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Citation

CAI, Yundong; MIAO, Chunyan; TAN, Ah-hwee; and SHEN, Zhiqi. Context modeling with evolutionary fuzzy cognitive map in interactive storytelling. (2008). *2008 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE): Hong Kong, June 1-6: Proceedings*. 2320-2325.

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Context Modeling with Evolutionary Fuzzy Cognitive Map in Interactive Storytelling

Yundong Cai, Chunyan Miao, Ah-Hwee Tan and Zhiqi Shen

Abstract—To generate a believable and dynamic virtual world is a great challenge in interactive storytelling. In this paper, we propose a model, namely Evolutionary Fuzzy Cognitive Map (E-FCM), to model the dynamic causal relationships among different context variables. As an extension to conventional FCM, E-FCM models not only the fuzzy causal relationships among the variables, but also the probabilistic property of causal relationships, and asynchronous activity update of the concepts. With this model, the context variables evolve in a dynamic and uncertain manner with the according evolving time. As a result, the virtual world is presented more realistically and dynamically.

I. INTRODUCTION

In recent years, interactive storytelling in the virtual environment has gain a lot of interests from both industry and academy research. To generate a believable and dynamic virtual world becomes a great challenge, which affects the immersive experience of users as well as the context awareness property to be realized for the intelligent agents. Context awareness is one of the most important characteristics of an intelligent agent. It means that an agent is able to make reasonable actions according to the context changes. For interactive storytelling in the virtual environment, the contexts become more dynamic and complex, so the modeling of contexts is more challenging. As context changes are reflected in the virtual environment directly, incorrect context update might affect the user's experience over the entertainment seriously. Therefore, an effective and efficient context modeling is very important in order to achieve both character believability and environment believability in the interactive storytelling. Moreover, how to make the virtual world evolve rationally and dynamically is very challenging. Currently there are a lot of researches done to model the dynamic causal relationships among the context variables, e.g. Cognitive Maps [1], ontology-based context modeling[14] etc. However, how to measure the causal relationships among the variables quantitatively is not addressed well. Fuzzy Cognitive Map (FCM) [4] is one efficient inference engine to model such complex causal relationships by Kosko based on Cognitive Maps. Kosko and Dickerson [3] also use it to model a virtual world by keeping on updating the involved activities. However, as a generic model, FCM is not powerful or robust enough to model a more dynamic and

evolving virtual world. Based on FCM, a lot of extensions are proposed. In a real situation, different context variables might change in different schedules. Take an example of “flower in the rainy day”, the causal variable *rain*'s update time is 1 second, while the effect variable *flower*'s update time is 1 hour. Miao et. al. [12] propose 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.[15] proposes probabilistic causal relationships among concepts in a system. In order to describe the generous rule-based (AND/OR) inference, rule-based FCM is also proposed[2]. Evolutionary Multilayered Fuzzy Cognitive Maps (ECNFCM)[7] 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 modeling tools, and currently there isn't a solution that combines all the above features of the FCM extensions in order to model real-time context variables.

In this paper, we propose a model, namely Evolutionary Fuzzy Cognitive Maps (E-FCM), to model the evolving process of dynamic context variables. The model is built up upon the basic Fuzzy Cognitive Map (FCM), but with the following differences. Each state will not update at the same time, but at its own evolving time asynchronously. The causality between two variables is both probabilistic and fuzzy. Moreover, each state variable will evolve itself with certain probability. As a result, the model presents the real-world situation more intimately, which enhances the user experience eventually. In an interactive storytelling, it models evolution of the context variables' states in a virtual world as in the real time.

The paper is organized as below. Section 2 will illustrate the elements of Evolutionary Fuzzy Cognitive Maps model with comparison to conventional FCM. Then how E-FCM can be adopted in the context modeling will be shown in Section 3. An example scenario is also demonstrated to shows its advantages over FCM.

II. EVOLUTIONARY FUZZY COGNITIVE MAP (E-FCM)

Evolutionary Fuzzy Cognitive Map (E-FCM) is based on conventional Fuzzy Cognitive Map (FCM). “Evolutionary” means that each state is evolving, based on its internal mental state, as well as external causalities. The causalities are non-deterministic in a real-time situation: fuzzy and probabilistic. Moreover, different from FCM, E-FCM updates the concepts' internal mental states asynchronously rather, and updates mental states with a small mutation probability.

