# Research on Affection-based Implicit Interaction in Entertainment

**Wang Wei***, **Huang Xiaodan**

*School of Information & Electrical Engineering, Hebei University of Engineering, Hebei Handan 056038, China*

*Received 30 May 2014, www.cmnt.lv*

**Abstract**

Achieving implicit interaction in entertainment is a topic worth investigating. For a game or entertainment product to become more interesting, computers must interact and collaborate with human beings actively and adaptively. This paper proposes and applies a method to increase the entertainment value of a computer game. First, the main part of this method, namely, the emotional Hidden Markov Model (eHMM), is investigated. Second, the details on the construction of the emotional state transferring probability and observed matrices are provided. Third, the application of this model in a chess game, particularly with consideration of the current behaviors of the user, is described. Finally, some experiments are performed, during which the gaming process is recorded and analyzed. By adjusting the entertainment process, we find that the proposed model can cause computers to be more active and adaptive to their users, hence demonstrating the favorable application of such model.

*Keywords:* implicit interaction, affective computing, modeling, entertainment, chess gaming

## 1 Introduction

The development of cognitive and affective computing has resulted in the emergence of theories and technologies related to human–computer interaction. Cognition and affection can be applied into entertainment either by analyzing the affection of human beings [1–3] or by integrating the cognitive–affective model into the application [4–6]. While searching for suitable measurement methods for the affective state of videogame players, Jonathan Sykes investigated the hypothesis that arousal of the player would correspond with the pressure exerted on the gamepad buttons. To achieve such objective, Sykes developed a videogame that could detect the amount of pressure placed on each button during the game. Sykes found that players would hit the gamepad buttons harder as the difficulty level of the game increased [1]. Abdullah Al Mahmud suggested that psycho-physiological measurements should be incorporated into the gaming experience and that a desktop game should be integrated within its real surroundings (i.e., the entire room) to promote more physical activity [2].

The authentic behaviors of non-player characters (NPCs) in artificial intelligence games present considerable challenge to NPC intelligence. Emotions help enhance the quality and intelligence of behaviors as well as increase the entertainment value of games. Zhou and Yu described several common emotional behaviors of NPCs by constructing a simple emotion–behavior model for emotion transition, and simulating such behaviors in a developing project [3]. They found that the quality and intelligence of the behaviors of NPCs were improved by emotion, which subsequently increased the entertainment value of the game. Munoz K applied qualitative and quantitative approaches to investigate the achievement emotions of learners. Such emotions were inferred from two sources, namely, from their observable behaviors and from their answers to in-game questions. This study focuses on the design and creation of the affective student model employed by Munoz K. PlayPhysics, an emotional games and learning environment, is implemented to teach Physics at the undergraduate level. Our affective student model will be incorporated into PlayPhysics after finalizing our results. A preliminary prototyping study has conducted to ensure the accuracy of the recognition method. The results from the prototyping phase will be presented and discussed [4].

Driven by computational models of user experience, Yannakakis provided a taxonomy of procedural content generation (PCG) algorithms and introduced a PGC framework. The personalization of user experience via affective and cognitive modeling, coupled with real-time content adjustment according to the needs and preferences of users, are important steps toward the development of an effective and meaningful PCG. Games, Web 2.0, interface, and software design are among the most popular applications for automated content generation.

Wang proposed a method for investigating the effects of the Cognitive Affective Interaction (CAI) strategy on the creative performance of novices in game design. The CAI strategies, which include visualization and discrepancy strategies, were administrated and served as experimental treatment [5].

* ***Corresponding author's*** e-mail: wangwei83@hebeu.edu.com

Human–computer interaction (HCI) must be expanded from the traditional interactive style (explicit HCI or EHCI) to a ubiquitous style (implicit HCI or IHCI) to drive participants to focus on content without interaction devices. Given that this new interactive style can reduce the cognitive burden placed upon gamers, studies on IHCI-related theories and technologies have become increasingly important.

