Using Fuzzy Cognitive Map for System Control

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Abstract: - Fuzzy cognitive map is a powerful modeling tool. It has several desirable properties on control. In this paper, we utilize the feature and the inference mechanism of fuzzy cognitive map, and present a control method, which study combines control theory with fuzzy cognitive map theory. The causal relationship of variables is constructed by online learning or offline learning, the values of control variables are given by the inference of FCM model, and the control variables are used to adjust the value of controlled variables in actual process and carries out the control of multi-input and multi-out.

Key-Words: - fuzzy cognitive map, system control, system modeling, control framework

1 Introduction

Automatic control as a discipline has made great contribution to science and technology both in theory and practice. Today, Control technology has played a key role in the development of science and technology. However, there exist some essential challenges in the control-area. These challenges come from the interaction among techniques such as computers and AI, the demands for current and future applications, and the new concepts and ideas in science and engineering. It is clear that the rapid development and great progress in modern science and technology have resulted in new demands to the control and system science.

The traditional control, which includes the classical feedback control, modern control, modern control theory and large-scale control system, has encountered many difficulties in its applications. First of all, the design and analysis for the traditional control systems are based on their precise mathematical models that are usually difficult to achieve owing to the complexity, non-linearity, uncertainty, time-varying, and incomplete characteristic of the existing practical systems. On the other hand, some critical hypotheses have to forward in studying and modeling the control systems, these hypotheses are hard to match in practice. Thirdly, in order to increase the control performances, the complexity of the control systems has to be increase too. As a result, the reliability of the control systems should be decreased. The degree to which a control system deals successfully with the above difficulties depends on the level of intelligence in the system. For these reasons, automatic control has been looking for new ways to overcome the difficulties; one of the more effective ways to solve the problems mentioned above is to use the technique of intelligent control to the control systems, or to apply a hybrid methodology of the traditional and intelligent control techniques to the control systems [1, 2, 3, 4].

In this paper, we propose a control method based on fuzzy cognitive map (FCM), which study combines control theory with fuzzy cognitive map theory. It aims to explore new control method for solving the complex system and high non-line system control problem.

The rest of the paper is organized as follows: Section 2 introduces an overview of control. Section 3 introduces an overview of FCM. Section 4 introduces the control process based on FCM. Section 5 is the conclusion and suggestions for future works.

2 The Overview of Control

In the 1960s, with space technology, computer technology and the emergence of artificial intelligence and development, the idea of artificial intelligence, principles and methods are introduced to control system. This promoted the change of the traditional control theory to the intelligent control; this led to combination the control technology with the Computational Intelligence. Fuzzy logic, neural networks, genetic algorithms are used complex systems control; this gradually formed a theory of intelligent control. In 1967, Leondes first use of "intelligent control". Sarids proposed a control system of hierarchical organizational structure; he defined "entropy" as an intelligence control system to measure the performance, and Proved that the optimal control equivalent to use of minimum entropy method [5]. Astrom introduced the expert system technology into the intelligence control system to form the "expert control" [6]. In 1965, Zadeh first proposed the theory of fuzzy sets [7], laid the foundation for fuzzy control. In recent years, neural network control is attended in the field of automatic control; it has become another hot spot [8.9, 10] In addition, there have been variety control approach of intelligence technology cross-integration Such as: fuzzy neural network control [11], neural network expert's control [12]. Due to the personality differences of the complex system can not be determined to find a common approach to adapt to all the complex system control, so complex control theory itself should be rich, to explore different control strategies to adapt the diverse complexity of the system may be a success path.

3 Fuzzy Cognitive Map

Fuzzy cognitive map (FCM) is a soft computing tool that is a result of the synergy of fuzzy logic and neural network methodologies. A FCM is a type of cognition network, which is developed by experts, using an interactive procedure of knowledge acquisition or using learning method Automatic construction [13,14,15]. It offers a more flexible and powerful framework for representing human knowledge and for reasoning, unlike traditional expert systems that explicitly implement “IF/THEN” rules[16,17], it emphasizes the connections of concepts as basic units for storing knowledge, and the structure represents the significance of system. It may help describe the schematic structure, represents the causal relationships among the elements of a given decision environment, and the inference can be computed by numeric matrix operation. It is advantage tool for the design of knowledge base and the modeling of complex systems.

