Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps – A Comparative Study

João Paulo Carvalho José A. B. Tomé
INESC - Instituto de Engenharia de Sistemas e Computadores
IST – Instituto Superior Técnico
R. Alves Redol, 9, 1000 Lisboa, PORTUGAL
Phone: +351.1.3100262 Fax: +351.1.3145843
E-mail: uke@eniac.inesc.pt jbt@eniac.inesc.pt

Abstract

This paper focus on the comparison between Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps. The paper shows FCM limitations to represent non-monotonic non-symmetric causal relations, presents results that exhibit the stability of RBFCM in systems where FCM is not stable due to its non-fuzzy inherent nature and presents RBFCM potential to model qualitative real-world dynamic systems.

1. Introduction

Decision makers usually face serious difficulties when approaching significant, real-world dynamic systems. Such systems are composed of a number of dynamic concepts or actors which are interrelated in complex ways, usually including feedback links which propagate influences in complicated chains. Axelrod work on Cognitive Maps (CMs)[1] introduced a way to represent these systems, and several methods and tools like [2] or [3] allow the analysis of causal maps structure. However, complete, efficient and practical mechanisms to analyse and predict the evolution of data in CMs are necessary [4] but not yet available for several reasons. System Dynamics tools like [5] could be a solution, but since numerical data may be uncertain or hard to come by, and the formulation of a mathematical model may be difficult, costly or even impossible, then efforts to introduce knowledge on these systems should rely on natural language arguments in the absence of formal models. Fuzzy Cognitive Maps (FCM), as introduced by Kosko [6], are a qualitative alternative approach to dynamic systems. However, in most applications, a FCM is indeed a man-trained Neural Network which is not Fuzzy in a traditional sense, and doesn't explore usual Fuzzy capabilities. This limits FCM use to systems involving simple causal relations between concepts.

The use of Fuzzy sets, logic and inference in its traditional rule based form, as introduced by Zadeh [7] and developed throughout these 30 years is particularly more adequate to represent qualitative knowledge involved in cognitive maps due to its linguistic nature [8]. So, it seems a straightforward solution to try to implement FCM starting from a traditional rule based fuzzy architecture with feedback in order to overcome FCM weaknesses: the Rule Based FCM (RBFCM) [9]

This paper compares FCM and RBFCM, showing their main characteristics, advantages, disadvantages and capabilities to predict the evolution and consequences of changes in qualitative dynamic systems.

2. Fuzzy Cognitive Maps (FCM)

Fuzzy Cognitive Maps (FCM), as introduced by Kosko [6], are a combination of Neural Networks and Fuzzy Logic that allow us to predict the change of the concepts represented in Causal Maps. They are fuzzy directed graphs with feedback, consisting of various nodes (representing the change in concepts like Inflation or Police_Vigilance) and directed arcs that connect and represent the causal relation between those nodes (Figure 1).

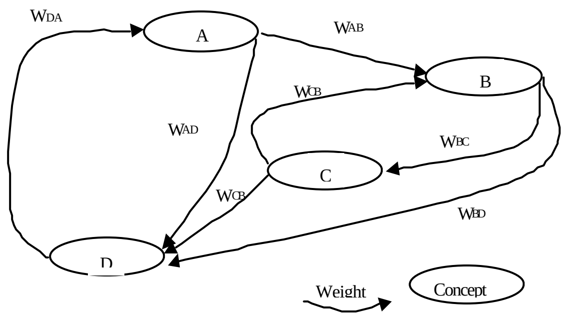

Figure 1 – FCM structure

Each concept has a fuzzy value usually ranging from [0..1] or [-1..1], and each arc is associated to a fuzzy weight with range [-1..1]. A positive weight represents a causal increase and a negative weight represents a causal decrease (opposite effect). For example, in Figure 2 a weight value of –0.8 could represent the effect of a large decrease in Theft due to a Police_Vigilance increase (or the Theft increase due to the P_V decrease). A smaller weight would represent a smaller effect.