As a frontier in the HCI area, IHCI has attracted significant attention from various research organizations [6]. Nicole Kaiyan from Swinburne University of Technology in Australia proposed the IHCI concept in 1996, but failed to investigate this concept further [7]. Such concept has been gradually studied in several universities and institutes in many countries, such as the USA, Germany, China, and Australia, since 2005. Albrecht Schmidt from the University of Karlsruhe in Germany introduced several IHCI-related theories. He regarded perception and interpretation as key points of IHCI, emphasized the importance of context information in the interactive process, and modelled interactions using an extensible mark-up language [8]. Through computer vision technologies, Andrew Wilson and Nuria Oliver from Microsoft Research in the USA developed four systems to realize the IHCI process [9]. In 2007, Tao Linmi from Tsinghua University in China developed an adaptive vision system that could detect and understand the behavior of users in an implicitly interactive style [10]. During the same year, Tian Feng from the Institute of Software in the Chinese Academy of Sciences investigated the implicit interaction features from the aspect of post-WIMP [11].

IHCI also has very important uses in entertainment. The quality of entertainment can be improved by the context perceptions and interpretations generated from the context information of users, such as their behavior, emotional state, physiological status, and location.

The rest of the paper is organized as follows. Section 2 briefly reviews extant literature on affection modeling and introduces the emotional Hidden Markov Model (eHMM), which is the affective model used to describe the emotional stimuli transferring process in this paper. Section 3 discusses the application of the eHMM model in a horn chess game. Section 4 describes the experiments, provides an analysis of the experimental results as well as a comparison of the gaming processes with and without the model. Section 5 provides the conclusions and suggestions for future work.

## 2 Affection modeling

Many national and international research institutes have investigated affective computing and affection modeling. The OCC affective model is the first and most famous model for affective computing. This model determines rule-based relationships by analyzing various affections that are connected with events in the physical world and by examining interactions among certain subjects. This model also suggests that affection is generated by the consequences of an event, the actions of an agent, and the feel of an object.

The Kismet affective model is used in a robot named Kismet, which is designed by C Breazeal from the Massachusetts Institute of Technology. This model combines environment, inner stimuli, and action, and is comprised of four parts, namely, stimuli, evaluation, arousal, and expression. Based on this model, Kismet acts differently by considering the outside stimuli and the inner demand.

The Euclidean space affection model is proposed based on emotional psychology and by regarding basic emotion as the base vector [12]. The transition from one emotion to another occurs in the affection space. However, this model is discrete. Teng modeled the affective changing process by using the Markov chain and hidden Markov models in probability space. Affective transition can be described accurately whether or not a stimuli occurs.

Botelho from Waseda University investigated the Salt & Pepper model [13], which is the affection model of the humanoid WE-4R [14]. Other researchers have investigated several theories based on random events [15] and self-organization theory.

An affective model for simulating how individuals generate and change their emotions must be devised. We apply the eHMM model as an emotional engine to realize the emotional stimuli transferring process in a computer.

Based on a probability space, Teng regarded an emotional stimuli transferring process as random that could be described using the hidden Markov model. The quintuple form, $l=(N,M,\vec{\mathbf{P}}^{\mathbf{0}},\hat{\mathbf{A}},\hat{\mathbf{B}})$, where $N$ denotes the number of emotional dimensions, is used to determine the model. The emotional dimensions are described as follows:

$$S=\{S_1,S_2,\cdots,S_N\}=\{1,2,\ldots,N\},\quad S_i=i\ (i=1,2,\cdots,N) \tag{1}$$

In the stimuli transferring process of emotional states, the probability distribution of emotional states, $\vec{\mathbf{P}}=[p_1,p_2,\cdots,p_N]$ is denoted by the following probability distributions:

1) The initial emotional state probability distribution, $\vec{\boldsymbol{\pi}}=[\pi_1,\pi_2,\cdots,\pi_N]$, which is the initial probability distribution in the HMM model.

2) The current emotional state probability distribution is, $\vec{\mathbf{P}}^{(T)}=[p_1^{(T)},p_2^{(T)},\cdots,p_N^{(T)}]$ and represents the type and intensity of the external stimulus. Therefore, $\vec{\mathbf{P}}^{(0)}=\vec{\boldsymbol{\pi}}$.

