Proceedings of the 12th IEEE
International Symposium on Intelligent Control
16-18 July 1997, Istanbul, Turkey

INTRODUCING THE THEORY OF FUZZY COGNITIVE MAPS IN DISTRIBUTED SYSTEMS

Chrysostomos D. Stylios, Voula C. Georgopoulos and Peter P. Groumpos*

Laboratory for Automation and Robotics, Department of Electrical and Computer Engineering
University of Patras, Rion 26500, GREECE
**School of Electrical Engineering and Computer Science, Ohio University, Athens, OH 45701, USA*

Abstract

This paper investigates a novel hybrid fuzzy neural system, Fuzzy Cognitive Map (FCM), and its implementation in distributed systems and control problems. The description and the methodology of this system will be examined and then it will be shown the application of FCM in a process control problem, which will reveal the characteristics and qualities of FCM. There is an oncoming need for more autonomous and intelligent systems, which could be satisfied with the application of FCM in the field of systems and control.

1. Introduction

In this paper a new theory, Fuzzy Cognitive Map (FCM) Theory, the methods that it uses to describe and model the behavior of a system and its application in the broad field of distributed systems are examined. FCMs describe the behavior of a system in terms of concepts, each concept represents a state or a characteristic of the system; they illustrate the whole system by a graph showing the cause and effect along concepts, and are a simple way to describe the system's behavior in a symbolic manner, exploiting the accumulated knowledge of the system.

Fuzzy Cognitive Map theory was originated by Kosko [1],[2] and applied by several others in a wide field of science. Fuzzy Cognitive Maps have been used for decision analysis [3], for modeling and planning in the fields of international relations, administrative science, management science and operations research[4], modeling and processing political knowledge[5], analyzing extend graph-theoretic behavior[6], analyzing electrical circuits[7], and as a method tool to structure Virtual worlds [8]. FCMs have been used to model and support a plant control system [9], to construct a system for Failure Modes and Effects Analysis[10],[11],[12] and to model the Supervisor of a control system [13].

The objective here is to focus on the use of FCM in modeling systems and show how appropriate FCM are to exploit the knowledge and experience which has been accumulated for years on the operation of a complex plant. This can be achieved by using a FCM which is a hybrid method as it lies in some sense between fuzzy systems and neural networks. These technologies are crude analogs of systems that exist in human and animal systems and have their origins in behavioral phenomena related to these beings [14]. So FCM represents knowledge in a symbolic manner and relates states, events and inputs in an analogous to beings manner. This methodology could help human intention to construct more intelligent systems, since as the more intelligent a system becomes, the more symbolic and fuzzy a representation it utilizes.

2. Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM) is an integration of Fuzzy Logic and Neural Networks. At first, R. Axelord [15] used Cognitive maps as a formal way of representing social scientific knowledge and modeling decision making in social and political systems. Then B.Kosko [1] enhanced cognitive maps considering fuzzy values for them, where causality between concepts allows degrees of causality and not the usual binary logic. A Fuzzy Cognitive Map describes a system in a one-layer network whose nodes can be assigned concept meanings and the interconnection weights represent relationships between these concepts (Figure1). FCMs are fuzzy-graph structures which are used in unsupervised modes. They used to model knowledge base of the examined system.

A Fuzzy Cognitive Map stores knowledge in the nodes and edges of the network, each node-concept represents one of the key-factors of the modeled system and it is characterized by a number A_i that represents its level of activation. Relationships between concepts have three possible types; either express positive causality between two concepts ($W_{ij} > 0$) or negative causality ($W_{ij} < 0$) or no relationship ($W_{ij} = 0$).

The value of W_{ij} indicates how strongly concept C_i influences concept C_j. The sign of W_{ij} indicates whether the relationship between concepts C_i and C_j is direct or inverse. The direction of causality indicates whether concept C_i causes concept C_j, or vice versa. These three parameters have to be considered when assigning a value to W_{ij}.