It has several desirable properties, for example, it is relatively simple to use for representing structured knowledge , and the inference can be computed by numeric matrix operation. There are two significant characteristics.

- ✧ Causal relationships between nodes are fuzzy. Instead of only using signs to indicate positive or negative causality, a number if associated with the relationship to express the degree of relationship between two concepts.
- ✧ The system is dynamic involving feedback, where the effect of change in the concept node affects other nodes, which in tern can affect the node initiating the change, the presence of feedback adds a temporal aspect to the operation of the FCM.

3.1 Background

Robert Axelord in 1976 first used cognitive maps as a formal way of representing social scientific knowledge and modelling decision making in social and political systems. Then, Kosko extended cognitive map considering fuzzy value for them in 1986. In 1992, Hagiwara proposed expansion of cognitive map [18] on the basis of fuzzy cognitive map. In 1994, Wellman proposed a qualitative probability network [19], it is a cognitive map as a network of unknown probability, but he could not quantify the concept of cause and effect relationship between the degrees of change. 1997, Obata and Hagiwara proposed a neurons cognitive map [20], Its main purpose is to deal with the complex relationship between cause and effect, the method effectively reduces distortion of the real-world simulation, but can not use the expert knowledge. In 1999, Carvalho and others proposed a model cognitive map based on rule [21, 22, 23, 24], its aims to resolve non-monotonic reasoning and treatment and the issue of non-causation. In 2001, M Yuan and ZQ Liu dynamic cognitive networks [25], the model is the expansion of FCM, This model has a strong environmental adaptability. In 2003, Luo and others discussed the probability fuzzy cognitive map [26], it inherited the advantages of FCM model, and the conditional probability measure has been introduced in the concept of cause and effect relationship. In addition to the above models, There are also the analysis and improvement of methods on the basis of the original model [27,28,29,30], such as: the expansion of the relationship between cause and effect and improving the state function.

The construction of FCM requires a large amount of concepts and connections that need to be established, which substantially adds to the difficulty of manual development process. These problems led to the development of computational methods for learning FCM. In 1992, Kosko had initially proposed the Differential Hebbian Learning (DHL), but without any mathematical formulation and applications in real problems [31]. In 2002, the Balanced Differential Learning Algorithm [32] for FCM training was proposed. This new algorithm is an extension of DHL and is based on weight updating formula, for which the updated value depends on values of all concepts that are acting at the same time as a cause of change for the concept, but this method was applied only with binary concept to FCM. In 2003, another unsupervised learning algorithm—Nonlinear Hebbian Learning (NHL)[33] was developed, so as to learn connection matrix of FCM. The NHL algorithm is based on the nonlinear Hebbian learning rule and updates only the initially suggested (non-zero) weights of the FCM. These weights are synchronously updated at each iteration step till the termination of the algorithm. The algorithm requires human intervention before the learning process starts, which is a disadvantage. In 2003, Particle Swarm Optimization (PSO) method, one of the swarm intelligence algorithms [34, 35] was proposed to learn FCM connection matrix. This algorithm finds, on the basis of historical data which consist of a sequence of state vectors, the connection matrix in the search space, which, in turn, is restricted to certain FCM concepts values, and imposes constraints on the connection matrix. All these were specified by domain experts.

FCM as a result of intuitive knowledge representation, and fast numerical reasoning ability, as well as with neural networks, graph theory, fuzzy logic and other areas in close contact, making it has a wide range application, the studies Involve fault detection [36,37,38,39], medical diagnosis [40], management decision-making [41,42,43,44,45,46,47], the analysis of social phenomena [48,49,50,51,52], circuit analysis [53], geographic information systems [54, 55], stock analysis [56], the chess game [57, 58], the control system [59,60,61,62,63], the complex system modelling of other areas [64, 65,66,67,68,69].

