

Unit Formation Planning In RTS Game By Using Potential Field And Fuzzy Integral

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Abstract— Unit formation planning and target of attack is the core of micro management in real time strategy (RTS) game. It is more complicated than macro management, such as building and unit production sequence. It consists of a great quantity of possibility. Multiple targets and the non-additive property of unit formation leads the micro-management remains a problem. Traditional tree searching or A* searching is unable to handle these two properties. They are time consuming in runtime and difficult to manage in the AI programming development as there are too many weightings and each of them will interact with the others. In this paper, we applied potential field, fuzzy measure and integral to solve the micro-management. Potential field is suitable for complicated and various environment with multiple targets. However, it does not consider non-additive property. We integrated it with fuzzy measure and integral to extend simple additive property to non-additive property and provide the ability to handle interaction among different targets.

Keywords—component; Fuzzy Measure, Fuzzy Integral, Potential Field, Real time Strategy Game, unit formation planning, Micro-management, Warcraft III

I. INTRODUCTION

Nowadays, RTS game consists of complicated game rule, hundreds of unit type, various battlefields and decision making under the time pressure. More and more researchers such as Buro [1], Lucas [2], Alexander [3] are interested in it and have recently generated much important outputs in both macro and micro management for the RTS game AI community. RTS game provides a fruitful environment for AI research.

The fundamental game play of a typical RTS game is allocating resources to build an army, design units' combination and defeat the enemy by killing the opponent units. Control of RTS game can be classified into two types. The first type is macro management which is also named game strategy. It involves resource gathering, base building and technology upgrade. The second type is micro management, i.e., tactics, involves planning of the unit movement and control. For the macro-management, many researchers have applied case based reasoning CBR to solve it. CBR is potentially a very useful approach in game AI strategy planning and design. Usually, cases can be collected, learned from real game data or constructed using simulation [4], such

as ORTS, MadRTS, Wargus, etc. These cases can be reused according to some similarity and effectiveness measures. However, if cases are continuously accumulated, the time to retrieve solutions will be too long in RTS games. Fast indexing methods is needed such as Peter [5] and Pao [6] approaches. In our previous research [7][8], we also applied CBR concept and combined with fuzzy measure and integral to solve macro management, i.e., the unit production planning problem by considering the non-additive property of different unit combination. In this research, we extended the usage of trained fuzzy measure and applied to the micro management. We combined the potential field and fuzzy integral to solve the unit formation and target of attack planning. The methodology extended the normal additive property of potential field to non-additive property and provided the ability to handle the interaction among different targets. We simulated our experiment in Warcraft III. Details step and experimental result are shown in this paper.

II. LITERATURE REVIEW

A. Fuzzy Measure and Integral

Unit formation planning involves unit combinations selection. The unit combination are enormous in RTS game and the combined power of different units is usually "non-linear", i.e., the sum is not simply the total of the individuals [9] and is not additive. Let $X = \{x_1, x_2, \dots, x_n\}$ be the unit combination where n is the total number of unit types and f be the combined power. We believe that there exists non-additive property, i.e., $f(X) \neq \sum_{i=1}^n f(x_i)$. Formally speaking, when the interaction is positive, $f(X)$ is considered as super additive, i.e., $f(X) \geq \sum_{i=1}^n f(x_i)$, for all x in the domain of f . This could be easily found in many RTS game designs, such as the melee unit should be supported by magic or range unit. When the interaction is negative, the model is considered as sub additive, i.e., $f(X) \leq \sum_{i=1}^n f(x_i)$. If the interaction is

zero, then it will be considered as normal additive model, i.e.,

$$f(X) = \sum_{i=1}^n f(x_i).$$

As the non additive properties in unit combination, weighted average and weighted A* searching cannot give a good result in our experiment, we need to find a solution to indicate the interaction. Therefore, the combined power of units can be evaluated. We applied fuzzy measure and integral and the basic idea is illustrated in Fig. 1. All the units, and their possible combinations are assigned with (i.e., learnt from data) some fuzzy measures, μ , and an overall assessment is computed using fuzzy integral. Then, the case's assessment can be computed by referring to known fuzzy measures, and the fuzzy integral. The final strategy selected can be based on these assessments.

