2018.htm

TABLE IV
RESULTS OF A FRIEDMAN TEST ON AHDTG IN EACH GROUP

Name	p-value
Expert	.078
Intermediate	.017*
Beginner	.006**

TABLE V
RESULTS OF A FRIEDMAN TEST ON POSITIVE AFFECT IN EACH GROUP

Name	p-value
Expert	.658
Intermediate	.084
Beginner	.723

average HP difference at the end of the game against the MctsAi, using the k-means method with $k = 3$. Table III shows the result of subject grouping. In Table III, the column Average represents the aforementioned average HP difference and the standard deviation of subjects belonging to each group, each playing three games.

B. AHDTG

Fig. 5 shows the average AHDTGs against eAI, TPOSAS and BEAI in each group. In Fig. 5, the x-axis represents the group names, the y-axis represents the value of AHDTG, and the error bars represent standard deviations of AHDTG for the three AIs in each group. We can see that BEAI obtains less AHDTG than eAI and TPOSAS against Intermediate and Beginner. According to our analysis of the gameplay, BEAI tends to behave aggressively especially in the game situation where the HP difference is around zero, due to the new evaluation term about its aggressiveness, compared with other two AIs. Therefore, one can consider that compared to eAI which tends to behave strangely like intentionally filling up the HP difference after the value becomes too large (AI losing too much), BEAI could evenly fight against the opponent like a seesaw game shown in Fig. 2 (d).

However, BEAI obtains more AHDTG than eAI and TPOSAS against Expert. According to our observation, some players in Expert adopted a fighting style like "counter-attack" by which they appropriately hit their attacks to the opponent against the opponent's conducted actions. We could often see that these players hit their strong attacks such as the ultimate attack to BEAI when it stepped forward in order to shorten the distance; in other words, they exploited BEAI's aggressive behaviors against the AI. For this reason, BEAI couldn't adjust

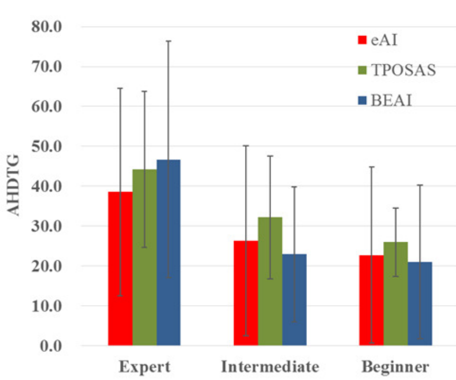

Fig. 5. Average AHDTGs against eAI, TPOSAS and BEAI, in each group

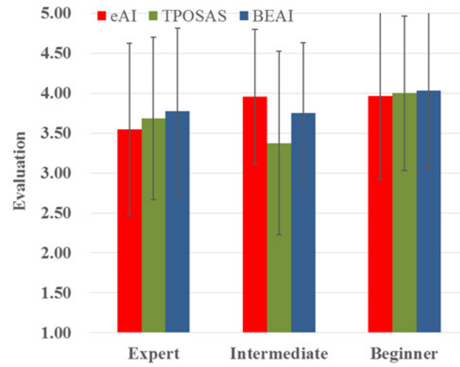

Fig. 6. Average evaluations of Positive Affect toward gameplay against eAI, TPOSAS and BEAI, in each group

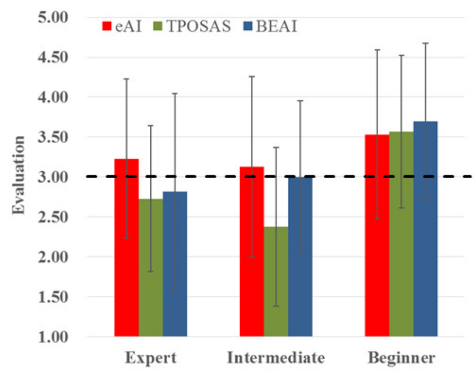

Fig. 7. Average evaluations of Challenge toward gameplay against eAI, TPOSAS and BEAI, in each group

its strength against expert players compared with the other two AIs.

Table IV shows the results of a Friedman test on AHDTG in each group. There are significant differences at 5% and 1% between the three AIs in Intermediate and Beginner, respectively. From these results, we can conclude that BEAI could dynamically adjust its difficulty against intermediate and beginner players throughout the game compared to the existing DDA methods.

C. Positive Affect

Fig. 6 shows the average evaluations of Positive Affect toward gameplay against eAI, TPOSAS and BEAI, in each group. In Fig. 6, the x-axis represents the group names, the y-axis represents the evaluation value (1: Boring $\sim$ 5: Enjoyable) of Positive Affect, and the error bar represents the standard deviation of it in each group. We can see that BEAI obtains higher evaluation values than eAI and TPOSAS against Expert and Beginner. However, it obtains a lower evaluation value than eAI against Intermediate. From our analysis, we could observe that BEAI often forced players to fight in the close range compared to the other two AIs. Subjects belonging to Intermediate fought against their opponent AIs using various actions and strategies, similar to those players in

TABLE VI
RESULTS OF A FRIEDMAN TEST ON CHALLENGE IN EACH GROUP

Name	p-value
Expert	.187
Intermediate	.024*
Beginner	.840

TABLE VII
RESULTS OF A FRIEDMAN TEST ON BELIEVABILITY IN EACH GROUP

Name	p-value
Expert	.886
Intermediate	.042*
Beginner	.420

Expert. However, since their skill is not that high, compared to Expert, they couldn't fight the way they wanted because of the BEAI's aggressive behavior compared to eAI, which led to the decrease in affect evaluation toward gameplay against BEAI. Although having this issue, BEAI obtains more than 3.75 points in all groups. Thus, we can still say that the subjects evaluated fighting against BEAI favorably.