3.2 Formalization of Fuzzy Cognitive Map

An FCM illustrates the model of a system using a graph of concepts and showing the cause and effect among concepts. Each node represents one of the factors of the modeled system. The interconnections among concepts of FCM signify the cause and effect relationship one concept has on the others. These weighted interconnections represent the direction and degree with which concepts influence the value

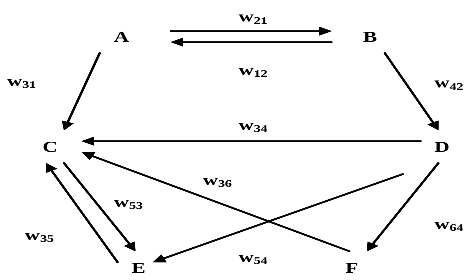

Fig.1. A Fuzzy Cognitive Map

$$W = \begin{bmatrix} 0 & W_{12} & 0 & 0 & 0 & 0 \\ W_{21} & 0 & 0 & 0 & 0 & 0 \\ W_{31} & 0 & 0 & W_{34} & W_{35} & W_{36} \\ 0 & W_{42} & 0 & 0 & 0 & 0 \\ 0 & 0 & W_{53} & W_{54} & 0 & 0 \\ 0 & 0 & 0 & W_{64} & 0 & 0 \end{bmatrix}$$

of the interconnected concepts, and it is described with the weight w_{ij}, taking value in the range –1 to 1. Apart from the graph representation, for computational purposes, a model can be equivalently defined by a square matrix, called connection matrix, which stores all weight values for edges between corresponding concepts represented by rows and columns. The system of n nodes can be represented by $n \times n$ connection matrix. An example of FCM model and its connection matrix are shown as follow:

From simple observation of the graphical representation of FCM, it becomes clear, which concept influences which other concepts, showing the interconnections among concepts and it permits thoughts and suggestions for the reconstruction of the graph, as the adding or deleting of an interconnection or a concept. In conclusion, FCM is fuzzy-graph structure, which allows systematic causal propagation, in particular forward and backward chaining.

Definition: An FCM is a directed graph with concepts like policies, events etc. as nodes and causalities as edges. It represents causal relationship between concepts.

An FCM consists of nodes-concepts, each node-concept represents one of the key-factors of the system, and it is characterized by a value $C \in (0,1)$, and a causal relationship between two concepts is represented as an edge w_{ij}, w_{ij} indicates whether the relation between the two concepts is direct or inverse. The direction of causality indicates whether the concept C_i causes the concept C_j. There are three types of weights:

$w_{ij}>0$ indicates direct causality between concepts C_i and C_j. That is, the increase (decrease) in the value of C_i leads to the increase (decrease) on the value of C_j.

$w_{ij}<0$ indicates inverse (negative) causality between concepts C_i and C_j. That is, the increase (decrease) in the value of C_i leads to the decrease (increase) on the value of C_j.

$\boldsymbol{w_{ij}}=0$ indicates no relationship between C_i and C_j.

In order to discuss conveniently, we presented the formal definition FCM as follows:

A fuzzy cognitive map $\boldsymbol{F}$ is a 4-tuple ($\boldsymbol{V, E, C, f}$) where:

--$\boldsymbol{V}=\{v_1, v_2, \dots, v_n\}$ is the set of n concepts forming the nodes of a graph.

--$\boldsymbol{E}$:$(v_i, v_j)\rightarrow \boldsymbol{w_{ij}}$ is a function $\boldsymbol{w_{ij}}\in \boldsymbol{E}$, $v_i, v_j \in \boldsymbol{V}$, with $\boldsymbol{w_{ij}}$ denoting a weight of directed edge from v_i to v_j.

Thus $\boldsymbol{E}\ (\boldsymbol{V}\times\boldsymbol{V})=(\boldsymbol{w_{ij}})$ is a connection matrix.

--$\boldsymbol{C}$: $v_i\rightarrow \boldsymbol{C_i}$ is a function that at each concept v_i associates the sequence of its activation degrees, such as $\boldsymbol{C_i(t)}$ given its activation degree at the moment t. $\boldsymbol{C(0)}$ indicates the initial vector and specifies initial values of all concept nodes and $\boldsymbol{C(t)}$ is a state vector at iteration t.

--$\boldsymbol{f}$ is a transformation function, which includes recurring relationship between $\boldsymbol{C(t+1)}$ and $\boldsymbol{C(t)}$.

$$\mathrm{C_i(t+1)} = \mathrm{f}\left(\left(\sum_{\substack{i=1 \\ j\neq i}}^{n} w_{ij} C_j(t)\right)\right) \tag{1}$$

Eq.(1) describes a functional model of FCM. An FCM represents a dynamic system that evolves over time, it describes that the value of each concept is calculated by the computation of the influence of other concepts to the specific concept. Three most commonly used transformation functions are shown below.

