Towards Social Facilitation in Audience Participation Games: Fighting Game AIs whose Strength Depends on Audience Responses

Pujana Paliyawan*, Kingkarn Sookhanaphibarn†, Worawat Choensawat†, Ruck Thawonmas‡
*Research Organization of Science and Technology
†Multimedia Intelligent Technology Lab
‡College of Information Science and Engineering
*‡Ritsumeikan University, Japan
†School of Information Technology and Innovation, Bangkok University, Thailand
ruck@is.ritsumei.ac.jp

***Abstract*—This paper presents two AIs that enable a fighting game to be played or live-streamed as an audience participation game. The proposed fighting game AIs imitates a social facilitation in human psychology by dynamically adjusting its strength based on audience responses during gameplay. The two AIs exploit Monte-Carlo Tree Search. They have three important mechanisms, for dynamic difficulty adjustment, human-like behavior promotion, and social facilitation integration. We developed the two AIs with different evaluation functions. The common feature is an integrated social facilitation parameter. However, the difference is that one AI is developed by generalizing an existing AI by simply adding a parameter for setting the targeted HP difference, whereas the other was particularly designed for an social facilitation by a strict control of damage score difference. Our experiment result shows that the former one yields more human-like behavior, while the latter one yields slightly better strength adjustment.**

***Index Terms*—audience participation games, game AI, dynamic difficulty adjustment, Monte-Carlo Tree Search (MCTS), social facilitation**

I. INTRODUCTION

The phenomenon on how an individual performs better, or worse, on tasks when others are around is known as "social facilitation [1]." There have been so far studies on influences of social facilitation in a variety of tasks and environments [2]. However, to the best of our knowledge, there is not yet a study on audience participation games (APGs) [3], a recently emerged style of games that allows audiences to not only watch but also participate in part of play.

This papers presents and compares two fighting game AIs, whose strengths are dynamically adjusted based on audience responses. Each of the AIs allows FightingICE[1] to be played as audience participation game. They are built based on Believable Entertaining AI (BEAI) [4] that is capable of dynamic difficulty adjustment (DDA) and has mechanisms for promoting human-like behaviors (Believability).

II. EXISTING AIS

FightingICE is an open-source fighting game AI development platform that covers most basic features of typical fighting games. Since 2014, it has been used for running an annual AI competition by IEEE Conference on Games (previously known as Computational Intelligence and Games). This section describes the state-of-the-art of MCTS-based AIs and their generations.

A. MCTS-based AIs

Since 2016, the winner AIs in FightingICE competitions have been based on MCTS concepts, and there have been several studies on MCTS-based AIs. For instances, Pinto and Coutinho [5] combined hierarchical reinforcement learning with MCTS, Kim et al [6] presented a hybrid AI using a combination of genetic operations and MCTS. Besides making a strong AI that solely aims to win, MCTS potentials in achieving other goals were also investigated. For example, Demediuk et al. [7] introduced a use of MCTS techniques for the AI strength adjustments to entertain the player in Player versus Environment (PvE) games. In addition, Demediuk et al. further improved their AIs by introducing a novel method for measuring player skill [8].

B. MctsAi

MctsAi by Yoshida et al. [9] is an example MCTS-based AI publicly available on the FightingICE website[2]. MctsAi uses Eq. 1 as its evaluation function, where $afterHP_j^{my}$ and $beforeHP_j^{my}$ are hit points (HPs) of the character after and before the j-th simulation, while $afterHP_j^{opp}$ and $beforeHP_j^{opp}$ are those of the opponent character. The AI aims to produce as much as possible damage to the opponent, while keeping its own HP remain as possible.

$$eval_j = \left(afterHP_j^{my} - beforeHP_j^{my}\right) - \left(afterHP_j^{opp} - beforeHP_j^{opp}\right) \quad (1)$$

C. eAI

Entertaining AI (eAI) [10] was built based on MctsAi by introducing a DDA mechanism. This AI can adjust its strength to the abilities of the player, with a goal to promote

[1] www.ice.ci.ritsumei.ac.jp/%7eftgaic/

[2] http://www.ice.ci.ritsumei.ac.jp/%7eftgaic/index-2h.html

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entertaining PvE gameplay. The evaluation function of eAI targets to have its HP equal to that of the player (Eq. 2).

$$eval_j = 1 - \tanh \frac{\left| afterHP_j^{my} - afterHP_j^{opp} \right|}{Scale} \quad (2)$$

In this function, $Scale$ is a constant with a value of 30, as in [10]. When the HP difference is closer to 0, $eval_j$ will obtain an evaluation value closer to 1. Thereby, strong actions are more likely to be chosen when the AI is losing; otherwise, weak actions

D. BEAI

Believable Entertaining AI (BEAI) [4] was built by adding to eAI a mechanism that promotes believable behaviors. As the developer found that, when having HP higher than or equal to the opponent, eAI often conducted unnatural actions such as repeating no-hit attacks and repeating step back, the solution presented was to add “aggressiveness” to eAI.