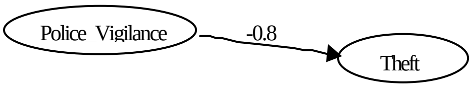

Figure 2 - Negative causal effect

To obtain the value of a concept, the value of each of its inputs (concepts) [-1..1] is multiplied by the respective weight [-1..1]; then the results are added and passed by a non-linearity. The process is the same as the one used on a common neuron in a Neural Network (Figure 3)

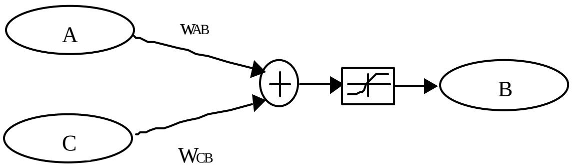

Figure 3 - Causal reasoning in a FCM

A FCM allows the answer to *what-if* questions in cognitive maps: what happens to a system if some of its concepts change, or if new concepts are introduced or removed. The evolution of a FCM is iterative: the current value of each concept is computed with its inputs previous values. After a certain number of iterations, the map might reach equilibrium, converging to a single state or a finite cycle of states

3. Rule Based Fuzzy Cognitive Maps (RBFCM)

A RBFCM is essentially a standard rule based fuzzy system where we add feedback and mechanisms to deal with causal relations [9][10]. It consists of fuzzy nodes (representing concepts) and fuzzy rule bases (which relate and link concepts) - Figure 4. Each concept contains several membership functions (mbf) which represent the concept's possible values or the possible values of its change.

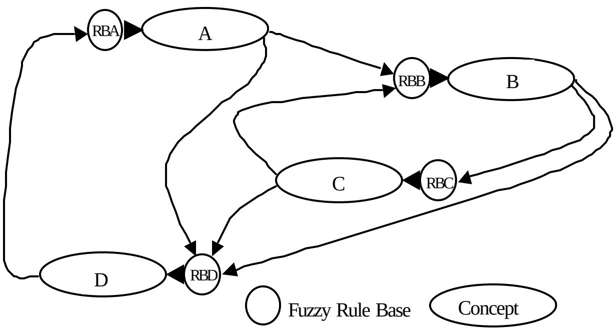

Figure 4 – RBFCM structure

Any kind of relation that can be represented by fuzzy rules is allowed: opposition, similarity, implication, classical fuzzy reasoning, etc. With the introduction of Fuzzy Causal Relations (4.)[9][10], RBFCM can also represent causality. Inputs can be combined using most fuzzy operations (and, or, etc.), or using the Fuzzy Carry Accumulation [9][10].

As in FCM, RBFCM are iterative and allow the answer to what-if questions in cognitive maps (not just causal maps).

Fuzzy rulebases define the relations between concepts. Each rulebase contains fuzzy *If…Then* rules like:

*"**If** Police_Vigilance Increases **then** Theft Decreases_Few"*

*"**If** Police_Vigilance Increases_Much **then** Theft Decreases"*

The mbf of a non-causal concept do not have any particular restriction, but those of a causal concept must abide by certain conditions in order to guarantee fuzzy causality [10]. Figure 5 shows one possible set of mbf for a given causal concept, ranging from *Decrease_Very_Much*, to *Increase_Very_Much*.

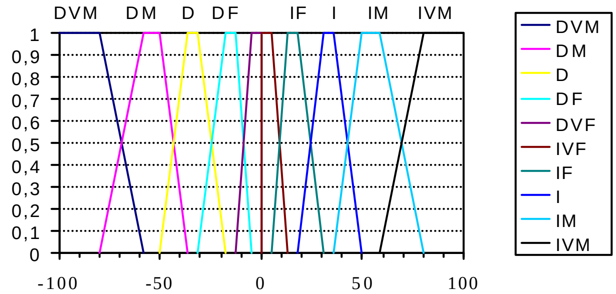

Figure 5 – Membership functions for a causal concept

4.Fuzzy Causality

Due to the importance of causal relations in cognitive maps, this section introduces Fuzzy Causal Relations (FCR).

There is a causal relation between two given concepts whenever a relative variation in one of those concepts cause a relative variation on the other one. For example, there is a causal relation between Police vigilance and Theft: a major increase in Police Vigilance will probably cause a decrease in Theft.

Causal relations in causal maps always involve change: the result of a causal effect is always a variation in one or more concepts. Therefore, causal maps show the variation of a concept's value, not the concept absolute value.

Another property of causal relations is that, by nature, causality is "accumulative". For example, using "natural language" we can say that if concept A and concept B each cause concept C to increase "little", then C will increase "more than a little". If two concepts A and B have the exact opposite effect on C, then C will not change. If A affects "little" and B affects "much", then C will increase "more than much". The effect when both decrease is similar.