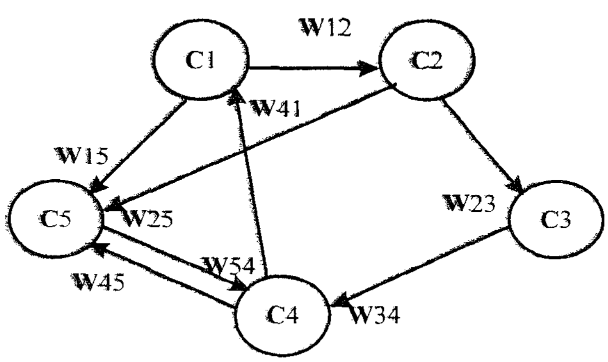

Figure 1. A simple Fuzzy Cognitive Map

The simplicity of the FCM model continues in its mathematical representation and operation, which evoke an inference. So, a FCM, which consists of n concepts, is represented mathematically by a $1 \times n$ state vector A, which gathers the values of the n concepts and by an $n \times n$ edge matrix F. The matrix F is n by n, and each element f_{ij} of the matrix indicates the value of the weight W_{ij} between concept C_i and C_j and the matrix diagonal is zero since it is assumed that no concept causes itself.

The activation level A_i for each concept C_i is calculated by the following rule :

$$A_i = f(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j W_{ji}) + A_i^{old} \qquad (1)$$

A_i is the activation level of concept C_i at time t+1, A_j is the activation level of concept C_j at time t, A_i^{old} is the activation level of concept C_i at time t, and W_{ji} is the weight arc from C_j to C_i and f is a threshold function. So the new state vector A which is computed by multiplying the previous state vector A by the edge matrix F, shows the effect of the change in the activation level of one concept on the other concepts.

It has become obvious that the most important is the construction of a Fuzzy Cognitive Map, during which expert's experience on system's modeling and operation is exploited. So an expert draws a FCM according to his experience, he determines the concepts, which in general stand for events, actions, goals, values, trends of the system. Moreover he determines the negative or positive effect of one concept on the others, with a fuzzy degree of causation. It is possible to exploit the experience of group of experts; they are polled together to determine the relevant factors that should be present in the map. Then, the experts are individually asked to express the relationship among these factors. In this way there will be a collection of individual FCMs that must be combined into a collective map. It could be considered that there are experts of different credibility on the knowledge of the system, and for these experts their factors are multiplied by a nonnegative 'credibility' weight b_i before combining them with other expert's opinions.

Generally, an augmented Fuzzy Cognitive Map could be combined by adding matrix F_i of each one FCM and constructing the whole matrix F:

$$F = \sum_{1}^{N} b_i F_i \qquad (2)$$

where F is the whole FCM, b_i is the weight for i_{th} expert and F_i is the weight matrix of expert's fuzzy cognitive map and N is the number of the experts.

A similar methodology could be used to integrate different Fuzzy Cognitive Maps in one augmented FCM. If there is a distributed system, for each subsystem a distinct FCM is constructed and then all FCM could be combined in one augmented matrix F for the whole system. The unification of the distinct FCM depends on the concepts of the segmental FCM, if there are no common concepts among different maps, the combined matrix F is constructed according to the equation (3) by the weight matrices F_i and the dimension of matrix F is $n \times n$ where n equals the total number of distinct concepts in all the FCMs.

$$F = \begin{bmatrix} F_1 & & & \\ & F_2 & \underline{O} & \\ & \underline{O} & \ddots & \\ & & & F_N \end{bmatrix} \qquad (3)$$

But, in most cases, the unification is used because there are common concepts among the distinct FCM and the intention is the ~~construction of a more~~ sufficient and integrated Fuzzy Cognitive Map. Then, segmental FCMs with common concepts, are combined together, calculating new weights for the interconnection between common concepts. Then, equation 3 is implemented to construct the weight matrix of the overall Fuzzy Cognitive Map which is consisted of n concepts that correspond to the total number of the different concepts that have been present in all the segmental FCMs.

Fuzzy Cognitive Map is an oriented graph which shows the degree of causal relationship between different factors, where knowledge expressions, in the causal relationship, are expressed by either positive or negative sign and different weights. A fuzzy cognitive map can avoid many of the knowledge-extraction problems which are usually posed by rule based systems. It must be mentioned that cycles in the graph are allowed.

