Fuzzy Cognitive Map Learning Based on Multi-Objective PSO (Invited Paper)

Hengjie Song, Chunyan Miao, Zhiqi Shen and Yuan Miao

***Abstract*— As a powerful paradigm for knowledge representation and causal inference, Fuzzy Cognitive Map (FCM) has gradually emerged as a powerful modeling and simulation mechanism applicable to numerous research and application fields. However, conventional FCM theory greatly depends on the experts' knowledge. The excessive subjective factors involved in the determination of FCM weights restrict accuracy and reliability of inference results generated by FCMs. A promising approach to reducing or even eliminating the subjective intervention is the development of learning algorithm for FCMs, namely FCM learning. This paper proposes a new learning algorithm for FCMs which is based on the application of multi-objective particle swarm optimization. The novel approach integrates the FCM learning with the inference mechanism of FCMs. In order to validate the proposed FCM learning algorithm, we explore it to model the mental and physical behaviors of an emotional agent in a virtual world. The simulation results show that the novel method not only implements inference process and FCM learning in parallel, but also overcomes some deficiencies of other learning algorithms, therefore, improves the efficiency and robustness of FCMs.**

***Index Terms*— Fuzzy cognitive maps, multi-objectives, particle swarm optimization, FCM learning.**

I. INTRODUCTION

FCM THEORY was proposed by Kosko to represent the causal relationships between concepts and to analyze inference patterns [12] [13] [14] [15]. By describing behaviors of a collection of concepts, FCMs are able to emulate the cognitive process of human experts on a specific domain, and to provide an approach to knowledge representation that is essential to intelligent systems [15]. Compared with traditional expert systems and neural networks, FCM has several desirable properties such as abstraction, flexibility, adaptability and fuzzy reasoning [22] [24] [25]. Therefore, FCM has gained considerable research interests [6] [8] and has been applied in various scientific fields, e.g. social-economic-political systems, virtual world, systems control, policy [1] [8] [11] [31].

Similar to the development of fuzzy systems in early days, the conventional methodology for developing FCMs requires experts to identify weights which represent the degrees of causal-effect relationships between concepts [7] [13] [35]. Inevitably, the development methodology relies heavily on subjective reasoning and the experts' knowledge. In this regard, FCM methodology can not be considered as a well-defined technique because the excessive subjective elements involved in design and inference mechanism restrict the accuracy and reliability of FCMs. In addition, for complicated causal systems that include lots of concepts, it is not possible to have experts to explicitly describe the causalities between concepts since the causal relationships between concepts are bewilderingly unclear. It is thus necessary to develop some algorithms for automated or semi-automated FCM learning in order to eliminate such deficiencies and to improve efficiency and robustness of FCMs. Currently several FCM learning approaches have been proposed. They can be categorized into the following approaches:

A. Approach 1

These approaches are based on artificial neural networks (ANN) [3] [14] [21] [27] [28]. Kosko [14] proposed the differential Hebbian learning, a form of unsupervised learning but without mathematical formulation and real implementation. Another algorithm named Adaptive Random Learning for FCM learning was proposed in [3]. This learning algorithm is based on random neural networks. However, the calculated weights appear large deviation from the actual FCM weights. Based on the previous research results, [21] [27] presented FCM learning based on improved nonlinear Hebbian rule. These approaches require experts to predetermine the steady state of the given causal system. In other words, the learning algorithm tends to work on the assumption that the convergence range of concept states can be specified prior to the learning process. Obviously, the assumption is unrealistic and impractical for complicated causal systems, such as social behavior systems and virtual world systems, because a wealth of nonlinear causalities and uncertainties involved in the real causal systems make it impossible to anticipate the steady states of the system in advance.

B. Approach 2

These approaches are based on Evolution Strategies (ES) [16] [26] and Particle Swarm Optimization (PSO) [29] [30]. For the existing FCM learning based on ES and PSO, FCM learning is considered as the optimization problem of single

Manuscript received December 04, 2007; revised December 06, 2008.

Song Hengjie and Miao Chunyan, School of Computer Engineering, Nanyang Technological University, Singapore. Shen Zhiqi, Information Communication Institute of Singapore, Nanyang Technological University, Singapore. Miao Yuan, School of Computer Science and Mathematics, Victoria University, Australia. Email: Yuan.Miao@vu.edu.au(Y. Miao)

Publisher Item Identifier S 1542-5908(08)10313-X/$20.00

objective function. In most cases, the optimization is defined to minimize the absolute deviation between calculated and desired states of a given causal system. Similar to the ANN-based FCM learning, the predetermined steady state is indispensable for these approaches. It leads the existing FCM learning based on ES and PSO to suffer from the same drawback as that of ANN-based FCM learning. Furthermore, the single objective function can not effectively reflect the inherent and diverse characteristics of the investigated system, due to the multi-criteria nature in most real world problems.

It is particularly necessary to stress that the existing FCM learning algorithms based on PSO [29] [30] lack mathematical formulation and concrete procedures which are necessary to apply PSO in FCM learning. In fact, the original scheme of PSO has to be modified when it is used for FCM learning. Unfortunately, these necessary and important modifications are not mentioned in previous publications. Although the FCM learning has been extensively studied, a formal methodology and algorithm suitable for FCM learning are still needed.

In this paper, as an initial attempt, we proposed the application of multi-objective PSO in FCM learning and investigated the concrete procedures to incorporate FCM theory and multi-objective PSO. Compared with other FCM learning, the novel approach doesn't need to predetermine the steady states of causal systems prior to FCM learning, as well as accomplishes the whole process from the determination of causalities in FCM to the inference process. The remainder of this paper is organized as follows. Section 2 gives a brief overview on FCM and its main principles. In Section 3, the PSO algorithm is briefly presented. Section 4 is devoted to the concrete approach to FCM learning based on multi-objective PSO. Section 5 presents a case study in which the proposed algorithm is validated by modeling the mental and physical behaviors of an emotional agent in a virtual world. The conclusions are discussed in Section 6.

