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Applying Fuzzy Control in Fighting Game AI

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***Abstract*— This paper proposes a novel approach that combines fuzzy control with kNN prediction and simulation for fighting game AI to tackle the problem of "cold start" and improve the performance of the existing method. Using FightingICE as the platform, past research has proven that the kNN algorithm is effective in predicting the opponent's action in fighting games, however, this method suffers a disadvantage in the beginning of the game when there is not enough opponent action data for prediction, hence the aforementioned problem. We overcome this problem by combining the existing technique with fuzzy control, which is more flexible than crispy rules and well-suited for the dynamic nature of fighting game mechanics.**

Keywords—fuzzy control; game AI; FightingICE; fighting game; game informatics;

I. FIGHTINGICE AND FIGHTING GAME AI COMPETITION

Unlike other games such as chess and poker, fighting games feature competition between two equal opponents in a real-time fight that demands fast response and rapid strategic planning. The dynamic nature and complex move sets of fighting games pose challenges to AI researchers who aim at creating strong fighting game AI. To encourage research in fighting game AI, our laboratory has developed FightingICE[1], a fighting game artificial intelligence competition platform, which allows researchers to develop and test AI algorithms in a 2D fighting game [1].

FightingICE maintains a frame rate of 60 frames per second; each round lasts for 60 seconds and one match comprises of 3 rounds. AIs of both sides can plan their next move using the game data provided by the game platform every frame. Similar to time delay in human vision, in our game, *game data is passed to the AIs after a delay of 15 frames*. The 15-frame delay is imposed so as to prohibit perfect-defense perfect-counter strategy. The score of player is calculated by the following formula. Player who has a score higher than 500 is considered the winner of that round.

$$score = \frac{opponentHP}{selfHP + opponentHP} \times 1000 \qquad (1)$$

Using FightingICE as the platform, our laboratory has organized several competitions, which attracted participants from different continents.

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

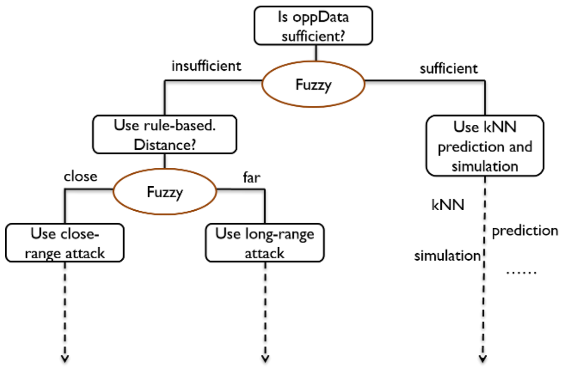

Fig 1. Overview of the proposed fuzzy control AI

II. KNN ALGORITHM IN FIGHTING GAME AI

To create an AI that can learn opponent's action patterns and adapt to different tactics, Yamamoto et al applied k-Nearest Neighbor (kNN) algorithm in fighting game AI and used a simulation-based approach to devise countermeasures against the opponent's movement [2]. In the technique proposed by them, every opponent's action and the relative position where it was performed was recorded in the data set. After accumulating enough data, the AI will start predicting the opponent's next move using the kNN algorithm. Based on the prediction result, the AI will devise a countermeasure through simulation and counterattack on its opponent. Although experiments have shown that the combination of kNN prediction and simulation is an effective technique in fighting game, such a strategy suffers "cold start" – in the beginning of the game when the AI has not accumulated enough data for prediction, the AI cannot react to its opponent and hence it performs poorly.

III. COMBINING FUZZY CONTROL WITH KNN AND SIMULATION

To avoid "cold start", we proposed the combination of fuzzy control with the existing algorithm. A simple illustration describing the structure or flow can be seen in Fig. 1.

