Computational model of implicit interaction for entertainment

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Received 21 May 2014, www.cmnt.lv

Abstract

Implicit interaction between human and computer is worthy of being researched, especially in the entertainment application. The reason is that in order to be more natural, computers need to interact and collaborate with persons actively. For this purpose, a computational model of implicit interaction is proposed and applied to a computer for entertainment. Firstly, emotional Hidden Markov Model (eHMM) as a part of the computational model of implicit interaction is researched. Then, three parts of ACT-R cognitive architecture are integrated into it to apply for entertainment. Finally, some experiments are carried out with styles of game process recording. Results indicate that the proposed model is helpful to make computers more active and adaptive to persons by adjusting entertainment process, which illustrates a good prospect of application.

Keywords: implicit interaction, ACT-R, affective computing, entertainment

1 Introduction

In order to make the participants more focus on interactive content without interaction devices, human-computer interaction (HCI) need to be expanded from the traditional interactive style, explicit HCI (EHCI), to the ubiquitous one, implicit HCI (IHCI). This new interactive style can reduce the user's cognitive burden. So research on its theories and technologies becomes more and more important.

As a frontier of HCI area, IHCI has draw lots of attention from many research organizations [1]. Nicole Kaiyan in Swinburne University of Technology in Australia proposed the concept of IHCI in 1996, but did not research deeply [2]. Gradually, from 2005, universities and institutes in many countries, such as USA, Germany, China, Australia, and so on, studied on IHCI deeper and deeper. Albrecht Schmidt in the University of Karlsruhe in Germany worked on IHCI theories earlier. He regarded perception and interpretation as the key point of IHCI, considered that context information is extremely important for the interactive process, and modelling the interaction based on extensible markup language (XML) [3]. With computer vision technologies, Andrew Wilson and Nuria Oliver in Microsoft Research of the USA developed four systems to realize IHCI process [4]. In 2007, adaptive vision system was developed by Tao Linmi in Tsinghua University in China, which can detect and understand users' behavior through implicit interactive style [5]. At the same time, Tian Feng in the Institute of Software, Chinese Academy of Sciences, researched on the implicit interaction features from the aspect of post-WIMP [6]. The development of IHCI is sorted as shown in Figure 1.

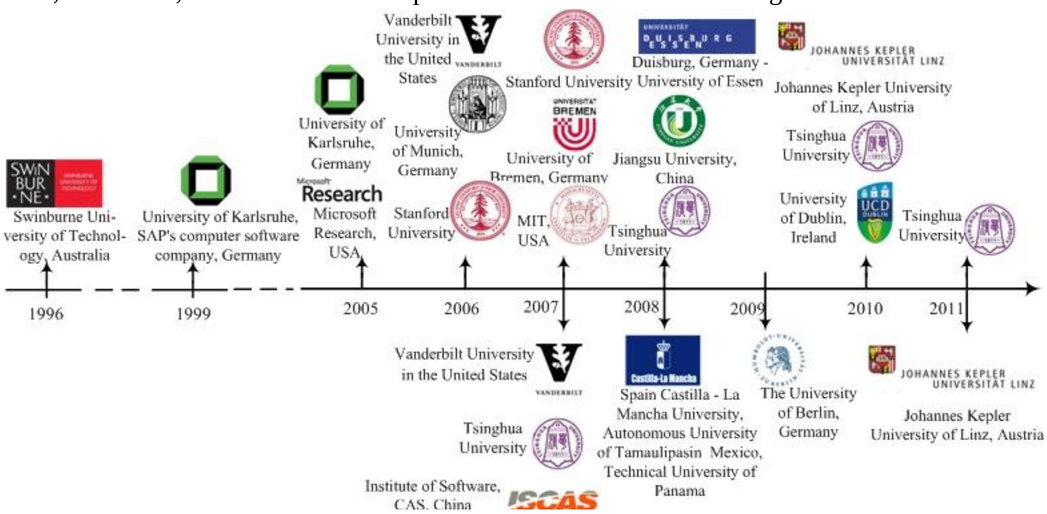

FIGURE 1 Developing process of IHCI

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Entertainments also need the IHCI. With users' context information, such as behavior, emotional states, physiological status, location, and et al, the amusement quality can be improved by context perception and interpretation.

The rest of the paper is organized as follows. In Section 2, a brief literature review is provided on affection modeling and cognitive-affective interactions in entertainment. Section 3 presents a computational model of implicit interaction for entertainment based on adaptive control of thought-rational (ACT-R) cognitive architecture model. Section 4 discusses realizations of a card and a chess playing processes with the model above, analyzes the real experiment results and compare with the processes without the model. Section 5 provides the conclusions and the future work.