II. FUZZY COGNITIVE MAPS

FCM is derived from Cognitive Map (CM) [4] [36]. The research about CMs sprung from findings in physic-psychological experiments, which are used to trace and interpret the functionalities of various mental and cognitive tasks, abilities and phenomena in animals or humans. Tolman [36] and later Axelrod [4] described CMs in the formal and systemic manner. In order to avoid the binary logic that CMs enclose, Kosko [15] extended CMs to FCMs by introducing fuzzy relationships between concepts to describe the strength of causal relationships.

The main incentive that leads to further research and development on FCMs is the wide recognition of FCM as a promising modeling and simulation methodology, with remarkable characteristics such as abstraction, flexibility, adaptability and fuzzy reasoning [7] [31] [33]. This section introduces the basic concepts of traditional FCMs.

A. Basic Definitions and Structure

A FCM is a signed directed graph with feedback, which consists of a collection of nodes and directed weighted arcs interconnecting nodes. Nodes in the graph represent the concepts which are system variables, describing the behavioral characteristics of the system. Directed weighted arcs denote the causal relationships among different concepts. An example of a FCM that has been presented in various published studies [1] [8] is demonstrated in Figure 1 which depicts the topology structure of a FCM.

In FCMs, the weights companying with arcs take the value in the interval $[-1, 1]$ describing the type and the magnitude of the causalities in FCMs. For the example in Figure 1, the value of the link between the nodes "Modernization" and "Migration into city" means that an increase of "Modernization" state causes an increase of "Migration into city" state and, analogously, a decrease of "Modernization" state causes the decrease of "Migration into city" state. The weight taking negative number means an opposite tendency exists among concepts.

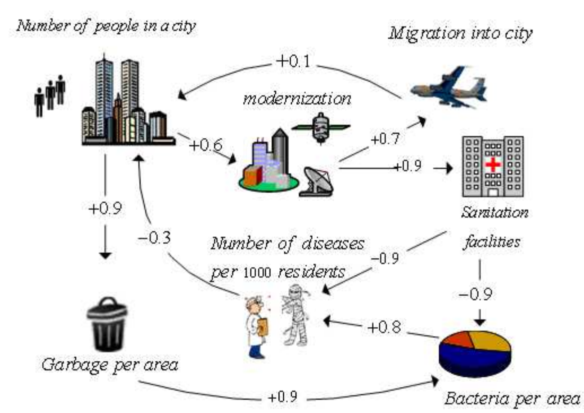


Fig. 1. The FCM Representing the System of Public Health

Obviously, the weights with high absolute values signify strong casual-effect relationships between concepts. Additionally, conventional FCMs adopt fuzzy sets as the concept value sets, which mean the concept states taking the value in the interval $[0, 1]$.

For the sake of convenience, the weights involved in FCMs can be described as matrix,

$$W = \begin{pmatrix} \cdots & \cdots & \cdots \\ \cdots & w_{ij} & \cdots \\ \cdots & \cdots & \cdots \end{pmatrix}_{N \times N}$$

where N denotes the number of concepts included in a given FCM. $w_{ij}(i, j = 1, 2, \ldots, N)$ denotes the strength of causal relationship from concept i to concept j.

B. Inference Process of FCM

Besides the graphical representation of a FCM, the mathematical formulation to describe the FCM and the inference mechanism are proposed in many publications [15] [18] [23].

The detailed inference process of traditional FCMs is to update the values of state vector in discrete time manner based on a given weight matrix W and initial state vector. The inference process of FCMs is described as following equation,

$$\begin{cases} \mathbb{C}(t) = (C_i(t))_{1\times N} \\ C_i(t+1) = f\left(\sum_{j=1}^{N} C_j(t)\dot{w}_{ji}\right) \end{cases} \quad \begin{pmatrix} i,j = 1,2,\ldots,N \\ t = 0,1,2,\ldots,T \end{pmatrix} \tag{1}$$

where t indicates the inference steps. $\mathbb{C}(t)$ denotes the state vector of the investigated causal system at step t. $C_i(t)$ indicates state value of concept i at the inference step t, and $f(*)$ is a threshold function. Therefore, the inference process of a traditional FCM can be regarded as an iterative process that applies the summation and threshold function to get the discrete time series of state vectors until the following requirements on convergence are satisfied,

- A fixed point equilibrium is reached. In this case,
$$\mathbb{C}(t_0+1) = \mathbb{C}(t_0), \quad (t_0 \in T)$$
where $\mathbb{C}(t_0)$ is the final state vector.
- A limited cycle is reached. In this case,
$$\mathbb{C}(t_0 + \triangle T) = \mathbb{C}(t_0), \quad (t_0 \in T)$$
where $\mathbb{C}(t_0)$ is the final state vector. This case means that the system falls in a loop of a specific period, and after a certain number of inference steps $\triangle T$, it reaches the same state $\mathbb{C}(t_0)$.
- Chaotic behavior is exhibited [6] [18] [20].

III. PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) was originally introduced by J. Kennedy as a stochastic, population-based optimization algorithm [19]. Recently, PSO has been extensively used in various fields of research, for example fuzzy systems [37], self-organizing maps [38], and hidden Markov model training [32].

The basic PSO consists of a swarm of particles moving in an D-dimensional search space. The core of PSO is to manipulate the position of a particle by using its previous position information and its current velocity. According to a given objective function, each particle keeps track of its best-achieved position (personal best, 'pbest') and the best position ever achieved in the group (group best, 'gbest') among all personal bests. These principles are formulated as,

$$v_i^{t+1} = w \times v_i^t + r_1 \times (pbest_i - x_i^t) + r_2 \times (gbest_i - x_i^t) \tag{2}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{3}$$

where w is inertia weight; r_1,r_2 are learning factors taking value between 0 and 1; v_i^t indicates the velocity of particle i at iteration t; x_i^t indicates the current position of particle i at iteration t; $pbest_i$ is personal best of particle; $gbest$ is best position in the swarm;

Recently, PSO is selected for FCM learning [29] [30], due to its efficiency and effectiveness on a plethora of applications in science and engineering, as well as its straightforward applicability [2]. However, the existing FCM learning based on PSO lacks mathematical formulation and concrete procedures to integrate FCM theory with PSO. In fact, the original scheme of PSO has to be modified when it is used for FCM learning. Unfortunately, these necessary and important modifications are not mentioned in previous publications.

