Cognitive maps: A Review of Applications and Advancements

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Abstract: **This paper presents the concept of cognitive maps as an effective means of modeling physical systems as well as conceptual frameworks. The basic structure of cognitive maps is discussed by detailing the role of each of its basic constructs. System simulation using cognitive maps is also briefly discussed. Advanced variants as well as advancements pertaining to cognitive map modeling proposed by researchers over the past two decades are reviewed. A brief discussion on application areas of cognitive maps and its variants is also included. Looking at the increasing trend of applications of cognitive map modeling in the past two decades, it can be concluded that there is good potential in cognitive maps to play an important part in the developing arenas of artificial intelligence and soft computing.**

1. INTRODUCTION

Cognitive maps were introduced by the political scientist Robert Axelrod [1] in 1976 as a means of modeling decision making scenarios in social and political systems [2]. A cognitive map is essentially a signed digraph consisting of nodes (representing concept variables) and directed arcs (representing causal relationships). In its simplest form as introduced by Axelrod, it consists of concept variables interconnected with causal arcs labeled with either a "+" or "-" sign. Figure 1 shows an example of such a cognitive map which models the relationship between working conditions in a factory and the profits accrued.

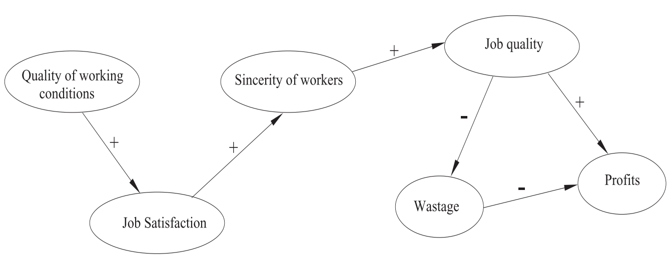

Fig. 1. Example of a simple cognitive map

A "+" sign on an arc connecting two concepts implies that an increase or decrease in the antecedent concept leads to an increase or decrease respectively in the consequent variable. While on the other hand, a "-" sign implies that an increase or decrease in the antecedent concept leads to a decrease or increase respectively in the consequent concept. However, due to the simplistic nature of the type of cognitive map mentioned above, apart from giving a graphic representation of causality, it is of not much use in modeling real world scenarios. Moreover, due to lack of any form of quantification, it is difficult to derive any useful inference.

The topology of cognitive maps was completely revolutionized by the introduction of fuzzy cognitive maps (FCMs) in 1986 by Bart Kosko [3]. Since then many variants of FCMs have been advocated for numerous applications in science and engineering too besides their originating domain of social sciences. The major developments that have taken place in the field of cognitive maps since their introduction are reviewed next.

2. FUZZY COGNITIVE MAPS

The first appearance of an appropriate quantification in cognitive maps was through Kosko's fuzzy cognitive maps. Apart from having a "+" or "-" sign showing the type of causality, the arcs in Kosko's FCMs also carry weights (usually in the interval [0, 1]) expressing the strength of causality. A numerical quantity is associated with each node in an FCM, representing the state/level of that node. Interestingly, quite contrary to what the term 'Fuzzy', in the name 'Fuzzy cognitive map' suggests, an FCM has no relation with fuzziness or fuzzy logic in the traditional sense.

An FCM is simulated in discrete/continuous time (as the case may be), during which the weights on the arcs remain constant, but the concept values change. During simulation, the updated value of any given concept is evaluated by passing the weighted sum of all concept values that are input to the given concept node, through an appropriate threshold function. For more clarity, let us take an example of a concept node (of a discrete time FCM) with value $(C_j)_t$ at time step *t* with *n* number of input nodes having values $(C_i)_t$ (where $i = 1$ to n). Let w_{ij} be the respective weights on the arcs. Then at the end of time step *t*, the updated value of the j^{th} node will be given by equation (1).

