Modeling Believable Virtual Characters with Evolutionary Fuzzy Cognitive Maps in Interactive Storytelling

Yundong Cai
School of Computer Engineering
Nanyang Technological University
Singapore 639798
cai0004@ntu.edu.sg

Chunyan Miao
Ah-Hwee Tan
School of Computer Engineering
Nanyang Technological University
Singapore 639798
{ascymiao, asahtan}@ntu.edu.sg

Zhiqi Shen
Information Communication Institute
Nanyang Technological University
Singapore 639798
ZQshen@ntu.edu.sg

Abstract

To generate believable virtual characters in real-time is a key issue to improve users' engaging experience in the interactive storytelling. In real life, the emotions and behaviors of characters evolve inductively according to the mutual causal relationships, with some stochastic variations. This is not addressed well in the virtual environment with conventional models, e.g. rule-based expert system, Fuzzy Cognitive Map and so on. In this paper, we use a computational model, namely Evolutionary Fuzzy Cognitive Map (E-FCM), to model the attributes of characters (such as emotions and behaviors) as concepts with the dynamic causal relationships among them. As an extension to FCM, E-FCM models not only the fuzzy causal relationships among the variables, but also the stochastic causal relationships, and asynchronous activity update of the concepts, so that the variables evolve in a dynamic manner with their respective evolving time schedules. As a result, the characters are presented with more realistic and dynamic emotions and behaviors, which enhances the user experience at last.

Introduction

Interactive storytelling in the virtual environment has gained a lot of interests from both industry and academy research as a new genre of interactive entertainment. In Aristotle's *Poetics* (Aristotle 300BC), *character* is the most important factor other than *plot* in a story. People can remember a story easily though a vivid character, such as Hamlet in the drama "Hamlet".

Dynamic and realistic virtual characters are very important for users to gain an immersive or engaging experience. Two most important aspects of character modeling includes: emotion modeling and behavior modeling. Because the characters inhabit and present in the virtual environment, the behaviors and emotions of the virtual characters are evolving in real-time. Prior works (Mateas 1997; Mateas & Stern 2003; Cavazza, Charles, & Mead 2002; Magerko & Laird 2003), have studied believable characters with reasonable planning of their behaviors and the modeling of the behaviors or emotions.

Compared to conventional storytelling, the character modeling in interactive virtual storytelling become complex, which have the following properties:

1. *Complex Causal Relationships*: The causal relationships are complex causal related, which include the mutual causal relationships between the characters and environment and the causal relationship between the emotions and behaviors, especially when the story scenario is complex and in large scale and a lot of context, emotion and behavior variables need to be modeled.
2. *Dynamic*: In order to bridge the experience in virtual world and real world, the emotions and behaviors of characters keep on changing as the story is going on. The characters need to respond rationally to the story changes, and show correctly from the behaviors and emotions.
3. *Randomness*: The virtual characters do not perform in a deterministic way always. There are some stochastic behaviors of the variables.

Currently, there have been a lot of researches done on modeling the dynamic causal relationships among a set of variables, e.g. rule-based expert system, Fuzzy Cognitive Maps etc. Fuzzy Cognitive Map (FCM) (Kosko 1986) by Kosko is an efficient inference engine to model such complex causal relationships. Kosko and Dickerson (Dickerson & Kosko 1994) also make a simple study to model the characters (Fish, Shark etc) in a virtual world. However, as a generic model, FCM is not powerful or robust enough to model a dynamic and evolving virtual world. Based on FCM, numerous extensions are proposed to enhance its capabilites. Miao et. al. (Miao, Liu, & Miao 2001) proposed Dynamic Causal Network to model the concepts quantitatively with time variables. Moreover, the causality between two variables might be probabilistic rather than deterministic, beyond the fuzziness. Song et. al. (Song *et al.* 2006) proposed probabilistic events to model the uncertain concepts. In order to describe the general rule-based (AND/OR) inference, rule-based FCM is also proposed (Carvalho & Tom 2000). In addition, Evolutionary Multilayered Fuzzy Cognitive Maps (ECNFCM) (Mateou, Andreou, & Stylianou 2006) is also proposed as an inference tool for a real-time system with evolutionary strategy. However, the models above are mostly used as inference engines rather than real-time simulation modeling. Currently, there is not a solution that combines all the above features of the FCM extensions in order to model real-time character variables, e.g. behaviors and emotions.

