An Emotional Agent in Virtual Learning Environment

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Abstract. Integrating emotional agent into virtual learning environment is a flourishing research topic to assist the pedagogical applications. However, most of existing emotional agents still lack of a straightforward and understandable computational strategy for both educational experts and developers. In this paper, we integrate an emotional agent into a pedagogical project which uses OCC-based rules to do cognitive appraisal and involves Fuzzy Cognitive Map to do the numerical computation. In this way, the system can not only provide agents flexible reactions in both qualitative and quantitative aspects, but also bring designers an easy-to-use approach.

Keywords: Emotional Agent, Virtual Learning Environment, DINO project, OCC-Based rules, Fuzzy Cognitive map.

1 Introduction

Emotion plays a very important role in people's everyday life. It influences our attention persisting, memory retrieving, decision making, as well as problem solving. Specifically from the perspective of education, emotion also influences the entire learning process. The emotionality of instructors can affect their teaching strategies so that they may provide students different cognitive scaffoldings. Moreover, the interaction quality between learners and instructors/pedagogical systems highly depends on the involved emotional factors. Since education does not merely focus on the final teaching results but the entire teaching process, we should enhance the agent-augmented pedagogical system with emotional agents.

In several existing pedagogical systems [1-3], emotional agent has already been applied. However, these systems still have limitations such as the one-size-fits-all design and the lack of precise computational approach to provide flexible reactions and protean behaviors for agents. To solve these problems, this paper proposes an emotional pedagogical agent which can qualitatively elicit various emotions and quantitatively do the computation in a simple and straightforward approach.

Typical emotional behaviors of a pedagogical agent in a virtual learning environment consist of two categories. One is related to agent's internal feeling due to its own perceptions over environment changes, and the other is related to agent's sympathetic emotions to learners as a feedback of student's performance. The two categories functionally serve different parties, but their emotion eliciting process can be unified. To elicit the emotions, first we use OCC-based rules to analyze conditions and do the

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qualitative cognitive appraisal, and then we use Fuzzy Cognitive Map (FCM) [4] to represent the causal relations and do the quantitative computation. This mechanism can qualitatively analyze what type of emotion needs to be generated, and quantitatively compute the specific intensity of emotions under a certain situation. With the help of this emotional approach, the emotional agent will work as an emotionally believable learning companion for learners during a learning process.

The rest of this paper is organized as follows. In Section 2, we first introduce a pedagogical system developed by our research group called “DINO” and discuss why we need to involve emotional agents in this project. Section 3 specifically describes the emotion qualitative elicitation strategy in our system, and the corresponding quantitative computational approach is presented in Section 4. Section 5 briefly explains how an emotional agent based on the approaches in Section 3 and 4 is integrated into the DINO project. The final section concludes this paper and discusses some future work.

2 Related Work and the Project DINO

Concerning the generation of emotions in agent system, many researchers have been looking for answers from the psychological models of emotions. These models normally use the cognitive conditions to elicit emotions such as the Ortony Clore Collins (OCC) model [5], the Roseman’s cognitive model [6], the Plutchik Robert’s three-dimensional circumplex model [7], and Russell’s circumplex model [8]. As OCC provides a more concise classification of the cognitive generation of emotions, and is easier to be applied in the virtual environment, OCC is more common to be used in this field. However, with all the advantages of OCC it is still hard to be directly integrated in agent design, because there is a gap between the real operation of agent system and the psychological theories.

To bridge this gap, many extensions and applications emerged. In summary, there are five types of extensions to the OCC model: 1) the rule-based emotion inference [9] which directly transforms the elicitation process of OCC into hard coded rules to control agent, 2) the fuzzy logic approach [10] to map elements in OCC, 3) the dynamic decision networks [11] to depict the relationships in OCC, 4) the PAD (Pleasure-Arousal-Dominance) emotional state [12] to measure emotions, and 5) the logical formulization [13] of OCC. Except the first work, the rest research work all can do the quantitative computation, and they used different ways to represent OCC model. However, these models do not have a straightforward representation for educational designers, and if the design has some mistakes it is hard to find out where the problem is. As the research of emotional pedagogical agents is related to cross-disciplinary experts of education and computer science, an easy understanding and simple use of models are very important. For this concern, we propose using FCM to represent OCC model and realize the elicitation of agents’ emotions. Its straightforward formulation and simple computation can meet the designing requirements of a pedagogical agent.