1) Bivalent

$$f(x) = \begin{cases} 1, x > 0 \\ 0, x \leq 0 \end{cases} \tag{2}$$

2) Trivalent

$$f(x) = \begin{cases} 1, x \geq 0 \\ 0, -0.5 < x < 0.5 \\ -1, x \leq 0.5 \end{cases} \tag{3}$$

3) Logistic

$$f(x) = \frac{1}{1+e^{-Cx}} \tag{4}$$

3.3 Inference in Fuzzy Cognitive Map

We can reason with FCM. We pass state vectors C repeatedly through the FCM connection matrix W, or non-linearly transforming the result after each pass. Independent of the FCM size, it quickly settles down to a temporal associative memory limit cycle or fixed point which is the hidden pattern of the system for that state vector C. The limit cycle or fixed-point inference summarizes the joint effects of all the interacting fuzzy knowledge.

We pass state vectors X repeatedly through the FCM connection matrix W, transforming or non-linearly transforming the result after each pass.

$$X(t+1) = \begin{bmatrix} x_1(t+1) \\ x_2(t+1) \\ \vdots \\ x_n(t+1) \end{bmatrix} = f(WX^T(t))$$

$$= f(\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix} \tag{5}$$

The inference of FCM includes forward-evolved inference and backward-evolved Inference. The forward-chains of FCM is uses a series of vector-matrix multiplication to find attractors for a given stimulus vector. Input the event into the FCM is equivalent to asking the question "what will happen if this even occurs".

The forward-chains of FCM to derive future states of the system it represents.. The backward-evolved inference uses the transpose of FCM matrix; backward-evolved inference yields a specific concept node value that should be accompanied with a given consequence.

The forward inference process of FCM starts with a stimulus event vector. Inputting the event into the FCM, multiplying the stimulus vector to the FCM matrix is the first in a series of such multiplications that eventually yields one of the following:

A fixed point: if the FCM equilibrium state of a dynamical system is a unique state vector, the state vector remains unchanged for successive iterations, and then it is called the fixed point.

$$X(k+1)=X(k)$$

Examples: node number n=4, the connection matrix

$$W = \begin{bmatrix} 0 & 0.517 & 0.7655 & 0 \\ 0.316 & 0 & 0.812 & 0 \\ 0.213 & 0 & 0 & 0.875 \\ 0.215 & 0 & 0.662 & 0 \end{bmatrix}$$

The initial state vectors X [0.264， 0.679， 0.512， 0.322], at t time, all nodes evolve by formula (1), his evolution curve along with t of $x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$ are shown in Fig .2.

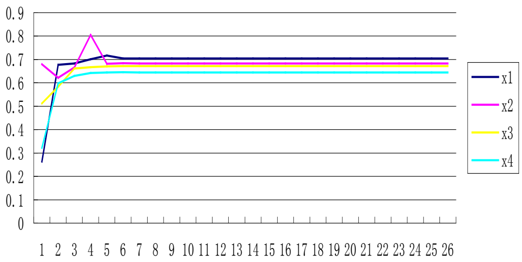

Fig. 2 evolution curve

A limit cycle: if the FCM settles down with a state vector repeating in the form:

$$A_1 \rightarrow A_2 \rightarrow \ldots \rightarrow A_i \ldots \rightarrow A_1$$

Or

$$\begin{cases} X_{j+l} = f(WX_j), \; j = 1,2,\ldots,r-1 \\ X_l = f(WX_r) \end{cases}$$

Then this equilibrium is called a limit cycle.

Examples: node number n=4, the connection matrix

$$W = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

initial state vectors X [1,1,1,0] at t time, all nodes evolve by formula (1), the evolution curve along with t of $x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$ are shown in Fig .3.

