Dynamical Cognitive Network-an Extension of Fuzzy Cognitive Map

Yuan Miao[1], Zhi-Qiang Liu[2], Shi Li[3], Chee Kheong Siew[1]

[1]*Information Communication Institute of Singapore, School of Electrical and Electronic Engineering Nanyang Technological University (S2-B3), Nanyang Ave., Singapore 639798*
eymiao@ntu.edu.sg

[2] *Department of Computer Science and Software Engineering, the University of Melbourne, Australia*
zliu@cs.mu.oz.au

[3] *Computer Science and Technological Department Tsinghua University, Beijing, P. R. Chian*

Abstract

In this paper we present Dynamic Cognitive Network (DCN) which is a systematic extension of the Fuzzy Cognitive Map (FCM). Each concept in Dynamic Cognitive Network can have its own value set, depending on how precisely it needs to be described in the network. This enables dynamic cognitive network to describe the strength of the cause and the degree of the effect. This ability also enables DCN to carry out inferences via numerical calculation instead of symbolic deduction. The arcs of DCN define dynamic relationships between concepts and describe the causal procedures. DCN overcomes the problems of FCM without losing the essential advantages.

1. Introductions

Fuzzy cognitive map was proposed by Kosko [1] to represent the causal relationship between concepts and analyze inference patterns. Compared with the traditional expert systems and neural networks, it has several desirable properties such as: it is relative easy to use fuzzy cognitive map for representing structured knowledge, especially for knowledge containing causal relationships; fuzzy cognitive maps can be combined by merging their adjacency matrix with different, weighted coefficients [2]; the inference of fuzzy cognitive map can be computed by numeric matrix operation, instead of explicit IF/THEN rules as that found in most expert systems.

Fuzzy cognitive maps have gained considerable research interests and have been applied to many areas [1-8,10]. However, a certain flaws of FCM restrict its applications. FCM does not provide a robust and dynamic inference mechanism; FCM lacks the temporal concept that is crucial in many applications; additionally, in a causal system, there are three fundamental elements: the cause, the causal relationship, and the effect. Fuzzy cognitive map improves cognitive map (CM) by describing the strength of the causal relationship, leave the description of the cause and the effect binary.

This paper will systematically extend fuzzy cognitive map to Dynamic Cognitive Network (DCN) in the three fundamental elements. DCN allows each concept to select its own value set according to the requirement of the system. The value set can be a binary set, a fuzzy set or a continuous interval. In dynamic cognitive networks, the procedure of how the cause takes effect is modeled by a dynamic system. Therefore using DCN, it can model causal systems more precisely and flexibly. It can behave as a cognitive map, or a fuzzy cognitive map, or a nonlinear dynamic system. Dynamic Cognitive Network maintains all the advantages fuzzy cognitive map has as long as finite value sets are used.

2. Problems of FCM

Fuzzy Cognitive Map is developed from Cognitive Map [9], which represents concepts and their causal relationships in a digraph. Cognitive map cannot represent the strength of the causal relationship. As a consequence, using cognitive maps we cannot tell whether the state of a concept will increase or decrease when several arcs converge in the concept.

Fuzzy cognitive map introduced quantitative (fuzzy) relationship between concepts to describe the strength of the causal relationship. This improves a lot. However, there are still several crucial flaws.

FCM lacks of temporal concepts; Thus it is inadequate to model real, dynamic systems. For instance, generating profit from building a bridge will happen in a long run and cannot be represented as a immediate causal relationship.

Another flaw is that the concepts in fuzzy cognitive map are usually binary. Based on binary concepts, fuzzy cognitive map is unable to model the strength of cause and degree of effect. This may also lead to unreliable inference. When we consider a causal relationship, for example, **'A causes B**', we need to specify three aspects:

- the strength of the causal relationship,
- the strength of the cause,
- the degrees of the effect.

Cognitive Map indicates only the causal relationship between concepts without specifying any of the three aspects. Fuzzy cognitive map improves it by specifying the strength of causal relationship, leaving the strength of the cause and the degree of the effect unspecified. In general, different strengths of causes result in different effects. For example, although innovations usually increase the competitiveness of an enterprise, if there are only minor innovations, the competitiveness cannot be improved significantly. Lacking of the ability to describe the concept strength, FCM regards all concepts equally: an innovation is an innovation, and that's it! Sometime, this may lead to wrong prediction of the effect.