In contrast, a traditional fuzzy relation tends to reinforce itself. If A and B cause C to increase "little" with a belief of 0.3 and 0.6, then concept C will increase "little" with a stronger belief (0.9). If A causes C to increase "little" and B causes C to increase "much", then C would increase somewhere between "little" and "much". Opposed effects tend to nullify each other (as in a causal relation).

This essential intrinsic difference causes a total incompatibility in the use of classical fuzzy to represent causal relations. Therefore, in order to introduce causal relations in fuzzy systems, it is necessary to find new ways to make both worlds compatible. In [9][10] we introduce FCR and the Fuzzy Carry Accumulation (FCA), which is a new fuzzy operation that provides the intended accumulative effect between several fuzzy rules representing a causal relation. Under certain conditions [10], the FCA is associative and commutative, which allows the introduction and removal of concepts and/or rules in RBFCM without special requisites.

It is important to note that several fuzzy additive systems exist (like Kosko's SAMs [6] for instance), which are not accumulative in the above sense. Those systems add the beliefs of the variables (Y-Axis), not the values in their universe of discourse (UoD – X-Axis), which means that they can not be used to emulate the intended causal behaviour.

5. Why RBFCM? – A comparison with FCM

Although FCM can use fuzzy weights and represent the value of concepts using fuzzy numbers, they can not be mixed with classical fuzzy rules or operations. FCM are indeed man-trained Neural Networks (Multilayer perceptron) whose values can (but usually are not) be computed using fuzzy arithmetics. They don't share the properties of other fuzzy systems and can not be mixed with traditional fuzzy rules and operations. Besides, almost current FCM examples and applications simply ignore their fuzzy part and are limited to bivalent or trivalent concepts ({0,1} or {-1,0,1}) and crisp weights. Although this is not a problem by itself since these simple FCM can perform rather well when trying to represent the evolution of simple management, organisational or socio-economic problems, these restrictions limit FCM to the representation of systems that use only simple monotonic and symmetric[1] causal relations between concepts.

But many real world causal relations are not symmetric or monotonic. Positive and negative causality often produce different non-symmetric results as we can see in [9]. For example, the amount of increase in Anti_Pollution_Measures due to an increase in Industrial_Pollution could be larger than the decrease in Anti_Pollution_Measures caused by a similar decrease in Industrial-Pollution (the measures could even not diminish at all). One might argue that FCM could model non-monotonic (n-m) and/or non-symmetric (n-s) causal relations by the use of n-m/n-s non-linearities (Figure 6). However, this solution would affect all the inputs of a concept, i.e., all causal relations between a concept and all its inputs would be equally n-m/n-s, which is obviously a serious limitation to its application in real world systems. In Figure 6 we can see that in order to model correctly the relation between Ind_Pollution and Anti_Pol_Measures, the causal effect of the Industrial_Lobbies' pressure could be incorrect.

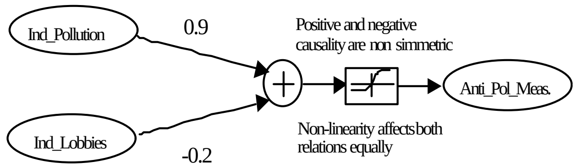

Figure 6- Non-monotonic /non-symmetric causal reasoning in a FCM

In [9] we can see that RBFCM can easily model almost kinds of n-m/n-s causal reasoning given enough mbf and fuzzy rules.

Causal associations are the major way in which understanding about the world is organised [11], but besides causal relations, cognitive maps should use other kind of relations in order to allow a better representation of real world systems that involve cognition. In the area of social sciences and/or psychology we can find several sets of possible relevant relations between concepts, like the Cognitive Base Schemes defined in [12] and [13]. To represent the qualitative knowledge involved in these relations, the use of Fuzzy sets, logic and inference in its traditional rule based form is particularly more adequate than the association of fuzzy weights with a non-linearity (due to the linguistic nature of the relations) [8]. RBFCM use linguistic fuzzy rules to describe relations among concepts. Therefore, they are not limited to causal relations. Besides, concepts can combine causal (accumulative) reasoning with "classic fuzzy reinforce" reasoning: classic fuzzy operators (And, Or, etc.) are allowed. However, as we have seen before, FCR impose restrictions on mbf. If these restrictions prevent the definition of other kinds of relations, then if necessary, other mbf could/should be added to the concepts.