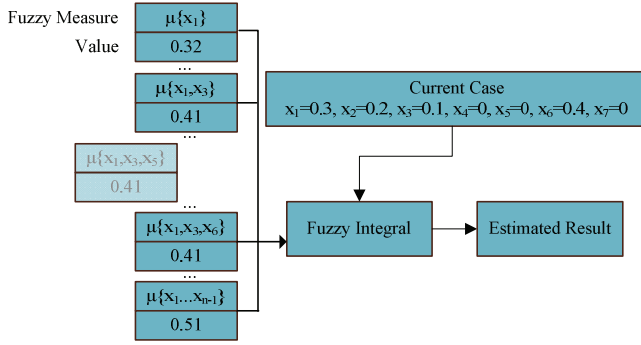


Fig.1. Apply Fuzzy Measure and Integral on Regression

Non additive fuzzy measure is used in our experiment. Non additive fuzzy measure is the original one and can be considered as the basic form of fuzzy measure [10]. It can be regarded as generalization of the classical probability measure. A value is assigned to each combination of variables, i.e., for n variables, there are $2^n - 1$ measures.

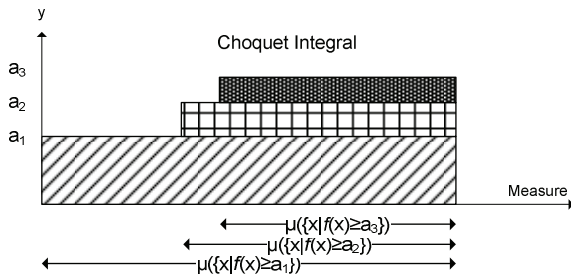


Fig.2. Choquet Integral. μ is the fuzzy measure of a function $f(x)$

$$(c) \int f(x) \circ \mu(X) = \sum_{i=1}^n (a_i - a_{i-1}) \cdot \mu(x | f(x) \geq a_i) \quad (1)$$

where $a_0 = 0$ and $a_0 \leq a_1 \leq a_2 \leq \dots \leq a_n$

Choquet Integral (CI) is a kind of fuzzy integral. It has been a general tool for dealing with multiple criteria decision making and is able to model the interactions among different criteria. Sugeno [11] [12] has applied it to the problem of prediction of wooden strength and plant operator. Both of them show a better result than a linear regression. Peter [13] has applied CI in software cost estimation with multiple attribute. Suppose a fuzzy measure $\mu : P(X \rightarrow [0,1])$ and $\mu(\emptyset) = 0$, definition of CI, see Fig. 2, is shown as follows and a_i is the sorted sequence of x_i

B. Potential Field

Potential Field is designed for searching the next movement location in multiple goals and various environments under the time pressure. The classic potential field consists of two virtual forces. One is attractive potential force,

$$U_{att}(q) = \frac{1}{2} \xi p_g^2, \text{ where } \xi \text{ is a positive constant scaling factor}$$

and $p_g = \|q - q_g\|$ is the Euclidean between the object and the goal. Another force is repulsive potential force,

$$U_{rep}(q) = \frac{1}{2} \eta \left(\frac{1}{p(q)} - \frac{1}{p_0} \right)^2 \text{ where } \eta \text{ is a positive constant}$$

scaling factor, $p(q)$ is the minimum distance from the object to the obstacle and p_0 is a positive constant that presents the influence distance of the obstacles.

Multi-agents Potential Fields of Hagelback [14] [15] and Johan [16] showed the importance to micro management and tactics development. Their experiment result had been proven in events such as Open Real Time Strategy (ORTS) AI competitions which have been held for many years provide a good platform for players to test out their control tactics. They showed a possible solution on micro management in RTS game. Potential field is normal additive. Therefore, it may not have the ability to handle interaction among different goals, especially the sub additive problem, i.e., $f(X) \leq \sum_{i=1}^n f(x_i)$.

III. METHODOLOGY

A. Obtain the Fuzzy Measure from real game data

Case = {Unit Combination, Situation, Scores}

In our previous research, we try to create a method to evaluate the power of unit combination for macro-management planning, i.e., building sequence and unit production planning [7][8]. A set of fuzzy measure is learnt from real game data. We will briefly explain the flow in this session. A set of game logs which is the replay data of Warcraft III is collected. We converted each replay data, i.e.,

each battle into one case as shown above and divided it into three parts. They are unit combination, situation and scores.

We define the “Unit Combination” of a case as the creation of player and enemy unit production, e.g., player created 10% peasants, 50% footman, 40% rifleman and the enemy created 30% peasants, 70% footman.

“Situation” is used to describe some common circumstances the player is dealing with. For example, if a player faces similar conditions, races, enemy units, etc, we can still think that the player is dealing with similar “situation” or he is under certain typical circumstances. The purpose is to help cluster cases into several similar groups. Depending on the number of training data and game play design, other information, such as map or starting location, could also be selected as the cluster criterion.