First, the AI will determine whether there is enough data for action prediction using fuzzy logic. In particular, the AI will read the number of data entries in the data set (oppData) and decide whether the data is sufficient for prediction using pre-defined membership functions and the center-of-gravity singleton defuzzification method. If the data set has sufficient data, the AI will perform prediction and simulation as described in Section II. Otherwise, the AI will use fuzzy rule-base to determine the next move. In other words, the probability of whether kNN prediction and simulation is used equals to the membership value of current oppData in the "sufficient" membership function (Fig. 2).

In the fuzzy rule-base, the AI will again use a fuzzy rule to decide whether the opponent is in close-range or long-range, and perform attacks accordingly. Depending on whether the opponent is in close-range and in the air, the AI will select one attack move out of 3 preset rules randomly. For example, if the AI recognized that the opponent is in close-range and on ground, it will randomly perform an attack action, selected from a pre-defined close-range-on-ground move set that contains three moves (punch, throw and short jump kick). On the other hand, if the opponent is in long-range, action will be selected from a long-range attack move set (projectile, slide attack and air punch).

IV. Performance Evaluation

To evaluate the performance of the proposed method, an AI named ChuMizunoAI is implemented, and 200 games were performed against mizunoAI, the AI proposed in previous work [2], and ChuMizunoAI_crispy, the AI proposed in this paper but with fuzzy control being replaced by crispy thresholds (oppData = 10, distance = 60). Among the 200 games played,

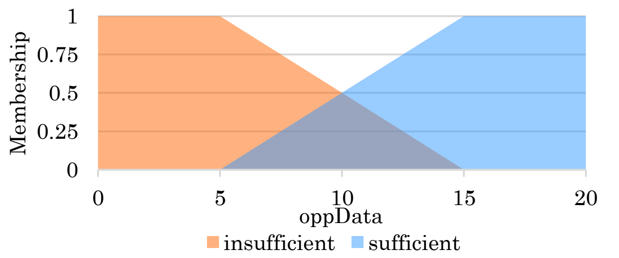

Fig 2. Membership functions for determining whether there is sufficient data or not

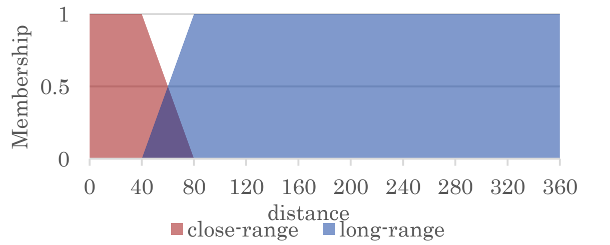

Fig 3. Membership functions for determining whether close-range attack or long-range attack should be used

TABLE 1
AVERAGE SCORES AND RESULTS OF 200 GAMES AGAINST MIZUNOAI, CORRECTED TO NEAREST INTEGER

	Round 1	Round 2	Round 3
Average	647	572	542
Results	174 wins 26 loses	71 wins 110 draws 19 loses	56 wins 119 draws 25 loses

TABLE 2
AVERAGE SCORES AND RESULTS OF 200 GAMES AGAINST CHUMIZUNOAI_CRISPY, CORRECTED TO NEAREST INTEGER

	Round 1	Round 2	Round 3
Average	542	502	514
Results	129 wins 3 draws 68 loses	67 wins 70 draws 63 loses	83 wins 52 draws 65 loses

ChuMizunoAI took player 1's role in 100 games and player 2's role in the other 100 games. The test was conducted on FightingICE version 1.02 and the results are shown in Table 1 and Table 2.

Analyzing the test result, one can conclude that combining fuzzy control with kNN prediction and simulation can vastly enhance the performance of the existing technique. A more interesting finding is that fuzzy control achieved better result than crispy threshold. This result may be attributed to the flexibility and unpredictability of fuzzy control.

V. Conclusions and Future Work

This paper proposed the use of fuzzy control in fighting game AI and proved that fuzzy logic is effective in improving an existing technique. The test result testifies to the superior performance of fuzzy control over crispy thresholds in fighting game AI. Realizing the potential of fuzzy control in fighting game AI, we consider that application of fuzzy logic in other techniques, such as dynamic scripting, can be a promising research direction in the future.

References

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