Our proposed approach will be used in a virtual learning environment, the Dino project. The full name of this project is "Serious Immersion and Embodied Learning: Traces of Dinosaurs in Earth System Science"[14]. The main purpose of this project is

Fig. 1. Screen shots of Dino project

to conduct a research and develop an interactive digital media to support learning of geography for secondary school students in Singapore. In the form of an immersive game, interactive virtual worlds with dinosaur agents are created for users to explore. The game is in a 3D virtual world and provides first-person-view for students. A screen shot is shown in Fig. 1.

The learners can enter the present virtual world to collect dinosaur fossils and traverse the "time tunnel" to past world to see the ancient creatures and play with dinosaurs. During performing a series of tasks, students can learn earth knowledge in an open-ended problem-solving space.

In order to trigger students' learning interest and make them engage more time in the earth knowledge study, a learning companion is involved which is an emotional agent as a dinosaur, to interact with students. The emotional reactions of the dinosaur include its own emotional reactions according to the environment (such as fear for the earthquake) and having sympathy for the student (such as feel happy when the student dose well and feel sorry when does not). The benefits of involving emotional agents as a learning companion include three aspects:

1. First, the interesting and attractive emotional responses of the agent can increase the believability of the virtual world and make students have more immersive experiences which attract their interests and bring them deeper remembrances.
2. Secondly, when the emotional agent expresses sympathetic reactions to students, the students can have the feeling of being cared and being thought of. Such experience will encourage them to inquire and explore.
3. Thirdly, since the learning companion usually comes with a cartoon appearance, when it has fancy emotional expressions students may be easily released from learning burden and be more willing to learn.

The details of how to build the emotion generating system will be introduced in the following two sections.

3 OCC-Based Emotion Elicitation

In this paper, we are particularly interested in OCC model, which concisely depicts the classification of emotions under different eliciting conditions. According to the cognitive structure of OCC, we will analyze this process with a rule-based formulization. After this qualitative analysis, we will continue to do the quantitative computations in Section 4.

3.1 Rule-Based Emotion Elicitation

In this part, we will explain how to build up a rule-based emotion elicitation model based on OCC upon a scenario in a virtual learning environment. The OCC model assumes that emotions arise from the evaluation of three aspects of the world, events, agents and objects. The three aspects regard the different valenced reactions of the emotional agent to situations, and are naturally overlapping with each other. Therefore at the beginning of resolving a scenario, the first procedure is to identify from which perspective the causation of emotion is aroused. Subsequently from the corresponding perspective, one continues to decide whether the valenced reaction is focused on consequences for the other or for oneself. This is the general logic flow of OCC to differentiate emotions.

The causation of emotion, denoted as $Emo\_Causation$, belonging to the scenario is an entity which initiates an emotion, an $Emo\_Causation \in \{Event, Agent, Object\}$, where $Event$, $Agent$ and $Object$ are the sets of all possible events, agents and objects across the environment. Among the three groups, event-based emotions are the most complicated, yet they are the ones which most frequently occur in a virtual learning environment. Since virtual worlds are commonly modeled as event-driven (implemented by event listeners), and a virtual agent's behavior is usually considered as a certain reaction to virtual world events, in this paper we only consider cases where $Emo\_Causation \in Event$. However, the eliciting processes of both agent-based and object-based emotions are resembled closely to the proposed approach, and thus are left for the interest of space.

An event at time t is defined as $event_t = \langle event\_content_t, event\_endurer_t \rangle$, where an event with $event\_content_t$ happens to $event\_endurer_t$, and $event\_endurer_t$ belongs to the set of virtual agents. An event with multiple event endurers can always be considered as multiple events with a single endurer, and therefore in this paper a single agent as the event endurer is discussed. The factor, desirability, applies to all event-based emotions, which does not only distinguish an emotion from its opposite within a subgroup, but also influences the computation of emotion intensity. Function $desirable(event_t, Goal) \in \{True, False\}$ returns a boolean value to specify whether an event is desirable in the light of endurer's goal, where $Goal = goalof(event\_endurer_t)$.