3. Features of FCM for Control Systems Problems

With Fuzzy Cognitive Maps the knowledge and human operator experience is exploited. The operator of a system knows the operation of a system and has it stored in his mind in terms of concepts. He relates the operation of a machine or a chain of machines to a concept, or a concept stand for a specific production procedure, such a simple example is depicted in Figure2.

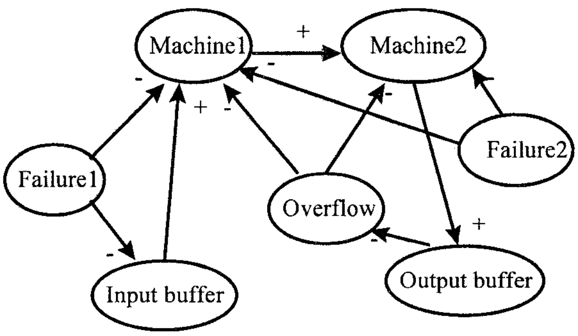

Figure 2. Fuzzy Cognitive Map of a simple production line

From the presentation of FCM, discussed in the previous paragraph, it is clear that the essential part is the drawing of a FCM, the determination of concepts that best describe the system, the direction and the grade of causality between concepts. So, the selection of the different factors of the system, that must be present in map, it must be the result of a close-up on system's model and operation behavior. Causality is another important part in the FCM design, it indicates whether a change in one variable causes change in another, and it must include the possible hidden causality that it could exist between several concepts.

Concepts and causality are determined by experts involved in the construction of FCM, but this methodology would lead to a distorted model of the system. In order to minimize this likelihood, learning methods to train the FCM can be used. A learning law based on Differential Hebbian learning has been proposed [2] to use in the training of FCM. The Differential Hebbian learning law adjust the weights of the interconnection between concepts, it grows a positive edge between two concepts if they both increase or both decrease and it grows a negative edge if concepts move in opposite directions. Moreover, it is an unsupervised method and thus, its computational load is light.

Another important characteristic of FCM is its simplicity and beauty, which comes out when it is considered its mathematical representation with matrix, vectors and the results after each FCM's cycle are computed from the multiplication of a vector with a matrix. Moreover the addition or subtraction of a concept means changes in one row and one column of the weight's matrix without requires a complete reconstruction of the model. Furthermore the computational cost for each FCM cycling is minimal and it permits parallel computation. Generally, it is an advantageous methodology if it takes into account the high process speed attainable by its parallel processing capability, and its adaptability to any inference with or without feedback and the fact that the employment of matrix expression allows system unification.

4. Practical Process Control Problem

In this section the application of Fuzzy Cognitive Map model in a well known problem in process industry is shown. Through this example it will become clear how a Fuzzy Cognitive Map is constructed, how concepts are chosen, how are assigned values to the interconnections between concepts and eventually how this FCM models and controls a process.

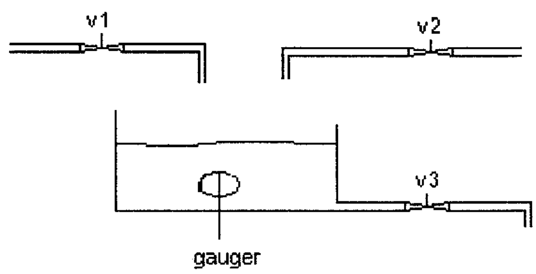

Figure 3. The system of a simple process

The considered system consists of one tank and three valves that influence in the amount of liquid in the tank; figure 3 shows an illustration of the system. Valve1 and valve2 empty two different kinds of liquid into tank1, during the mixing of the two liquids some chemistry takes place into the tank. Into the tank there is an instrument tool that measures the specific gravity of the liquid that is produced into tank and when gravity takes value in the range between (G_{max}) and (G_{min}), this means that it has been produced the desired liquid into tank. Moreover there is a limit on the height of liquid into tank, which cannot excess an upper limit (H_{max}) and a low limit (H_{min}). So the control target is to keep these variables in the middle of their range of values :

$$
\begin{aligned}
G_{min} \le G \le G_{max} \\
H_{min} \le H \le H_{max}
\end{aligned}
\tag{4}
$$

In order to construct a Fuzzy Cognitive Map which will model and control this simple system, the concepts of the map must be determined. Concepts will stand for the variables and states of the plant as it is the height of liquid in the tank or the state of the valve. So a primitive FCM will have five concepts and later any new concept, which will help our view and control of the system can be added:

Concept1 The amount of the liquid which tank1 contains. This amount is dependent on valve1, valve2 and valve3.