Finally, “Score” is the points obtained after the game. It is used for evaluating the outcome of the Warcraft III battle, and is used to guide the training of fuzzy measure, i.e., we can interpret as the higher the scores the more powerful unit combination.

Ontanon [17] [18] and Sharma [19] applied similar approach to index the player action. They used building or architectures as an index to organize the game actions. In our study, we try to use the possible unit that can be produced by player as an index. Game actions are much simplified for the purpose of reducing the complexity of each case description.

After the preprocessing of the game data, we use Genetic Algorithm (GA) to obtain the non additive fuzzy measure [20] [21], i.e., $\mu(X)$ or $\mu(\text{Unit Combination})$, for calculating unit combinations and its’ interactions as Fig. 3.

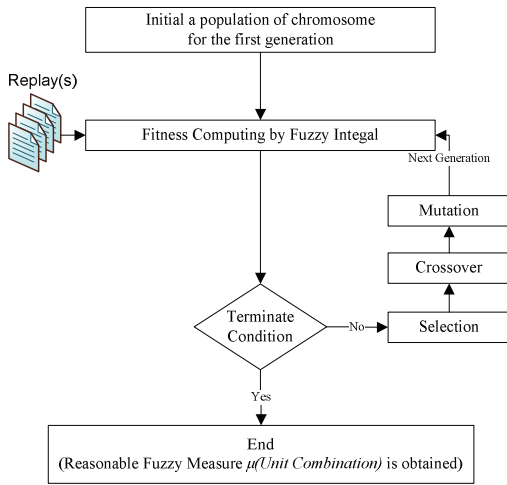


Fig.3. Overview of GA to obtain the Fuzzy Measure

First, a number of chromosomes are generated randomly. Each chromosome represents a fuzzy measure. It is combined by $2^n - 1$ fuzzy measure of $\mu(X)$, where $X = \{x_1, x_2, \dots, x_n\}$ is the unit combination and n is total number of unit type. $\mu(X)$ involves $\mu(x_1)$, $\mu(x_2)$,

$\dots, \mu(x_1, x_2)$, $\dots$, $\mu(x_1, x_2, \dots, x_n)$, each of them represents the fuzzy measure of the unit type sub-set. They are corrected to seven decimal places. Then they are converted into binary form and combined into one chromosome. Population of each generation is set to 50 in our experiment. To simplify the fuzzy measure, the unit types that are not produced in all the replays within the same cluster are not considered.

Each chromosome represents a fuzzy measure. Unit combination in each replay will be extracted and processed by function f . $f(x)$ presents the power of unit combination where x represents a unit combination of a replay, i.e., $f(x) = f(\text{Unit Combination}_{\text{Replay } i, \text{Player}})$. Throughout the function f , all the unit productions of player and enemy in the battle (i.e., unit(s) of unit type 1... unit(s) of unit type n) are normalized separately and presented in proportion. We used Choquet Integral (CI) in our experiment to calculate the estimated scores from unit combination, i.e., $f(x)$ and the fuzzy measure chromosome, i.e., $\mu(X)$. The equation is shown in (1).

All the differences between the real scores and the estimation using fuzzy integral in all replays will be summed up and the average is calculated. Then it will become the fitness value of chromosome as shown in (2) where N is the total number of case. We apply Wang’s fitness value [22] to calculate the fitness of each chromosome. Finally, after GA operation (100 generations), a reasonable fuzzy measure is learnt.

$$\text{Fitness value} = -\frac{1}{1+e}$$

$$\text{where } e = \frac{1}{N} \sum_{i=1}^N |(c) \int f(x_i) \circ \mu(X) - \text{score}(i)| \quad (2)$$

B. Apply Fuzzy Integral in Unit Formation Planning

The fuzzy measure has shown improvement on macro-management. We want to extend the usage of trained fuzzy measure to micro-management during the battle, i.e., unit formation planning and target of attack. First, we will discuss about applying fuzzy integral in unit formation planning as shown in Fig.4. When the player decided to fight against the enemy unit in the Warcraft III, the player will divide their army into subgroup and attack the enemy. This is known as formation. We applied fuzzy integral to perform this task.