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A. Fuzzy Cognitive Map (FCM)

Fuzzy Cognitive Map (FCM) is a kind of qualitative modeling tool proposed by Kosko[4]. It provides a simple and straightforward way to model causal relationships among different factors. Currently, FCM has been widely used in many applications. Kosko and Dickerson[3] use FCMs to model the hunting process among sharks, dolphins and fishes. In [6], the author uses FCMs to model the intentions/movements of the sheepdog and sheep in the virtual world. In our previous work, FCMs have been used as agent knowledge models in different application domains([5], [8], [9], [10]). Besides conventional FCM, extensions are proposed to improve the capability of FCM, e.g. Rule-based FCM[2], PFCM[15], Dynamic Cognitive Network[12], Evolutionary Multilayered Fuzzy Cognitive Maps (ECNFCM)[7] and so on. Relationships between extended FCM models have also been studied([11], [13]).

FCM includes two elements: *concepts* and *causal relationships*. An example is shown in Figure 1. *Concepts* are represented as circles, which denote the related causes and effects in the model. The concepts are represented as fuzzy values. The *causal relationships* are represented as directed arcs, each of which has a sign and a weight. The sign shows the causal relationship between two concepts, which is compulsory. The '+' sign means 'positive causal relation', in which the increase of the starting concept value will cause the increase of the ending concept value. The '-' sign means 'negative causal relation', in which the increase of starting concept value will cause the decrease of the ending concept value. For example, increase of 'bad weather' causes increase of 'freeway congestion'; on the other hand, 'freeway congestion' causes decrease of 'own driving speed'. The weights differentiate the significance levels of causality from the start concept to certain end concept, and they are represented as fuzzy terms also. For example, 'bad weather' usually causes 'auto accidents'. The term 'usually' is a fuzzy item to describe the level of significance. If there is no arc linking two concepts, it means that there is no causal relationships between the two concepts, i.e. the two concepts are independent. A Fuzzy Cognitive Map represents a knowledge base in a domain about how concepts relate to each other. Knowledge from different experts can be accumulated through combining several FCMs into a big FCM, which is done by merging same concepts. Fuzzy Cognitive Map provides qualitative information about the relationships. It ties facts, things, processes to values and policies and objectives, which allows to predict how complex events interact and play out.

To facilitate the analysis of FCM, each concept is represented as a state value whose range is $[0, 1]$ or $[-1, 1]$, while the causal relation is represented as a weight, whose range is $[-1, 1]$. Suppose the current value of concept i is S_i , its new value can be updated as

$$S_i^{t+1} = f(k_1 \sum_{j=0}^n S_j^t \cdot w_{i,j} + k_2 \cdot S_i^t) \quad (1)$$

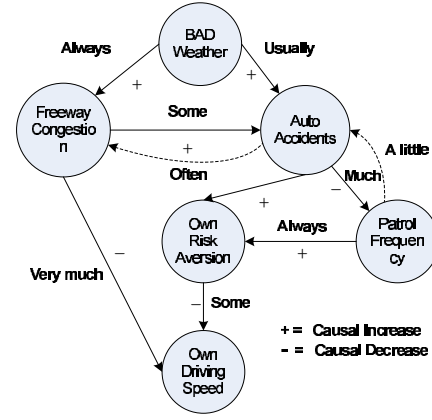


Fig. 1. Sample Fuzzy Cognitive Map [4]

where $f(\cdot)$ is the activation function and S_j is the state value vector. As there might be loops involved in the FCM, the values of concepts will evolve to an equilibrium point or a limited cycle in long run.

However, currently FCMs and its extensions are mostly used or studied as an inference engine to anticipate the result of a system in long-run, to check the equilibrium state or cycle. Fast convergence and less inference steps are the main research points for FCM and a lot of extensions of it. In the inference process, the intermediate states are missed or neglected. However, the intermediate states are actually quite important in some case, especially in real-time systems, as each real-time state provides the basis for system execution. Take interactive storytelling as an example, an intelligent agent might not be so sophisticated to make a long-run decision but an instant one with the current state.