2 Related Works

2.1 AFFECTION MODELING

Currently, there are lots of affective models proposed by international and national research institutes. For instance, the OCC affective model is the first one for computing and used more widely [26]. By analyzing various affections connecting with events in the physical world and interactions with another subject, the relations based on rules can be got. Moreover, the theory of OCC affective model also suggests that the reason why affection generates includes event result, agent's action, and the feel to object.

Kismet affective model is used in a robot named Kismet, which is designed by C Breazeal in MIT [27]. It combines environment, inner stimuli with action and includes four parts. They are stimuli, evaluation, arousing and expression. Based on this model, the robot acts differently by considering outside stimuli and inner demand.

Based on the emotional psychology, Euclidean space affection model is proposed by regarding basic emotion as base vector [7]. In the affection space, the author discusses transition between one emotion and the other. But this model is a discrete one. Teng models the affective changing process by using Markov chain and hidden Markov model in probability space [8]. Affective transition can be described well whatever stimuli happen or not.

Moreover, Salt & Pepper model proposed by Botelho [9], affection model of a humanoid robot WE-4R researched in Waseda University [10], and some ones based on random event [11] and self-organization theory [12] are also discussed by researchers with different views.

2.2 COGNITIVE-AFFECTIVE INTERACTIONS IN ENTERTAINMENT

With the development of cognitive and affective computing, related theories and technologies apply in the human computer interactions. There are two ways bringing cognition and affection into entertainment application. One is analyzing the human being's affection [13-15], the other is integrating cognitive-affective model into the application [16-18]. In search of suitable methods for measuring the affective state of video-game players, Jonathan Sykes investigates the hypothesis that the player's state of arousal will correspond with the pressure used to depress buttons on a gamepad. A video game was created that would detect the force of each button press during play. It was found that as the difficulty level of the game increased, players would hit the gamepad buttons significantly harder [13]. Abdullah Al Mahmud propose to incorporate psycho-physiological measurements as a part of the gaming experience, and to integrate a desktop game within its real surrounding (i.e., the entire room) in order to promote more physical activity [14].

Moreover, in AI (Artificial Intelligence) game, authentic behaviours of NPC (Non-Player Character) are great challenges to NPC intelligence. Emotions help to enhance the quality and intelligence of behaviours, contribute to increase entertainment value of game. Zhou and Yu describe several common emotional behaviours of NPC, construct a simple emotion-behaviour model for emotion transition, and simulate in their developing project [15]. The quality and intelligence of NPC's behaviours are improved by the emotion to increase the game entertaining. And Munoz K is focused on a qualitative and quantitative approach to recognizing the learner's achievement emotions. Learners' emotions are inferred from two sources: from observable behaviours and from answers to questions in a game dialogue. The analysis and design involved in the creation of this affective student model are the central focus here. PlayPhysics, an emotional games learning environment, is being implemented for teaching Physics at undergraduate level. When our results are finalized our affective student model will be incorporated into PlayPhysics. To ensure accuracy of the recognition method, a preliminary prototyping study has been conducted. The results from this prototyping phase are presented and discussed [16].

Yannakakis provides taxonomy of PCG algorithms and introduces a framework for PCG driven by computational models of user experience. Personalization of user experience via affective and cognitive modelling, coupled with real-time adjustment of the content according to user needs and preferences are important steps toward effective and meaningful PCG. Games, Web 2.0, interface, and software design are among the most popular applications of automated content generation.

Wang proposed a method to investigate the effects of Cognitive Affective Interaction (CAI) strategy on novices' creative performance in game design. The CAI strategies, including the visualization and the discrepancy strategies, were administrated and served as the experimental treatment [18].

3 Computational Model Generation

3.1 OVERVIEW

IHCI required equipment, hardware and software, to provide active services. Moreover, the users are no longer focused on the task process, and only receive services without notice. So building a computable model of human cognitive behaviours is necessary in order to organize knowledge and produce intelligent behaviours in ICHI. ACT-R (Adaptive Control of Thought-Rational) cognitive architecture, proposed by the American psychologist Anderson in 1976, is widely used to simulate different aspects of the human being's cognition behaviours, such as perception and attention, learning and memory, problem solving and decision making, language processing, intelligent agents, intelligent tutoring systems, and human-computer interaction. Because its characteristics fit needs of the implicit interaction precisely, we can build a computable model of human cognitive behaviours, which is based on ACT-R cognitive architecture for different applications, to realize implicit human-computer interaction and improve interactive quality effectively.