Table V shows the results of a Friedman test on Positive Affect in each group. There is no significant difference between the three AIs in all groups. From these results, although there is no significant difference, we can conclude that BEAI could entertain expert and beginner players more than the existing DDA methods.

D. Challenge

Fig. 7 shows the average evaluations of Challenge toward gameplay against eAI, TPOSAS and BEAI, in each group. In Fig. 7, the x-axis represents the group names, the y-axis represents the evaluation value (1: Too weak $\sim$ 3: Good difficulty $\sim$ 5: Too strong; note that 3 is the best) of Challenge, and the error bar represents standard deviation for each AI in each group. We can see that BEAI obtains higher evaluation values than eAI and TPOSAS against Expert and Intermediate. However, BEAI obtains lower evaluation than the other two AIs against Beginner. From our analysis, we could observe that subjects belonging to Beginner often used simple strategies such as stepping forward and punching or kicking. As BEAI behaves aggressively, there were many situations where subjects and BEAI gave damage to each other in close ranges. Thus, they evaluated BEAI to be too strong due to these situations, compared to the other two AIs.

Table VI shows the results of a Friedman test on Challenge in each group. There is a significant difference at 5% between the three AIs in Intermediate. From these results, we can conclude that BEAI could adjust its difficulty against expert and intermediate players in a way that they felt the opponent AI's difficulty was suitable for them.

E. Believability

Fig. 8 shows the average evaluations of Believability toward gameplay against eAI, TPOSAS and BEAI, in each group. In Fig. 8, the x-axis represents the group names, the y-axis

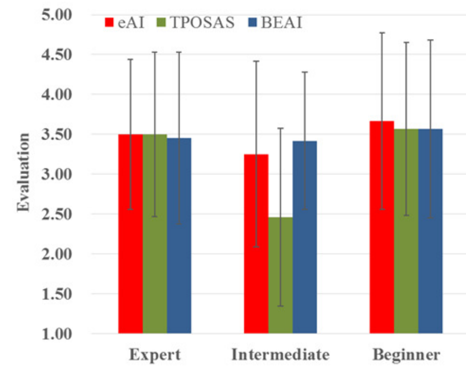

Fig. 8. Average evaluations of Believability toward gameplay against eAI, TPOSAS and BEAI, in each group

represents the evaluation value (1: Unnatural $\sim$ 5: Believable) of Believability, and the error bar represents the standard deviation for each AI in each group. We can see that BEAI obtains higher evaluation than eAI and TPOSAS against Intermediate. From our analysis, we could observe that BEAI conducted less unnatural actions as mentioned in Section III-C, especially the game situations where the HP difference is around zero. Thus, our proposed evaluation function could dynamically adjust the AI's difficulty while restraining its unnatural actions, and improve the evaluation value of Believability evaluated by intermediate players.

Table VII shows the results of a Friedman test on Believability in each group. There is a significant difference at 5% between the three AIs in Intermediate. From these results, we can conclude that BEAI could adjust its difficulty while restraining its unnatural actions against intermediate players.

VII. CONCLUSIONS AND FUTURE WORK

In order to improve players' skill while at the same time entertaining them, AIs are needed that can evenly fight against their opponent beginner and intermediate players; such AIs are called DDA-AIs. In addition, in order not to impair the players' playing motivation due to the AI's unnatural actions, DDA methods that can restrain their unnatural actions are needed. In this paper, we proposed an MCTS fighting game AI capable of DDA while maintaining its believable behaviors, targeting beginner-level and intermediate-level players. We used eAI proposed previously by our group [1] as a based AI (eAI) and introduced a new evaluation term on action believability, to the AI's evaluation function, that focuses on increasing the amount of damage to the opponent. In addition, we introduced a parameter that dynamically changes its value according to the current game situation in order to balance this new term with the existing term in the evaluation function.

From our experimental results, our proposed DDA-AI showed the best performance in terms of average HP difference throughout the game (AHDTG), Challenge and Believability against intermediate players, and AHDTG against beginner players. As a result, we conclude that our proposed DDA-AI could dynamically adjust its strength to its opponent human players' skill, especially intermediate players, while restraining its unnatural actions throughout the game. The proposed evaluation function (6) has a potential to be applied to MCTS-based AIs in other games to maintain the aggressiveness while shrinking the performance gap with the opponent human player, in particular when the AI is winning.

However, although our proposed DDA-AI was evaluated favorably by intermediate and beginner players, it could not significantly improve the evaluation value of Positive Affect, compared to eAI. For future work, we plan to develop a new mechanism for entertaining players while keeping its believability. It might also be interesting to combine the proposed DDA-AI with a mechanism that directly emulates human players [18]. In addition, we will also develop much stronger AIs as based AIs for new DDA-AIs that can adapt to expert players.

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