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Top-down Behavior Planning for Real-life Simulation

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ABSTRACT

This paper describes a top-down behavior planning framework in a simulation game from personality to real life action selection. The combined behavior creating system is formed by five levels of specification, which are personality definition, motivation extraction, emotion generation, decision making and action execution. Along with the data flowing process in our designed framework, NPC selects actions autonomously to adapt to the dynamic environment information resulting from active agents and human players. Furthermore, we illuminate applying Gaussian probabilistic distribution to realize character's behavior changeability like human performance. To elucidate the mechanism of the framework, we situated it in a restaurant simulation game.

Keywords: Real Life, Autonomous Agent, Behavior Planning, Personality, Motivation, Emotion, Gaussian Probabilistic Distribution

1. INTRODUCTION

Recently, simulation games which contain a mixture of skill, chance, and strategy to simulate an aspect of reality are quite popular. In the game or virtual reality, real life aspect is extending investigations to approximate human-like NPC performance. Categories of real life games or life simulation are mainly defined as virtual environments where autonomous agents exist and human players control one or more artificial lives. The virtual reality genres such as SimCity, Civilization, Roller Coaster Tycoon, and The Sims give a perfect explanation of 'real-life.'

However, human players sometimes feel that non-player character (NPC) behavior is represented in the same manner. NPC characteristics have not been represented observably and reasonably enough. Therefore, NPC personality is suggested to be integrated into games as high level specifications in the behavior planning process. Meanwhile, AI plays by several kinds of random algorithms which are not real game AI. The random action data with proper probability distribution are essential and popular in AI game production. To solve the problem that behavior should be reasonably changeable and uncertain, Gaussian probability distribution integrated in action parameters' re-estimation is proposed.

In simulations and games, we do not only need to know which action should be taken, but also to consider which time and position is adaptive for environment and reactive to interact with other agents. Finite-state Machine (FSM) remains popular for planning design. However, in order to complete the research about character's probability distribution, FSM is not enough. Instead of "once…, will…" mode, we propose an emotion based hierarchical FSM model in this paper to provide NPC character behavior with feeling attributes. Meanwhile, the behavior time and spatial variables

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are derived from both motivation and personality.

This paper is organized as follows. In section 2, related works on real life simulation are introduced. In section 3, real-life top-down behavior framework is designed in five levels. In section 4, the behavior framework is experimented on in a virtual restaurant environment. In section 5, a conclusion is offered and a comparison with other research is remarked upon.

2. RELATED WORKS

Intelligent game agents should be provided with capabilities such as perception, learning, memory and planning. In addition, human personality and expression of emotion is proposed for achieving human-like agent. Xiaoming Zhou [1] presented a probabilistic model based on Dynamic Decision Networks to assess user emotion expression from possible causes of emotional arousal. Pizzi, D. [2] describes a prototype in which character behavior is driven by a real-time search-based planning system, applying operators whose content is based on a specific inventory of feelings. Maic Masuch and Knut Hartman [3] structured perception-processing-behavior agent architecture in order to simulate autonomous agents with a rich, individual personality and emotional behavior.

Etienne de Sevin and Daniel Thalmann [4] propose a motivational model of action selection and a hierarchical classifier system, in which the behavior is selected according to the motivation. However, the author remarks that personality is not sufficiently considered in his research. As a real human planning method, behavior selection can identify different types of behavior such as attack and defend according to different personalities and emotions. In particular, behavior time and special factors estimation should also be considered.

In this paper, we research the problem of building real-life character behavior by choosing personality, extracting motivation, creating emotion, making decisions and executing actions. The autonomous agent behavior planning system is divided into these five parts from the top level to the bottom level in order to enhance the activity of real life simulation games. These human-like activities achieve playing the role by generating coherent autonomous behavior in a dynamic environment.

It's not only enough for NPC to make planning, but the action variables should also be taken into consideration with changeable values in order to program multiform actions in the game. Just like human behavior performance, the NPC behavior generating process is considered planning and acting. These two parts are represented differently in reality. For example, somebody decides to start an assignment at expected time *t*. However, he doesn't do it on time. After sampling, the start time is followed by Gaussian distribution around time t. Therefore, we proposed a planning-to-acting translation process using Gaussian probabilistic distribution to generate more reasonable and dynamic actions according to the planning result.