This paper focuses on IHCI in entertainments. By designing ACT-R production rules and bringing in emotional factors, computable model of IHCI for entertainment is established as shown in Figure 2.

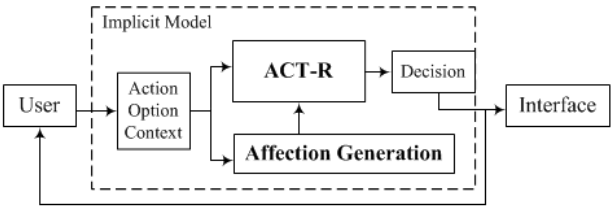


FIGURE 2 Computational model of implicit interaction for entertainment

The devices acquire inputs by users in entertainment, such as behaviours, selections, and situations. Under the influence of emotions, judge user's implicit interaction information after pattern matching and reasoning with ACT-R. And then adjust the interaction process adaptively to improve interaction quality. It is obviously seen that the realization of the model contains two main parts: 1) the generation of machine emotion; 2) the design and implementation of implicit interaction computable model based on ACT-R cognitive architecture in entertainment.

3.2 AGENT AFFECTION

To simulate the emotion generating and changing of human being, an affective model is necessary. As stated above, given the computable feature, we select one named eHMM, for emotional stimuli transferring process proposed in [15] as an emotional engine.

Based on a probability space, Teng regarded an emotional stimuli transferring process as a random one which could be described using hidden Markov model [15]. In other words, a quintuple form determines the model, where N is the number of emotional dimension; M is the number of stimuli type; is an initial emotional state vector; is a state transferring probability matrix, which is calculated by:

$$\hat{A}=\{\hat{a}_{ij}\}_{N\times M}=\begin{bmatrix} \frac{\hat{\theta}\hat{\pi}_1^*-(N-1)}{\hat{\theta}\hat{\pi}_1^*} & \frac{1}{\hat{\theta}\hat{\pi}_1^*} & \cdots & \frac{1}{\hat{\theta}\hat{\pi}_1^*} \\ \frac{1}{\hat{\theta}\hat{\pi}_2^*} & \frac{\hat{\theta}\hat{\pi}_1^*-(N-1)}{\hat{\theta}\hat{\pi}_1^*} & \cdots & \frac{1}{\hat{\theta}\hat{\pi}_2^*} \\ \vdots & \vdots & \cdots & \\ \frac{1}{\hat{\theta}\hat{\pi}_N^*} & \frac{1}{\hat{\theta}\hat{\pi}_N^*} & \cdots & \frac{\hat{\theta}\hat{\pi}_N^*-(N-1)}{\hat{\theta}\hat{\pi}_N^*} \end{bmatrix},(1)$$

where, $\hat{\theta}$ is a parameter that will be discussed later. $\hat{\pi}^*=[\hat{\pi}_1^*,\hat{\pi}_2^*,\cdots,\hat{\pi}_N^*$ is a limiting probability. $\hat{B}_{N\times M}$ is an observation matrix, supposing that $M=N$ in this paper, it could be deduced that:

$$\hat{B}=\begin{bmatrix}\hat{B}_1\\ \hat{B}_2\\ \vdots\\ \hat{B}_N\end{bmatrix}=\begin{bmatrix} a & b & \cdots & b\\ b & a & \cdots & b\\ \vdots & \vdots & \cdots & \vdots\\ b & b & \cdots & a\end{bmatrix}, \qquad (2)$$

Where $\begin{cases} a=\dfrac{r}{N-1+r} \\ b=\dfrac{1}{N-1+r}\end{cases}$, $r>1$, r is a parameter that will also be discussed later.

The user's current behaviour reflects the current level during entertainment. If the current user's behaviour indicates that the entertainment level is higher, the computer treats the entertainment process with caution, and is of positive machine emotion. Otherwise, it indicates that user's entertainment level is not high. The computer generates negative emotions. Based on the eHMM, for emotional stimuli transferring process, emotional value can be got by positive and negative stimulus, which shows the user's current entertainment level.

3.3 MODEL CONSTRUCTION

For the implicit interaction in entertainment applications, three parts of ACT-R cognitive architecture, basic modules, buffering, and pattern matching, are designed as shown in Figure 3. The first part, basic module, has two types of sub-modules. They are a motion perceiving submodule, which is responsible for interacting with the outside world, and a memory sub-module. The input information of this module is user's mouse or keyboard actions and selecting tendency; and the output is visual and auditory information, including reminders and evaluation for user's entertainment process and feedbacks after entertaining. The second part, buffer, is an interface for generation rules interacting with other basic module. And the contents in buffer identify the current status of ACT-R.