A reasonable causal inference may look like as follows:

$$\underbrace{(slight)}_{\alpha}\ \boldsymbol{A}\ causes\ \underbrace{(much)}_{\beta} \rightarrow$$
$$\underbrace{(lot)}_{\gamma}\ \boldsymbol{B}\ causes\ \ (lot) \rightarrow (somehow)\ \boldsymbol{C},$$

where α, β, γ are the fuzzy descriptors of the cause, the relationship and the effect respectively. In FCMs, *B* has its value in a binary set, it can only tell difference between 0 and 1, or -1 and 1. Thus the reasonable result, (*somehow*) **C**, cannot be derived from those concepts that have direct effect on it (here is **B**). It also needs to know how **B** is derived:

$$(slightly)\ \boldsymbol{A}\ cause\ (min\{much,\ lot\}) \rightarrow (somehow)\ \boldsymbol{C} \quad (1)$$

This was proposed by Kosko [1]. However, we cannot simply use it in the numeric inference of FCM described by

$$x_i(k+1) = f_i(Wx(k)) = f_i(w_{ji}x_j(k))\ . \qquad (2)$$

Numeric inference is one of the major advantages of FCM. Equation (2) is used as the inference formula in almost every publication on FCM. Adopting (1) as the inference mechanism will lose the advantage. Furthermore, inference described by Equation (1) also has some other critical problems. 1. The concept loses the ability to make decisions, because there is no mechanism that can represent the information that has brought about the state of the concept. The inference process needs to know how the state is derived as shown in (1). 2. It cannot handle the circle structure (or the feedback mechanism) in FCMs.

In general, a process can combine the information from several FCMs into one. The problem, however, is that FCM is a causal model of the same world, different experts may have different models. It is important that the behavior of the FCM be robust; that is, slight change of the FCM should not result in totally different inference patterns. Unfortunately, it is not the case with FCM, especially when several FCMs are combined. This is also because of the binary concept value set and the lack of temporal concept.

3. Dynamic Causal Network

We propose Dynamic Cognitive Network (DCN) to solve the problems discussed above. It improves FCM by quantifying the concepts and introducing nonlinear, dynamic functions to the inference process.

Similar to FCM, concepts in DCN can be causes or effects that collectively represent the system's state. A concept is distinguished from others by its properties. As discussed, properties of some important concepts in complicated systems need to be specified in more detail to specify their strengths. We define a value set in which the concept property can be represented properly. Let v indicate a concept and V for the set of concepts in DCN. Define a concept (value) set S_v as the non-empty set that has the order according to its properties P_v . For Example, the value set of a concept bridge damage can be S_v = {*not damaged, very slightly damaged, slightly damaged, minimum damaged, seriously damaged, totally damaged*} or S_v = {0,0.001, 0.1, 0.3, 0.7, 1}. The state of a concept v is its position (or value) in the concept value set according to the order of the property P_v. For example, the value set of concept height of a person is a set containing all the persons that every two of the elements (persons) can be ordered by their height. Tom's height is a concept instance. Its state can be 1.90m $\in$ [0,4m]= S_v, or or *tall*$\in$ {*short, normal, tall*}= S_v , or *quite tall* $\in$ { *very short, quite short, short, normal, tall, quite tall, very tall*}= S_v . The value set of a DCN, S_V is the product space of the value sets of the concepts which the DCN contain,

$$S_V = \prod_{v \in V} S_v \ .$$

The state of the DCN is a *n-tuple*, $x=(x_1,\cdots,x_n)^T$ where n is the number of concepts in the DCN.

As we have seen, in a DCN, every concept has its own value set according to its properties. It can be a binary set, triple set, fuzzy set, or real interval. The states of the concepts can now well represent the strength of the cause and the degree of the effect. The quantitative concepts provide not only the ability to describe the strength of the cause and degree of the effect, but also enable the inference of DCN to be carried out via numeric calculations instead of symbol deduction. This is because that the state of a concept now can be derived from those concepts that have direct effect on it exclusively.

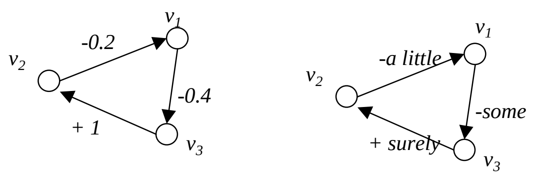

Figure2 Importance of Quantitative Concepts in Feedback Mechanism

Quantitative concepts can also help to make the feedback mechanism realistic. For example, in the DCN shown in Figure 2, x_1 may increased by 0.08 (Figure 2(a)), or {*a little*} (Figure 2(b)). After cycles 13 times, x_1 will reach its extreme state 1. This mechanism cannot be represented by binary FCM. Most real systems contain many parts that affect and restrict each other. Therefore feedback is a very important mechanism that must be included in a causal model. For example, a small company needs several profitable production periods to accumulate fund before expansion; an army needs several battles to weaken the strength of its enemy before a decisive battle. These economic and social phenomena require feedback mechanisms.