$$(C_j)_{t+1} = T\{\textstyle\sum_{i=1}^{n}[(C_i)_t \,.\, w_{ij}]\} \tag{1}$$

Here, *T* is an appropriate threshold function. The purpose of a threshold function is to constrain the values of concept nodes within a certain interval (usually [0, 1], or [-1, +1]). Equation 1 represents the traditional node updating process in FCMs. Stylios et al. [4] use a modified node updating process for cognitive maps in modeling systems. This modification, as given in equation (2) updates each node by including their previous value too.

$$\left(C_j\right)_{t+1} = T\left\{\sum_{i=1}^{n}\left[(C_i)_t \,.\, w_{ij}\right] + \left(C_j\right)_t\right\} \tag{2}$$

Hence, FCMs using equation 2 for updating nodes have one time step memory capability.

FCM simulation can also be shown using simple matrix multiplications as given by equation 3.

$$C_{t+1} = T[C_t + (C_t \,.\, E)] \tag{3}$$

Here, C_t is a $1 \times n$ matrix containing the node values $(C_i)_t$ at any given time step *t*; E is an $n \times n$ matrix (called the adjacency or connection matrix) that contains all the weights stored in the arcs of a cognitive map having *n* number of nodes; and *T* is the threshold operation on matrices.

FCMs that were initially in common use were either bivalent or trivalent in nature. An FCM is called bivalent if the concept nodes take values from the set {0, 1}, and trivalent if concepts take values from the set {-1, 0, +1}. The type of values taken by concepts in an FCM is dictated by the threshold function used. Equations (4) and (5) give the threshold functions that result in the formation of bivalent and trivalent FCMs respectively.

$$T(x) = \begin{Bmatrix} 0 & if\ x \le \tau \\ 1 & if\ x > \tau \end{Bmatrix} \tag{4}$$

$$T(x) = \begin{Bmatrix} -1 & if\ x \le \tau_1 \\ 0 & if\ \tau_1 < x < \tau_2 \\ 1 & if\ x \ge \tau_2 \end{Bmatrix} \tag{5}$$

Where $\tau,\ \tau_1, and\ \tau_2$ are pre-specified threshold values.

Bivalent and trivalent FCMs have the limitation that they can be used to represent an increase or decrease in concept values (also a stable or neutral condition in the case of trivalent FCMs). They cannot represent the degree of an increase or decrease that has occurred. For a more realistic representation of real world applications involving non-linearity, the more recent, continuous FCMs are better. These FCMs make use of continuous non-linear transformation/threshold functions, thus enabling the concepts to take values from a real interval (usually [0, 1] or [-1, +1]). Most commonly used among these are the sigmoid (logistic) and *tanh* (hyperbolic tangent) threshold functions which are given in equations 6 and 7 respectively.

$$T(x) = \frac{1}{\left(1 + e^{-\lambda x}\right)} \tag{6}$$

$$T(x) = \frac{\left(e^{\lambda x} - e^{-\lambda x}\right)}{\left(e^{\lambda x} + e^{-\lambda x}\right)} \tag{7}$$

In the above equations, λ is a constant parameter that determines the slope or steepness of the threshold function.

Final inference in fuzzy cognitive maps

Once a cognitive map model of a system is made, its simulation is done by triggering the map with an initial set of values of all the nodes contained within it. This trigger updates the values of the nodes. The final inference is obtained after conducting multiple iterations with subsequent triggers using updated nodal values.

The inference procedure of a cognitive map is the methodology or algorithm applied to it in order to derive a meaningful inference through simulation. The inference procedure details out, or in other words, sets the rules of interaction among the nodes and arcs. However, the final inference for fuzzy cognitive maps is obtained in the form of one of the following conditions:

(i) *A Unique Solution*: This is a condition where the states of all concept variables remain unchanged for successive iterations. In the absence of any feedback loop in the cognitive map, the simulation terminates after the first iteration. In such cases the cognitive map is said to be trivial.

(ii) *A Limit Cycle*: In this condition, a particular set of concept states' configuration keeps on repeating indefinitely with successive iterations.

(iii) *Chaos*: In this condition, the iterations will go on indefinitely, giving neither a final terminating solution nor any repeating configuration of concept states. The subsequent result of iterations is always a different set of values for the concepts.