Moreover, conventional FCM has some limitations. The states will converge to same state vector, whatever the initial vector is, i.e. the equilibrium state or cycle is determined by the weight matrix only. This can not be explained well in the real-life situation.

B. Model Description of E-FCM

The main consideration of E-FCM is not the equilibrium/final state or cycle, but each and every temporal/real-time state of the system. The temporal state is keen to real-time evaluation of the system. In our system, we name it as *Evolving State*.

A sample of E-FCM is depicted in Figure 2. *E* shows the environment of the system, which is the closure of all the context variables and other relevant information. *Clock* is the reference time for the update of the context variables, which is not mentioned in FCM.

Compared to conventional FCM, E-FCM is also constructed with two main components: *concepts* and *causal relationships*, but with more restrict definitions. Each concept represents a variable involved in the system. It can be

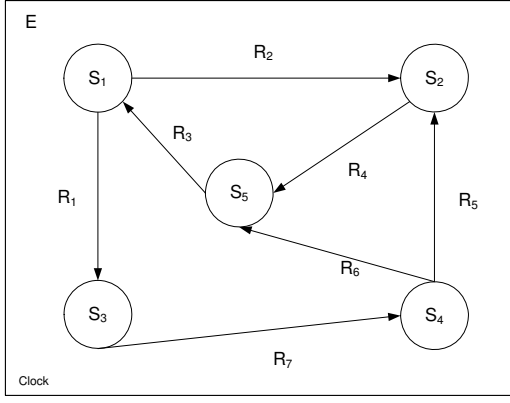


Fig. 2. Evolutionary Fuzzy Cognitive Map Structure

expressed as a tuple:

$$S = [S_V, T, P_s] \quad (2)$$

Here, S_V denotes the state value of the concept, which is a fuzzy value. For simplicity, it uses a value from $[-1, 1]$ or $[0, 1]$. T denotes the evolving time for the concept. For simplicity, T represents a multiple of a fixed time slice t_0 . P_s denotes the probability of self mutation.

The 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:

$$R = [W, S, P_m] \quad (3)$$

Here, W denotes weight matrix of the causal relationship, whose values are in the range of $[0, 1]$. S shows whether the causal relationship is positive (+ve) or negative (-ve). P_m denotes the probability that the causal concept affects the result concept.

Different from the description of FCM, E-FCM includes: fuzzy causal relationships of concepts, probabilistic causal relationships of concepts and self mutation of concepts.

1) *Fuzzy Causal Relationships*: The causal relationship between two variables is fuzzy, i.e. how much one variable will affect the other variable. Some fuzzy terms are used, e.g., “much”, “a little”. 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} :

$$\mathbf{W} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{i1} & w_{ij} & \cdots & w_{in} \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix} \quad (4)$$

Here, the row is the “cause-from” concept, and the column is the “cause-to” concept. The item w_{ij} means the fuzzy weight of how much variable i causes variable j .

2) *Probabilistic Causal Relationships*: The uncertainty of the system variables can be twofold: fuzziness and probability [6]. The uncertainty is the conditional probability of one event over another event. Some terms can be used, e.g. “always”, “often”. For a system with N variables, it can be represented as a $N \times N$ matrix \mathbf{P}_m (\mathbf{P}_m denotes mutual causal probability):

$$\mathbf{P}_m = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ p_{i1} & p_{ij} & \cdots & p_{in} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix} \quad (5)$$

Here, the row is the “cause-from” concept, and the column is the “cause-to” concept. The item p_{ij} means the conditional probability of how much variable i causes variable j .

3) *State Evolving Time*: Different variables might have different evolving time, i.e. update time. With a system defined reference clock, all variables update their states according to their own evolving time. For a system with N variables, it can be represented as a vector \mathbf{T} :

$$\mathbf{T} = \begin{pmatrix} t^1 \\ t^2 \\ \vdots \\ t^i \\ \vdots \\ t^n \end{pmatrix} \quad (6)$$

Here, t^i shows the evolving time of variable i .