Cai et. al. (Cai *et al.* 2008) proposed Evolutionary Fuzzy Cognitive Map (E-FCM), which models the system simulation more precisely and completely. In E-FCM, each concept not only has its value, but also has an evolving time schedule (as different concepts update asynchronously), and has a small self-mutation probability. The causality between two concepts is not just a fuzzy value, a probability value is used to constrain the possibility of causality. As a result, E-FCM is able to simulate the real-time states with uncertainty behaviors.

In this paper, we use Evolutionary Fuzzy Cognitive Maps (E-FCM) to model the dynamic character variables (emotions and behaviors) and their respective causal relationships. Each variable updates its value asynchronously in response to the changes of the causal concepts, subject to the causal probabilities. As a result, the model presents the real-world character more intimately with believable behaviors and emotions, which enhances the user experience in the interaction eventually.

Character Modeling in the Interactive Storytelling

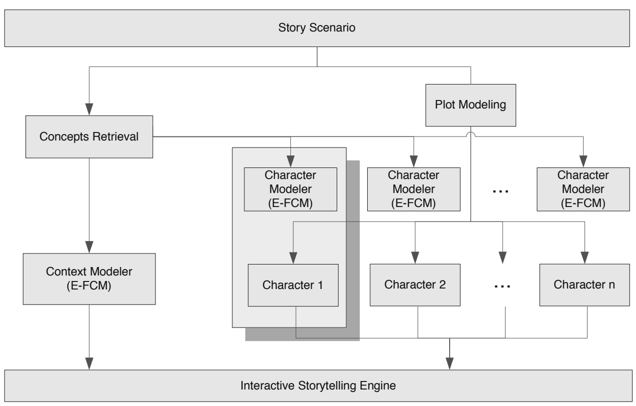

Figure 1: Interactive Storytelling Architecture

Figure 1 shows our interactive storytelling architecture, which is composed of several components:

1. Story Scenario: It denotes the original text-based story scenario.
2. Concept Retrieval: It retrieves the interested variables from the story scenario. For the characters, the variables include the emotions (sad, happy etc.), behaviors (walk, sleep, rest etc.) and characteristics (age, gender, personality etc.). For the contexts, the variables include the background, time, place, objects and so on.
3. Context Modeler: It models the real-time simulation of the context variables which are retrieved from the story scenario. It aims to build an immersive eco-system that the virtual agents inhabit. Some context variables might affect the interactions of user and virtual character behaviors in real-time. For example, when the weather changes from sunny to rain, the virtual character needs to find an umbrella before going out.
4. Plot Modeling: It constructs the story plot from the story scenario. Then the plot will be assigned to the characters to perform.
5. Character Modeler: It models the real-time simulation of the virtual character, which includes the emotion modeling and behavior modeling. For example, “the little red riding hood” goes to grandma’s house. Once it is closer, she becomes happier. However, when the “wolf” appears, she becomes less happier. Same as the changeful emotions, the behaviors of character change in real-time in correspondence with the stimulus. For example, when the “wolf” is near, the “little red riding hood” expects to run away.
6. Character: It represents a virtual character which is involved in the story.
7. Interactive Storytelling Engine: It represents the low-layer engine to support the graphics, artificial intelligence etc.

In this paper, we are focusing on the character modeling with the Evolutionary Fuzzy Cognitive Map (E-FCM).