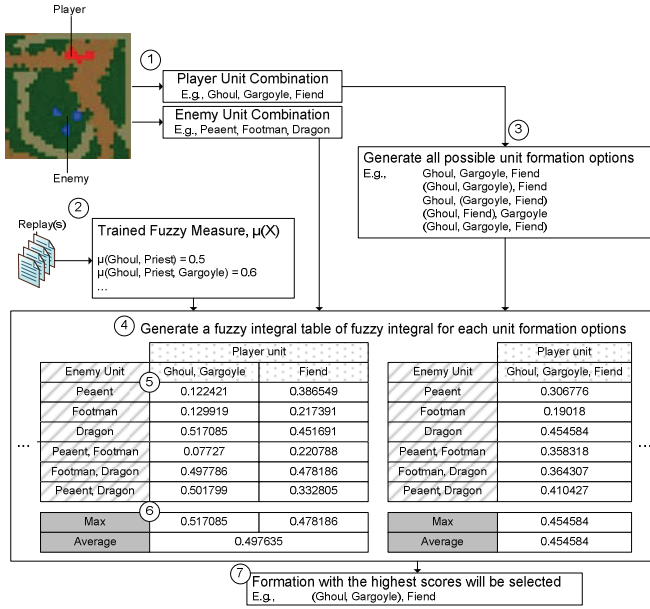


Fig.4. Overview of applying Fuzzy Integral on unit formation planning

1. Fuzzy measure is trained by the replay data.
2. Player and enemy unit proportion is extracted during the battle.
3. When the player decides to fight against the enemy, AI bot will generate all the possible unit formation according player unit type.
4. For each formation, a fuzzy integral table will be generated. Each cell in the table represents the power of the player subgroup to fight against certain the enemy subgroup as shown in Fig. 4
5. The value of each cell is calculated by Choquet integral as shown in (1) by using trained fuzzy measure and unit proportion of the selected player and enemy unit. We can interpret as the higher value the higher chance to win.
6. The maximum fuzzy integral of each player subgroup will be selected and the average will be taken as the score of this unit formation.
7. The unit formation with the highest scores will be selected.

C. Potential Field with the Fuzzy Integral value

After AI bot decided unit formation, it needed to decide the target of attack for each subgroup. We applied potential field to perform this task. Player army will be divided into different subgroups according to unit formation planning that described in part B. Then a potential field will be generated for each subgroup of player army as shown in Fig. 5. The centre of the potential field was the middle point of enemy army. The size of potential field was set as 50 x 50 in our experiment. The initial potential field was an empty two dimension array. Each cell of the two dimension array will store the attractive force, , for one coordinate, (x,y) .

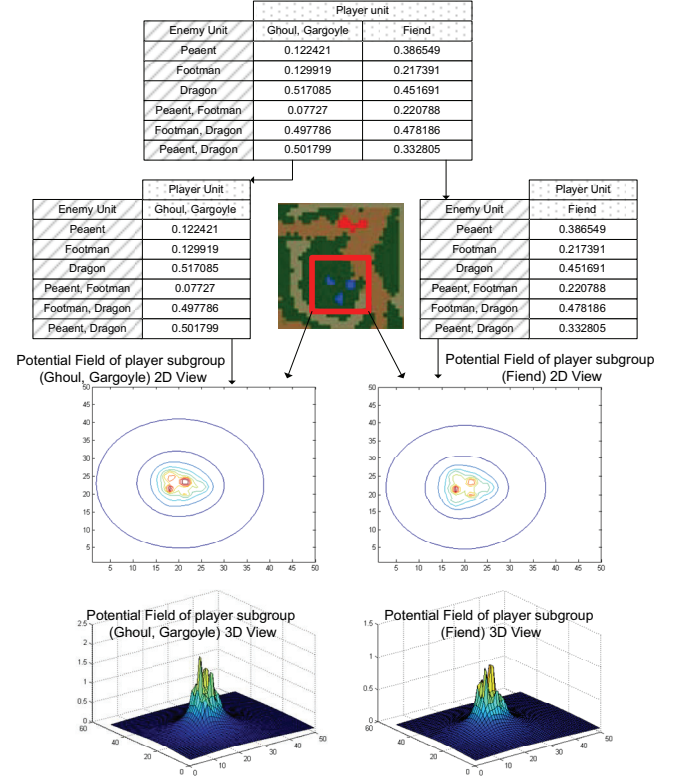


Fig.5. Overview of generating Potential Field by Fuzzy Integral value

$$U(x,y) = \sum_{i=1}^j (c) \int f(x) \circ \mu(X) \times d(P_i, P(x,y))^{-1} \quad (3)$$

We modified the attractive force of potential field, $U(x,y)$ as shown in (3) by applying the idea of opponent force from Johan [14][15]. Each value in the fuzzy integral table will be a point of interest, P_i . Each P_i will generate symmetric surrounding field with the highest attractive force, i.e., fuzzy integral value, $(c) \int f(x) \circ \mu(X)$, in the centre. We used the value that is learnt from real game data instead of expert knowledge. The force will be weakened when it moved away from the center, d where $d(P_i, P(x,y))^{-1} \leq 1$, is used to perform this task.