Concept2 The state of the valve1 (closed, open, partially opened).

Concept3 The state of the valve2.

Concept4 The state of the valve3.

Concept5 The reading on the instrument of specific gravity.

After having selected the concepts that can represent the model of the system and its operation behavior, the interconnections between concepts must be decided. At first, it is decided for each concept with which other concept it will be connected. Then, the sign and weight of each connection is determined. All this procedure has been done by a specialist who has experience on the system's operation, or better resulting FCMs could be trained with a unsupervised method [2].

The connections between concepts are:

Event1 It connects concept2 (valve1) with concept1 (amount of liquid in the tank). It relates the state of the valve1 with the amount of the liquid in tank.

Event2 It relates concept3 (valve2) with concept1; valve2 causes the increase or not of the amount of liquid in tank.

Event3 It connects concept4 (valve3) with concept1; the state of valve3 causes the decrease or not of the amount of liquid into tank.

Event4 It relates concept1 with concept2; when the height of the liquid in tank is high, valve1 (concept2) needs closing and so the amount of incoming liquid into tank is reducing.

Event5 It connects concept1 (tank) with concept3; when the height of the liquid in tank is high, the closing of valve2 (concept3) reduces the amount of incoming liquid.

Event6 It connects concept5 (the specific gravity) with concept4 (valve3). When the quality of the liquid in the tank is the appropriate, valve3 is opened and the produced liquid continues to another process.

Event7 It shows the effect of concept1 (tank) into concept5 (specific gravity). When the amount of liquid into tank is varied, this influence in the specific gravity of the liquid.

Event8 It relates concept5 (specific gravity) with concept2 (valve1), when the specific gravity is very low then valve1 (concept2) is opened and liquid comes into tank

It is obvious that FCM permits adding or removing of any concept if this improve system's description and furthermore, the adding or removing of any connection between the concepts that describe the system. This is a very useful ability that will help the designer of a system to evaluate the influence in the process of some system's characteristics.

Figure 4 shows the FCM that is used to describe and control this simple system, the initial value of each concept, the interconnections and the weights between concepts can be seen. The values of concepts correspond with the real measurement of the physical magnitude. The values of the each event (connection between concepts) has been arbitrary determined after observation of the changes in the real experimental system, by the specialist who designed the map.

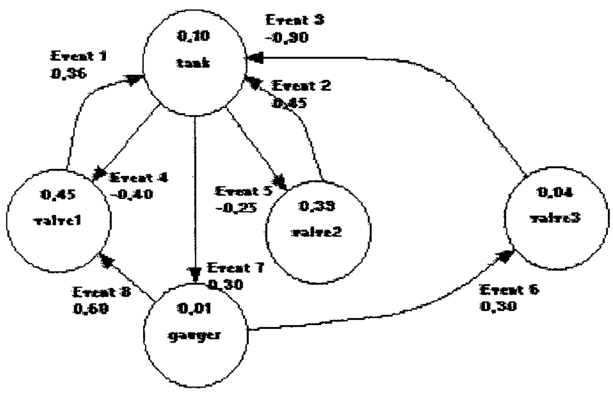

Figure 4. The initial FCM.

Each concept has a value which ranges between [0,1] and it is obtained after thresholding the real value of the concept. It is apparent that an interface is needed, which will transform the real measures of the system to their representative values in the FCM and vice versa. It should be mentioned that the transformation from the real values of the physical measurements to the values of the concepts, needs investigation and must take into consideration the actual mechanisms depicted in the FCM.

At each running step of the FCM, the value of concepts is calculated according to the equation (5).

$$A_i = f\left(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j W_{ji}\right) \tag{5}$$

The value of each concept is defined by the result of taking all the causal event weights pointing into this concept and multiplying each weight by the value of the concept that causes the event. Then the sigmoid function is used and so the result is in the range [0 ,1].