External stimuli can be described using the observed values, observed matrix, and observed sequence of the HMM model. The observed value set, which is the stimulus set, is described as follows:

$$V=\{V_1,V_2,\ldots,V_M\}=\{1,2,\cdots,M\},\quad V_m=m\ (m=1,2,\cdots,M) \tag{2}$$

$M$ denotes the number of stimuli types. If a certain stimuli can trigger a certain kind of emotional state deterministically, then $M = N$.

$\hat{\mathbf{A}}_{N\times M}$ is an emotional state transferring probability matrix, which limiting probability is expressed as $\vec{\boldsymbol{\pi}}^* = [\hat{\pi}_1^*, \hat{\pi}_2^*, \cdots, \hat{\pi}_N^*]$. The element in $\hat{\mathbf{A}}_{N\times M}$ is denoted as $a_{ij} = \begin{cases} x_i, & i = j \\ y_i, & i \neq j \end{cases}$, and supposes that $k_i = \dfrac{x_i}{y_i}$, where $\begin{cases} x_i = \dfrac{k_i}{N-1+k_i}, \\ y_i = \dfrac{1}{N-1+k_i} \end{cases} \quad i = 1,2,\ldots,N$.

Given that $\vec{\boldsymbol{\pi}}^* \hat{\mathbf{A}} = \vec{\boldsymbol{\pi}}^*$ and $\pi_1^* + \pi_2^* + \cdots + \pi_N^* = 1$, the following expressions are formulated:

$$\begin{cases} \pi_1^* \dfrac{k_1}{N-1+k_1} + \pi_2^* \dfrac{1}{N-1+k_2} + \cdots + \pi^*_{(N-1)} \dfrac{1}{N-1+k_{(N-1)}} + \pi_N^* \dfrac{1}{N-1+k_N} = \pi_1^* \\ \pi_1^* \dfrac{1}{N-1+k_1} + \pi_2^* \dfrac{k_2}{N-1+k_2} + \cdots + \pi^*_{(N-1)} \dfrac{1}{N-1+k_{(N-1)}} + \pi_N^* \dfrac{1}{N-1+k_N} = \pi_2^* \\ \vdots \\ \pi_1^* \dfrac{1}{N-1+k_1} + \pi_2^* \dfrac{1}{N-1+k_2} + \cdots + \pi^*_{(N-1)} \dfrac{1}{N-1+k_{(N-1)}} + \pi_N^* \dfrac{k_N}{N-1+k_N} = \pi_N^* \end{cases} \tag{3}$$

Therefore, we can deduce the following

$$\begin{cases} \pi^*_2 = \pi_1^* \dfrac{N-1+k_2}{N-1+k_1} \\ \pi^*_3 = \pi_1^* \dfrac{N-1+k_3}{N-1+k_1} \\ \vdots \\ \pi^*_N = \pi_1^* \dfrac{N-1+k_N}{N-1+k_1} \end{cases} \tag{4}$$

By considering $\pi_1^* + \pi_2^* + \cdots + \pi_N^* = 1$, we generate the following equation:

$$\pi^*_1 = \frac{N-1+k_1}{(N-1)N + k_1 + k_2 + k_3 + \cdots + k_N} = \frac{N-1+k_1}{(N-1)N + \sum_{i=1}^{N} k_i} \tag{5}$$

Therefore, the following expression is obtained:

$$\begin{cases} \pi^*_1 = \dfrac{N-1+k_1}{(N-1)N + k_1 + k_2 + k_3 + \cdots + k_N} = \dfrac{N-1+k_1}{(N-1)N + \sum_{i=1}^{N} k_i} \\ \pi^*_2 = \dfrac{N-1+k_2}{(N-1)N + k_1 + k_2 + k_3 + \cdots + k_N} = \dfrac{N-1+k_2}{(N-1)N + \sum_{i=1}^{N} k_i} \\ \vdots \\ \pi^*_N = \dfrac{N-1+k_N}{(N-1)N + k_1 + k_2 + k_3 + \cdots + k_N} = \dfrac{N-1+k_N}{(N-1)N + \sum_{i=1}^{N} k_i} \end{cases} \tag{6}$$