In addition, the current applications of PSO in FCM learning are based on single-objective function optimization. In many cases, the single objective function doesn't coincide with multi-criteria nature of practical systems because single objective function can not completely describe the diverse and distinctive characteristics of the investigated system. In order to meet the requirements of practical applications, an intensive study of the application of PSO in FCM learning is still required.

IV. THE PROPOSED APPROACH

A. Objectives of FCM Learning

For the inference mechanism of FCMs, the weight matrix plays a crucial rule to guarantee the rational inference processes and results. Therefore, the determination of weights in a FCM is significant to construct FCM as a robust methodology. In this respect, the FCM learning aims at determining proper values of weights that will be able to accurately quantify the causal-effect relationships in a FCM. Moreover, in the inference process of FCMs, the fine-tuning of the weights is very important to reflect the nonlinear causalities among concepts[23] [17] [34].

Taking the requirements of FCM learning and multi-criteria nature of real world problems into account, it is necessary to employ multi-objective functions to describe the intrinsic characteristics of the investigated system and to distinguish the investigated system from others. For the example in Figure 1, the objective functions can be described as,

$$\begin{cases} max(C_{modernization}) \\ min(C_{num\ of\ diseases}) \end{cases} \tag{4}$$

where $C_{modernization}$ and $C_{num\ of\ diseases}$ indicate the state values of concept "Modernization" and "The number of diseases per $1,000$ residents respectively. Formula 4 implies that the objectives of the causal system are to improve the "Modernization" level as well as to keep "The number of diseases per $1,000$ residents" as less as possible.

Without loss of generality, the objectives functions of a given casual system can be described in the following form, Minimize

$$F(\mathbb{C}(t) = \{f_1(\mathbb{C}(t)), \ldots, f_k(\mathbb{C}(t), \ldots, f_K(\mathbb{C}(t))\} \tag{5}$$

In this formulation, $f_k(\mathbb{C}(t))$ denotes the k^{th} objective function. $\mathbb{C}(t)$ is the state vector of the given system which is described as

$$\mathbb{C}(t) = (C_1(t), \ldots, C_i(t), \ldots, C_N(t)) \tag{6}$$

$C_i(t)$ denotes the state value of the i^{th} concept at iteration step t, and N indicates the number of concepts in the causal system.

In most cases, the specific multi-objective functions could be derived from the investigated causal system. Evidently, the multi-objective functions are more efficient to reflect the inherent characteristics of the real causal systems. Moreover, the multi-objective functions associated with concept states of FCMs make it possible to integrate multi-objective PSO with FCM inference process.

B. Main Algorithm

In order to satisfy above requirements, PSO needs to be incorporated into the inference process of FCMs. Therefore, the original scheme of PSO has to be modified when it is applied into FCM learning. The Figure 2 outlines the concept model of the proposed approach.

As shown in the left side of Figure 2, the states of a causal system at $(t+1)^{th}$ step are completely determined by the states and the weights matrix of the system at t^{th} step. This process is consistent with the inference mechanism of FCMs which is described in formula 1.

The right side of Figure 3 shows the FCM learning based on the application of multi-objective PSO. For the k^{th} objective function, the FCM learning generates candidate weight matrix $W^{(k)}(t+1)$ according to $W^{(k)}(t)$ and the $\mathbb{C}(t)$. In this way, the proposed approach implements the FCM inference and FCM learning in parallel.

In order to describe the procedures in detail, Table 1 gives the pseudocode of the main algorithm.

The main algorithm consists of three nested cyclic iterative processes, which represent the index of objective functions, the iteration numbers of FCM inference and PSO iteration numbers respectively. Detailed introduction of the main algorithm is as in Table I.

Step 1: The proposed approach comes into effect for the k^{th} objective function, where objective functions are extracted from the investigated system by the method discussed in Section 4.1.

Step 1.1: In this step, the weight matrix $W(0)$ and state vector $\mathbb{C}(0)$ are initialized according to the initial conditions of a given FCM. Additionally, the positions and velocities of particles are initialized according to formula (8) and formula (10) respectively. Furthermore, personal best value of each particle and global best particle are also initialized randomly.

Noted that the size of the swarm and the dimensions depend on the number of concepts in FCMs. Additionally, the positions and velocities of each particle within the swarm need to be initialized according to $W^{(k)}(t)$ and $\mathbb{C}(t)$. All positions of particles are specified as following matrix,

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2N} \\ \dots & \dots & \dots & \dots \\ x_{N1} & x_{N2} & \dots & x_{NN} \end{pmatrix} \tag{7}$$

where N denotes the number of particles and the number of dimensions. x_{ij} denotes the position of the i^{th} particle on the $j^{th}(j \in N)$ dimension. At the beginning of the t^{th} inference step, the positions of particles are initialized with the corresponding element in weight matrix $W^{(k)}(t)$of the FCM,