Evolutionary Fuzzy Cognitive Map (E-FCM) at Character Modeling

Based on conventional Fuzzy Cognitive Map (FCM), Cai et. al. proposed an evolutionary extension which monitored the real-time variable states, named as Evolutionary Fuzzy Cognitive Map (E-FCM), and used it to model the dynamic and real-time complex causal-related context variables (Cai *et al.* 2008). The main consideration of E-FCM is to simulate every temporal/real-time state of the system, which is named as *Evolving State* specifically in the model. In the interactive storytelling, the real-time emotions and behaviors are expected to evolve rationally.

Figure 2 shows an overview of E-FCM structure. The

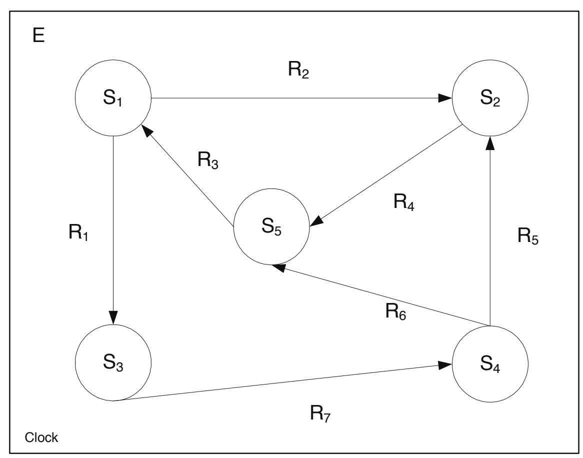

Figure 2: Evolutionary Fuzzy Cognitive Map Structure Overview

bounding box shows the enclosure (E) of the scenario or system, which is comprised of all the variables and causal relationships. *Clock* is the reference time for the update of the variables, which is not mentioned in FCM. E-FCM model is constructed with two main components: *concepts* and *causal relationships*.

Concepts

Concepts represent the interested variables involved in the real-time system. Concepts can be expressed as a tuple of properties:

$$S = [S_V, T, P_s] \tag{1}$$

where S_V denotes the fuzzy value of the concept, which is same as FCM. For simplicity, it uses a real value from [-1, 1] or [0, 1]. As different concepts have different unit scale, the concept value is represented as a relative scale over the concept standard value.

To model the character in the interactive storytelling, the emotions and behaviors are the concepts which need to be retrieved from the scenario first. Take the story "Little Red Riding Hood" for example, the concepts might include: emotions ("happy", "scared", "hesitated"), behaviors ("walk", "escape", "call help", "collect mushroom"), and the related external contexts ("wolf near", "grandma near", "weather", "daytime").

The value of the concept is a qualitative description, which ranges from 0 to 1. Take the emotion "happy" for example, if its value is 0, it means "the character is not happy at all"; if the value is 1, it means "the character is very happy"; and if the value is 0.5, it means "the character is somewhat happy".

State Evolving Time Schedule In real-time, different variables evolve in different time schedules, i.e. update times. In E-FCM, all variables update their states according to their respective evolving time schedules with reference to a global clock. For a system with N variables, it can be represented as a vector $\mathbf{T}$:

$$\mathbf{T} = \begin{pmatrix} t^1 \\ t^2 \\ \vdots \\ t^i \\ \vdots \\ t^n \end{pmatrix} \tag{2}$$

where t^i denotes the evolving time schedule of variable i.

In some computer games, a "tick" is used as a time base to update the events. In our model, the evolving time schedule is calculated as number of "ticks". In the storytelling, a commonly used "tick" is 1 second, then we can assume that the refreshing rate for the emotions is 2 "ticks", i.e. they update for every 2 seconds. The refreshing rate for the behavior "runaway" is 1 tick, as the "little red riding hood" acts quite fast to the context changes, e.g. when the "wolf" is near.