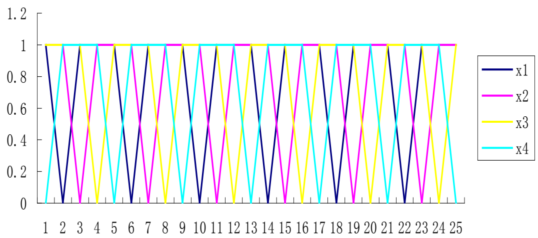

Fig .3 evolution curve

We illustrate this by the following example:

The first concept node vector be $\mathbf{X}_1$ = (1 0 0 0 0), the connection matrix W

$$W = \begin{bmatrix} 0 & 0 & -1 & 0 & 1 \\ 0 & 0 & 0 & -1 & 0 \\ 0 & -1 & 0 & 0 & -1 \\ -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

X_1W=[0,0,-1,0,1] $X_2=f(X_1W)$ (1,0,0,0,1) $=X_2$
X_2W=[0,0,-1,1,1] $X_3=f(X_3W)$ (1,0,0,1,1) $=X_3$
X_3W=[-1,1,-1,1,1] $X_4=f(X_3W)$ (1,1,0,1,1) $=X_4$
X_4W=[-1,1,-1,0,1] $X_5=f(X_4W)$ (1,1,0,0,1) $=X_5$
X_5W=[0,0,-1,0,1] X_6=f(X5W) (1,0,0,0,1) $=X_6=X_2$

So X_2 is a fixed point of the FCM dynamic system. This example illustrates that we can apply this kind of FCM-based forward-evolved inference approach to decision-making problems.

We can also compute backward-evolved inference by using the transpose of W, our FCM matrix, Wt. Backward-evolved inference yields a specific concept node value that should be accompanied with a given consequence, it does the opposite with forward-evolved inference.

3.4 Motivation and Objective

Fuzzy cognitive map has a good quality of intelligent control, such as:

- Knowledge representation and reasoning of FCM can be integrated into a unified framework.
- It can simulate the behaviour of dynamic systems for modelling complex systems;
- FCM is a kind of numerical reasoning, data-driven, so high flexibility;
- A strong learning ability can achieve on-line and off-line learning;
- each node and arc of FCM has a strong meaning, so that the FCM as a whole has very strong semantics;
- FCM is no clear input and output, each node can be as input, output, as can be easily applied to multi-variable control system.

Above characteristics can meet on the demand as intelligent tool in intelligent control systems. So we propose a control method based on FCM, the proposed method aims to provide a new control means of complex system.

4 The Control Based on FCM

The control system can make conditional decision in the environment with uncertainties. The controller is required to have stronger adaptively, real-time capability and fine control quality.

The control based on FCM is a closed loop control method, it is shown in Fig.4. It can replace traditional controller to complete all function.

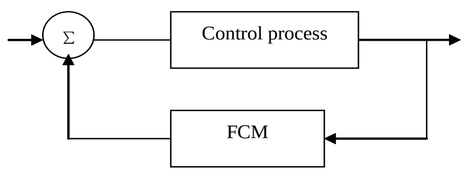

Fig. 4 FCM control structure

4.1 The Control Framework

The control framework utilizes the feature and the inference mechanism of FCM. The causal relationship of variables is constructed by online learning, the values of control variables are given by the inference of FCM model, and the control variables are used to adjust the controlled variables in actual process and carries out the control of multi-input and multi-out. The control framework is shown in Fig .5.

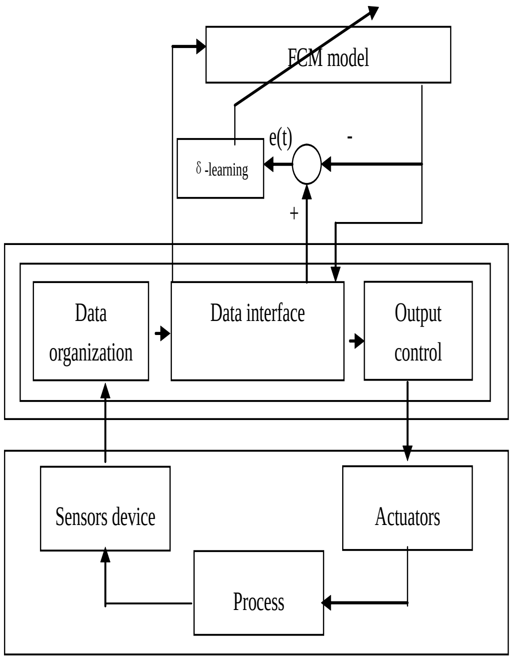

Fig. 5 the control framework of FCM

The proposed control framework has three layers, below we will discuss each layer of the frameworks what should is done in turn.

The Physical layer: The layer is the physical system of devices that measure the control variables of the process and can carry out the control of process. It is concerned with accepting the control information transmitted by upper layer and transmitting the collected data of sensors to the upper layer.