$$x_{ij} = w_{ij}^{(k)}(t) \tag{8}$$

TABLE I

THE ALGORITHM OF FCM LEARNING BASED ON MULTI-OBJECTIVE PSO

Pseudocode of FCM and Multi-Objectives PSO

1. for (k = first objective function ; k $<$ Last Objective Functions; k ++)
{
1. 1. Initialization
1. 2. for (t = 0; t$\leqslant$ Max Inference Iteration; t++)
{
1.2.1. for (m = 0; m $\leqslant$ Max number of PSO Iteration; m++)
{
do
{
1.2.1.1. Update the velocities of the i^{th} particle according to formula (10.1);
1.2.1.1. Update the positions of the i^{th} particle according to formula (10.2);
1.2.1.3. Calculate the fitness value of the i^{th} particle according to the k^{th} objective function;
1.2.1.4. if (Current fitness is better than the personal best value (pbest) of the i^{th} particle)
Set pbest value equal to the current fitness and update the personal best positions of the i^{th} particle equal to the current positions;
1.2.1.5. if (Current fitness is better than the fitness of global best particle (gbest))
Reset gbest to the current particle's array index and corresponding positions;
} while(until all particles are computed)
}
1.2.2. Calculate concept state $\mathbb{C}(t+1) = Sigmod\left(\mathbb{C}(t) \bullet \mathrm{W}(t)\right)$;
1.2.3. Update weight matrix $W^{(k)}(t+1)$ by setting $w_{ij}(t+1) = pbest_{ij}$;
1.2.4. Reset $\mathbb{C}(t) = \mathbb{C}(t+1)$ and $W(t) = W(t+1)$;
}
}

Analogous with the initialization of positions of each particle, the velocities of particles within the swarm is described as,

$$\mathbf{V} = \begin{pmatrix} v_{11} & v_{12} & \dots & v_{1N} \\ v_{21} & v_{22} & \dots & v_{2N} \\ \dots & \dots & \dots & \dots \\ v_{N1} & v_{N2} & \dots & v_{NN} \end{pmatrix} \tag{9}$$

and each velocity of a particle is initialized as

$$v_{ij} = \frac{C_i(t)}{\sqrt{N}} \tag{10}$$

where v_{ij} is the velocity of the i^{th} particle on the $j^{th}(j \in N)$ dimension.

Taking the definition of weights of FCMs into account, namely $-1 \leq w_{ij} \leq 1$, the best positions of a particle on each dimension are clamped to the range $[-1, 1]$. If the particle's position on a certain dimension is larger than $+1$, then the position on that dimension is limited to $+1$. Similarly, if the particle's position on the dimension is smaller than -1, the position on that dimension is limited to -1.

Step 1.2: Main algorithm executes FCM inference and FCM learning.

Step 1.2.1: Main algorithm executes optimization process.

Step 1.2.1.1$\sim$Step 1.2.1.2: Updating positions and velocities of the i^{th} particle as following formulas,

$$\begin{aligned} v_{ij}^{m+1} = w \times v_{ij}^{m} + r_1 \times (pbest_{ij}^{m} - x_{ij}^{m}) \\ + r_2 \times (gbest_j - x_{ij}^{m}) \end{aligned} \tag{11}$$

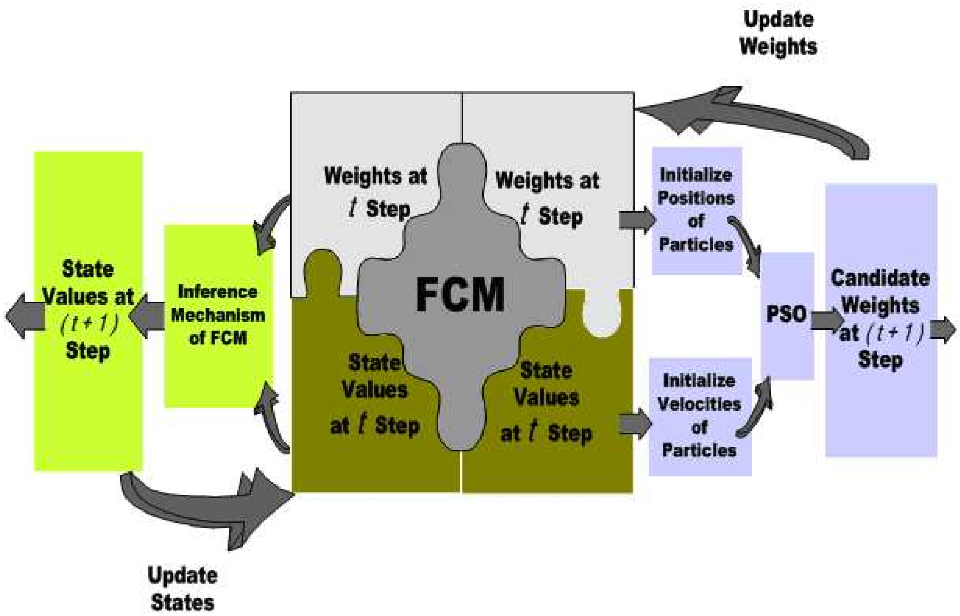


Fig. 2. Flowchart of the proposed learning

$$x_{ij}^{m+1} = x_{ij}^{m} + v_{ij}^{m+1} \tag{12}$$

v_{ij}^{m} velocity of the i^{th} particle in the j^{th} direction at the m^{th} PSO iteration;
$pbest_{ij}^{m}$ personal best position of the i^{th} particle in the j^{th} direction at the m^{th} PSO iteration ;
x_{ij}^{m} position of the i^{th} particle in the j^{th} direction at the m^{th} PSO iteration;
$gbest_j$ position of the global best particle in the j^{th} direction at the m^{th} PSO iteration ;
r_1, r_2 learning factors taking values between 0 and 1;

Step 1.2.1.3: Calculating the fitness value of the i^{th} particle for the k^{th} objective function,

$$fit\_val_i = f_k(\mathbb{C}(t)) \tag{13}$$

Step 1.2.1.4: if $fit\_val_i < pbest_i$, then reset $pbest_i = fit\_val_i$ and update the personal best positions $pbest_{ij}^{m+1} = x_{ij}^{m+1}$

Step 1.2.1.5: If $fit\_val_i < gbest.fitval$, then reset the $gbest$ as the current i^{th} particle and update the positions of $gbest$ as $gbest_j = x_{ij}^{m+1}$ where
$gbest$ overall best particle within the swarm;
$gbest.fitval$ fitness value of $gbest$;

Step 1.2.2: Calculating the concept state $\mathbb{C}(t+1)$ according to the inference mechanism of FCM.