We can deduce the $N$ equation as follows:

$$(N-1)N + \sum_{i=1}^{N} k_i = \frac{N-1+k_1}{\pi_1^*} = \frac{N-1+k_2}{\pi_2^*} = \cdots = \frac{N-1+k_N}{\pi_N^*} = \hat{\theta}. \tag{7}$$

Matrix $\hat{\mathbf{A}}_{N\times M}$ is defined as follows:

$$\hat{\mathbf{A}} = \{\hat{a}_{ij}\}_{N\times M} = \begin{bmatrix} \dfrac{\hat{\theta}\hat{\pi}_1^* - (N-1)}{\hat{\theta}\hat{\pi}_1^*} & \dfrac{1}{\hat{\theta}\hat{\pi}_1^*} & \cdots & \dfrac{1}{\hat{\theta}\hat{\pi}_1^*} \\ \dfrac{1}{\hat{\theta}\hat{\pi}_2^*} & \dfrac{\hat{\theta}\hat{\pi}_1^* - (N-1)}{\hat{\theta}\hat{\pi}_1^*} & \cdots & \dfrac{1}{\hat{\theta}\hat{\pi}_2^*} \\ \vdots & \vdots & \cdots & \\ \dfrac{1}{\hat{\theta}\hat{\pi}_N^*} & \dfrac{1}{\hat{\theta}\hat{\pi}_N^*} & \cdots & \dfrac{\hat{\theta}\hat{\pi}_N^* - (N-1)}{\hat{\theta}\hat{\pi}_N^*} \end{bmatrix} \tag{8}$$

The observed matrix, also called the stimuli matrix, is defined as follows:

$$\hat{\mathbf{B}}_{M\times N} = \begin{bmatrix} b_1(1) & b_2(1) & \cdots & b_N(1) \\ b_1(2) & b_2(2) & \cdots & b_N(2) \\ \vdots & \vdots & \cdots & \vdots \\ b_1(M) & b_2(M) & \cdots & b_N(M) \end{bmatrix} \tag{9}$$

where $\vec{\mathbf{B}}(V_m) = [b_1(m) \quad b_2(m) \quad \cdots \quad b_N(m)] \quad (1 \le m \le M)$ corresponds to the stimuli vector of the $m^{\text{th}}$ type of emotional states. The following equations are then generated:

$$\sum_{m=1}^{M} b_i(m) = 1, \quad (1 \le i \le N) \tag{10}$$

$$\sum_{i=1}^{N} b_i(m) = 1, \quad (1 \le m \le M) \tag{11}$$

The elements in matrix $\hat{\mathbf{B}}_{N\times M}$ are expressed as follows:

$$b_i(j) = \begin{cases} a, & (i = j) \\ b, & (i \neq j) \end{cases}, \text{and } a \ge b \tag{12}$$

Therefore, the matrix is described as follows:

$$\hat{\mathbf{B}} = \begin{bmatrix} \vec{\mathbf{B}}_1 \\ \vec{\mathbf{B}}_2 \\ \vdots \\ \vec{\mathbf{B}}_N \end{bmatrix} = \begin{bmatrix} a & b & \cdots & b \\ b & a & \cdots & b \\ \vdots & \vdots & \cdots & \vdots \\ b & b & \cdots & a \end{bmatrix}. \tag{13}$$

where $\begin{cases} a = \dfrac{r}{N-1+r} \\ b = \dfrac{1}{N-1+r} \end{cases}$, $r > 1$, $r$ is a stimuli factor and $r = a/b$.

The current behavior of a player reflects his or her level of entertainment. If the current behavior indicates a higher level of entertainment, the computer expresses a positive machine emotion and treats the gaming process with caution. Otherwise, the computer generates negative emotions. Based on the eHMM model, the emotional value in the emotional stimuli transferring process can be obtained through positive and negative stimuli that indicate the current level of entertainment of the player.

## 3 Designing the playing process using the affective model

We use the affective model in a horn chess game to determine the implicit interaction. Horn chess derives its name from its horn-shaped board, shown as figure 1.