The data interface layer. This layer have three functions: (a) the information is organized and classed; (b) the information is transformed into FCM term and transmitting to model layer; (c) the information of the upper layer is accepted, organized and transformed into real system required format and transmitting to the physical layer.

The model layer: The key function obtains the value of control variables by inference according to input state, and transforms, transmits them to the data interface layer.

4.2 The Explanation of Control Process

The control principle of FCM utilizes the feature and the inferential mechanism of FCM. The causal relationship of variables is constructed by online learning; the values of control variables are given by the inference of FCM model. The control variables are used to adjust the controlled variables in actual process and carries out the control of multi-input and multi-out. The main steps of this method are as follows:

1) Make certain the initial state of system.
2) Obtain the value of control variables.
3) Process Control.
4) The value of control variables and the value of controlled variables from sensors are regarded as next input, go to step 2). Repeat implement until arrives control goal of system.

In the physical layer, sensors measure the variables of the process and this information is passed to the Data interface layer, at this stage, the information is organized and transformed into FCM model required format, then, it is again passed into the FCM, which lies in the upper layer. The FCM concepts interact and an fix point is reached. The new value of control variable can be obtained from fix point. In the data interface, the reverse procedure is followed, values of concept are transformed in suitable output information, classed, cause control signals and influence the process through the actuators.

4.2.1 Selecting of State Value

We use an example to explain the method of obtaining the value of control variable.

Example: node number n=4, initial state vectors X（0）＝（0.264，0.679，0.512，0.322）at t time, the connection matrix is W:

$$W=\begin{bmatrix} 0 & 0 & 0.765 & 0 \\ 0.315 & 0 & 0.812 & 0.543 \\ 0 & 0 & 0 & 0.875 \\ 0.215 & 0 & 0 & 0 \end{bmatrix}$$

At each simulation step of the FCM, the values of concepts are calculated according to below formula:

$$y(t+1)=f\,(u_i)=f\left(\left(\sum_{j\neq i}^{n} w_{ij}x_j(t)\right)\right) \qquad (6)$$

The FCM interacts for the initial values of concepts. In table 1 the values of concepts for eleven simulation steps are represented, it can be seen that after only eight simulation steps, the FCM reaches a fixed equilibriums point: 0.615411, 0.727684, 0.614531, 0.53303. It must be mentioned that the duration of each simulation step is one time unit. The equilibriums point is a needed result.

Table 1 the values of FCM concepts for eleven simulation steps

x1	x2	x3	x4
0.264	0.679	0.512	0.322
0.596687	0.662401	0.569975	0.514186
0.607313	0.717192	0.610619	0.532028
0.614703	0.844725	0.614324	0.532597
0.615374	0.72756	0.614442	0.532992
0.615395	0.727663	0.614524	0.533028
0.61541	0.727682	0.614531	0.533029
0.615411	**0.727684**	**0.614531**	**0.53303**
0.615411	0.727684	0.614532	0.53303
0.615411	0.727684	0.614532	0.53303
0.615411	0.727684	0.614532	0.53303

Its evolution curve along with t of x1(t), x2(t), x3(t), x4(t) is shown in Fig .6.

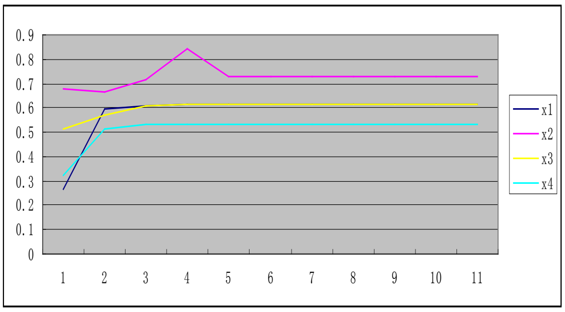

Fig 6 evolution curve

4.2.2 The Learning Control Principle of FCM

The learning control possesses have four functions: searching, recognition, memory, and reasoning, in the early research stage of learning control, research was done mainly on searching and recognition, and seldom on memory and reasoning. Similar to the learning systems, there are two kind of learning control systems, one is the on-line learning control system, and the other is the off-line learning control system as shown in Fig .7. and Fig .8.