State Mutation Besides the causal effects from other variables, each variable might alter its internal state randomly in real time, as it is observed that objects in the real world presents the stochastic behaviors often. This is modeled with a very small mutation probability, i.e. the probability of self-mutation. For a system with N variables, it can be represented as a vector $\mathbf{P_s}$:

$$\mathbf{P_s} = \begin{pmatrix} p_s^1 \\ p_s^2 \\ \vdots \\ p_s^i \\ \vdots \\ p_s^n \end{pmatrix} \tag{3}$$

where p_s^i shows the self-mutation probability of the variable i.

In the simulation, the probability value used would be normally less than 0.1. The experiments of evolutionary algorithm show that the system becomes unstable when it is greater. To model the characters in the storytelling, normally we put 0 for those variables that are stable in the scenario. For variables that might not so stable, e.g. emotions, we can set a small value to simulate it.

Causal relationship

Causal relationship R represents the strength and probability of how much effect one concept has on the other concept. It can be expressed as the following tuple:

$$R = [W, S, P_m] \tag{4}$$

Fuzzy Causal Relationships The causal relationship between two variables, i.e. how much one variable affects the other variable, is defined as a fuzzy value. For example, the increase of "unemployment" would cause the increase of "inflation" greatly. Some fuzzy terms are often used to describe the strength, e.g., "none", "very little", "little", "nearly same", "much" and "greatly". For a system with N variables, the fuzzy causal relationships of the system can be represented as a $N \times N$ weight matrix $\mathbf{W}$:

$$\mathbf{W} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{i1} & w_{ij} & \cdots & w_{in} \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix} \tag{5}$$

where the rows indicate the index of the causal concepts, and the columns indicate the index of the consequence concepts. The item w_{ij} means the fuzzy weight of how much the variable i affects the variable j, which is in the range of [0, 1]. A higher value of w_{ij} shows a stronger causal impact.

S shows whether the causal relationship is positive (+ve) or negative (-ve), which represents, the increase of input will lead to the increase/decrease of output respectively. It is usually combined into W at the computation.

Normally, the weight w_{ij} is determined by the expert or weighted sum of experts. However, if there are training datasets for the variables, the authors also propose the causal weight as the statistical correlation of the input data (changes of the causal variable) and output data (changes of the consequence variable in the next sequence), which is shown as the following formula:

$$w_{ij} = \frac{Cov(i,j)}{\sqrt{var(i) \times var(j)}} \tag{6}$$

where, $Cov(i,j)$ is the co-variance of changes of variable i and variable j, $var(i)$ is the variance of variable i and $var(j)$ is the variance of variable j.
In the character modeling, it is most important to find the causal relationships between any two variables. For example, the increase of "the wolf near" causes the decrease of "the little red riding hood been happy" greatly. The appropriate of the causality from "the wolf near" to "the little red riding hood been happy" would be -0.8. By tuning the fuzzy weight, the impact might vary in the simulation accordingly.

Probabilistic Causal Relationships The dynamics of the system variables can be twofold: fuzziness and probability (Marc Parenthoen 2001). The uncertainty of the causality can be computed as the conditional probability of one event over another event. Some terms can be used, e.g. "never", "sometimes", "often" and "always" etc. FCM has mentioned the terms but fails to define them in the model. For a system with N variables, it can be represented as a $N \times N$ matrix $\mathbf{P_m}$ ($\mathbf{P_m}$ denotes the causal probability):

$$\mathbf{P_m} = \begin{pmatrix} p_{1\to1} & p_{1\to2} & \cdots & p_{1\to n} \\ p_{2\to1} & p_{2\to2} & \cdots & p_{2\to n} \\ \vdots & \vdots & \ldots & \vdots \\ p_{i\to1} & p_{i\to j} & \cdots & p_{i\to n} \\ \vdots & \vdots & \ldots & \vdots \\ p_{n\to1} & p_{n\to2} & \cdots & p_{n\to n} \end{pmatrix} \tag{7}$$

where the rows indicate the causal concepts, and the columns indicate the consequence concepts. The item $p_{i\to j}$ means the conditional probability of how the change of variable i causes the change of variable j, which can be calculated as