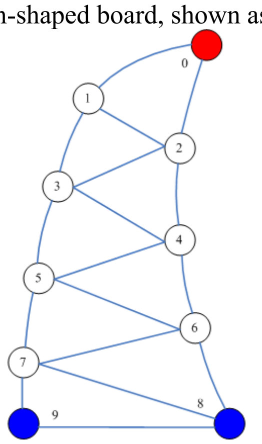


FIGURE 1 Horn chess board with the chess piece positions marked from 0 to 9

Only three pieces can be placed on the board, among which, one piece is colored red and the other two pieces are colored blue. The positions of these pieces at the beginning of the game are shown in Fig. 1. One player holds the red piece, while another player holds the blue pieces. The two sides move in turn, and they can only move the pieces one step forward or backward. The players cannot move a piece to a position currently occupied by another piece. If the blue pieces forces the red piece to a dead end (position 0 in the board), the player holding the blue pieces wins the game. In contrast, if the red piece reaches position 8 or 9, the player holding the red piece wins the game. The red moves first to maintain balance in the two sides of the board.

The implicit interaction between humans and robots in a horn chess game is discussed based on the affective model for entertainment. The emotion of the robot is affected when the robot correctly predicts the next move of the human player or if the human player makes an excellent move. The next move of the robot may be classified either as excellent or poor depending on its current emotion. Game-tree searching algorithm adopts a depth-first, mini–max method that is embedded in the α–β pruning technique. We focus on the implicit interaction that occurs in the gaming process. Details on the game playing algorithm are also presented.

In the experiments, a horn chess game is played between a human player and a humanoid player called Alice and Bob, respectively. Given that these players move in turns, the horn chess gaming process is affected by the level of entertainment in two basic steps, namely, the move of the humanoid player and the move of the human player. These basic steps are shown in figure 2.

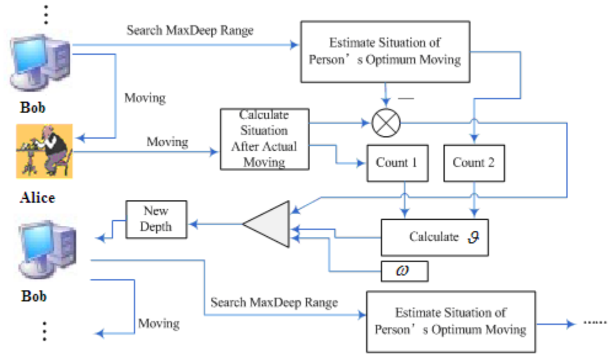


FIGURE 2 Basic steps of how horn chess is affected by the entertainment level of the player

The left part of the figure shows that the human and humanoid players move in turns. The gaming process is outlined as follows:

1) Based on a game-tree searching algorithm, Bob calculates the optimal move in light of maximum depth $MaxDeep$. While finding out the leaf of the game tree, Bob evaluates and records the best potential situation of the next move of Alice, which is denoted by $Mark_{Est}$. Bob then moves to its optimum position. The situation is calculated as $Max\{r\times100+b1\times10+b2, r\times100+b2\times10+b1\}$, where $r$, $b1$, $b2$ are the numbers that denote the chess piece positions as shown in Fig. 1. Their values are expressed as integers in domain $[0, 9]$.

2) Alice thinks of her next move and then moves her piece according to the gaming situation.

3) Bob calculates the actual situation $Mark_{Act}$ after Alice makes her move.

4) A computational implicit interaction model for the horn chess game is built according to the mechanism of the model for the Iowa Gambling Task context as stated in a previous study [16]. The stimuli intensity of emotion is calculated as follows:

$$I(t) = INT(\frac{abs(Mark_{Est} - Mark_{Act})}{\Delta Mark_{Max}} \times I_{Max}), \quad (14)$$

where $\Delta Mark_{Max}$ is a maximum difference value for evaluating actual situations, which can be calculated as $\delta = abs(Mark_{Est} - Mark_{Act})$. Given that Alice holds the red piece and Bob holds the blue pieces, the maximum value can reach up to $\Delta Mark_{Max} = 100$. $I_{Max}$ is the legal maximum value of stimuli intensity, which is set to $I_{Max} = 55$ in this paper. If $Mark_{Est}$ and $Mark_{Act}$ remain equal throughout the game, the gaming level of Alice becomes higher than that of Bob. Therefore, Bob must play carefully, and his positive emotion is stimulated. Otherwise, Bob feels a proud emotion. The negative emotion $p_{\bar{E}m}$ can be calculated using $I(t)$ according to the statement in section 2 [14].