We experiment with a top-down behavior planning structure in a restaurant simulation game, "Crazy Waitress," so as to clarify how real life behavior is selected based on personality. In the game, NPC can express emotions and generate reasonable actions according to personality variables. Not only are the types of action considered, but the time and spatial factors are also taken into account. The performance in our experimental result is more dynamic and more reasonable than traditional randomly selecting actions.

3. REAL-LIFE BEHAVIOR FRAMEWORK

The main methodology to generate real life behavior is designed as the framework in Fig.1 with a "top-down" approach.

Just like human beings, NPCs should have distinguishable characteristics from each other which

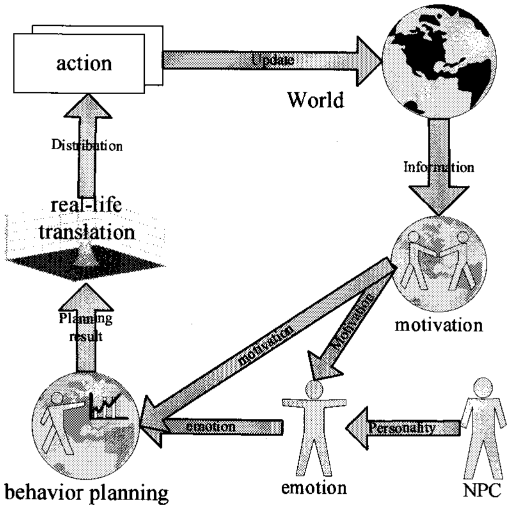


Fig.1. Real-life frameworks.

perform personality in video games. These characteristics provide the agent with an emotion during the motivation generating process in which motivational activities come from internal needs and external interactions. According to both the dynamic environment and the NPC agent's emotion, the behavior planning system is added in order to select more believable autonomous actions with more safety and satisfaction. The parameters of action can be considered in three parts which are when, where and how to implement. In real life simulation, the interface between planning and behavior is always represented differently. For example, when a date is arranged for two o'clock, someone will arrive earlier or later, not on time. After sampling in the real world, the arrival time distribution should be followed by the Gaussian distribution function. We follow this approach by representing these parameters with different values even for the same situation in the game so that the human players feel the uncertainty of the character behavior is reasonable and the game is more interesting.

Real-life translation is used to allow NPC behavior to be like that of human beings with uncertain parameter values. The main algorithm of this process is implemented by the Gaussian distribution function with the expected value and variance generated according to different NPC emotions and environmental information. Finally, the generated behavior will continually update the virtual world.

3.1 Personality level

Personality is that pattern of characteristic thoughts, feelings, and behaviors that distinguishes one person from another and that persists over time and situation. The behavior model begins with a static personality which imparts NPC characteristics to real life actions. Based on the "Big-Five" trait taxonomy [5], personality is represented as a vector which consists of five factors. These five categories are described as:

Extroversion: This attribute includes characteristics such as energy, positive emotions, surgency, and the tendency to seek stimulation and the company of others. This factor influences character behavior both positively and negatively.

Agreeableness: This trait includes attributes such as compassionate and cooperative rather than suspicious and antagonistic towards others. The affection to behavior manner is described as the relationship with others.

Conscientiousness: Common features of this dimension include self-discipline, acting dutifully, and aiming for achievement and planned rather than spontaneous behavior. The dynamics of emotional arousal can be adequately controlled by this factor.

Neuroticism: This factor gives a tendency to experience unpleasant emotions easily, such as anger, anxiety, depression, or vulnerability and is sometimes referred to as emotional instability. The behavior is affected towards hostile characters and interactive action is influenced with sympathy.

Openness: This trait features appreciation for art, emotion, adventure, unusual ideas, imagination, curiosity, and variety of experiences. The behavior is affected towards unknown characters or objects. [6]

We integrate five basic factors into the NPC personality definition by equation (1).

$\vec{P}=\{p_e, p_a, p_c, p_n, p_o\}$ represents personality vector. c_i is the personality generating compromise coefficient, and $c_i \in (0,1)$. v_i is the personality vector range.

$$\vec{P}=\begin{pmatrix} c_1 \\ c_2 \\ \cdots \\ c_5 \end{pmatrix} \times (\max(v_1), \quad \max(v_2), \quad \dots \quad , \max(v_5)) + \begin{pmatrix} 1-c_1 \\ 1-c_2 \\ \cdots \\ 1-c_5 \end{pmatrix} \times (\min(v_1), \quad \min(v_2), \quad \dots \quad , \min(v_5)) \tag{1}$$

3.2 Motivation level

Motivated automata allow the agent to choose the most appropriate emotion and action according to its perception of the environment and personal condition.