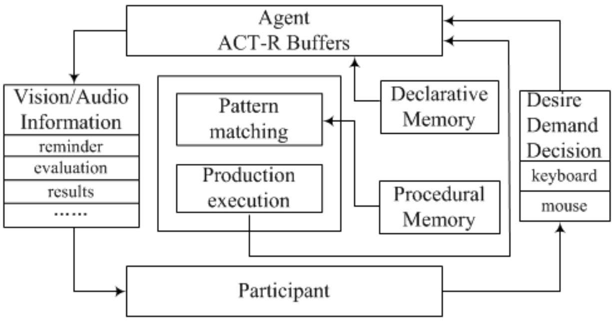


FIGURE 3 Three parts of ACT-R cognitive architecture

The third part, pattern matching, is implemented based on fuzzy inference. Suppose language variables are: the total number of errors X_1, the maximum number of consecutive errors X_2, the average time for thinking X_3, the user's historical entertainment level Y. And the corresponding universes are

$$U_{X1}=U_{X2}=\{x_i|0\le x_i\le Sup, x_i\in\aleph\},$$
$$U_{X3}=\{x_3|0<x_3\le Sec, x_3\in\Re\},$$
$$U_Y=\{y|0<y\le Gra, y\in\Re\},$$

where Sup, Sec and Gra are the maximum number of errors, the maximum time for thinking and the highest user's entertainment level. Their values are determined according to different applications. Linguistic variables are $T(X_1)=T(X_2)=T(X_3)=few+middle+many$ and $T(Y)=low+middle+high$. So the fuzzy sets of the total number of errors X_1 and the maximum number of consecutive errors X_2 are determined as below:

$$F_{Xi}^{few}=[few]=\sum\frac{\mu_{Xi-few}(x_j^i)}{x_j^i}=\sum_{j=0}^{Sup}\frac{\left[1-\frac{1}{Sup}j\right]}{x_j^i}, \quad (3)$$

$$F_{Xi}^{mid}=[middle]=\sum\frac{\mu_{Xi-mid}(x_j^i)}{x_j^i}=$$
$$\sum_{j=0}^{Sup/2}\frac{\left[\frac{j}{Sup/2}\right]}{x_j^i}+\sum_{j=Sup/2}^{Sup}\frac{\left[2-\frac{j}{Sup/2}\right]}{x_j^i}, \quad (4)$$

$$F_{Xi}^{many}=[many]=\sum\frac{\mu_{Xi-many}(x_j^i)}{x_j^i}=\sum_{j=0}^{Sup}\frac{\left[\frac{1}{Sup}j\right]}{x_j^i}. \quad (5)$$

The fuzzy set of the average thinking time X_3 is,

$$F_{X3}^{few}=[few]=\int\frac{\mu_{X3-few}(x)}{x}=$$
$$\int_{0<x\le Sec/4}\frac{1}{x}+\int_{Sec/4<x\le Sec}\frac{\left[1+\left[\frac{(x-Sec/4)}{10}\right]^2\right]^{-1}}{x}, \quad (6)$$

$$F_{X3}^{mid}=[middle]=\int\frac{\mu_{X3-mid}(x)}{x}=$$
$$\int_{0<x\le Sec}\frac{\left[1+\left[\frac{(x-Sec/2)}{10}\right]^2\right]^{-1}}{x}, \quad (7)$$

$$F_{X3}^{many}=[many]=\int\frac{\mu_{X3-many}(x)}{x}=$$
$$\int_{0<x\le 3\times Sec/4}\frac{\left[1+\left[\frac{(x-3\times Sec/4)}{10}\right]^2\right]^{-1}}{x}+\int_{3\times Sec/4<x\le Sec}\frac{1}{x}. \quad (8)$$

The fuzzy set of the user's historical entertainment level Y is,

$$F_Y^{low}=[low]=\int\frac{\mu_{Y-low}(y)}{y}=$$
$$\int_{0<y\le Gra/4}\frac{1}{y}+\int_{Gra/4<y\le Gra}\frac{\left[1+\left[\frac{(y-Gra/4)}{10}\right]^2\right]^{-1}}{y}, \quad (9)$$

$$F_Y^{mid}=[middle]=\int\frac{\mu_{Y-mid}(y)}{y}=$$
$$\int_{0<y\le Gra}\frac{\left[1+\left[\frac{(y-Gra/2)}{10}\right]^2\right]^{-1}}{y}, \quad (10)$$

$$F_Y^{high}=[high]=\int\frac{\mu_{Y-high}(y)}{y}=$$
$$\int_{0<y\le 3\times Gra/4}\frac{\left[1+\left[\frac{(y-3\times Gra/4)}{10}\right]^2\right]^{-1}}{y}+\int_{3\times Gra/4<y\le Gra}\frac{1}{y}, \quad (11)$$

The production rules for pattern matching are shown in Table 1.