Step 1.2.3: Updating the candidate weight matrix $W^{(k)}(t+1)$ as follow,

$$w_{ij}^{(k)}(t+1) = pbest_{ij} \tag{14}$$

where $pbest_{ij}$ denotes the personal best positions of each particle i after PSO iteration process. For the PSO optimization, although all particles access the same global best position, the personal best positions are specific to a given particle. The personal best positions can be represented by a $M \times N$ matrix,

$$\begin{pmatrix} pbest_{11} & pbest_{12} & \dots & pbest_{1N} \\ pbest_{21} & pbest_{22} & \dots & pbest_{2N} \\ \dots & \dots & \dots & \dots \\ pbest_{N1} & pbest_{N2} & \dots & pbest_{NN} \end{pmatrix} \tag{15}$$

Step 1.2.4: updating concept state $\mathbb{C}(t) = \mathbb{C}(t+1)$, weight matrix $W^{(k)}(t) = W^{(k)}(t+1)$ respectively, and then go-to Step 1.2.

C. The Weighted Aggregation Approach

For a given objective function $F_k(\mathbb{C}(t))$, the proposed approach generates corresponding weight matrix $W^{(k)}(t)$ in the FCM learning,

$$\mathrm{W}^{(k)} = \begin{pmatrix} \mathrm{W}^{(k)}(1) \\ \ldots\ldots \\ \mathrm{W}^{(k)}(t) \\ \ldots\ldots \\ \mathrm{W}^{(k)}(T) \end{pmatrix} = \begin{pmatrix} w_{11}^{(k)}(1)... & w_{1i}^{(k)}(1)... & w_{1N}^{(k)}(1) \\ ... & ... & ... \\ w_{N1}^{(k)}(1)... & w_{Ni}^{(k)}(1)... & w_{NN}^{(k)}(1) \\ \ldots\ldots & & \\ w_{11}^{(k)}(t)... & w_{1i}^{(k)}(t)... & w_{1N}^{(k)}(t) \\ ... & ... & ... \\ w_{N1}^{(k)}(t)... & w_{Ni}^{(k)}(t)... & w_{NN}^{(k)}(t) \\ \ldots\ldots & & \\ w_{11}^{(k)}(T)... & w_{1i}^{(k)}(T)... & w_{1N}^{(k)}(T) \\ ... & ... & ... \\ w_{N1}^{(k)}(T)... & w_{Ni}^{(k)}(T)... & w_{NN}^{(k)}(T) \end{pmatrix} \tag{16}$$

where $t = 1, 2, \ldots, T$ denotes the iteration step in FCM inference process. Given a causal system with different objective functions $F(\mathbb{C}(t))$, a set of weight matrix $\mathbb{W} = (W^{(1)}, \ldots, W^{(k)}, \ldots, W^{(K)},)$ can be obtained by the proposed approach. Therefore, we need to combine these weight matrixes to generate a candidate weight matrix.

Practically, a direct approach, namely weighted aggregation is used to generate the candidate weight matrix based on $\mathbb{W}$. In light of this approach, all the weight matrix $W^{(k)}(k \in K)$ are summed to a weighted combination,

$$W_{candidate}(t) = \sum\nolimits_{k=1}^{K} \lambda_k W^{(k)}(t) \tag{17}$$

where $\lambda_k (k = 1, 2, \ldots, K)$ is non-negative coefficient and $\sum_{k=1}^{K} \lambda_k = 1$. λ_k reflects the important degree of the objective in the investigated system, which is determined based on priori knowledge and specific requirements.

V. EXPERIMENT RESULTS

In this section, an emotional agent in a virtual world is modeled by a FCM and used to validate the proposed approach. The construction of virtual world and agents are presented in [39]. A scene of the virtual world is shown in Figure 3. In the virtual environment, a patient is assisted by a mobile nurse (emotional agent) who gets information from the virtual environment and perceives the patient's emotion as either "like" or "dislike". In terms of the external information, the emotional agent recognizes the patient's emotion as either "happy" or "angry" and determines her own intention to "approach" or "leave". Finally, the emotional agent responds with an appropriate physical behavior, namely move "forward" or "backward". The elements involved in the scene can be modeled by a FCM in which five concepts, namely 'Information', 'Emotion', 'Recognition', 'Intention' and 'Behavior' are represented as

$$\mathbb{C}(t) = (C_1(t), C_2(t), C_3(t), C_4(t), C_5(t))$$

where $C_1(t)$ is the stimulus of the system which corresponds to the concept "Information". As the response of the system, $C_2(t)$, $C_3(t)$, $C_4(t)$ and $C_5(t)$ represent different aspects of agent's mental and physical behavior as shown in Figure 4.

In most cases, complicated interactions and causal-effect relationships exist in the different aspects of a person's mental and physical behavior [5] [9] [10]. For the given causal system, the complex interactions and causalities make it impossible for conventional FCM to explicitly depict and to quantify the causalities. Therefore, we explore the proposed approach to determine the causalities in the FCM and to implement the inference process. As already mentioned, the ultimate purpose of the emotional agent is to make appropriate response to the patient's emotion. According to the nurse's target and role, the following three objective functions are defined to describe the multiple goals of emotional agent in the unpredictable environment,

Minimize $F(\mathbb{C}(t)) = \{f_1(\mathbb{C}(t)), f_2(\mathbb{C}(t)), f_3(\mathbb{C}(t))\}$, where

$$f_1(\mathbb{C}(t)) = \sum_{i=3}^{4} (C_i(t) - C_2(t))^2$$

$$f_2(\mathbb{C}(t)) = (C_4(t) - C_2(t))^2 + (C_3(t) - C_1(t))^2$$

$$f_3(\mathbb{C}(t)) = \sum_{i=2}^{4} (C_i(t) - C_1(t))^2$$

$$0 \leqslant C_i(t) \leqslant 1 \ (i = 1, 2, 3, 4, 5)$$

Evidently, these objective functions abstracted from the given example reflect the different aspects of the agent's main goals. For example, objective function $f_1(\mathbb{C}(t))$ signifies to simultaneously decrease the difference between state value of 'Intention' and that of 'Emotion', as well as the difference between the 'Recognition' and 'Emotion'. When the deviation amplitude is less than steady error ξ, 'Intention' and 'Recognition' could be considered to reflect the 'Emotion' efficiently.