There are many kinds of motivation to be considered in the real life simulation like hunger, thirst, sleepiness, danger avoidance and so forth. We define each motivation value in equation (2).

$$M(t)=\begin{cases} \int_{t_0}^{t} f(t)dt + M(t_0) + \sum_{i \in I} \int_0^t I_i(t)\delta(t-t_i)dt & M(t)>0 \\ 0 & M(t)\le 0 \end{cases} \tag{2}$$

In daily life, there are two kinds of motivation forms: cumulative and sudden situations. In equation (2) we use a integral function $\int_{t_0}^{t} f(t)dt + M(t_0)$ to simulate cumulative motivations like hunger and thirst, where $f(t)$ is the rate of motivation increment, and the integral constant $M(t_0)$ is the base value of the motivation happening at time t_0. Impulse function $\int I_i(t)\delta(t-t_i)$ is suggested to simulate sudden events like being beaten by others. Delta function $\delta(t)$ can be loosely thought of as a function on the real line which is zero everywhere except at the origin, where it is infinite (see Fig.2).

The mathematical definition is given in function (3), which is also constrained to satisfy the identity (4).

$$\delta(t)=\begin{cases} \infty & t=0 \\ 0 & t\neq 0 \end{cases} \tag{3}$$

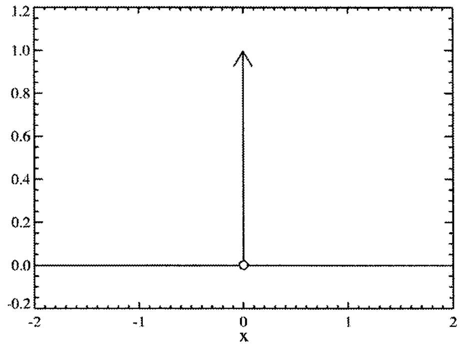


Fig. 2. Impulse function.

$$\int_{-\infty}^{\infty} \delta(t)dt = 1 \tag{4}$$

The following property of delta function can be used to formulize a sudden event. For any continuous function $I(t)$,

$$\int_{-\infty}^{\infty} I(t)\delta(t-t_0)dt = I(t_0) \tag{5}$$

According to equations (3), (4) and (5), the time of the sudden event is defined as t_0 and feed amplitude estimation to the motivation value.

The sudden events happen at unpredictable times so that autonomous agent should detect these real time signals which affect the emotion value. Getting the sum of the affection result and the cumulative motivation function, equation (2) can be used as the real time motivation evaluation function. The motivation value should be positive. If the generated value is negative, zero will be returned.

3.3 Emotion level

After NPC personality vector is defined and motivation is estimated, emotions will be selected in dynamic and temporal states. This selection process synthesizes personality elements as internal variables and environmental information as external variables. Fig. 3 shows the emotion generating process. According to different motivation types, the relevant personality parameter is abstracted to help NPC generate different emotions from the emotion database.

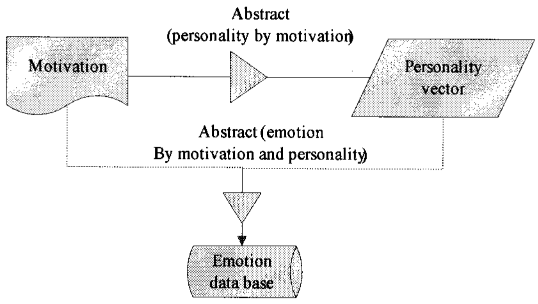


Fig. 3. Emotion generation.

Emotion changes according to both motivation evaluation and NPC personality. We should integrate the two factors into the process of emotion generation. Meanwhile, the same personality parameters can affect different emotion modes based on motivation classification by the threshold of relative personality parameter values.