The new evaluation function taking into account believability is defined by replacing Eq. 2 by Eq. 3. E_j (Eq. 4) is defined as the evaluation function of eAI as shown in Eq. 2, which is related to the difficulty adjustment. B_j (Eq. 5) is a new term introduced to suppress unnatural behaviors by promoting the AI’s aggressiveness. The term E_j is for difficulty adjustment, and α is for dynamically weighs which term should be emphasized, determined using Eq. 6; the more the AI is winning, the closer α reaches 1, the more the AI is losing against, the opponent, the closer α reaches 0, and when the HP difference is zero, α will be 0.5.

$$eval_j = (1 - \alpha) B_j + \alpha E_j \quad (3)$$

$$E_j = 1 - \tanh \frac{\left| afterHP_j^{my} - afterHP_j^{opp} \right|}{Scale} \quad (4)$$

$$B_j = \tanh \frac{beforeHP_j^{opp} - afterHP_j^{opp}}{Scale} \quad (5)$$

$$\alpha = \frac{\tanh \left(\frac{beforeHP_j^{my} - beforeHP_j^{opp}}{Scale} \right) + 1}{2} \quad (6)$$

III. Proposed AIs

Two AIs that incorporate the social facilitation feature to BEAI are presented: gBEAI (Generalized BEAI) and rSFAI (Responsive Social Facilitation AI). These AIs are our fourth generation MCTS-based AIs (cf. Table I), designed for playing FightingICE as an APG.

A. Conceptual Design for the Two AIs

By default, a social facilitation AI (each of the two AIs) adjusts it strength to match the opponent, but it will be weakened or strengthened based on a given social facilitation parameter F, whose value is dynamically set during APG based on audience cheering and jeering. At the maximum strength (minimum F), the AI targets to have an HP 120 more than the player’s, and at the weakest strength (maximum F), the AI targets to have an HP 120 less than the player’s. The number 120 is the amount of damage produced by the ultimate attack in FightingICE, thus is the difference in HP that allows turning the tide in the game by one ultimate attack.

B. Difference between the two AIs

gBEAI was built by introducing the parameter δ to BEAI’s functions for setting the targeted HP. rSFAI was built by modifying the term B in BEAI so as to not only consider a decrease in the opponent HP but also a defense of the AI’s own HP.

Our assumption (to be tested in IV) was that rSFAI would faster converge the targeted HP and better control the HP difference. However, believability might decrease as some aggressiveness was sacrificed.

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C. Generalized Believable Entertaining AI (gBEAI)

BEAI derived the evaluation function and the term B_j from BEAI (Eqs. 3 and 4). Functions for computing E_j and α were modified by adding a parameter δ (Eqs. 7-9), whose value is the targeted HP difference the opponent is expected to exceed the AI. d (Eq. 9) represents a gap/difference to the target HP difference before the simulation. δ is determined by the value of F (Eq. 10); positive values make the AI aims to lose, while negative values make the AI aims to win. The term F will be later introduced in Sec. III-E. The constant δ_{max} is set to 120.

$$E_j = 1 - \tanh \frac{\left| afterHP_j^{my} - afterHP_j^{opp} + \delta \right|}{Scale} \quad (7)$$

$$\alpha = \frac{\tanh \left(\frac{d}{Scale} \right) + 1}{2} \quad (8)$$

$$d = beforeHP_j^{my} - beforeHP_j^{opp} + \delta \quad (9)$$

$$\delta = F \delta_{max} \quad (10)$$

TABLE I
Comparison of AIs

Gen	AI Name	Developer	W	D	L	B	F
1	MctsAi	Yoshida et al. [9], 2016	✓	-	-	-	-
2	eAI	Ishihara et al. [10], 2016	-	✓	-	-	-
3	BEAI	Ishihara et al. [4], 2018	-	✓	-	✓	-
4	gBEAI	This paper	✓	✓	✓	✓	✓
4	rSFAI	This paper	✓	✓	✓	✓	✓

Capabilities: **(W)** The AI can target to win, **(D)** The AI can target to draw (i.e., aims for zero HP difference), **(L)** The AI can target to lose, **(B)** The AI has mechanisms for promoting Believability, **(F)** The AI has mechanisms for integrating Social Facilitation

D. Responsive Social Facilitation AI (rSFAI)

The new evaluation function was presented (Eq. 11). rSFAI shared the same E_j function with gBEAI (Eq. 7). S_j (Eq. 12) is a term targeting strong actions; it was designed by putting the evaluation function of MctsAi (Eq. 1) into a hyperbolic function. β (Eq. 13) is a weight dynamically adjusted based on social facilitation, computed using d in Eq. 9.