For above objective functions, we respectively explore the proposed approach to generate corresponding weight matrix $W^{(k)(k=1,2,3)}$ and to obtain the candidate weight matrix according to formula 14 in which the equivalence coefficient is defined as $\lambda_1 = 0.2$, $\lambda_2 = 0.25$, and $\lambda_3 = 0.55$.

In order to validate the proposed algorithm, we adopt different initial conditions $\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$, $\mathbb{C}(0) = (0.575, 0.5, 0.5, 0.5, 0.5)$, and $\mathbb{C}(0) = (0.9, 0.5, 0.5, 0.5, 0.5)$ as stimulus to drive the mental and physical behavior of agent. In the above initial conditions, C_2, C_3, C_4 and C_5 have the same state value 0.5 which means the mental and physical behaviors of the agent are neutrality. As the stimulus of the system, C_1 is initialized with 0.0, 0.575, 0.9 respectively, which denote the 'Information' obtained from the environment is very unfavorable, slight favorable and very favorable respectively. For the sake of simplicity and without loss of generality, we define the initial weight matrix randomly and specify the number of PSO iteration as steps.

Figure 5, 6, 7 illustrate the simulation results of the system. As the responses of the given system, the state values of 'Emotion', 'Recognition', 'Intention' and 'Behavior'

Fig. 3. A scene of Virtual emotional agent

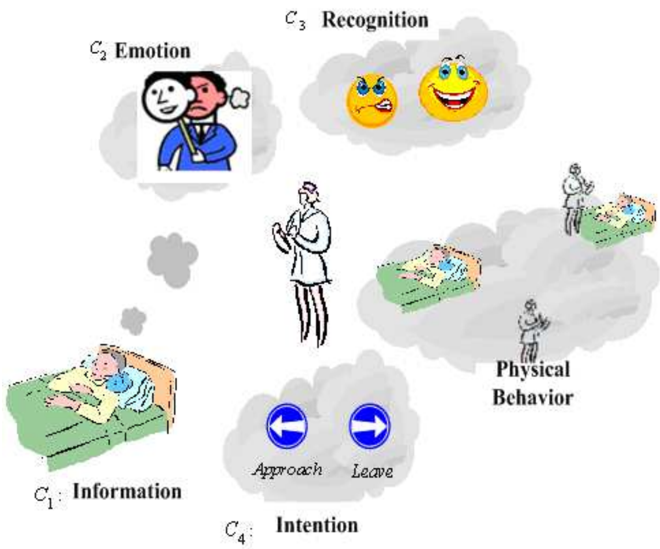
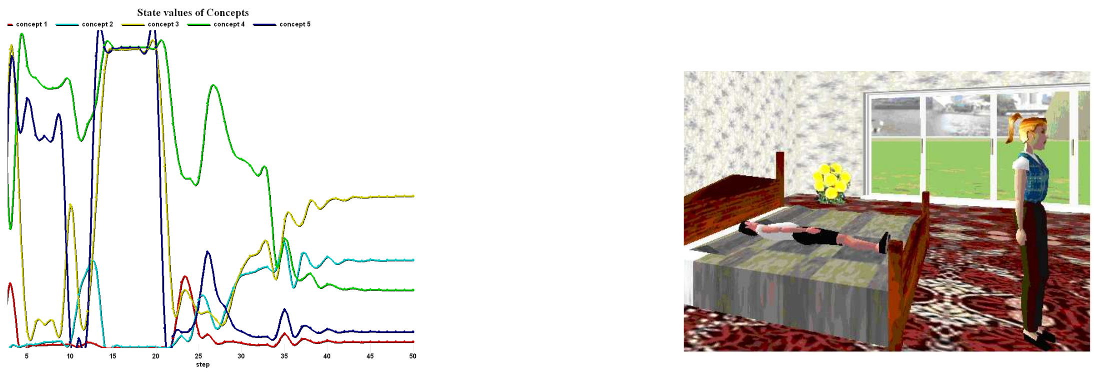


Fig. 4. Concepts associated with the emotional agent

epitomize the performance of the agent. Therefore, they can be considered as the criteria to measure the rationality of FCM learning.

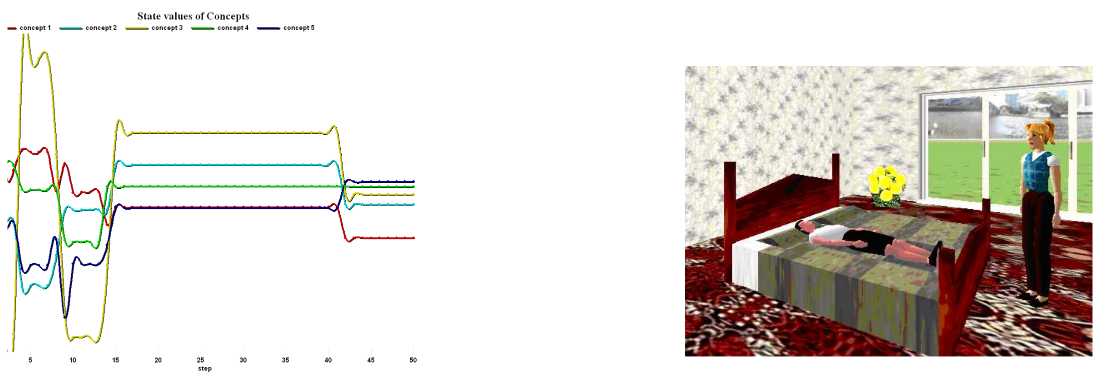
As shown in Figure 5(a), for the initial condition $\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$, the given system reaches the steady state, $\mathbb{C}(40) = (0.015, 0.28, 0.48, 0.18, 0.04)$, at 40^{th} inference steps. This simulation result indicates that the emotional agent's judgment on external information, $C_1(40) = 0.015$ approximates the given stimulus $C_1(0) = 0.0$. Additionally, the state values of the agent's mental behavior described by concepts C_2, C_3, C_4, are less than 0.5. Finally, as denoted by $C_5(40) = 0.04$, agent moves backward to the patient as shown in Figure 5(b).