We take neuroticism as a personality factor and food need as motivation, for instance. Hunger degree is defined in equation (6):

$$H(t) = \int_0^t h(t)dt = \int_0^t 0.001e^{0.001t}dt \quad (6)$$

Emotions are generated from the neuroticism factor with emotions such as panic and relaxed. The threshold T_n from happiness to afflicted emotion is estimated by neuroticism as one of the personality elements, which reflects emotions interacting with hunger motivation. The threshold value varies directly with the relevant personality value as defined in equation (7):

$$T_n \propto \lambda p_n \quad (7)$$

If the current hunger degree is beneath the threshold T_n, the relaxed emotion will be generated, and if above the threshold, the panic emotion will be generated. (see Fig.4) In other words, if the neuroticism value is high, the agent should be easily angered in an unsatisfying situation.

Emotion classification is complex for the real human. By extending Ekman's study [7], we propose 5 pairs of basic emotions: anger and patience; fear and boldness; sadness and excitement; happiness and affliction; disgust and delight.

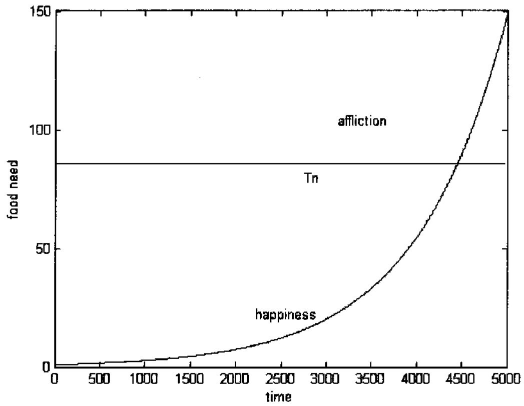


Fig. 4. Emotion generating.

3.4 Planning level

The work of the NPC planning step, also called 'thinking,' helps to generate the action parameters, including where, when and how, in order to adapt to the environment. In real life, humans have many motivations to satisfy at the same time and, finally, often compromise behaviors that are chosen because they better maintain the homeostasis of the need, decrease the risk of oscillations, and increase the flexibility of the autonomous action selection capability.

However, the traditional motivation based planning makes the behavior so common that personality can not be represented. Also, agent autonomy is not sufficient and treatment of sudden events are not efficient enough just by the support from motivation. To solve this problem, emotion expression is proposed to increase the flexibility and sociability of the planning model.

From external motivation and internal personality, emotion is generated to effect behavior planning as shown in Fig.5. The autonomous agent has rapid reactions in the dynamic, so the motivation value is updated continuously. When the motivation is high, the relevant emotional state will be selected by relevant personality parameters as the

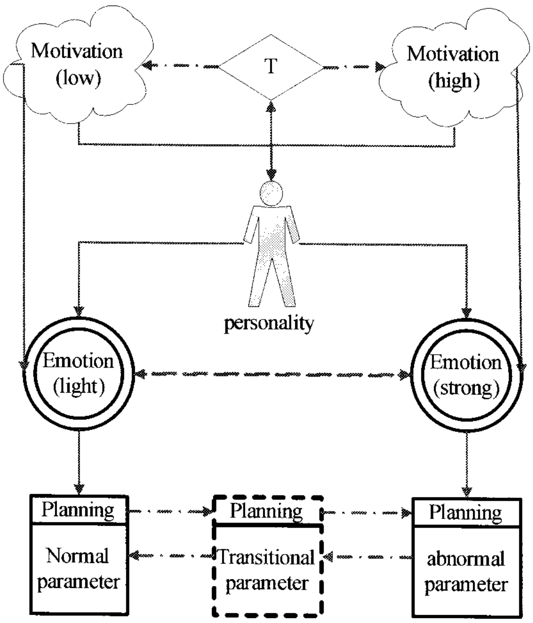


Fig. 5. Relationship of motivation, emotion and planning.

threshold intercepting the motivation value. In real life, the character with different emotions will make different plans, or the same plan in a different manner. If there is a transition among different emotions, intermediate action may take place. For instance, the agent's emotion is from patient to angry. Firstly, the agent makes positive planning while he is patient. When he becomes angry, maybe an impulsive action will occur to show he is angry. Then the agent makes the planning with negative parameters when he's angry.