The inferring part of this ACT-R model infers user's historical entertainment level, which demonstrates the user's whole performance in entertainments, with the total number of errors, the maximum number of consecutive errors and the average thinking time. Moreover, considering the user's current entertainment level, which is demonstrated by computer's emotion, the computer's entertainment level is determined. The level is able to change dynamically with the user's whole entertainment level to enhance the playability entertainment process and improve the quality of human-computer interaction.

TABLE 1 Conditions - Response production rules for implicit interaction in entertainment

If	Then	If	Then
x_1-few, x_2-few, x_3-few	$y-high^4$	x_1-many, x_2-few, x_3-few	$y-middle$
x_1-few, x_2-few, x_3-middle	$y-high^2$	x_1-many, x_2-few, x_3-middle	$y-middle$
x_1-few, x_2-few, x_3-many	$y-high^2$	x_1-many, x_2-few, x_3-many	$y-low$
x_1-middle, x_2-few, x_3-few	$y-high^2$	x_1-many, x_2-middle, x_3-few	$y-low$
x_1-middle, x_2-few, x_3-middle	$y-high$	x_1-many, x_2-middle, x_3-middle	$y-low$
x_1-middle, x_2-few, x_3-many	$y-high$	x_1-many, x_2-middle, x_3-many	$y-low^2$
x_1-middle, x_2-middle, x_3-few	$y-high$	x_1-many, x_2-many, x_3-few	$y-low^2$
x_1-middle, x_2-middle, x_3-middle	$y-middle$	x_1-many, x_2-many, x_3-middle	$y-low^2$
x_1-middle, x_2-middle, x_3-many	$y-middle$	x_1-many, x_2-many, x_3-many	$y-low^4$

4 Experimental and analysis

In this paper, we use the computational model of implicit interaction in horn chess playing entertainment. Firstly, introduce the method to use it, and secondly, analyze results after several rounds. It is called Horn Chess because the board looks like a horn shown in Figure 4.

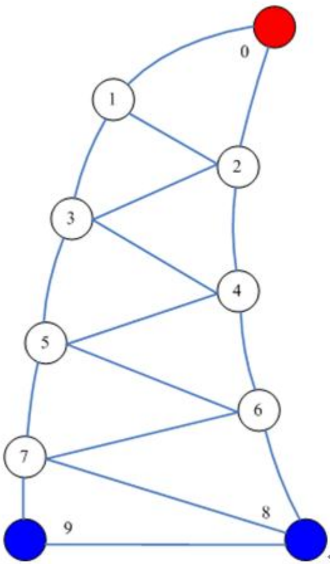
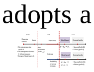


FIGURE 4 Board of horn chess. Positions (0-9) are marked to state conveniently.

On the checkerboard, there are three pieces. One player takes the red, and the opponent takes the blue. The initial pieces position is shown in Table 1. Two players move in turn. And they can only move forwards or backwards one step along lines, rather than no crossing over a piece or moving to the position where there is a piece. If the player taking the blue forces player taking the red to a dead end (position 0 in the board), the former wins. And if the player taking the red could run away to position 8 or 9 of the board, he wins. In order to keep balance, when a new game starts, the player, who takes the red piece, moves first.

4.1 DESIGN OF PLAYING PROCESS WITH IHCI

In this paper, we discussed implicit interaction in Horn Chess gaming based on the affective model for entertainment above. First of all, we suppose the computer has emotion. And in the game process, when the player has an excellent move, or the computer predicts his human opponent's move correctly, the computer's emotion is affected. As we know, it usually influences the computer's next moving strategy to produce excellent or bad move. The game-tree searching algorithm adopts a depth-first mini-max method which is embedded  pruning technique in. Because this paper focuses on the implicit interaction problem of gaming process, the details on game playing algorithm is not discussed more.