Moreover, a virtual agent who is experiencing an emotion is known as Emo_Holder. Note that $event\_endurer_t$ can be the Emo_Holder (consequences for the self) or other agents (consequences for the other). If $event\_endurer_t$ is not the Emo_Holder, subgroup *fortunes-of-others* is raised. Then we need to access the will of Emo_Holder towards $event\_endurer_t$, and define $will(Emo\_Holder, event\_endurer_t) \in \{good\_will, ill\_will\}$ as a function. In this subgroup, emotion is *happy-for* if *desirable* returns true and *will* returns well; *pity* if *desirable* false and *will* good; *resentment* if *desirable* true and *will* ill; and *gloating* if *desirable* false and *will* ill.

If $event\_endurer_t$ is the Emo_Holder, we need to differentiate subgroups according to $prospect\_relevant(event_t) \in \{True, False\}$ which means whether prospects are relevant or irrelevant. If $prospect\_relevant$ is false, subgroup *well-being* is raised, and further emotion is *joy* if desirable or *distress* if undesirable.

By contrast, if $prospect\_relevant$ is true, subgroup *prospect-based* is raised, and include emotion *hope* or *fear* if *desirable* returns true or false. Four more emotions can be elicited by the status of *hope* or *fear* which may be confirmed or disconfirmed: emotion is *satisfaction* if *hope* is confirmed; *disappointment* if *hope* disconfirmed; *fears-confirmed* if *fear* confirmed; and *relief* if *fear* disconfirmed.

Using above primitives and functions, the process of eliciting an emotion of a virtual agent can be implemented, for which inputs are $Emo\_Causation_t \in Event$ and Emo_Holder, and output is the generated current emotion of the underlying emotion holder, $emotion_t$. A sample fragment of rule-based emotion elicitation is illustrated in Fig. 2.

```
queue ← Emo_Causation_t ∈ Event
while (queue != null)
    causation_t = pop − out(queue);
    set Goal = goalof(event_endurer_t);
    get desirablity = desirable(causation_t, Goal);
    if  desirablity = true
        if event_endurer_t = Emo_Holder
            if prospect_relevant(event_t) = True
              ⋮
            else  emotion_t = Joy;
        else
            if will(Emo_Holder, event_endurer_t) = good_will
                    emotion_t = Happy − for;
            else    emotion_t = Resenment;
    else
      ⋮
```

Fig. 2. Sample fragment of rule-based emotion elicitation

3.2 Illustration

To illustrate the soundness of the proposed implementation, we take one scenario as an example to illustrate how to elicit the dinosaur companion's emotion. The following example is related to the dinosaur's sympathetic emotion about the student. In this case, the event does not directly happen to dinosaur. Rather, it is the situation where dinosaur perceives what happens to the learner and generates a type of sympathetic emotion.

Example: Given that a student (ID: studentA) gets a bonus for 100 scores when he/she successfully completed a learning task (event_content ID: event_content001).

Inputs:

1. $Emo\_Causation_t = event_t = \langle event\_content001, studentA \rangle \in Event$
2. $Emo\_Holder = avatarA$, and it is the agent dinosaur.

Details:

1. Get $Goal = goalof(studentA)$ which is $'obtain\_highest\_score'$.
2. Check $desirable(event_t, Goal)$ which returns $True$.
3. Check $prospect\_relevant(\langle event\_content001, studentA \rangle)$ which returns $False$, because getting a bonus has already happened, so it is prospect irrelevant.
4. Since $event\_endurer_t \neq Emo\_Holder$, we need to check the will of the emotion holder to the event endure. As we presume the learning companion dinosaur is a friend of the student, the dinosaur always holds a good will to the student, and $will(Emo\_Holder, event\_endurer_t)$ returns $good\_will$.

Output: $emotion_t = happy\_for$ that the agent is happy for the student getting a bonus.

Quick check: Comparing the event (*event_content ID: event_content001*) and the goal 'obtain_highest_score', we know that the event is desirable. Moreover, the emotion that the dinosaur will have is not related to its internal feeling due to its own perceptions over environment change, but is regarding a learning companion's attitude to the student's performance. As the dinosaur is always pleased to see the student performing well, it will feel happy for the learner when he gets a high score.