Figure 6(a) and Figure 7(a) show that, corresponding to the initial condition $\mathbb{C}(0) = (0.575, 0.5, 0.5, 0.5, 0.5)$ and $\mathbb{C}(0) = (0.9, 0.5, 0.5, 0.5, 0.5)$, the system reaches the steady state and respectively. In light of the simulation results, the agent moves forward to the patient and moves close to the patient (shown in Figure 6(b) and Figure 7(b)). Additionally, the responses for initial condition $\mathbb{C}(0) = (0.9, 0.5, 0.5, 0.5, 0.5)$ and $\mathbb{C}(0) = (0.575, 0.5, 0.5, 0.5, 0.5)$ are superior to that of



(a) (b)

Fig. 5. (a) Concept state values corresponding to the initial condition $\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$ (b) Resulted behavior of the emotional agent with initial condition $\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$



(a) (b)

Fig. 6. (a) Concept state values corresponding to the initial condition $\mathbb{C}(0) = (0.575, 0.5, 0.5, 0.5, 0.5)$ (b) Resulted behavior of the emotional agent with initial condition $\mathbb{C}(0) = (0.575, 0.5, 0.5, 0.5, 0.5)$

$\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$. This difference is caused by the equivalence coefficient $\lambda_i (i = 1, 2, 3)$. In spite of this, the responses corresponding to the initial conditions $\mathbb{C}(0) = (0.0, 0.5, 0.5, 0.5, 0.5)$ is still acceptable.

Overall, these simulation results suggest that by exploring FCM learning based on multi-objective PSO, the emotional agent can make appropriate responses to the different external information, which is dependent on the rational weights obtained from FCM learning.

VI. Conclusion

In this paper, as an initial attempt, we have proposed and discussed the application of multi-objective PSO in FCM learning.

By defining multi-objective functions associated with the given causal system, the novel method not only effectively reflects the intrinsic characteristics of the investigated system, but also integrates the FCM learning with FCM inference process. Additionally, the proposed approach avoids to predetermine the steady state of the investigated system which is indispensable existing FCM learning algorithms. Therefore, the proposed approach effectively eliminates the excessive subjective interventions in construction and inference process of FCMs. To demonstrate the effectiveness of FCM learning based on multi-objective PSO, we explored the method to model the mental and physical behaviors of an emotional agent in a virtual world. The promising simulation results suggest that the novel method overcomes some deficiencies of existing FCM learning algorithms, therefore, improves the efficiency and robustness of FCMs.

References

[1] Andreou. A.S, Mateou. N.H, Zombanakis. G.A, Soft computing for crisis management and political decision making: the use of genetically evolved fuzzy cognitive maps, Soft Computing, v 9, n 3, March 2005, 194-210.

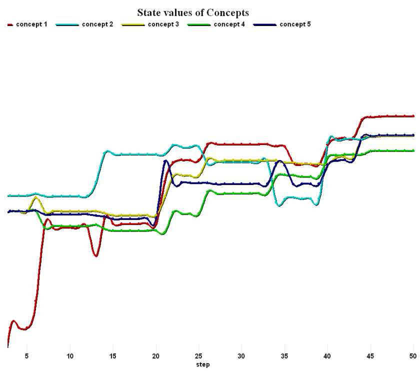
[2] Agrafiotis. D.K, Cedeno. W, Feature Selection for Structure -Activity Correlation Using Binary particle Swarms, Journal of Medicinal Chemistry, 45 (5), 2002, 1098-1107.

[3] Aurada. J, Adaptive random Fuzzy Cognitive Maps, Lecture Notes in Artificial Neural Systems, West Publishing Company, 1992.

[4] Axelord. R, Structure of Decision. The Cognitive Maps of Political Elites, Princeton, New Jersey: Princeton University Press, 1976.

[5] Beaudoin. L, Cause and Consequences of Feeling, Cambridge University Press, 2000.

[6] Carvalho. J, Tome. J, Issues on the stability of fuzzy cognitive maps and Rule-Based fuzzy cognitive maps, in Proc. 21st Annual Meeting of the North American Fuzzy Information Society Processings, New Orleans, 2002, 105-110



(a)

(b)

Fig. 7. (a) Concept state values corresponding to the initial condition $\mathbb{C}(0) = (0.9, 0.5, 0.5, 0.5, 0.5)$ (b) Resulted behavior of the emotional agent with initial condition $\mathbb{C}(0) = (0.9, 0.5, 0.5, 0.5, 0.5)$

[7] Carvalho. J, Tome. J, Rule based fuzzy cognitive maps: Fuzzy Causal Relations, Computational Intelligence for Modeling, Control and Automation, 1999, 276-81.

[8] Craiger. P. and Coovert. M. D, Modeling dynamic social and psychological process with fuzzy cognitive maps, in Proc. IEEE World Congress on Computational Intelligence, Fuzzy Systems IEEE, Orlando, 1994, 1873-1877.

[9] Gratch. J, Marsella. S, Tears and fears: modeling emotions and emotional behaviors in synthetic agents, in Proc. Fifth International Conference on Autonomous Agents, 2001, 278-285.

[10] Gratch. J, Evaluating a computational model of emotion, Autonomous Agents and Multi-Agent Systems, v 11, n 1, July 2005, 23-43.