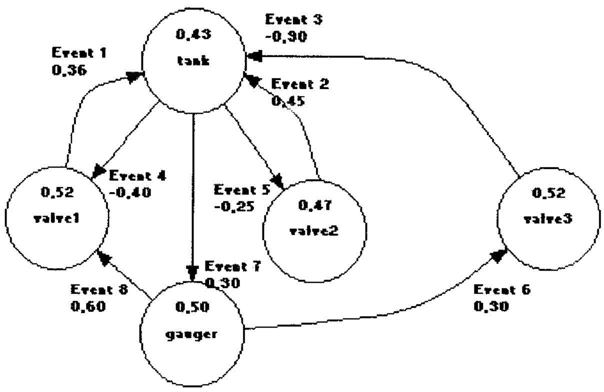

Figure 5. The FCM after 18 running cycles.

Figure 5 shows the FCM after 18 cycles running; it must be mentioned that each running cycle holds for a time unit. In Table I the value of each concept for the first eighteen (18) cycles is represented. Observing this table it can be seen that after some cycles the FCM reaches a limit cycle and the values of concepts have a slight variation.

It must be mentioned that this FCM never reaches a fixed point, because it is considered that there is a random noise which influences the value of the interconnections between concepts. In this way, the disturbances, that influence the real system, and the uncertainty about the FCM's weights pass into the model of the system.

Table I. The values of FCM concepts for the first 18 running cycles

	tank	gauger	valve1	valve2	valve3
1	0,10	0,01	0,45	0,39	0,04
2	0,54	0,50	0,49	0,50	0,50
3	0,52	0,51	0,50	0,49	0,52
4	0,45	0,51	0,50	0,48	0,51
5	0,54	0,53	0,49	0,48	0,52
6	0,46	0,50	0,48	0,49	0,52
7	0,50	0,51	0,53	0,47	0,50
8	0,55	0,52	0,56	0,49	0,53
9	0,47	0,50	0,55	0,49	0,53
10	0,47	0,52	0,52	0,48	0,51
11	0,49	0,52	0,51	0,49	0,51
12	0,53	0,52	0,50	0,50	0,54
13	0,45	0,51	0,48	0,49	0,50
14	0,53	0,53	0,54	0,48	0,52
15	0,41	0,52	0,51	0,49	0,53
16	0,49	0,53	0,51	0,48	0,53
17	0,47	0,51	0,50	0,47	0,53
18	0,43	0,50	0,52	0,47	0,52

5. Enhancement of the process problem

The control problem that is illustrated in the previous section can be improved if a two-level structure is considered. In the lower level of the structure will lie the FCM that has just constructed and it will reflect the model of the process during normal operation conditions. In the upper another FCM will be built, which will be used for failure modes, effects analysis and strategic planning, decision analysis. In this FCM can be implemented analysis of the data coming from the lower level, which will represent vital components of the plant detecting features that reflect the operational state of the plant. For drawing this FCM the integration of several expert opinions will needed in order to achieve its diagnosis and predictive task, which is extremely difficult.

A part of the upper FCM generally will include concepts for: failure mode variables, failure effects variables, failure cause variables, descriptive variables, severity of the effect, design variables. In the examined example, the FCM could describe the failure states of the valves, possible malfunction in the specific gravity instrument, leaks in tank and other alarm schemes. This FCM will interact with the other in the lower level. But in case of a catastrophic alarm or other emergency signal, the failure analysis Fuzzy Cognitive Map must act directly to the shop floor level, and for this case a separate mechanism is needed. Another part of the upper level FCM can be used for decision making, Fuzzy Cognitive Maps are well suited for dealing with this kind of problem and many other knowledge oriented problem.

The cooperation of two-level FCM seems to be alluring and it could lend itself to more sophisticated systems. Moreover, it gives the stimulus to investigate another approach, a hybrid system, where in the lower level is a more conventional controller, like Neural Networks, and the supervisor in the upper level is a FCM.