$$p_{i\to j} = P_{ij}/P_i \tag{8}$$

where, P_{ij} is the probability that both the changes of causal concept i and consequence concept j happen and P_i is the probability that the causal concept i happens.
P_m denotes the probability that the causal concept affects the consequence concept, as the causal relationship is not certain, but some of probabilities.
The causalities are not guaranteed to be there in the real world. "The wolf near" might not decrease "the little red riding hood been happy" always, but with a high likelihood. A causality probability 0.8 can be used to describe it. Higher the probability is, more likely the causality will work in the simulation.

Pseudo-code of Running E-FCM in Real-Time

Here is the pseudo-code for running the E-FCM in real-time.

Some terms as used in the pseudo-code are defined as follows.

Algorithm 1 E-FCM(n)

Require: Global clock t
1: Extract the relevant concepts into $concept\_list$
2: **for all** $Concept_i$ in $concept\_list$ **do**
3:     **if** $Concept_i$ at Update time, i.e $t\%T_i = 0$ **then**
4:         Update the concept value as
5:         $S_i^{t+T} = f(k_1 \cdot \sum_{j=0}^{n} \Delta S_j^t \cdot w_{i,j} + k_2 \cdot \Delta S_i^t)$ //addition subject to probability
6:         $S_i^{t+T} = S_i^t + \Delta S_i^{t+T}$ //self mutation with probability
7:     **end if**
8:     $t \Leftarrow t+1$
9: **end for**

1. $f(\cdot)$: the activation function to regulate the state values, e.g. bipolar, tri-polar and logistics.
2. Variable State S_i^t: state value for the concept variable i at time t.
3. Variable State Change ΔS_i^t: state value change for concept variable i at time t.
4. Evolving Time Schedule T: time for concept i to update its value. Different concept may have different evolving time.
5. Time Slice t_0: an atomic time slice to update all the variables.
6. k_1 and k_2 are two weight constants.

Here, the summation of $\Delta S_j^t \cdot w_{i,j}$ is subjected to the conditional probability P_m^j, and the summation of ΔS_i^t is subjected to the self-mutation probability P_s.

An Example

To illustrate the character modeling with E-FCM, a sample story, namely "Mystery of Village", is implemented.

> "...The protagonist John comes to a village for investigation of environment. People are sick due to some unknown diseases. He needs to visit the village, talk to people around and find some clues."

In order to achieve a believable "John", the following variables need to be modeled: how "John" is affected by the environment, e.g water, mosquito, how the emotion of "John" changes as story is going on. To describe the elements in the scene, a E-FCM is constructed in Figure 3. A total of nine concepts are extracted in the scenario, which update in real-time:

C_1: Polluted Water

C_2: Dirty

C_3: Mosquito

C_4: Energy

C_5: Walk Speed

C_6: Happy

C_7: Get Food

C_8: Clean

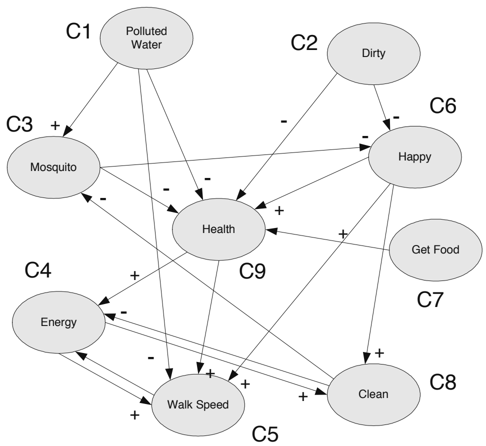

Figure 3: Character Model of “John”

C_9: Health

Among the concepts, C_1 to C_3 are context variables that will affect the character’s attributes and can be changed by the character. C_4 to C_9 are the character variables, including properties (energy and health), emotion (happy) and actions (walk, get food and clean), which are the main concern of this paper.
The weight matrix and the conditional probability matrix of the causal relationship are determined with experts’ knowledge as shown in Table 1 and 2 respectively.