$$eval_j = \begin{cases} (1-\beta)E_j + (\beta)S_j, & \text{if } d < 0 \\ E_j, & \text{else if } d = 0 \\ (1-\beta)E_j + (\beta)(1-S_j), & \text{otherwise} \end{cases} \quad (11)$$

$$S_j = \frac{\tanh \frac{eval_j \text{ of MctsAi}}{Scale} + 1}{2} \quad (12)$$

$$\beta = \tanh \frac{|d|}{Scale} \quad (13)$$

In summary, based on d, when $d = 0$, only E_j is considered. When $d < 0$, S_j and E_j will be maximized; the closer d to 0, the less impact of S_j in trying to win, and vice versa. When $d > 0$, $(1 - S_j)$ and E_j will be maximized; the closer d to 0 the less impact of $(1 - S_j)$ in trying to lose, and vice versa.

E. Social Facilitation (F)

F should be in the range of [-1,1]. F can be implemented in several ways, depending on the design for audience participation and how interface for detecting positive facilitation (PF) and negative facilitation (NF) is set up. For example, if we set up an APG in which gBEAI/rSFAI fights against another AI, and audiences can cheer (denoted as PF^{my}) and jeer (denoted as NF^{my}) the gBEAI/rSFAI, Eq. 14 can be used. On the other hand, if we set an APG in which the player fight against gBEAI/rSFAI, and the AI is expected to become weaker when audiences cheer the player (denoted as PF^{opp}), and become stronger when audiences jeer the player (denoted as NF^{opp}), Eq. 15 can be used. The above-mentioned PF and NF may represent the percentage of time cheering and jeering is detected.

$$F_{example1} = NF^{my} - PF^{my} \quad (14)$$

$$F_{example2} = PF^{opp} - NF^{opp} \quad (15)$$

IV. Experiment and Results

We evaluate the AIs in terms of strength adjustment and believability. Strength adjustment refers to how well the AI can converge the targeted HP difference. Believability refers to how naturally strength adjustment is done (e.g., no unnatural behavior when the AI targets to lose its HP).

A. AI Test for Strength Adjustment

We compared the two AIs under six different settings of F: F = 0, F = -1, F = 1, F = -1 to 1 (in each 60-second round in FightingICE, F was set to -1 for the first 30 seconds, and switched to 1 for the last 30 seconds), and F = 1 to -1 (the reverse of -1 to 1). Opponents chosen were TOVOR, the weakest AI from 2019 competition, and MctsAi. Per setting, the test consisted of 1000 rounds in Time Mode (the round time is fixed to 60 seconds, HPs starts from 0 to negative). Each AI was Player 1 in 500 rounds and Player 2 in the other 500. Both sides used ZEN as their characters. Settings of MCTS parameters was based on the previous BEAI study [4].

The results are shown in Fig. 1. The HP difference denoted as ΔHP, was computed by subtracting the opponent's HP from the HP of gBEAI/rSFAI. In most cases, rSFAI seemed to outperform gBEAI in converging the ideal HP difference. Both AIs could not reach the HP difference of -120 against TOVOR because TOVOR could not do much damage. Similarly, they could not reach the HP difference of 120 against MctsAi because MctsAi is slightly stronger than gBEAI, and is as strong as rSFAI, at their maximum strengths. It was also found that, for rSFAI, to catch up the strength of MctsAi, F must be set to -1 instead of 0.

B. User Evaluation for Believability Assessment

We conducted an online survey to evaluate the two proposed AIs in terms of believability. A case when each AI with F = 0 fighting against TOVOR was considered. From 500 replays when each AI was Player 1, we selected the best, the median, and the worst replays, based on the average of absolute ΔHP throughout the whole round (denoted as $\overline{|\Delta HP|}$), and recorded videos. $\overline{|\Delta HP|}$ of the six videos are shown in Table II. Each participant watched a pair of videos, either a pair of the best, the median, or the worst performance of the two AIs. They watched two videos in a random order and answer a question asking "P1 in which video is more believable (human-like)?," and optionally gave reasons.

TABLE II
$\overline{|\Delta HP|}$ in Best, Median, and Worst VDOs, and averages from 500 VDOs.