Causal relationships differ not only on how long the cause will take effect, but also on how the cause will take effect. This requires dynamic modeling. The causal relationships in a DCN is represented as

$$y_{ji}(s) = w_{ji}(s)\, x_i(s) \ , \qquad (3)$$

$$x_j(t) = \sum_i y_{ji}(t) \ , \qquad (4)$$

or more generally

$$x_j(t)=f_j\,(y_{j1}(t),\ \cdots,\ y_{jn}(t))\ , \qquad (5)$$

where y_{ji} is the direct causal effect from $v_i(x_i)$ on $v_j\ (x_j)$. y_{ji} denotes the arc output of a_{ij} . $y_{ji}\ (s)$, $w_{ji}(s)$ and $x_i(s)$ are Laplacian transformation of $y_{ji}\ (t)$, $w_{ji}(t)$ and $x_i(t)$. Concept v_j can determine its state x_j , given the causal inputs $\{y_{j1}(t),\ \cdots,\ y_{jn}\ (t)\ \}$ according to Equation (4) or Equation (5), where f_j is the vertex function of v_j. Therefore every arc in DCN represents a sub-differential dynamic system. We define the states of these differential dynamic systems as the arc inner states of DCN, denoted as $Z_{ji}=(z_{ji}^{1},\cdots,z_{ji}^{r_{ji}})^T$. Then Equation (3) can be written as

$$\frac{dZ_{ji}(t)}{dt}=AZ_{ji}(t)+Bx_i(t),$$

$$y_{ji}(t)=CZ_{ji}(t)+Dx_i(t),$$

$$x_j(t)=\sum_i\ y_{ji}(t),$$

or more generally,

$$\frac{dZ_{ji}(t)}{dt}=\ f_{Z_{ji}}(Z_{ji}(t),x_i(t)),$$

$$y_{ji}(t)=g_{ji}(Z_{ji}(t),x_i(t)),$$

$$x_j(t)=f_j(y_{j1},\cdots,y_{jn})\ .$$

As an FCM has at most 2^n states, this means that the state will be either a static state or be trapped in a limit circle after 2^n inference steps. Under these conditions, FCM does not possess complicated dynamic properties such as pseudo-periods and chaos. However, DCN can be as complicated as a nonlinear dynamic system [11] and its concept-value set may be binary sets, triple sets, fuzzy sets or real intervals. One thing needs to be noted is that a general differential dynamic system is usually very complex. The concept sets of a DCN should be fuzzy sets and should be kept as simple as possible as long as they adequately model the system. A DCN has a finite number of states and the final inference pattern is also either in static state or limit circle.

Reference

1. Kosko B., “Fuzzy Cognitive Maps”, *International Journal Man-machine Studies Studies*, No 24, pp 65-75 (1986).
2. Silva,P.C. “New Forms of Combined Matrices of Fuzzy Cognitive Maps”, *Proc. IEEE Int. Conf. on Neural Networks*, Vol.2, 1995,pp.771-776.
3. Schneider,M. et.al., “Constructing Fuzzy Cognitive Maps” *Proc. IEEE Int. Conf. on on Fuzzy Systems*, 1995, pp. 2281-2288.
4. Kosko B., “Fuzzy System as Universal Approximators”, *Proc. the 1st IEEE International Conference on Fuzzy Systems*, 1992,pp.1153-1162.
5. Ndousse, T. D. and Okuda, T., “Computational Intelligence for Distributed Fault Management in Networks Using Fuzzy Cognitive Maps”, *Proc. IEEE Int. Conf. on Communications Converging Technologies for Tomorrow's Application*, vol.3, 1996, pp.1558-1562.
6. Peaez, C. E. and Bowles, J. B., “Applying Fuzzy Cognitive Maps Knowledge-Representation to Failure Modes Effects Analysis”, *Information Sciences*, Vol.88, 1996, pp.177-199.
7. Satur R. and Liu, Z.Q., “A context-driven Intelligent Database Processing System Using Object Oriented Fuzzy Cognitive Maps”, *Int. J. of Intelligent Systems*, Vol.11, No.9, 1996, pp.671-689.
8. Hagiwara, M.,“Extended Fuzzy Cognitive Maps”, *Proc. IEEE Int. Conf. on Fuzzy Systems*, 1992, pp.795-801.
9. Axelrod, R., *Structure of Decision: the Cognitive Maps of Political Elites*, Princeton, NJ:Princeton University Press, 1976.
10. Miao, Yuan and Liu,Zhi-Qiang, “On Causal Inference in Fuzzy Cognitive Map”, (to appear), *IEEE Trans. Fuzzy Systems.*
11. Phillips, C. L. and Harbor, R. D.,*Feedback Control Systems*, Prentice Hall, 1991.