Equation (14) shows how the move of Alice affects the emotion of Bob. The historical game level score $\vartheta$ must also be considered in this equation. By supposing that $num_{=}$ is the number of $\delta = 0$ and $num_{\neq}$ is the number of $\delta \neq 0$, the historical game level score can be computed as follows:

$$\vartheta = \frac{num_{=} - num_{\neq}}{num_{=} + num_{\neq}}. \quad (15)$$

The pride of Bob is boosted when Alice plays poorly in the current and previous games. Therefore, Bob begins to play carelessly in the current game, which will result in additional errors. This goal can be achieved by decreasing the maximum searching depth $Depth$ of the game tree. Therefore, $Depth$ must be updated as follows:

$$Depth(t+1) = Depth(t) + \vartheta \cdot \omega \cdot p_{Em}^{-}. \quad (16)$$

5) Run the game-tree searching algorithm again with the updated maximum depth $Depth(t+1)$. Step 1 is repeated afterwards.

## 4 Experimental and analysis

Based on the affective model for implicit interaction, a horn chess game is performed between Alice and Bob. The maximum searching depth in this paper is set to 15. Fig. 1 shows that a specific emotion is stimulated in Bob under the senses stimuli and that the historical gaming level of Alice is calculated from the environment. Such level influences the decision-making process of Bob, including his adjustment of the maximum searching depth or width. This paper focuses on the adjustment of the maximum searching depth. Such adjustment dynamically changes along with the gaming level of Alice. Explicit and implicit interactions also coexist throughout the game.

Based on the six aspects, including the move, the best potential situation of Alice's next move estimated by Bob's $Mark_{Est}$, 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 $Depth(t+1)$, we record a gaming process between Alice and Bob in which four possible situations can be observed. These situations are shown separately in Tables 1 and 2.

TABLE 2 Gaming process when Bob moves first

(a) The first time

| Record | Moving | Estimating situation | Actual situation | Emotion | Max searching deep |
|---|---|---|---|---|---|
| 1 | B:0→1 A:(8,9)→(7,9) | 169 | 179 | 0.80624 | 8 |
| 2 | B:1→0 A:(7,9)→(5,9) | 59 | 59 | 0.45653 | 12 |
| 3 | B:0→1 A:(5,9)→(5,7) | 139 | 157 | 0.92846 | 10 |
| 4 | B:1→3 A:(5,7)→(6,7) | 347 | 367 | 0.95854 | 9 |
| 5 | B:3→5 A:(6,7)→(7,8) | 547 | 578 | 0.99247 | 9 |
| 6 | B:5→6 A:(7,8)→(8,9) | 658 | 689 | 0.99247 | 8 |
| 7 | B:6→7 A:LOSS | - | - | - | - |

(b) The second time

| Record | Moving | Estimating situation | Actual situation | Emotion | Max searching deep |
|---|---|---|---|---|---|
| 1 | B:0→1 A:(8,9)→(6,9) | 169 | 169 | 0.45653 | 15 |
| 2 | B:1→0 A:(6,9)→(6,7) | 49 | 67 | 0.92846 | 14 |
| 3 | B:0→1 A:(6,7)→(5,6) | 147 | 156 | 0.75957 | 13 |
| 4 | B:1→2 A:(5,6)→(4,6) | 236 | 246 | 0.80624 | 12 |
| 5 | B:2→0 A:(4,6)→(3,6) | 26 | 36 | 0.80624 | 11 |
| 6 | B:0→2 A:(3,6)→(3,4) | 216 | 234 | 0.92846 | 10 |
| 7 | B:2→1 A:(3,4)→(2,3) | 123 | 123 | 0.45653 | 12 |
| 8 | B:1→0 A:(2,3)→(1,2) | 123 | 123 | 0.45653 | 12 |
| 9 | B: LOSS | - | - | - | - |