Commonly, the factors of the action are decided with focus on when, where and how to represent them. Therefore, the expected value of the action parameters needs to be decided during the thinking or planning process. Also, we suggest using both the relevant personality factor and the motivation value to simulate the expected value estimation. The expected value, also called mean value, is expressed:

$$E(\vec{r}) = \frac{|M-T|}{M} \times \max(\vec{r}) + (1 - \frac{|M-T|}{M}) \times \min(\vec{r}) \qquad (8)$$

where vector $\vec{r}$ is composed of the action parameter; $\vec{v}$ is the action vector value range; M is the motivation degree and T is the threshold defined by relevant personality factors.

3.5 Action level

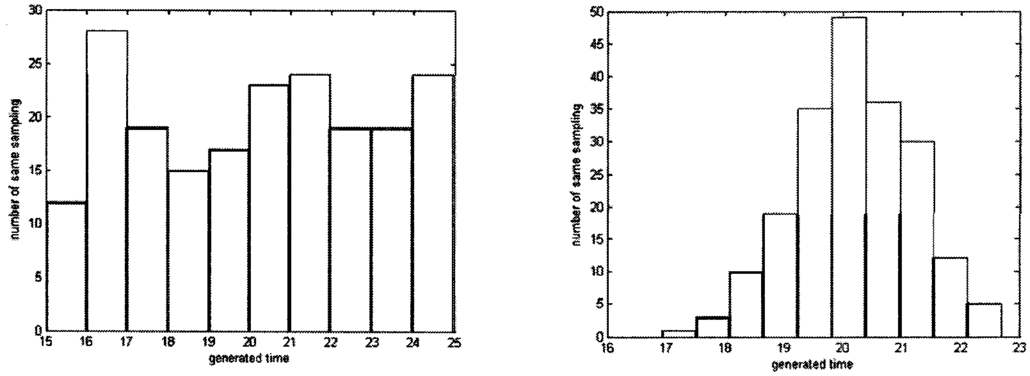
Action without personality or emotion is always performed by FSM or Probabilistic State Machine (PSM). In this way, one of the behavior attributes, 'how,' can be implemented. Furthermore, time and special factors are not sufficiently resolved. Although the action parameter vector $\vec{r}$ containing time and spatial factors solves this problem, the NPC behavior occurs during the fixed states that satisfy the expected value. Human players feel that the character's performance is less changeable which makes the game a little boring.

Thanks to probability distribution, game programmers can make action randomly changeable. Traditionally, the uniform probability mode is used to generate random values in a certain range (see Fig.6 (a)). The diagram shows that uniform samplings have no center. In the simulation result, behavior parameter selection performance is even. But human action should represent around the expected value estimated from the planning process.

Gaussian distribution, also called normal distribution, is proverbially authentic for stochastic human and nature actions. The helpful property of Gaussian random variable is that there is a center of expected value and variance can be controlled by a variance factor (see Fig.5 (b)). Instead of uniform distribution, we propose to apply Gaussian random variable for real life behavior generating.

If the probability density function (PDF) of X follows formula (9), it can be determined that X is a Gaussian random variable, $N(\mu, \sigma^2)$ in shorthand [8].

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} \qquad (9)$$



(a) Uniform (b) Normal

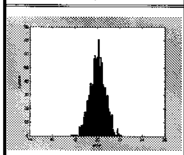
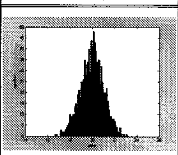
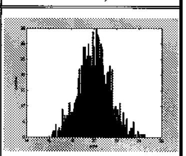
Fig. 6. Behavior sampling comparison.

In the formula (9), μ is regarded as the mean or expected value of a certain behavior parameter; and σ^2 is the variance determined by NPC relevant personality parameter values.

Expected value is an important factor for the NPC to estimate the when the action will occur. Furthermore, to achieve real-life simulation, another factor about character uncertainty should be taken into consideration by the means of variance σ^2. Table 1 gives a sampling of Gaussian random variables according to different variance values and mean values equal to 20. By testing 1000 samples, it shows that an occurance takes place after around 20 seconds.

Variance σ^2 is an important variable for describing NPC activity. For a larger value, the character performs more randomly around the expected value and the NPC actions are more optional. Therefore, it's not better to enlarge the variance value as much as possible. If not, the NPC will not be represented clearly. Therefore, a personality-dependent degree is proposed for character

Table 1. Gaussian random sampling

$N(20,0.25)$	$N(20,1)$	$N(20,2)$
		

design. This degree determines the variance value σ^2 for behavior Gaussian distribution.