In order to manifest the Horn Chess playing process obviously, we named the two chess players, a person and a computer, Alice and Bob respectively. So affecting by the person's entertainment level, the whole process repeats two basic steps. One is Bob's move; the other is Alice's move. Two steps are designed as shown briefly in Figure 5.

The left part of the figure shows that human and the computer move in turn. The process is described as follows:

Step 1: Bob calculates optimal move according to the maximum depth *Maxdeep* based on a game-tree searching algorithm. While searching to the leaf of the game-tree, the best potential situation of Alice's next move is evaluated and recorded, which is signed as $Mark_{Est}$. Then, move to its optimum position. The calculating situation method is $\max\{r\times 100+b_1\times 10+b_2, r\times 100+b_2\times 10+b_1\}$, where r, b_1, b_2 are the numbers signed in Figure 4. Their values are integer in domain [0, 9] .

Step 2: Alice thinks and moves according to gaming situation.

Step 3: Bob calculates actual situation $Mark_{Act}$ after Alice moves again.

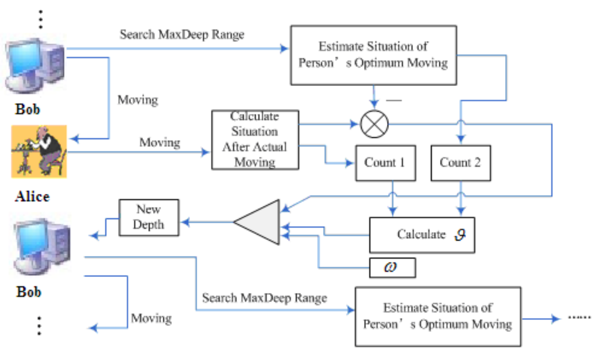


FIGURE 5 Basic steps of Horn Chess gaming affected by the person's entertainment level

Step 4: In the whole process, we need a computational model of implicit interaction for entertainment, especially for Horn Chess Game. To build this model, we can reference the mechanism of the model for Iowa Gambling Task context [19]. Stimuli intensity of emotion is calculated with:

$$I(t) = INT\left(\frac{abs(Mark_{Est} - Mark_{Act})}{\Delta Mark_{Max}} \times I_{Max}\right), \quad (12)$$

where, $\Delta Mark_{Max}$ s a maximum difference value of evaluating and actual situations, which could be calculated by $\delta=abs(Mark_{Est}-Mark_{Act})$. While Alice holds the red piece and Bob holds the blue ones, the maximum value $\Delta Mark_{Max}=100$ may occurs. I_{Max} is a legal maximum value of stimuli intensity. In this paper, $I_{Max}=55$. While game is continuing, given that whether $Mark_{Est}$ and $Mark_{Act}$ is equal. If yes, it is explained that Alice's game level is higher. So Bob should play carefully. And His positive emotion is stimulated. Otherwise, for Alice is bad at gaming, Bob is of proud emotion. Negative emotion $p^{-}{}_{,Em}$ could be calculated with $I(t)$ based on the statements in the section 3.2 [8]. Equation (12) only shows influence on Bob's emotion caused by Alice's single move, but according to long-memory effect, historical game level scored with Y should be considered too.

Considering one situation that Alice plays badly both in a single step and in history, Bob becomes proud to moves unwarily. So there will be much error steps. It can be realized by diminishing the maximum searching depth *Depth* of the game-tree. Update *Depth* as:

$$Depth(t+1) = Depth(t) + \omega \cdot [y(t+1) - y(t)] \cdot p^{-}_{Em} \quad . \quad (13)$$

Step 5: Run the game-tree searching algorithm again with updated maximum depth $Depth(t+1)$. Repeat step 1.

4.2 EXPERIMENT AND ANALYSIS

Alice and Bob play the Horn Chess game with the rules one by one based on the computational model of implicit interaction above. In order to avoid the searching depth increasing continually, we set the maximum searching depth is 15. As stated above, while stimuli occur and Alice's historical entertainment level is calculated, it could be clearly seen that Bob's emotions is stimulated. And then it influences on his decision-making, such as adjustment of maximum searching depth, width or something else. This paper focuses on the adjustment of maximum searching depth. It changes along with Alice's game level dynamically. Explicit and implicit interactions coexist too.

Alice and Bob carry on a gaming process four times which are Bob moves first and Alice moves first separately, shown in Table 2, 3. To show the experiments result obviously, six aspects, such as the move, the best potential situation of Alice's next move estimated by a Bob $Mark_{Est}$, the actual situation $Mark_{Act}$ after Alice moves, Bob's negative emotion $p^{-}{}_{,Em}$, Alice's historical playing level y and the self-adjusting maximum searching depth $Depth(t+1)$ are recorded.