4) *State Mutation*: Besides the causal effects from other variables, each variable will also alternate its internal state randomly in real time. It is modeled with a very small mutation probability. If the probability is big, the system would become very unstable. For a system with N variables, it can be represented as a vector \mathbf{P}_s :

$$\mathbf{P}_s = \begin{pmatrix} p_s^1 \\ p_s^2 \\ \vdots \\ p_s^i \\ \vdots \\ p_s^n \end{pmatrix} \quad (7)$$

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

5) *State Update*: The variables in a system will update their states in their respective evolving time. The state value of concept i is updated according to the following formulas:

$$\begin{cases} \Delta S_i^{t+T} = f(k_1 \cdot \sum_{j=0}^n \Delta S_j^t \cdot w_{i,j} + k_2 \cdot \Delta S_i^t) \\ S_i^{t+T} = S_i^t + \Delta S_i^{t+T} \end{cases} \quad (8)$$

Some terms which are defined in the model:

- 1) $f(\cdot)$: the activation function to regulate the state value, e.g. bipolar, tri-polar and logistics.

- 2) Variable State S_i^t : state value for 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 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 context variables.
- 6) k_1 and k_2 are two weight constants.

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

III. CONTEXT MODELING WITH E-FCM

Stories are meaningful only when certain contexts are defined. The context determines the story plot and characters performance. A dynamic and realistic virtual environment is very important for users to gain an immersive or engaging experience. The context variables of the virtual world are evolving all the time with different schedule. For interactive storytelling in the virtual environment, the contexts become complex, which have the following properties:

- 1) *Multiple Domains*: there are contexts about virtual environment, about story background, about character information etc.
- 2) *Dynamic*: the contexts keep on changing as the story is going on.
- 3) *Randomness*: the virtual world doesn't run in a deterministic way. There are some randomness of the variables.

A. An Example

A story scene of "Little Red Riding Hood" was illustrated as an example. In the scene, the little red-riding hood meets the wolf in the forrest. The wolf is very hungry, and wants to eat the food prepared by little red-riding hood, otherwise, to eat little red-riding hood. To describe the elements in the scene, a E-FCM is depicted in Figure 3. Within the scenario,

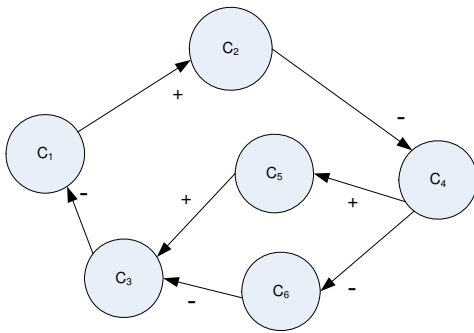


Fig. 3. Little Red Hood

6 concepts are involved, which update in real-time:

- C_1 : Little Red Riding Hood is very happy.

W_{ij}		j					
		C_1	C_2	C_3	C_4	C_5	C_6
i	C_1	0	1	0	0	0	0
	C_2	0	0	0	-1	0	0
	C_3	-1	0	0	0	0	0
	C_4	0	0	0	0	1	-1
	C_5	0	0	1	0	0	0
	C_6	0	0	-1	0	0	0

TABLE I
WEIGHT MATRIX OF CAUSAL RELATIONSHIP

P_{ij}		j					
		C_1	C_2	C_3	C_4	C_5	C_6
i	C_1	0	0.4	0	0	0	0
	C_2	0	0	0	0.5	0	0
	C_3	0.8	0	0	0	0	0
	C_4	0	0	0	0	1	1
	C_5	0	0	0.8	0	0	0
	C_6	0	0	1	0	0	0

TABLE II
CONDITION PROBABILITY MATRIX OF CAUSAL RELATIONSHIP

- C_2 : Little Red Riding Hood prepares food.
- C_3 : Little Red Riding Hood is afraid.
- C_4 : Wolf is very hungry.
- C_5 : Wolf wants to attack.
- C_6 : Wolf wants to act good.

The weight matrix and conditional probability matrix of the causal relationship are determined in Table I and II respectively.