From this simple example, we can find that the information required by the eliciting process is non-trivial. But fortunately in a virtual learning environment, a lot of data can be easily collected by the system and used for analysis. However, the rule-based elicitation only returns qualitative results. In order to get the quantitative results for precise agent control, we need another phase—using FCM to compute the intensity of emotions.

4 Computing Intensities of Emotions

Using the OCC-based elicitation rules described in the above section, we are able to find out what emotions the agent will generate according to the current situations in virtual world. However, only identifying what emotions are likely to be is not enough. We also need to compute the specific intensity of emotions to achieve the precise control of agent behaviors. In this section, we will illustrate how to provide a convenient way to transform the OCC-based rules to a computable causal graph, which flexibly depicts the dynamic features and the interactions between emotional elements.

4.1 Using FCM as a Computational Tool for Emotion Modeling

Fuzzy Cognitive Map (FCM) is a fuzzy-graph structure which can simulate the complex systems in the world through causes, effects, and the causal relationships in between. FCM as an efficient fuzzy tool can be defined as a trio (C, R, W), in which $C = \{C_1, C_2, ..., C_n\}$ is the Concept set. Each element, concept, is represented as a node in FCM graph, and the causes and effects are all defined as concepts in this set. $R = \{R_1, R_2, ..., R_m\}$ refers to the Causal Relation set. Each element $R_k = \overrightarrow{C_i C_j}$ refers to the causal relation between concepts C_i and C_j. The relations are represented as arcs in FCM graph. Each causal relation has a weight to depict the influential degree from the former concept to the latter one, and it is defined as $W = \{W_1, W_2, ..., W_m\}$. All weights of the causal relations can be also compactly represented as an element of connection matrix $\mathbf{W} = [w_{ij}]$.

FCM as a fuzzy tool not only has the potential to describe the causal elicitation process of emotions based on emotional theory, but also can do mathematical computations to guide the emotional agent. The advantage of using FCM involves three aspects as follows,

1. FCM represents knowledge in a symbolic manner. The relationship between each concept can be directly signed by inter-linkages. The graphical representation of FCM is convenient for representing the elicitation rules mentioned previously.
2. Besides graphical representation FCM also provides the mathematical way to analyze the problem. Each concept can be defined as a fuzzy set. In addition, the causal strength and the interactive relations can be depicted by weighted values for each connection. The symbolic and numeric transformation in FCM is straightforward.
3. For building a dynamic system, FCM is efficient to describe a complex dynamic process, because FCM makes the complex operation of the whole system transparent through defining the causal relationships merely within each concept pair, while preserving the complex dynamics by iterative calculations. Therefore, no matter how complicated the elicitation process of emotions will be, FCM is a powerful tool for designers to model such processes.

4.2 Integration

In order to use FCM to analyze the dynamic system of emotions and compute the emotion intensities, we need to do three phases of integration. First phase is to map the inputs, outputs, and related concepts of the OCC-based rules into the concept set C of FCM. This phase is to model the rule-based entities as a collection of concepts, and these concepts will then be used to simulate the dynamic process through the causal relationships between them. Therefore, the concepts collected to set C should contain those factors of which numerical values are necessary for computing the intensity of emotions. Based on the OCC theory, the factors (local factors in OCC) affecting the intensity of event-based emotions include

1. the degree of desirability of an event,
2. the degree of belief that an anticipated event will occur (likelihood),
3. the degree to which resources were expended in obtaining or avoiding an anticipated event (effort), and

4. the degree to which an anticipated event actually occurs (realization).

Besides these factors, some other important concepts also need to be drawn into the FCM. These are

1. the impact of the causational event,
2. the impact of reactions of the emotion holder, and
3. the intensity of emotions

where the first factor can reflect the environmental changes of the system, and the second and the third factors reflect the behaviors of the emotional agent.

The second phase, after collecting all the concepts, is to find out the causal relations between these concepts and represent them to set R . In FCM the causal relations are divided into two categories, *positive* and *negative*. The positive causal relation refers to relations for which the increase of the starting concept value may cause the increase of the ending concept value. Conversely, the negative causal relation refers to those by which the increase of starting concept value will cause the decrease of the ending concept value. To precisely describe the quantitative degree of causal relations, each relation or each element in set R is associated with a weight or weight function. The weight values and the concept values generally are real numbers, but sometimes they may use predefined functions to achieve stability or dynamics which provides various feasibilities for modeling a dynamic system.