In the gaming process recorded in Table 2(b), B represents Bob's moving step, and A represents Alice's moving step. Bob moves first. Taking the first row for example, from row view, B: 0→1 A :(8, 9) → (7, 9) indicates that Bob holds the red piece, and moves from position 0 to position 1 according to Figure 4. Simultaneously, Alice holds blue pieces. One of his pieces moves from position 8 to position 7. And the other keeps still. After Bob's moving, the best potential situation of Alice's next move is estimated, $Mark_{Est}=169$, which is corresponding to Alice's best move. Then, Alice moves, and Bob calculates the current actual situation $Mark_{Act}=179$. While the negative emotion $p^{-}{}_{,Em}=0.80624$ and Alice's historical playing level is set to 0.5 initially, we can obtain the maximum searching depth $Depth(t+1)=8$ with the model above.

In addition, the smaller situation is, the more advantaged to Alice's move is according to the min-max game-tree searching theory, when Bob moves first from column view. Alice usually does not move best. So, generally speaking, the actual situation $Mark_{Act}$ is larger than $Mark_{Est}$. That is $Mark_{Est} \leq Mark_{Act}$. When Alice's move is not the best one estimated by Bob, his proud emotion is stimulated. The negative emotion $p^{-}{}_{,Em}$ is larger than its initial value (0.5). Moreover, the worse move is, the larger $p^{-}{}_{,Em}$ is. When Alice's gaming level is lower, and Bob is proud, Bob reduces the maximum searching depth automatically. Otherwise, the searching depth will be increasing to reflect that emotion and historical game level influences on entertainment process. Similarly, another experiment process in which Bob moves first is recorded in Table 2(a). The analysis to this continued table is the same as statement above.

TABLE 2 Gaming process when Bob moves first

(a) The first time

Record	Moving	Estimating situation	Actual situation	Emotion	Historical entertainment level	Max searching deep
1	B:0→1 A:(8,9)→(6,9)	169	169	0.45653	0.50	8
2	B:1→0 A:(6,9)→(6,7)	49	67	0.92846	0.46	7
3	B:0→1 A:(6,7)→(5,6)	147	156	0.75957	0.41	6
4	B:1→2 A:(5,6)→(4,6)	236	246	0.80624	0.41	6
5	B:2→0 A:(4,6)→(3,6)	26	36	0.80624	0.36	5
6	B:0→2 A:(3,6)→(3,4)	216	234	0.92846	0.32	4
7	B:2→1 A:(3,4)→(2,3)	123	123	0.45653	0.46	6
8	B:1→0 A:(2,3)→(1,2)	123	123	0.45653	0.53	7
9	B: LOSS	-	-	-	-	-

(b) The second time

Record	Moving	Estimating situation	Actual situation	Emotion	Historical entertainment level	Max searching deep
1	B:0→1 A:(8,9)→(7,9)	169	179	0.80624	0.50	8
2	B:1→0 A:(7,9)→(5,9)	59	59	0.45653	0.87	11
3	B:0→1 A:(5,9)→(5,7)	139	157	0.92846	0.74	9
4	B:1→3 A:(5,7)→(6,7)	347	367	0.95854	0.67	8
5	B:3→5 A:(6,7)→(7,8)	547	578	0.99247	0.61	7
6	B:5→6 A:(7,8)→(8,9)	658	689	0.99247	0.55	6
7	B:6→7 A:LOSS	-	-	-	-	-

TABLE 3 Gaming process when Alice moves first

(a) The first time

Record	Moving	Estimating situation	Actual situation	Emotion	Historical entertainment level	Max searching deep
1	A:0→1 B:(8,9)→(6,9)	-	-	-	-	-
2	A:1→2 B:(6,9)→(5,9)	369	369	0.54347	0.50	8
3	A:2→3 B:(5,9)→(5,7)	459	359	0.54347	0.42	7
4	A:3→4 B:(5,7)→(5,6)	457	457	0.45653	0.59	9
5	A:4→2 B:(5,6)→(4,6)	356	256	0.54347	0.51	8
6	A:2→0 B:(4,6)→(2,6)	346	346	0.25728	0.66	9
7	A:0→1 B:(2,6)→(3,6)	126	126	0.45653	0.74	10
8	A:1→2 B:(3,6)→(3,4)	236	236	0.45653	0.82	11
9	A:2→0 B:(3,4)→(2,4)	134	134	0.54347	0.82	11
10	A:0→1 B:(2,4)→(2,3)	124	124	0.45653	0.90	12
11	A: 1→0(LOSS) B: (2,3)→(1,2)	23	23	0.45653	0.97	13