Therefore, characteristic actions can be generated by estimating expected values and determining variance. The game or the real-life simulation will be less boring because of the Gaussian random function.

4. EXPERIMENT

To elucidate the mechanism of the real-life behavior planning framework, we examine the problem of building character personality using Gaussian distribution in a restaurant simulation game, 'Crazy Waitress'.

This game is implemented using C++.NET as the main developing environment and game engine G-Blender as the programming tool.

4.1 Design and implementation

As the aim creating autonomous character with interactive and characteristic behavior, the top-down behavior planning structure is implemented in the real life simulation game (see Fig. 9). The game environment is a restaurant where the waitress is controlled by a human player and the guests are non-player characters.

In this project we examine the problem of building real life behavior starting from dynamic environment information and personality vector. Then reasonable emotion and planning is selected. After sampling from normal distribution, the action parameter is created. Fig.7 describes the FSM for NPC as a guest. Traditional FSM [9] is limited to realizing personality and controlling emotion. So the hierarchical FSM is used to extend capability to personality and emotion level. Fig.8 gives an example of the emotion shifting process as a sub-FSM.

In different situations, the NPC's external and internal motivations are different. The motivations presented in our simulation are food need, drink need, reply need and toilet need.

Table 2 gives an instance for planning data flow starting from the emotions of food need and reply need. During the waiting period, the degree of food-need is increasing and the neurotic personality is motivated. The emotion can be selected

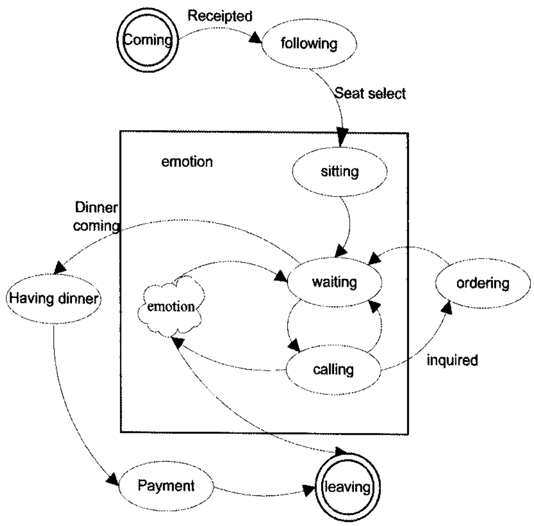


Fig. 7. Guest FSM design.

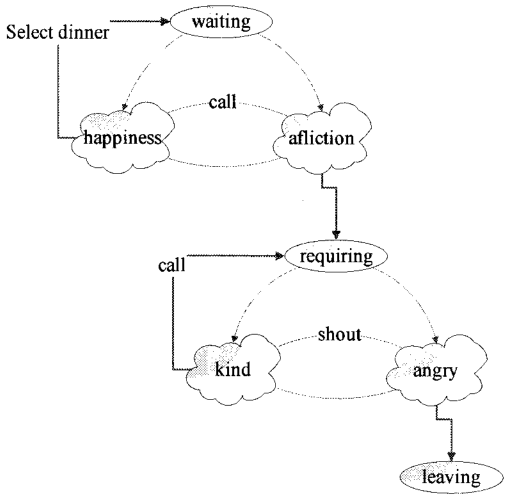


Fig. 8. Guest emotion shifting process.

between happiness and affliction effected by the neurotic personality. The emotion will shift when the motivation value of food need is across the threshold induced by the neuroticism degree. If the emotion of affliction is generated, the action of calling will be selected. According to Table 2, emotion based FSM is designed in Fig. 8.

The other two factors of action, time and position, are derived from function 8. Take the calling, for example, the hungrier, the more frequently the calling action occurs. This process can be expressed as:

$$E(r.t) = \frac{|M_h - T_n|}{M_h} \times \max(r.t) + \left(1 - \frac{|M_h - T_n|}{M_h}\right) \times \min(r.t) \quad (10)$$

The last step is to make some 'noise' for behavior's changeability. Gaussian probability is used for NPC to execute creative dynamic behavior around the expected value given from the Gaussian dis-

Table 2. Planning data flow

state	motivation	personality	emotion	planning
waiting	Food need	neuroticism	affliction	Call
			happiness	Select dinner
requiring	Reply need	agreeableness	angry	Shout or knock
			patient	Call

tribution, formula 9.