Take t_0 as an unit of evolving time, the evolving time schedules of the nine variables are initialized as

$$(1 \quad 4 \quad 1 \quad 1 \quad 2 \quad 3 \quad 2 \quad 3 \quad 1)$$

Suppose the initial scenario is, ”there are polluted water and dirties around the place, but no mosquitoes are found. John comes to the village with full of energy and health.” Then, the state vector representing the concepts $C_1, ..., C_9$ is encoded as

$$(1 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 1)$$

Figure 4 (b)-(d) show the transitions of concepts C_4 to C_9 evolving at individual schedules with E-FCM. As shown, the concepts update their values asynchronously. Moreover, with the same initial vector, the state vectors are evolving differently in different round of experiments, due to the involvement of probabilistic causalities. For each round, the concept states cover most combinations of the whole state vector space. Comparatively, we also model the variables with Fuzzy Cognitive Map with the same weight matrix by ignoring the evolving time steps and the probability causal relationship. The results are shown in Figure 4(a). Different from E-FCM, “steps” is used to describe the time as all the states update at the same time. It is shown that, the variables reach the equilibrium state quickly, with the same sequence of state vectors in different round of experiments.
We implement the story with Torque Game Engine. Two screenshots are taken in the first run as shown in Figure 5.

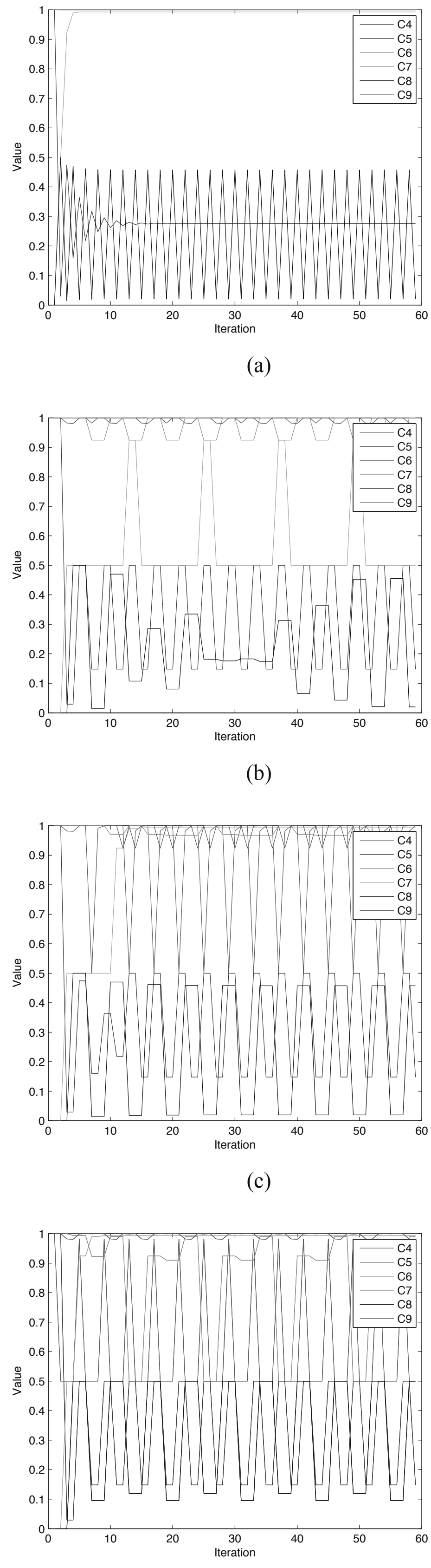

Figure 4: (a) Runs with FCM (b) First Run with E-FCM (c) Second Run of E-FCM (d) Third Run of E-FCM