(b) The second time

Record	Moving	Estimating situation	Actual situation	Emotion	Historical entertainment level	Max searching deep
1	A:0→2 B:(8,9)→(6,9)	-	-	-	-	-
2	A:2→4 B:(6,9)→(7,9)	469	469	0.45653	0.50	8
3	A:4→5 B:(7,9)→(7,8)	679	579	0.54347	0.43	7
4	A:5→6 B:(7,8)→(7,9)	678	678	0.45653	0.51	8
5	A:6→8 B:LOSS	879	879	0.45653	0.65	10

When Alice moves firstly, recorded in Table 3, the bigger situation is, the more advantaged to Alice's move is according to the min-max game-tree searching theory, when he holds the red piece from column view. Moreover, Alice usually does not move best. So, actual situation $Mark_{Act}$ is smaller than $Mark_{Est}$. The rest analysis is the same as Table 2.

Moreover, record the detail information of four experiment processes above to contrasting and analyzing. They are total number of errors x_1, the maximum number of consecutive errors x_2, and the average thinking time x_3. With their maximum values shown in Tables 2 and 3, the percentages (TE, MCE, ATT, MaxSD, and MinSD) can be calculated and demonstrated in Figure 6. TE, MCE, ATT, MaxSD, and MinSD means the percentage of total number of errors, the percentage of maximum number of consecutive errors, the percentage of average thinking time, the percentage of maximum searching depth and the percentage of minimum searching depth respectively.

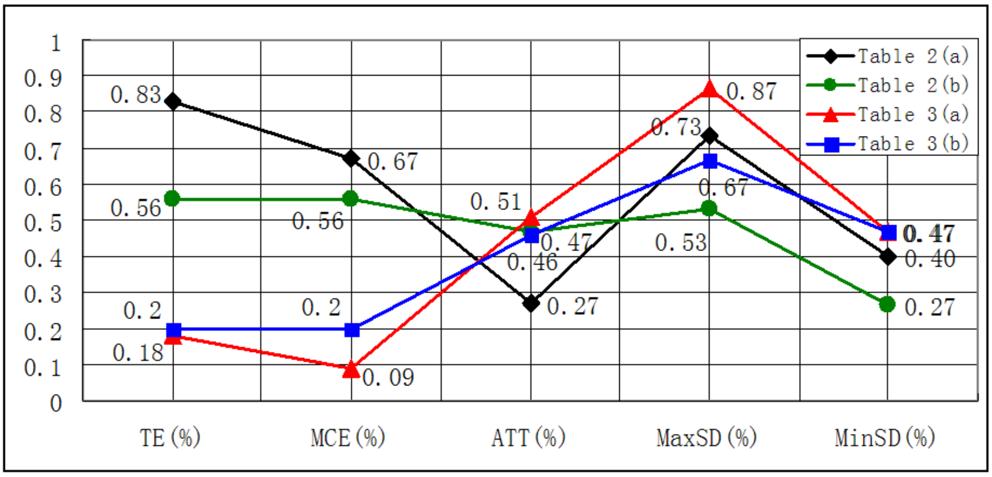


FIGURE 6 Statics of the four gaming processes

In this figure, five percentages of every experiment are put together. No matter Alice or Bob moves firstly, generally speaking, MaxSD and MinSD are bigger when TE, MCE and ATT are smaller, which means Alice is good at gaming and has a high level in entertainment, so Bob must take the game process seriously by thinking deeply. But for the line of Table 2(a), because ATT influences more than TE and MCE, MaxSD and MinSD are getting bigger.

5 Conclusions

In this paper, a computational model of implicit interacttion based on emotional Hidden Markov Mode (eHMM) and ACT-R cognitive architecture is devised, which will be used for human computer interaction or corporation, especially for entertainment. We considered the influence of agent's affection and cognition. So eHMM and ACT-R are merging with each other.

The focus of present research is how to construct a hierarchical structure to link agent's affection and cognition. From our point of view, agent's affective state is influenced by current behaviors coming from the inner world and environment. It makes agent react rapidly. Moreover, because of memory and inference, cognition reflects long-term influences. So we integrated them together. No matter in simulation experiments or in practice, there are good results. The proposed model is effective.

Acknowledgements

This work was supported by the Foundation for Young Scholars of Hebei Educational Committee (QN20131152, Q2012070).

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