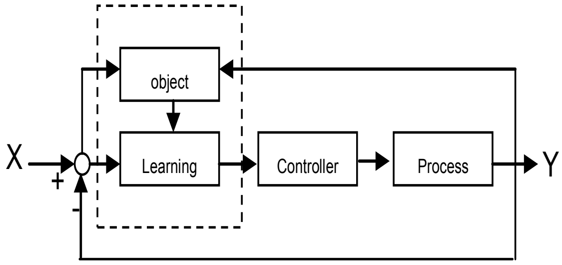

Fig .7 on-line learning control system

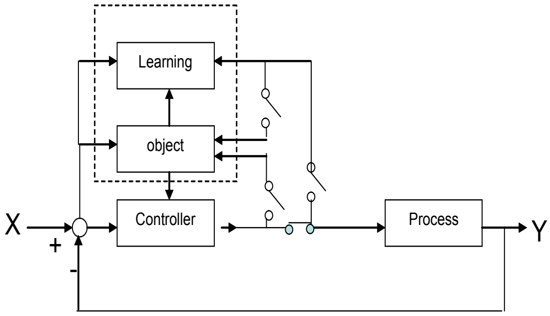

Fig .8 off-line learning control system

The off-line learning control system is used widely, while the on-line learning control is mainly used in more complex and stochastic environment. The on-line learning control system needs higher speed and larger capability of computers, and spends more time to signal processing. In many cases, the two methods are connected with each other; first, the prior experience is acquired by the off-line method whenever possible, then the one-line learning control is operated.

The work of the control system is divided two stages, control period and learning period. When k^{th} control period start, let input state vector X(k), according to the formula as follows to get out $y_m(k+1)$.

$$y_m(k+1)=f\,(u_i)=f\,\left(\left(\sum_{j\neq i}^{n} w_{ij}\, x_j(k)\right)\right)$$

The values of control variables from the output model $y_m(k+1)$ are translated to the data interface layer, the concepts value are transformed physical signal and the information is organized, filtered, translated to control part of system. The control part of system will determine the control actions that must be applied to the process and some variables of the process will be influenced by the control signals.

The weights of the interconnections will be adjusted according to existing measurements and data on the operation of the system. The different value between the outputs of system with the output of FCM model is as training signal. The learning method is a supervised learning; system provides goal value as teacher. In the learning stage, the real output is y_p, the output of FCM model is y_m, the weight of FCM is adjusted according to δ learning rule.

$$\Delta w = \alpha(y_p - y_m)/c \quad (7)$$

Where, Δw denotes the change of weight, α is learning rate, c is generalized coefficient, $\mathbf{y_p - y_m}$ is the different of the different value between the outputs of system with the output of FCM model.

When system is running, the connection matrix is constructed, the weight of FCM is adjusted along with learning, and the output of the model approximates the real system.

If the weight of controlled system is changeless, we may use offline-learning method [70, 71] to construct FCM, and use proposed framework and method carries out the control of multi-input and multi-out.

4.2.3 The Application Process Statement

The control process of FCM is a process that control while learning. In the control framework, FCM is an adjustable controller; it can on-line learn weight parameter. Generally, recurrence method is used in the online learning. In the study, we use δ learning.

Step 1: First all, we analysis problem and make certain the control variable and controlled variable of system.

Step 2: The control variable and the controlled variable can be represented the model of system and its operational behaviour. In the study, we use δ learning to construct FCM.

Step 3: The FCM is initialised; each concept takes an initial value.

Step 4: The control information is inputted, the controlled variables will be changed in the value of concept of the FCM, and concepts of the FCM interact each other until a fix point is reached.

Step 5: If the control goal is reached according to the fact of being observed, the control process finish, otherwise the control variables from the model of FCM is taken out, go to step 4. Repeat implement until arrives control goal of system.

We use the following example to illustrate the control process.