Fuzzy measure is able to handle the interaction between different units type. To extend this property to potential field, P_i will also consider the outer defense line, i.e., the interaction between different enemy subgroup as shown in the fuzzy integral table. The center of the interaction was set as the middle point of enemy subgroup. Fig. 6 is an example to illustrate our work. The fuzzy integral value of interaction between different enemy subgroup may be negative. Therefore, it changes the simple normal additive property of potential field to non-additive property, especial the sub additive.

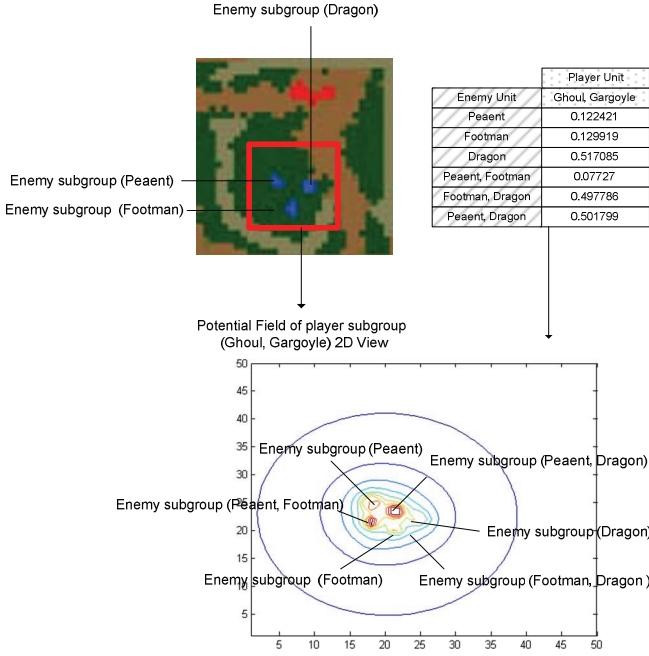


Fig.6. Example of generating Potential Field by Fuzzy Integral value for one subgroup of player army

D. Apply multi-agent Potential Field in Micro-Management

The advantage of applying potential field in micro management of RTS game is the result can be easily multiplied by complicate RTS terrain properties. In RTS game, some unit type can pass through the blocked area or gain extra attack bonus in some special area. All kind of these information could be stored in another two dimensional array as shown in Fig. 8, e.g., zero is set to the blocked area. Once the potential field has been computed by Part C, it can be multiplied by terrain properties array and the resultant potential field could be computed as shown in Fig. 9. The area with the highest attractive force will be the target of attack for certain player subgroup.

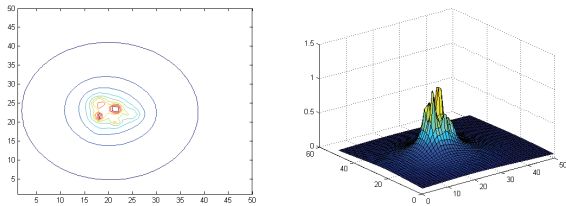


Fig.7. Potential Field by Fuzzy Integral value of one player subgroup

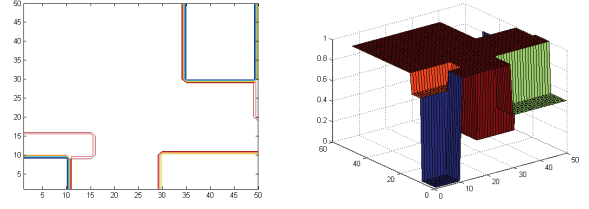


Fig.8. Terrain properties of one player subgroup

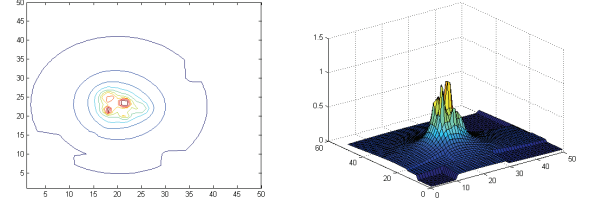


Fig.9. Resultant Potential Field

IV. EXPERIMENTAL RESULT

A. Data Collection

We selected Warcraft III expansion, The Frozen Throne (WIII: TFT) which is a well known and popular RTS game. It is regarded as the best RTS game on the market because of its' interesting, attractive and yet complicated game plays. The purpose of this experiment is to prove our methodology can provide a unit formation and target of attack planning. Hence, the result should be better than Warcraft III AI bot, i.e., the enemy unit scores should be lower.