4.2 Simulation result

The restaurant simulation game, 'Crazy Waitress,' is presented in Fig.9. The simulation game is a multi-agent serving system in which NPCs act synchronously. They should follow such action sequence as coming, following, waiting, calling, eating and leaving. The human player should serve these actions with the parallel behaviors: receiving, leading, inquiring and dinner serving. It's a complex system for making autonomous planning with different personalities.

The coherent behavior decision making results are shown in Fig.10. The red and blue curves represent hunger and anger motivation respectively. The horizontal line is the threshold determined

(a) A screen shot of experimental game

10000.00					
1	state	motivation	personality	motivation	planning
2	state	motivation	personality	motivation	planning
	requring	reply need	agreeableness	patient	call
3	state	motivation	personality	motivation	planning
4	state	motivation	personality	motivation	planning
5	state	motivation	personality	motivation	planning
	requring	reply need	agreeableness	angry	knock
6	state	motivation	personality	motivation	planning
7	state	motivation	personality	motivation	planning
8	state	motivation	personality	motivation	planning
	waiting	food need	neuroticism	happiness	select
9	state	motivation	personality	motivation	planning
10	state	motivation	personality	motivation	planning

(b) Status information of the shot (a)

Fig. 9. Simulation environment.

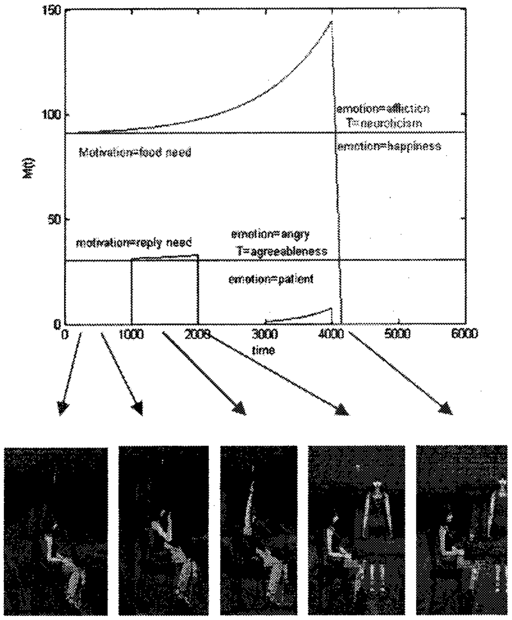


Fig. 10. simulation result.

from personality neuroticism in red and agreeableness in blue. After intercepting the motivation value by the relevant threshold, the emotion is generated. Finally, according to both motivation and emotion, the real life behavior planning is generated.

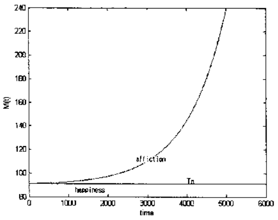
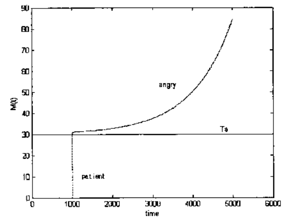
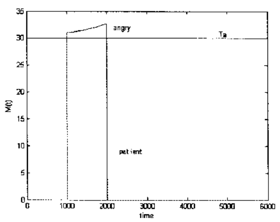
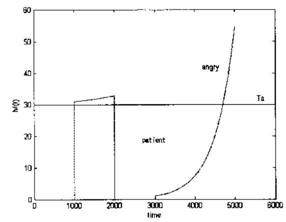
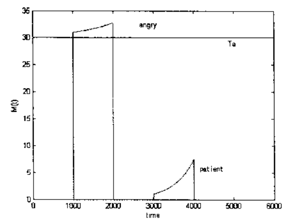
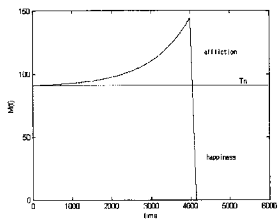
We define a character's "big five" personality vector as {0.5, 0.3, 0.8, 0.9, 0.4}. Table 3 gives an illustration about the emotion generating process. Firstly, motivation is caused by character state. The motivation value is calculated by a cumulative function, derived from equation (2). Then selected by threshold which calculates from personality value, different emotions will be generated.

According to the planning and action factors generation method in Fig.8 and equation (10), the behavior is created. Based on Gaussian distribution, the final step of real life simulation is completed.