Limitations of fuzzy cognitive maps

In 1999, Carvalho and Tomé [5] brought to light, a significant shortcoming of FCMs in the fact that the relations in FCMs are monotonous in nature. This however is not the case in most of the real world applications. Further, they also comment on the inability of traditional FCMs in modeling the dynamics of complex qualitative systems.

FCMs have always been considered to have close similarities with artificial neural networks. However, one major difference among them is in the number of arcs connecting nodes with each other; which is typically much higher in the case of neural networks. This fact brings to light one of the main shortcomings of FCMs. According to Khor [6], while a small amount of error that may happen to be introduced in one or a few arcs of the neural net is compensated by the other arcs; such errors are usually retained in the case of FCMs owing to the fewer number of arcs available for compensation. Further, Carvalho and Tomé [7] opine that this problem is aggravated if feedback loops are also present in FCMs.

Another common problem with FCMs is associated with the use of continuous threshold functions. It is observed from equations 6 and 7 that the steepness/gradient of the threshold functions is governed by the parameter λ. There is much ambiguity in the choice of this parameter. This limitation of FCMs that totally different results (simulations) are possible by using different values of λ was sufficiently demonstrated by Khor [6] using several examples.

Another shortcoming of most FCM variants is their inability to deal with complex AND/OR relationships that may exist among nodes.

Advanced variants of fuzzy cognitive maps

Enough research effort has been expended by various researchers towards improving the inference capabilities of FCMs. For example, in order to overcome the shortcoming of monotonous relations in FCMs, Hagiwara [8] proposed the use of non-linear arcs. In the same work, an improvement in the inference procedure of FCMs is also proposed in the form of time delay arcs. The use of time delay in arcs compensates for the fact that in real world applications, there is a time delay before the effect of an antecedent node is materialized in a consequent node. In order to improve the qualitative modeling capabilities of FCMs, Carvalho and Tomé [5] proposed rule-based FCMs (RBFCMs). RBFCMs use an inference procedure that is in an actual sense based on fuzzy theory. In continuation of their work, Carvalho and Tomé [9] elaborate cognitive map concepts as fuzzy variables defined by fuzzy membership functions and the relations (arcs) with fuzzy rule bases. RBFCMs employ single antecedent fuzzy rules in the rule bases that are stored in the arcs. For any given node, the concept state at the end of a time step is evaluated by aggregating the fuzzy inference outputs of all the nodes antecedent to it using a mechanism called 'Fuzzy carry accumulation'. When the concept value exceeds a certain maximum limit (usually 1), an 'overflow' occurs, which is carried over to the next point in the universe of discourse. However, Khor [6] opines that there are certain limitations and shortcomings with RBFCMs which limit their application to modeling simple problems only. For example, Carvalho and Tomé [5] themselves admit that under certain conditions RBFCMs (developed by them) do not allow the use of singleton (crisp) inputs. Moreover, RBFCMs do not provide a basis for supporting multi-antecedent rules.

Khor [6] proposed the fuzzy knowledge map (FKM) as another variant of rule based FCMs. FKMs also use the same modeling constructs as the RBFCMs with fuzzy variables as concepts and single antecedent rule bases populating the arcs. The justification given for the use of single antecedent fuzzy rule bases is that it reduces problem complexity and eliminates the rule explosion problem generally observed in multi-antecedent rule bases. However, the main drawback with this approach lies in the fact that the algorithm that implements the approach requires specific quantitative data related with the variables involved, which might not be available always. Moreover, simple common sense reasoning that goes hand in hand with most qualitative assessments cannot be performed using Khor's algorithm. On the contrary, it is interesting to note that this type of reasoning can be performed quite easily using the traditional multi-antecedent rule bases.