In this research, 65 replay data are collected to train the fuzzy measure. The player race is Undead and the enemy race is Human. The enemy unit type is peasant, footman and dragon. 5 cases are randomly selected to extract the player and enemy unit combination for simulation.

B. Experimental Setup

For each selected case, player and enemy unit combination is extracted and passed to Matlab for computing the potential field. Then the result will be sent to Warcraft III for simulation.

In Warcraft III, player and enemy units are generated in an official competition field as shown in Fig. 10. Unit formation and the target of attack are set before the battle. After the battle, scores of player and enemy are accorded. For each selected case, 3 additional simulations are performed by using Warcraft III AI bot (Instance) as a comparison of our methodology.

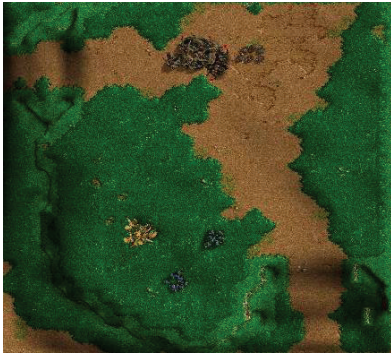


Fig.10. Simulation in Warcraft III

C. Result

As the player won all the selected cases, the scores of players in different simulation are the same. We cannot use it for comparison. We can only compare the scores of enemy. Better micro-management can avoid the enemy to obtain higher scores. Table I shows the enemy scores of using Warcraft III AI bot, while the Table II shows the enemy scores of using potential field and fuzzy integral. Potential field and fuzzy integral obtain a better result in 80% of simulation. The enemy score is lower than the Warcraft III AI bot. Fig. 11 shows the comparison of our methodology and average enemy score that obtained by Warcraft III AI bot. It shows an improvement in 4 selected cases.

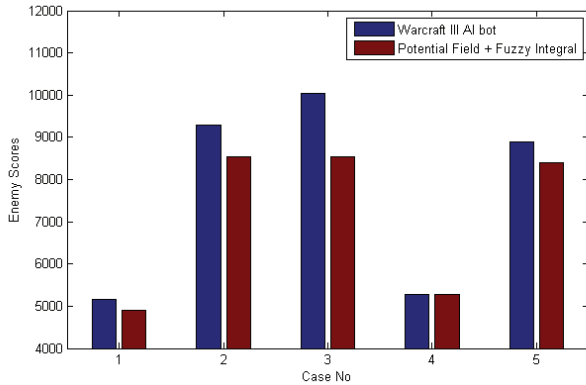


Fig.11. Comparison of our methodology and Warcraft III bot

TABLE I
ENEMY SCORE OF USING WARCRAFT III AI BOT

Case	1	2	3	4	5
Experiment 1	4970	9040	10285	5405	8780
Experiment 2	5350	9295	10160	5165	8950
Experiment 3	5150	9550	9695	5280	8965
Average	5156	9295	10046	5283	8898

TABLE II
ENEMY SCORE OF USING POTENTIAL FIELD AND FUZZY INTEGRAL

Case	1	2	3	4	5
P.F. + F.I.	4990	8530	8540	5285	8410

V. CONCLUSION

In this paper, we applied potential field, fuzzy measure and integral to perform a solution on micro management in RTS game. Therefore, the AI bot is able to divide the army

into subgroup and perform the unit formation planning. After that the AI bot is also able to consider the interaction among different enemy unit type and decide the target of attack for each player subgroup. Simulation on Warcraft III has been done to test our idea and it shows an improvement.

By integrating the potential field with fuzzy measure and integral, it provides a machine learning approach to obtain the constant scaling factor instead of expert suggestion. It also extends the non-additive property from fuzzy measure and integral to potential field.

Our research is very preliminary. There are still many research problems remain, such as updating and maintaining the fuzzy measure and considering different unit types in player subgroup. We believe that this approach can generate a reasonable solution for AI development in RTS game.

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