4.3 Discussion

VRlab, led by Pro.Thalmann, researches real time simulation for the virtual world. They make

Table 3. Emotion generating simulation

<table>
<tr><th>state</th><th>motivation</th><th>personality</th><th>state</th><th>motivation</th><th>personality</th></tr>
<tr><td>waiting
(t=0)</td><td>M=food need
$M(t)=\int_0^t 0.001e^{0.001t}dt+\int_0^t 90\delta(t)dt$

</td><td>Neuroticism
$T_n=100P_n$
$=90$</td><td>not inquired after calling
(t=1000)</td><td>M=reply need
$M(t)=\int_{1000}^t 0.001e^{0.001(t-1000)}dt+$
$\int_0^t 30\delta(t-1000)dt$

</td><td>Agreeableness
$T_a=100P_a$
$=30$</td></tr>
<tr><td>Inquire
(t=2000)</td><td>M=reply need
$M(t)=M(2000)+$
$\int_0^t -M(2000)\delta(t-2000)dt$

</td><td>Agreeableness
$T_a=100P_a$
$=30$</td><td>Not served
(t=3000)</td><td>M=reply need
$M(t)=\int_{3000}^t 0.002e^{0.002t}dt$

</td><td>Agreeableness
$T_a=100P_a$
$=30$</td></tr>
<tr><td>Served
(t=4000)</td><td>M=reply need
$M(t)=M(4000)+$
$\int_0^t -M(4000)\delta(t-4000)dt$

</td><td>Agreeableness
$T_a=100P_a$
$=30$</td><td>Eating
(t=4001)</td><td>M=food need
$M(t)=\int_{4000}^t (-1)dt+M(4000)$

</td><td>Neuroticism
$T_n=100P_n$
$=90$</td></tr>
</table>

an algorithm to select motivation due to motivation value. Because of similar motivation value situations, the autonomous planning is difficult to select suitably.

Table 4 gives a mathematical comparison between the VRlab's research and our work. The defined threshold T_1 and T_2 of VRlab's algorithm is used to determine motivation equation in different situations.

Our method generates motivation following the character's current state, personality and emotion factors so that agent autonomy is sufficient and can deal with sudden evens. Because the motivation threshold is determined by personality, both emotion and behavior parameter values can be selected. The emotion expression is proposed to increase the flexibility and sociability of the planning model.

5. CONCLUSIONS

In this paper, we proposed a top-down real life simulation framework. The behavior planning is generated as a sequence of personality level, moti-

Table. 4 VRlab & RISE group

	VRlab	RISE group
Motivation	$\begin{cases} M = T_1 e^{(i-T_1)^2} & i < T_1 \\ M = i & T_1 \le i \le T_2 \\ M = \frac{i}{(1-i)^2} & i > T_2 \end{cases}$	$M(t) = \int_{t_0}^{t} f(t)dt + M(t_0) + \sum_{i \in I} \int_0^t I_i(t)\delta(t-t_i)dt$ $E(\vec{r}) = \frac{\lvert M-T \rvert}{M} \times \max(\vec{r}) + (1 - \frac{\lvert M-T \rvert}{M}) \times \min(\vec{r})$
Variables	T_1: threshold of comfort and tolerance zone. T_2: threshold of tolerance and danger zone. i : internal variable.	$f(t)$: internal increment rate $I_i(t)\sigma(t-t_i)$: feed from sudden event. T: Personality threshold of light and strong emotion r: vector of action factors.
Result	Motivation is generated	Motivation, emotion, action is generated

vation level, emotion level, planning level and real life action level. The proposed algorithms could make NPC behavior performance more lifelike in the virtual world and simulation game.

Our model increases the complexity of virtual human behavior planning by adding personality and emotion. Emotions enhance the autonomy and individuality of NPC with a certain personality. This allows NPC to make different decision in uncertain situations in order to embody more complex and realistic virtual humans.

This framework can not only be applied to the restaurant simulation, but other virtual reality games, like Sims, can also apply this planning system.

In the future, we will enhance this real life behavior planning framework with a parallel mechanism and implement it into the game AI engine developed by the RISE group.

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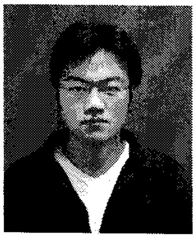

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