	Best VDO	Median VDO	Worst VDO	Average
gBEAI	6.90	15.18	87.08	18.92
rSFAI	2.12	7.78	54.97	9.41

Table III shows the result from 69 respondents; most of them were students from Graduate School, and College, of Information Science and Engineering, Ritsumeikan University ($\sim$2/3), and the rest participants ($\sim$1/3) were bachelor students in a class of AI for Games at Bangkok University. Personal information was not collected so as to make the questionnaire short and participants feel incognito. The questionnaire

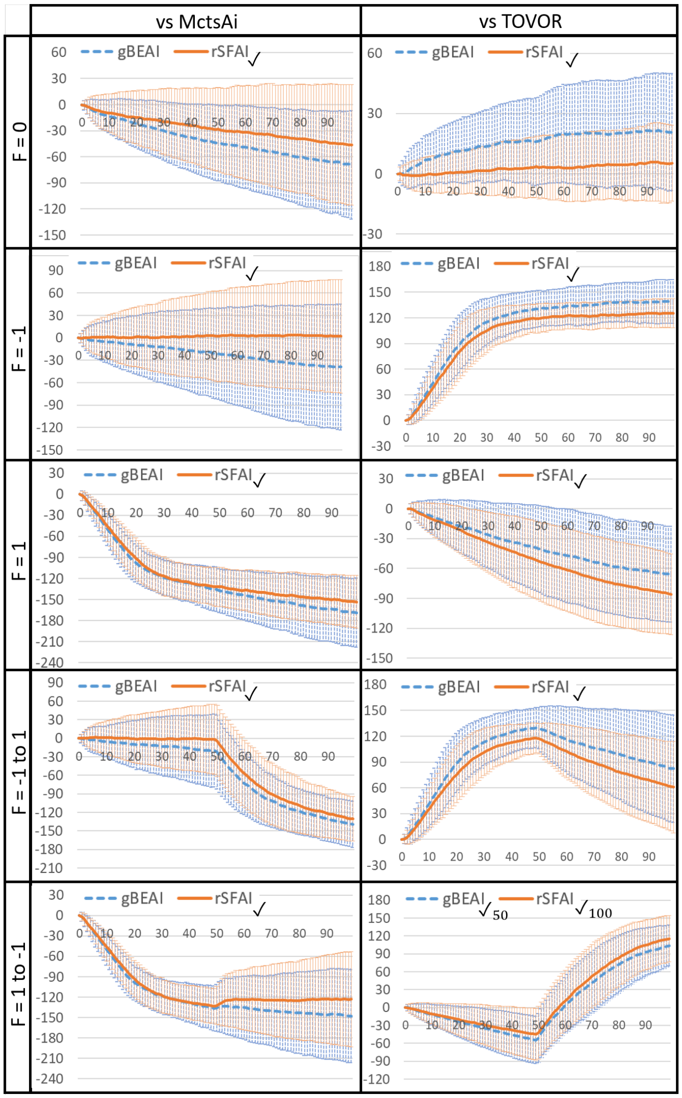

Fig. 1. Means with error bars of HP difference when gBEAI and sFEAI fought against TOVOR (Left) and MctsAi (Right). X-axis represents the timepoint (t), where t = 50 and 100 are the middle and the end of the round. Y-axis represents the HP difference (ΔHP). A check symbol (✓) is marked for the AI that control ΔHP better. Ideally, when ***F* = 0**, ΔHP should be 0 at most of the time (it may differ from 0 sometimes due to the aggressiveness presented for promoting believability). When ***F* = -1**, ΔHP should reach 120. When ***F* = 1**, ΔHP should reach -120. When ***F* = 1 to -1**, $\Delta HP_{t=50}$ and $\Delta HP_{t=100}$ should be at -120 and 120 respectively. And finally, when ***F* = 1 to -1**, $\Delta HP_{t=50}$ and $\Delta HP_{t=100}$ should be at -120 and 120 respectively.

consisted of three languages: English, Japanese, and Thai—estimated numbers of respondents were based on language they used to provide reasons. Most participants had heard the concept of believability before from previous lab meetings and lectures.

gBEAI was more believable, which is reasonable as rSFAI sacrifices some aggressiveness for better control of ΔHP. In the best and the median videos, most respondents, who provided reasons, mentioned that rSFAI dashed back frequently, which was considered unnecessary; rSFAI tended to keep distance away and wasted time.

TABLE III
RESPONSES ON WHICH AI IS MORE BELIEVABLE, WITH P-VALUE FROM CHI-SQUARE GOODNESS OF FIT TEST.

	Best VDO	Median VDO	Worst VDO	Total
gBEAI	13 (86.67%)	19 (70.37%)	13 (48.15%)	45 (65.22%)
rSFAI	2 (13.33%)	8 (29.63%)	14 (51.85%)	24 (34.78%)
p-value	.005	.034	.847	

V. CONCLUSION AND FUTURE WORKS

This paper compared two implementations of an AI for incorporating social facilitation in a fighting game. From our result, we suggest gBEAI over rSFAI for playing FightingICE as an APG. This is because, although their responsivenesses (i.e., abilities in strength adjustment) were only slightly different, gBEAI outperformed rSFAI in believability. In case that believability is not an issue of concern, rSFAI can be chosen. The idea of adding a social facilitation mechanism for AIs' strength adjustment, to allow audience participation, can be applied to other games. Our future plan includes testing FightingICE as an audience participation game that detects co-located audience responses through audio input.

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