W_{ij}		j								
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
i	C_1	0	0	0.6	0	-0.4	0	0	0	-0.8
	C_2	0	0	0	0	0	-0.5	0	0	-0.8
	C_3	0	0	0	0	0	-0.8	0	0	-0.9
	C_4	0	0	0	0	0.8	0	0	0.8	0
	C_5	0	0	0	-0.7	0	0	0	0	0
	C_6	0	0	0	0	0.5	0	0	0.5	0.7
	C_7	0	0	0	0	0	0	0	0	1
	C_8	0	0	-0.9	-0.8	0	0	0	0	0
	C_9	0	0	0	0.5	0.8	0	0	0.6	0

Table 1: Weight Matrix of Causal Relationships

P_{ij}		j								
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
i	C_1	0	0	0.8	0	0.2	0	0	0	0.9
	C_2	0	0	0	0	0	0.5	0	0	0.8
	C_3	0	0	0	0	0	0.5	0	0	0.8
	C_4	0	0	0	0	0.8	0	0	0.7	0
	C_5	0	0	0	0.4	0	0	0	0	0
	C_6	0	0	0	0	0.6	0	0	0.5	0.6
	C_7	0	0	0	0	0	0	0	0	0.9
	C_8	0	0	0.8	0.7	0	0	0	0	0
	C_9	0	0	0	0.3	0.8	0	0	0.6	0

Table 2: Condition Probability Matrix of Causal Relationships

Initially, the character is in good health when he is far away from the dirty water; the second picture shows that the health level drops when the avatar approaches the dirty water and the mosquitos. Different from traditional rule-based modeling, the variables are evolving even when no rules are executed, which presents a more dynamic picture of the virtual world and the character is more believable.

Discussions

Fuzzy Cognitive Map shows the long term result, which is useful as an inference tool; while E-FCM focuses on the real-time simulation, which is flexible to model real-time behaviors and emotions of characters easily.
Compared to FCM, E-FCM has the following improvements to character modeling in interactive storytelling:

1. It allows a different update time schedule for each variable. For example, “actions” may change fast than “emotions”.
2. It enables the self mutation of the context variables, which presents dynamics of character as evolving behavior.
3. It involves the probabilistic causality among the variables, which reflects more realistic relationships among the concepts, and adds more stochastic behaviors to the character as a result, i.e. not in a deterministic way.

Though E-FCM is quite similar to some extensions for FCM with the concepts of evolving strategy and probability, E-FCM models the entire process of emotion and behavior evolution as a simulation engine. Therefore, the evolution of the state vectors are the main concerns rather than the

(a)

(b)

Figure 5: Screenshots at First Run (a) Avatar with Full Health (b) Avatar with Decreased Health with Dirty Water and Mosquito Nearby

equilibrium state vectors, as each evolving time state shows a state of the system in real-time. This is important for describing a believable virtual environment, and for the intelligent agents to make instant decision making.
Currently, though E-FCM tries to model all the factors of uncertainty in a real-time system, e.g., probability, fuzziness and evolution, it still has some limitations. Firstly, the causalities are determined subjectively by the experts or there are no datasets available to get the values. It increases the difficulties to build a complex system. When new concepts are introduced into the system, the experts need to give values for all the related causal fuzzy weights and causal probabilities. Secondly, the causalities among the concepts are linear according to the fuzzy weights, which needs to be extended to non-linear, in order to represent some real-time system correctly.

Conclusions

In this paper, Evolutionary Fuzzy Cognitive Map (E-FCM) is used for the first time, to model the dynamic variables of virtual characters (emotions and behaviors) in the interactive storytelling. Beyond the fuzzy causally relationships as in FCM, the probabilistic causal relationship among the variables are modeled, and the variables update their states with respect to individual time schedules. By modeling the dynamic variables in the interactive storytelling, more dynamic and realistic characters are presented, which might provide users a more immersive experience. In the future, we will strengthen the theoretical foundation of the model and explore new automatic learning methods of the weight matrix and the probability matrix from the online storytelling process.

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