6. Summary

This paper has examined a new theory, Fuzzy Cognitive Map Theory and its use in modeling the behavior of distributed systems, which best utilizes existing experience in the operation of the system. For such systems it is extremely difficult to describe the entire system by a precise mathematical model. Thus, it is more attractive and useful to divide the whole plant in virtual parts and construct for each one part a FCM. For each part can be utilized the experience of different specialists who can easily judge the variables and states of a small process and then unify these to construct the final system by integrated the different Fuzzy Cognitive Maps into an augmented one, as it has described previously in this paper. This approach represents systems in graphical way showing the causal relationships between states-concepts and accomplishes the unification of knowledge by superposing plural small systems. It offers the opportunity to produce better knowledge based system applications, addressing the need to handle uncertainties and inaccuracies associated with real world problems. It is a symbolic method which can increase the effectiveness, autonomy and intelligence of systems.

This method has been implemented in a process control problem which has make apparent the qualities and characteristics of method. It has been observed how simply FCM describes the system's behavior, its flexibility in any change of the system and the capability to expand the control of the system, by adding a second FCM in a higher level for failure analysis, prediction and planning. A system using this technique has enhanced performance with regard to development efficiency, system quality and speed of execution.

FCM seems to be a useful method in complex system modeling and control, which will help the designer of a system in decision analysis and strategic planning. Fuzzy Cognitive Maps appear to be an appealing tool in the description of the supervisor of distributed control systems, which teamed up with other methods will lead to the next generation industrial systems.

References

[1] B. Kosko, 'Fuzzy Cognitive Maps' *International Journal of Man-Machine Studies*, vol. 24, pp. 65 - 75, 1986.

[2] B. Kosko, *Neural Networks and Fuzzy Systems*. Prentice-Hall, 1992.

[3] W.R. Zhang, S.S. Chen, and J.C. Besdek, 'Pool2 : a generic system for cognitive map development and decision analysis' *IEEE Transactions on Systems, Man, and Cybernetics*, vol 19, pp. 31-39, 1989.

[4] J.P. Craiger, D.F. Goodman, R.J. Weiss and A.B. Butler, 'Modeling Organizational Behavior with Fuzzy Cognitive Maps' *Intern. Journal of Computational Intelligence and Organisations*, vol. 1, pp. 120-123, 1996.

[5] R. Taber, 'Knowledge Processing with Fuzzy Cognitive Maps' *Expert Systems with Applications*, vol. 2, No.1, pp. 83-87,1991.

[6] W. Zhang and S. Chen, 'A logical Architecture for Cognitive Maps' *IEEE International Conference on Neural Networks*, 1988.

[7] M.A. Styblinski and B.D. Meyer, 'Signal Flow Graphs vs Fuzzy Cognitive Maps in Application to Qualitative Circuit *Analysis' International Journal of Man-Machine Studies*, vol. 35, pp. 175-186, 1991.

[8] J. A. Dickerson and B. Kosko, 'Virtual Worlds as Fuzzy Cognitive Maps' *Presence*, Vol. 3, No 2, pp. 173-189, 1994.

[9] K. Gotoh, J. Murakami, T. Yamaguchi and Y. Yamanaka, 'Application of Fuzzy Cognitive Maps to supporting for Plant Control' *SICE Joint Symposium of 15th Syst. Symp. and 10th Knowledge Engineering Symposium*, pp. 99-104, 1989.

[10] C.E. Pelaez and J.B. Bowles, 'Using Fuzzy Cognitive Maps for Failure Modes Effects Analysis' *Third Annual FT&T International Conference*, November 1994.

[11] C.E. Pelaez and J.B. Bowles, 'Using fuzzy Cognitive Maps as a System Model for Failure Models and Effects Analysis' *Information Sciences*, vol. 88, pp. 177-199, 1996.

[12] C.E. Pelaez and J.B. Bowles, 'Applying Fuzzy Cognitive-Maps Knowledge-Representation to Failure Modes Effects Analysis' *Proc. Annual Reliability and Maintainability Symposium*, pp. 450-455, 1995.

[13] C.D. Stylios, V.C. Georgopoulos and P.P. Groumpos, 'Applying Fuzzy Cognitive Maps in Supervisory Control Systems' *in Proc. of European Symposium on Intelligent Techniques*, pp. 131-135, Bari, Italy, March 1997.

[14] L.R. Medsker, *Hybrid Intelligent Systems*. Kluwer Academic Publishers, 1995.

[15] R. Axelrod, *Structure of Decision: the Cognitive Maps of Political Elites*. Princeton University Press, 1976.