A control system is composed of 5 variables x1, x2, x3, x4, x5, of which 3 variables x1, x2, x3 are control variables, the variables x4, x5 are controlled variables. Control objectives are known. The connection matrix is W:

$$W = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.36 \\ 0 & 0 & 0 & 0 & 0.45 \\ 0 & 0 & 0 & 0 & -0.9 \\ 0.6 & 0 & 0.3 & 0 & 0 \\ 0.4 & 0.25 & 0 & 0.3 & 0 \end{bmatrix}$$

Give x1, x2, x3 initial states x1=0.45, x2=0.39, x3=0.04, measure the value of controlled variables, as an initial state vector of system to enter the FCM model. According to the formula (6), the output result is as follows:

Table 2

	x1	x2	x3	X4	X5
1	0.4500	0.3900	0.0400	0.1000	0.0100
2	0.5009	0.501125	0.49775	0.570036	0.576275
3	0.55168	0.56447	0.373169	0.610607	0.621672
4	0.555718	0.569486	0.363662	0.608964	0.632968
5	0.556722	0.570731	0.361313	0.608862	0.63352
6	0.556771	0.570792	0.361198	0.608837	0.633678
7	0.556785	0.57081	0.361165	0.608836	0.633685
8	0.556786	0.57081	0.361164	0.608836	0.633687
9	**0.556786**	**0.570811**	**0.361163**	**0.608836**	**0.633687**
10	0.556786	0.570811	0.361163	0.608836	0.633687
11	0.556786	0.570811	0.361163	0.608836	0.633687
12	0.556786	0.570811	0.361163	0.608836	0.633687

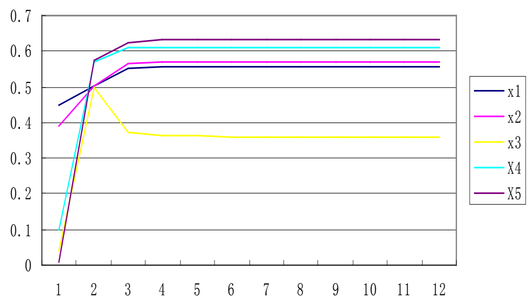

Fig 9 evolution curve

You can see from Table 2 that the simulation to Step 9, the system reached a fixed point, the state of system: 0.556786, 0.570811, 0.361163, 0.608836, and 0.633687.

Take the value of control variables x1, x2, x3 and send them to the actual system. x4, x5 obtain through the sensor to access and enter in the FCM. Convert them into the corresponding value of the variable, this constitutes a new input, and perform the second simulation.

The second simulation result is as follows: Table 3

	p_1	p_2	p_3	d	h
1	0.556786	0.5708	0.361163	0.2800	0.5000
2	0.544879	0.556014	0.389361	0.608836	0.610501
3	0.554725	0.568253	0.365992	0.609149	0.631721
4	0.556611	0.570594	0.361572	0.608886	0.633369
5	0.556758	0.570776	0.361229	0.60884	0.633662
6	0.556784	0.570808	0.361169	0.608836	0.633683
7	0.556785	0.57081	0.361164	0.608836	0.633687
8	**0.556786**	**0.570811**	**0.361163**	**0.608836**	**0.633687**
9	0.556786	0.570811	0.361163	0.608836	0.633687
10	0.556786	0.570811	0.361163	0.608836	0.633687
11	0.556786	0.570811	0.361163	0.608836	0.633687

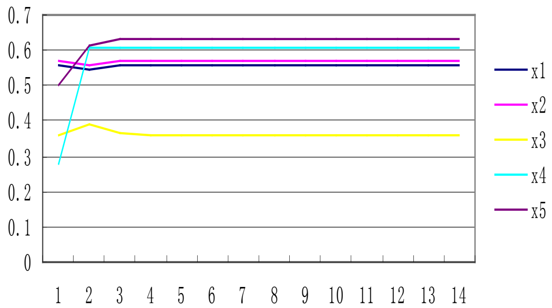

Fig 10 evolution curve

From the second, we can see that simulation to step 8, the system reached a fixed point, the state of system:
0.556786, 0.570811, 0.361163, 0.608836, 0.633687

The control process repeats until the control objectives have been achieved.

5 Conclusions and Future Work

We presented a control method, which study combines control theory with fuzzy cognitive map theory. We analysis the control principle and the control steps of FCM. The proposed framework utilizes the feature and the inference mechanism of FCM. The causal relationship of variables is constructed by online learning, the values of control variables are given by the inference of FCM model, and the control variables are used to adjust the controlled variables in actual process and carries out the control of multi-input and multi-out.

The control research based on FCM is still on initial stage, the theory system is not formed, and many problems remain to be solved. The problems are:

1) Because complex system exists a lot of uncertainly facts, and the modelling based on FCM is limited from the error of modelling, so the dependability of FCM model must be increased that apply in the control of complex system successfully.
2) The stability study of FCM control system remains to be researched.

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