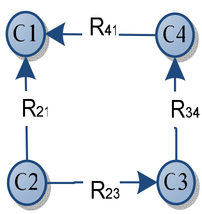

Fig. 3. An Example of FCM

$$W = \begin{bmatrix} 0 & 0 & 0 & 0 \\ w_{21} & 0 & w_{23} & 0 \\ 0 & 0 & 0 & w_{34} \\ w_{41} & 0 & 0 & 0 \end{bmatrix}$$

Fig. 4. The Weight Matrix

In the third phase, we draw the concepts as nodes and connect all the concepts in light of their relations with arcs as shown in Fig. 3. Moreover, we represent the weights of all the relation arcs in a matrix format. If there is no causal relation between two concepts, we define the weight as zero. The example weight matrix for Fig. 3 is given in Fig. 4. With the weight matrix we can use simple linear algebra to do the computation iteratively as $C_{i+1} = C_i \bullet W$. The details will be explained with an example in the case study.

5 Case Study

In this section, we will illustrate how to analyze a scenario with concrete environmental conditions and how to use it to do the intensity computation. We will introduce a simple example which has been used in Dino project.

Example: Given that a learning companion dinosaur called Dilong (ID: avatarA) notices that a giant carnassials dinosaur is coming (event_content ID: event_content002), and Dilong realizes that maybe he is in danger of being eaten by the giant dinosaur.

Analyzing by the rule-based elicitation process we have,

Inputs:

1. $Emo\_Causation_t = event_t = \langle event\_content002, avatarA \rangle \in Event$
2. $Emo\_Holder = avatarA$ and it is the agent dinosaur.

Details:

1. Get $Goal = goalof(avatarA)$ which is $'avoid\_giantDino'$.
2. Check $desirable(event_t, Goal)$ which returns $False$.
3. Check $prospect\_relevant(\langle event\_content002, avatarA \rangle)$ which returns $True$, because being eaten by the carnassials dinosaur is the "prospect" of this learning companion dinosaur.
4. Since $event\_endurer_t = Emo\_Holder$, and because of the undesirability of this event, we straightforwardly come to the conclusion.

Output: $emotion_t = Fear$ that Dilong feels fear when the giant dinosaur is near.

After the qualitative analysis, we generate the corresponding FCM to map the rules. First, collect relevant concepts of FCM. The concepts affecting the intensity of event-based emotions include *desirability*, *likelihood*, *effort* and *realization*. To simplify the situation, we only concern the first two factors, the Dilong's desirability about the event, and the degree of Dilong's belief of being eaten by giant dinosaur. The impact of the causational event is defined as the distance between Dilong and the giant dinosaur. The output concept Emotion is "fear", and the concept Action is a sequence of Dilong's frightened behaviors which controls Dilong's reaction in the application level. To sum up, all the concepts are listed in Table 1.

Table 1. List of FCM Concepts for Dilong

Concepts	Definition
C1 Event	Distance between Dilong and the giant dinosaur
C2 Desirability	Dilong's desirability
C3 likelihood	The degree of Dilong's belief of being eaten
C4 Emotion	Dilong's emotion "fear"
C5 Action	Dilong's frightened actions

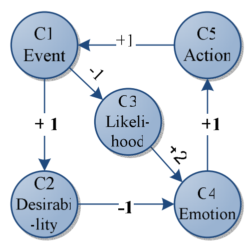

Fig. 5. Simplified FCM for Dilong being eaten situation

According to the distance between the giant dinosaur and Dilong C1, Dilong's desirability C2 is changed correspondingly. At the same time, C1 also affects Dilong's belief of being eaten, the likelihood of being eaten C3. Furthermore, the desirability C2 and the likelihood C3 will together determine Dilong's emotion C4. Emotional state will influence the agent's reaction to the event, and thus Dilong's emotional state C4 will regulate its reaction C5. Finally, this reaction directly changes the distance between the giant dinosaur and Dilong in return. The weights define the degree of the causal effect. Based on the relations between each concept, the FCM is drawn as Fig. 5.