Augustine et al. [10] modified the basic constructs of cognitive maps to introduce a new modeling framework for failure analysis of physical systems namely “Rate cognitive maps”. The proposed cognitive map based framework provides a robust approach for identifying a large variety of possible failure modes in a dynamic environment through a new cognitive inference process. While this methodology allows the identification of possible failure modes at multiple levels of abstraction, the network like representation of physical systems makes it easier to track the root causes of identified failure modes. The authors successfully demonstrated the capability of rate cognitive maps in predicting possible future failure modes of physical systems using mainly the structural models as input. The cognitive map model of a water heater was simulated for a five year run. The output was a listing of all possible failure modes along with their timestamps in the projected five years. Rate cognitive maps thus hold good potential in modeling and simulation of mechanical systems for the purpose of design-stage failure modes and effects analysis.

In recent years, many new variants have been proposed by various researchers. These variants have been propelled by the need to make cognitive maps more and more intuitive and adaptable to newer requirements in the field of modeling and simulation. Prominent research that has been done in this direction since the year 2010 is as follows:

Fuzzy Grey Cognitive Map was proposed by Salmeron [11] to deal with unstructured data occurring due to uncertainty. Their model can be considered as a generalization of the standard FCM obtained by the use of Grey numbers. Cai et al. [12] introduced Evolutionary Fuzzy Cognitive Maps. With their model, they demonstrated capability of modeling dynamic and complex causal relations. This capability was achieved by allowing the variable states to evolve in real time on the basis of external assignments and causalities. Expert knowledge is always required in some form or the other in order to construct a cognitive map of a system or a scenario in any domain. The variant of FCM developed by Iakovidis and Papageorgiou [13], which they named as Intuitionistic FCM, enables capturing the essence of an experts' opinion or decision rather intuitively, when there is hesitation in decision-making by the expert. This was achieved by using a combination of reasoning along with intuitionistic fuzzy sets. Ruan et al. [14] introduced belief-degree-distributed fuzzy cognitive maps. They used belief structures to facilitate assignment of linguistic terms to nodal relationships in FCM. Rough set theory was used by Chunying et al. [15] to develop a variant of FCM called as Rough Cognitive Map. This variant was developed specifically to target the problems involved in dealing with the diversity of relations that sometimes exist among concept nodes.

3. APPLICATIONS OF COGNITIVE MAPS

Owing to the capability of cognitive maps in modeling causality, both quantitatively as well as qualitatively, they have found applications in diverse fields of research. Papageorgiou and Salmeron [16] identify numerous application areas in their survey work. Prominent among these areas include social sciences, political sciences, expert systems, medicine, education, prediction, environmental sciences, engineering, robotics, information technology etc.

Aguilar [17] was the first researcher to compile a detailed review of FCM applications till the year 2004. Another review work of FCM applications worth mentioning was done by Papageorgiou [18].

After the year 2010, research using FCM has continued and has spread to even more areas of science and engineering. Some of the notable efforts include applications in the following areas: classification and Prediction [19], solar Energy [20], medical decision making [13], autonomous navigation systems [21], artificial emotions forecasting [22], enterprise resource planning [23], security risk assessment [24], water demand prediction [25], intelligent security systems [26], pattern recognition [27], Environmental Assessment [28].

4. CONCLUSION

Since its inception in 1976, the cognitive map of Axelrod has evolved and has found a plethora of applications in systems' modeling and simulation. The ease with which cognitive maps gained popularity and found acceptance in scientific circles can mostly be attributed to the inherent capability of their architecture in handling qualitative as well as quantitative data effectively.

This paper discussed the basic inference procedures used in a cognitive map and its more dominant successor, the fuzzy cognitive map. A brief discussion was included on the currently prevalent variants of FCMs. Finally, some light was thrown on the application areas of cognitive maps and its variants.

Although cognitive maps are increasingly becoming popular for modeling real world scenarios, it is surprising that very little effort has been expended towards incorporating the probabilistic nature of causal interactions in the cognitive map inference mechanism. In this regard, development of cognitive map variants with stochastic inference capabilities seems promising from the perspective of future research in this field.

Nevertheless, looking at the steep trend of increase in its applications in the past two decades, cognitive maps can be expected to play a major role in the emerging paradigm of artificial intelligence and soft computing.

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