[11] Gotoh. K, Application of fuzzy cognitive maps to supporting for plant control (in Japanese), in Proc. 10th Knowledge Engineering Symp, 1989, 99-104.

[12] Kosko. B, Neural networks and fuzzy systems: A dynamic system approach to machine intelligence, Englewood Cliffs, NJ: Prentice- Hall, 1992.

[13] Kosko. B, Dickerson. J, Fuzzy virtual worlds, AI Expert, July 1994, 25-31, [14] Kosko. B, Fuzzy Engineering, Englewood Cliffs, NJ: Prentice-Hall, 1997.

[14] Kosko, B, Fuzzy cognitive maps, Int. Journal of Man-Machine Studies, vol. 24, 1986, 65-75.

[15] Koulouriotis. D.E, Diakoulakis. I.E, Learning fuzzy cognitive maps using evolution strategies: A novel schema for modeling and simulating high-level behavior, IEEE Conference on Evolutionary Computation, ICEC, v 1, 2001, 364-371.

[16] Koulouriotis. D.E, Anamorphous of fuzzy cognitive maps for operation in ambiguous and multi-stimulus real world environments, IEEE International Conference on Fuzzy Systems, v 3, 2002, 1156-1159.

[17] Kottas. F.L, Boutalis. Y.S, A new method for reaching equilibrium points in fuzzy cognitive maps, in Proc. 2nd International IEEE Conference on Intelligent Sys. vol. 1, 2004, 53- 60.

[18] Kennedy. J, Eberhart. R. C, Particle Swarm Optimization, in Proc. IEEE International Conference on Neural Networks, Perth, Australia, 1995, 1942-1948.

[19] Lee. K.C, Kim. H.S, A Fuzzy Cognitive Map-Based Bi-Directional Inference Mechanism: An Application to Stock Mngmt, vol. 6, 41-57.

[20] Li. S.J, Fuzzy Cognitive Map Learning Based on Improved Nonlinear Hebbian Rule, Proceedings of the Third International Conference on Machine Learning and Cybernetics, ShangHai, August 2004, 26-29.

[21] Liu. Z. Q, Satur. R, Contextual fuzzy cognitive map for decision support in geographic information systems, IEEE Trans. Fuzzy System, vol. 7, Oct. 1999, 495-507.

[22] Miao. Y, Dynamic cognitive network - an extension of fuzzy cognitive map, IEEE Trans. Fuzzy System, vol. 9, 2001, 760-770.

[23] Meghabghab. G, Fuzzy cognitive state maps VS. Markovian modeling of user's web behavior, IEEE International Conference on Systems, Man and Cybernetics, Tuscon, AZ, 2001, 1167-1172.

[24] Pelaez. C. E, Bowles. J. B, Applying fuzzy cognitive maps knowledge-representation to failure modes effects analysis, in Proc. IEEE Annu. Reliability Maintainability Symp, New York, NY, Jan. 1995, 450-456.

[25] Papageorgiou. E. I, Groumpos. P. P, A new hybrid method using evolutionary algorithms to train Fuzzy Cognitive Maps, Applied Soft Computing Journal, v 5, n 4, July, 2005, 409-431

[26] Papageorgiou. E.I, Stylios. C.D, Fuzzy Cognitive Map Learning based on Nonlinear Hebbian Rule, Proceeding of 2004 International Conference on Machine Learning and Cybernetics, 2004, 2301-6.

[27] Papageorgiou. E.I, Stylios. C.D and Groumpos. P.P, Active Hebbian Learning Algorithm to Train FCMs, International Journal of Approximate Reasoning, 37(3), 219-249.

[28] Papageorgiou. E.I, Parsopoulos. K.E, Stylios. C.S, Fuzzy cognitive maps learning using particle swarm optimization, Journal of Intelligent Information Systems: Integrating Artificial Intelligence and Database Technologies, v 25, n 1, July 2005, 95-121.

[29] Parsopoulos. K.E, Papageorgiou. E.I, Groumpos. P.P, A first study of fuzzy cognitive maps learning using particle swarm optimization, Congress on Evolutionary Computation, Vol.2, 2003, 1440-7.

[30] Perusich. K, Fuzzy cognitive maps for policy analysis, in Proc. Int.Symp. Technol. Soc. Tech. Expertise Public Decisions, New York, 1996, 369-373.

[31] Rasmussen. T. K, Krink. T, Improved Hidden Markov Model training for multiple sequence alignment by a particle swarm optimization-evolutionary algorithm hybrid, Biosystems, vol. 72, Nov 2003, 5-17,

[32] Stylios. C.D, Groump. P.P, Fuzzy cognitive maps: a soft computing technique for intelligent control, in Proc. IEEE International Symposium on intelligent control, Italy, 2000, 97-102.

[33] Song, H. J, Shen. Z. Q, Miao. C.Y, Probabilistic Fuzzy Cognitive Maps, in Proc. IEEE International Conference on Fuzzy Systems, Canada, 2006, 6330-6337.

[34] Schneider. M, Constructing fuzzy cognitive maps, in Proc, IEEE Int, Conf Fuzzy Syst, New York, 1995, 2281-2288.

[35] Tolman. E.C, Cognitive maps in rats and men, Psychological Review, vol. 55, 1948, 189-208.

[36] Wei. H. Z, Yang. C, Gao. X, Extracting rules from fuzzy neural network by particle swarm optimization, Proceeding of IEEE Conference on Evaluation Computation, USA, 1998, 74-77.

[37] Xiao. X, Ernst. R. Dow, Gene clustering using self-organizing maps and particle swarm optimization, Concurrency Computation Practice and Experience, v16, n9, 2004, 895-915.

[38] Yundong. C, Miao. C.Y, Fuzzy Cognitive Goal Net for Interactive Storytelling Plot Design, ACM SIGCHI International Conference on Advances in Computer Entertainment Technology, 2006.