Take a unit of evolving time as t_0 , the evolving time for the 6 variables are set respectively as

$$(1 \ 2 \ 1 \ 3 \ 2 \ 1)$$

The 6 variables evolve in different time schedule. Here, the maximum number of combination of 6 variables is $2^6 = 64$. With the FCM, a fast converged to equilibrium is reached; thus, only very limited states are presented for the world context. However, once the probabilistic elements are added to the causal relationships and variable states, many more states can be achieved. Therefore, the world is presented with more variations and dynamics. Asynchronous state updates adds the dynamics in a further step.

Suppose the initial state vector from C_1 to C_6 is

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

Time	C_1	C_2	C_3	C_4	C_5	C_6
1	1	1	0	1	0	0
2	1	1	0	1	0	0
3	1	1	0	1	1	0
4	1	1	0	1	1	0
5	1	1	1	1	1	0
6	0	1	1	0	1	0
...						

TABLE III
STATE VECTOR AT RUNNING WITH E-FCM

Step	C_1	C_2	C_3	C_4	C_5	C_6
1	1	1	0	1	0	0
2	1	1	0	0	0	0
3	1	1	0	0	0	0
	...					

TABLE IV
STATE VECTOR AT RUNNING WITH FCM

Table III shows the sequence of states from C_1 to C_6 evolving at different times with E-FCM. The given initial vector has the following meaning, “initially, the little red-riding hood was very happy, she prepared some food, and the wolf was very hungry”. The state vector did not change at first two time slot. Then in time slot 3, “the wolf is still hungry”, it is not updated due to slow reactive time. But “wolf attach” is updated due to “the wolf is hungry”. From time slot 5 to time slot 6, “little red-riding hood is happy” changes to “little red-riding hood is not happy”, while at time same time, “the wolf is hungry” changes to “the wolf is not hungry”. And the states following shows how the little red-riding hood reacts to the wolf dynamically as a system. As shown, the concepts update their values asynchronously. Moreover, with the same initial vector, the state vectors are evolving differently in different rounds 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 models the context variables with Fuzzy Cognitive Map with the same weight matrix. The results are shown in Table IV. Different from E-FCM, “steps” is used to describe the time as all the states update at a same time. It is shown that, the context variables reaches the equilibrium state quickly, with same route of state vectors for different rounds of experiments.

B. Discussions

Fuzzy Cognitive Map shows the trend in long run, which is good as an inference tool; while E-FCM shows the state in real-time, which is good as a simulation tool. Compared to FCM, E-FCM has the following improvements to describe an evolving real-time system:

- 1) It allows different update time for different context variables.
- 2) It involves the self mutation probability for each context variable in the dynamic context.
- 3) It involves the probabilistic causality among the context variables, which reflects more realistic relationships among the concepts, and adds more dynamics to the environment as a result.

Though E-FCM is quite similar to some extensions for FCM with concepts of evolving strategy and probability, E-FCM models the whole process of context evolution as a simulation engine. Therefore, all the state vectors (i.e. *Evolving States*) are main concerns rather than the equilibrium state vectors as FCM, as each evolving time state shows a real-time state of the system, which is important to describe a believable virtual environment, and for the intelligent agent

to make instant decision making.

Currently, though E-FCM tries to model all the factors of uncertainty in a realtime system, e.g., probability, fuzziness, evolution etc, it still has some limitations. Firstly, the causalities are determined subjectively by the expert. It enhances the difficulties to build a complex system. At involving new concepts into the system, the expert needs to give values for all the related causal fuzzy weight, causal probability and so on. Secondly, the causalities among the concepts are linear according to fuzzy weight, which needs to be extended to non-linear, in order to represent some real-time system correctly.

IV. CONCLUSIONS

In this paper, we propose Evolutionary Fuzzy Cognitive Map (E-FCM) to model the dynamic causal relationships of the context variables in a virtual world. Beyond the fuzzy causally relationships as FCM, the probabilistic causal relationship among the variables are also modeled. And the variables update their states with respect to different update time. By modeling the dynamic context variables in the interactive storytelling, a more dynamic and realistic result of context evolution is presented, which provides a strong basis for real-time context-awareness. In the future, we are going to extend the model with non-linear causality among the concepts, and increase the scalability to model large-scale context system.

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