After the graphical FCM is represented, we need to focus on how to do the intensity computation. In light of OCC, this model is related to the emotion "fear". By using the formulation of emotion fear [15], we have $Fear = 2 \times Likelihood^2 - Desirability$. As we have mentioned in Section 4.2, each concept or weight can use a predefined function, and we adopts three functions for concepts C1, C3 and C5 to simulate the causal relations of fear emotion. $C_k^{'}$ denotes the original concept values before passing through the concept function. For C1, the function is $f_{C_1} = C_1^{'} / d_{\max}$, where $d_{\max}$ is the maximum distance defined for cases in the virtual world. By divided by $d_{\max}$, each real distance value between Dilong and giant dinosaur in the system is normalized within 0 and 1.

For C3, the function is defined as $f_{C_3} = \begin{cases} (1-|C_3^{'}|)^2, & C_3^{'} \in [-1,0) \\ C_3^{'}, & C_3^{'} \in [0,1] \end{cases}$. Because the likelihood of being eaten is decreased with the increasing of the distance, we use $(1-|C_3^{'}|)^2$ to keep the value positive.

Concerning C5, it refers to the reaction of Dilong. In this model, Dilong's emotion C4 directly influences its reaction C5. We simply define the variation of reactions is Dilong's running speed

$$v_{Dilong} = (emotion / emotion_{\max}) v_{Dilong\max} = (C_4 / C_{4\max}) v_{Dilong\max}$$

Then, we use function f_{C_5} to define the effect of Dilong's speed on the changes of distance. We assume, during the period of Dilong making running decision, the speed of the giant dinosaur remains the same. Thus we have,

$$f_{C_5} = C_1 - (v_{giantdino} - v_{Dilong}) / d_{\max}$$

With all these functions and the weight matrix, this approach can do the matrix computation with an initial concept vector. There is only one input in the vector, that is, the distance between Dilong and giant dinosaur C1, which can be read from the game engine directly. Given the distance d, the input vector of the five concepts is

$$\begin{array}{cccccc} & C1 & C2 & C3 & C4 & C5 \\ \vec{C_1} = & [\,d & 0 & 0 & 0 & 0\,] \end{array}$$

The matrix computation is an iterative process, and computations for iteration i are summarized as follows,

$$\begin{cases} \vec{C}_i \times \mathbf{W} = \overrightarrow{C'_{i+1}} = \left[C'_{1(i+1)} \quad C_{2(i+1)} \quad C'_{3(i+1)} \quad C_{4(i+1)} \quad C'_{5(i+1)} \right] \\ C_{1(i+1)} = f_{C_1}(C'_{1(i+1)}) \\ C_{3(i+1)} = f_{C_3}(C'_{3(i+1)}) \\ C_{5(i+1)} = f_{C_5}(C'_{5(i+1)}) \\ \overrightarrow{C_{i+1}} = \left[C_{1(i+1)} \quad C_{2(i+1)} \quad C_{3(i+1)} \quad C_{4(i+1)} \quad C_{5(i+1)} \right] \end{cases}$$

We used Matlab to simulate this computation, and got the results as shown below. Given $v_{giantdino} = 10$, $v_{Dilong\max} = 8$, $d_{\max} = 80$ and the initial vector $\vec{C}_1 = [0.9 \;\; 0 \;\; 0 \;\; 0 \;\; 0]$, the computation results are shown as Fig. 6. The figure shows how the distance between giant dinosaur and Dilong changes (blue line), and how the fearful feeling of Dilong changes (red line). When it runs to the 13th round, the distance is 0, and the whole computation terminated meaning Dilong has been caught. If we assume $v_{Dilong\max} = 20$, the corresponding results are given in Fig. 7. It shows that if we change the maximum speed of Dilong as 20, the distance between giant dinosaur and Dilong will reach a steady state at the 34^{th} step. In this way, Dilong will never be caught, and its emotion of fear will remain at a constant level.