TABLE 3 Gaming process when Alice moves first

(a) The first time

| Record | Moving | Estimating situation | Actual situation | Emotion | 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 | 9 |
| 3 | A:2→3 B:(5,9)→(5,7) | 459 | 359 | 0.54347 | 9 |
| 4 | A:3→4 B:(5,7)→(5,6) | 457 | 457 | 0.45653 | 11 |
| 5 | A:4→2 B:(5,6)→(4,6) | 356 | 256 | 0.54347 | 10 |
| 6 | A:2→0 B:(4,6)→(2,6) | 346 | 346 | 0.25728 | 11 |
| 7 | A:0→1 B:(2,6)→(3,6) | 126 | 126 | 0.45653 | 11 |
| 8 | A:1→2 B:(3,6)→(3,4) | 236 | 236 | 0.45653 | 11 |
| 9 | A:2→0 B:(3,4)→(2,4) | 134 | 134 | 0.54347 | 11 |

| | | | | | |
|---|---|---|---|---|---|
| 10 | A:0→1 B:(2,4)→(2,3) | 124 | 124 | 0.45653 | 12 |
| 11 | A:1→0(LOSS)<br>B: (2,3)→(1,2) | 23 | 23 | 0.45653 | 12 |

(b) The second time

| Record | Moving | Estimating situation | Actual situation | Emotion | 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 | 15 |
| 3 | A:4→5 B:(7,9)→(7,8) | 679 | 579 | 0.54347 | 13 |
| 4 | A:5→6 B:(7,8)→(7,9) | 678 | 678 | 0.45653 | 13 |
| 5 | A:6→8 B:LOSS | 879 | 879 | 0.45653 | 14 |

Bob moves first in the gaming process shown in Table 1(a). B represents the moves of Bob, whereas A represents the moves of Alice. The first row, 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 Fig. 1. At the same time, Alice moves one of the blue pieces from position 8 to 7, while the other piece remains in its initial position. After Bob makes his first move, the best potential situation of Alice's next move is estimated as $Mark_{Est}$=169 , which corresponds to the best move of Alice. After the first move of Alice, Bob calculates the current actual situation as$Mark_{Act}$=179. Based on the above model, the negative emotion is equivalent to $p_{\bar{\mathrm{Em}}}$ =0.80624 and the historical gaming level of Alice is initially set to 0.5 to obtain a maximum searching depth of $Depth(t+1)$=8 .

According to the min–max game–tree searching theory, Alice gains a higher advantage the smaller the situation is from the column view when Bob moves first. Moreover, Alice usually does not make the best move. Therefore, the actual situation $Mark_{Act}$ is larger than $Mark_{Est}$ ($Mark_{Est} \leq Mark_{Act}$). When the move of Alice is not the best move as estimated by Bob, the proud emotion of the latter is stimulated. The negative emotion $p_{\bar{\mathrm{Em}}}$ is larger than its initial value (0.5). A poorer move will generate a larger $p_{\bar{\mathrm{Em}}}$ . The lower gaming level of Alice and the proud emotion of Bob will automatically reduce the maximum searching depth. Otherwise, the searching depth will be increased to reflect the influence of emotion and historical gaming level on the gaming process. Another experiment in which Bob moves first is recorded in Table 1(b). The results of the analysis of this table are similar to the statements above.

The gaming process in which Alice moves first is shown in Table 2. A larger situation from the column view will increase the advantage of Alice according to the min–max game-tree searching theory when she holds the red piece. Moreover, Alice usually does not make the best move. Therefore, the actual situation $Mark_{Act}$ is smaller than $Mark_{Est}$ ($Mark_{Est} \geqslant Mark_{Act}$ ). The analysis results for Tables 2(a) and 2(b) are similar to those for Table 1.

## 5 Conclusions

This paper proposes a method for implicit interaction in entertainment, which will be used for studying the interaction between humans and computers. This method was developed based on the eHMM model. This method assumes the presence of an agent in the game or in another entertainment product. Given the affection of the agent, the eHMM model is used in the construction of the emotional state transferring probability and observed matrices. The affective state of the agent is influenced by the current behaviors from the agent's internal and external environments. Therefore, the behaviors of an individual during the game can influence the affection of the agent. Therefore, the entertainment process changes along with the behaviors of the individual. Favorable results are obtained in simulation experiments and practical applications, thereby proving the effectiveness of the proposed model.

## Acknowledgements

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

## References

[1] Jonathan S, Simon B 2003 Affective gaming: measuring emotion through the gamepad *Proceeding of CHI '03 Extended Abstracts on Human Factors in Computing Systems* 732-733
[2] Abdullah A M, Omar M 2007 Affective tabletop game: a new gaming experience for children *Second Annual IEEE International Workshop on Horizontal Interactive Human-Computer Systems* 44-51
[3] Zhou C N, Yu X L 2006 Affective computation based NPC behaviors modeling *Proceedings of IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology* 343-346
[4] Karla M, Julieta N 2010 Towards an emotional learning model for intelligent gaming *Proceedings of 2010 IEEE Frontiers in Education Conference*, T3G-1-2
[5] Wang L C, Chen M P 2012 The effects of cognitive-affective interaction strategy on novices' creative performance in game design project *Proceedings of 2012 IEEE 12th International Conference on Advanced Learning Technologies* 549-553
[6] Albrecht S, Wolfgang S 2010 Driving automotive user interface research *IEEE Pervasive Computing* **9**(1) 85-88
[7] Nicole K 1996 Exploratory study of implicit theories in human computer interaction *Proceedings of the 6th Australian Conference on Computer-Human Interaction*, 338-339
[8] Albrecht S 2000 Implicit human computer interaction through context *Personal Technologies* **4**(2&3) 191-199
[9] Andrew W 2005 Multimodal sensing for explicit and implicit interaction *Proceedings of the 11th International Conference on Human-Computer Interaction* 1-10
[10] Wang G J 2010 Distributed vision system for implicit human computer interaction *Journal of Image and Graphics* **15**(8) 1133-1138
[11] Tian F 2007 Research on the implicit interaction characteristic of Post-WIMP user interface *Journal of Frontiers of Computer Science and*

*Technology* **1**(2) 160-169
[12] Wang H 2004 Emotion model based on theory of artificial psychology and numerical simulation *Computer Applications* **22**(S1) 368-370
[13] Luis M B, Helder C 2001 Machinery for artificial emotions *Cybernetics and Systems* **32**(5) 465-506
[14] Miwa H, Itoh K 2003 Introduction of the need model for humanoid robots to generate active behavior *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems* 1400-1406
[15] Wang F, Wang Z L 2005 Affection mathematics model based on the processing of stochastic events *Control & Automation* **21**(3) 101-102
[16] WANG W, WANG Z L 2011 Research on the computational model of emotional decision-making *International Journal of Kensei Information* **2**(3) 167-172

## Authors

**Wei WANG, 1983.11, Handan, Heibei Province, P.R. China**

**Current position, grades:** the lecturer of School of Information & Electrical Engineering, Hebei University of Engineering, China.
**University studies:** received his Ms.Sc. in Control Theory and Control Engineering from Jiangnan University in China. He received his Dr.Sc. from University of Science and Technology Beijing in China.
**Scientific interest:** His research interest fields include Human-robot Cooperation, Implicit Interaction.
**Publications:** more than 30 papers published in various journals.
**Experience:** He has teaching experience of 3 years, has completed three scientific research projects.

**Xiao-dan HUANG, 1983.11, Handan, Heibei Province, P.R. China**

**Current position, grades:** the lecturer of School of Information & Electrical Engineering, Hebei University of Engineering, China.
**University studies:** received her Ms.Sc. in Electronic Information from from University of Science and Technology Beijing in China.
**Scientific interest:** Her research interest fields include Implicit Interaction, Robot.
**Publications**: more than 10 papers published in various journals.
**Experience:** She has teaching experience of 3 years, has completed two scientific research projects.