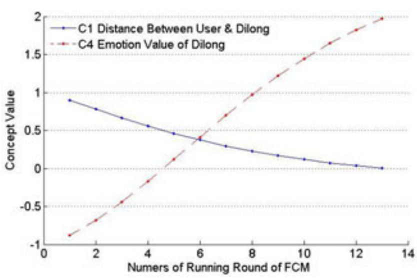

Fig. 6. Simulation1

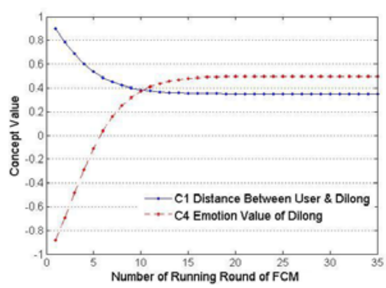

Fig. 7. Simulation 2

From the simulation results we find the relationship between distance and Dilong's fearful feeling, and these emotion values can control the Dilong's emotional expression in virtual world. We can also alter the value of $v_{giantdino}$ in real time and do the computation similarly. In this way we can achieve the adjustment of Dilong's fearful emotions in the virtual world with dynamic changing variables.

From this case study, we can see that this quantitative approach is simple and fast, and owing to FCM's symbolic representation it is very convenient to modify if having any design mistake.

6 Conclusion and Future Work

This paper proposed a practical approach which uses FCM to represent OCC-based emotional rules to bridge the gap between psychological theory and the real operation of agent system. We also examined how this model can achieve the requirements from the qualitative and the quantitative concern. FCM as an efficient fuzzy tool can not only bring a system logical formulization in a straightforward way, but also conduct the simple computation with matrix calculation. For future work, to provide more natural and believable agent behaviors the situation of mixed emotions especially the conflicting mixed emotions should be investigated deeply, and the agent behaviors controlled by the computational results should be made more creative and interesting.

References

1. Johnson, W.L., Rickel, J.W., Lester, J.C.: Animated pedagogical agents: Face-to-face interaction in interactive learning environments. International Journal of Artificial intelligence in education 11(1), 47–78 (2000)
2. Zakharov, K., Mitrovic, A., Johnston, L.: Towards emotionally-intelligent pedagogical agents. In: Woolf, B.P., Aïmeur, E., Nkambou, R., Lajoie, S. (eds.) ITS 2008. LNCS, vol. 5091, pp. 19–28. Springer, Heidelberg (2008)
3. Ortiz, A., Oyarzun, D., Puy Carretero, M.: ELEIN: E-Learning with 3D Interactive Emotional Agents. Springer, Heidelberg (2009)
4. Kosko, B.: Fuzzy cognitive maps. International Journal of Man-Machine Studies 24(1), 65–75 (1986)
5. Ortony, A.A., Collins, A.A.: The cognitive structure of emotions. Cambridge University Press, Cambridge (1988)
6. Roseman, I.J.: Cognitive determinants of emotion: A structural theory. Review of Personality & Social Psychology (5), 11–36 (1984)
7. Plutchik, R.: The nature of emotions. American Scientist 89(4), 344–350 (2001)
8. Russell, J.A.: A circumplex model of affect. Journal of personality and social psychology 39(6), 1161–1178 (1980)
9. Jaques, P.A., Vicari, R.M.: Infering emotions and applying affective tactics for a better learning. In: Agent-based tutoring systems by cognitive and affective modeling, pp. 135–155 (2008)
10. El-Nasr, M.S., Yen, J., Ioerger, T.R.: Flame fuzzy logic adaptive model of emotions. Autonomous Agents and Multi-Agent Systems 3(3), 219–257 (2000)
11. Zhou, X., Conati, C.: Inferring user goals from personality and behavior in a causal model of user affect. ACM, New York (2003)
12. Jiang, H., Vidal, J.M.: From Rational to Emotional Agents. University of South Carolina (2007)
13. Steunebrink, B.R., Dastani, M., Meyer, J.J.C.: A formal model of emotions: Integrating qualitative and quantitative aspects. IOS Press, Amsterdam (2008)
14. Zhang, H.L., et al.: Emotional agent in serious game (DINO). In: International Foundation for Autonomous Agents and Multiagent Systems (2009)
15. Price, D.D., Barrell, J.E., Barrell, J.J.: A quantitative-experiential analysis of human emotions. Motivation and Emotion 9(1), 19–38 (1985)