RBFCM main trade off for versatility and modelling potential is complexity and time consumption. While to define a causal relation in a FCM all we have to do is select positive or negative causality and a weight, in

[1] Symmetric weights produce symmetric results

RBFCM we have to define one fuzzy *If..Then* rule for each mbf in the input concept. We can reduce this complexity with the implementation of macros to define simple monotonic symmetric causal reasoning. For example, the macro *A Affects_Much_Negatively B*, could be associated to a set of *n* fuzzy rules (*n* = number of mbf of *A*) that express that a small positive change in A causes a large negative change in B. For example:

*"**If** A Decreases_Very_Few **then** B Increases_Few"*
...
*"**If** A Increases **then** B Decreases_Much"*
...
*"**If** A Increases_Much **then** B Decreases_Very Much"*

On a FCM this macro would be the equivalent of a weight *-0.7* (for instance). These macros can also be used to define other types of more or less common causal relations like exponential causality, for instance, but if we want to use all RBFCM modelling capabilities, then we have to define the relation rule by rule.

FCM main success resides in the fact that it provides an easy and fast method (albeit not very realistic or powerful) to create and simulate qualitative dynamic systems with feedback. Most people do not even use all FCM capabilities and limit their experience to bivalent nodes and positive (weight = 1) or negative (weight =-1) causality. They tend to believe that this way they can get a rough but valid prediction of the evolution of the system. However this assumption might not be true in several systems, especially when a system does not converge to a single state. Whenever the system converges to a cycle of states, the cycle can become quite different and lead to different conclusions as we increase the model complexity (by allowing more variety in values for concepts and weights) [14] – even if some states of the cycle are common. In order to obtain more reliable results it is very important to try to model a system as detailed as possible with the available information.

Another important side effect of increasing complexity in FCM is system stability. When we force the concept values to a bivalent or trivalent state, then systems tend to converge to a state or a cycle of states (unless the system is inherently unstable). But when we allow the range [-1..1] or [0..1], systems that previously converged can now become unstable [14]. We can identify main tendencies in cycles, but we do not have a real cycle (maybe this is the main reason why FCM are usually used in their simplest configuration). In RBFCM, when we use mbf like the ones depicted in Figure 5, the plateau of each mbf act as attractors, and the systems will tend to cycle through these values as if we were using n-valued concepts (n = number of mbf in the concept). RBFCM allow the use of an increased complexity without loosing inherent system stability. In section 6 we show this feature of RBFCM. Besides, while systems modelled with FCM are quite sensitive to initial state values, the same systems modelled by RBFCM usually converge to the same state or cycle of states.

Computing time is also better in FCM than RBFCM, however with current computers this is not a critical problem as long as the system does not involve hundreds of concepts and there is no need of real-time results.

One limitation of RBFCM is the fact that loop concepts (i.e. concepts that are part of a feedback loop) must be defuzzified before they are used as an input to other concepts. As in all fuzzy systems, feedback would cause the spread of the fuzzy value of each variable (concept) to all universe of discourse, voiding its meaning. It is easy to see this effect in the case of a single variable with its output connected directly to its input. That said, we can visualise each concept as a fuzzy variable in each iteration, but before the next iteration, we must defuzzify it.

To conclude this comparison we resume FCM and RBFCM main advantages and disadvantages:

FCM

⊕ Easy and fast crisp modelling
Fast computation

⊖ Simple monotonic symmetric causal relations
Non-compatible with classic fuzzy
Numeric modelling

RBFCM

⊕ Flexible causal relations
Can represent other than causal relations
Fuzzy compatible
Qualitative modelling
Improved stability and immunity to initial state

⊖ Complex
Time consuming modelling
Not 100% fuzzy classic: mbf have restrictions &
Intermediate concepts must be deffuzified

6. Example of application

In order to exemplify and compare the stability of RBFCM with FCM we used a system presented and analysed in [14] - Crime and Punishment (Figure 7). This system is quite sensitive to the initial state and to the type of concepts used in the FCM model, producing different results as they are changed – it even becomes unstable when we change to continuous valued concepts.

When we model the same system with RBFCM (limiting the RBFCM capabilities to simple monotonic symmetric causal reasoning in order to allow a fair comparison), the resulting cycle of states is always the same no matter the initialisation vector, converging to the following cycle of ten states:

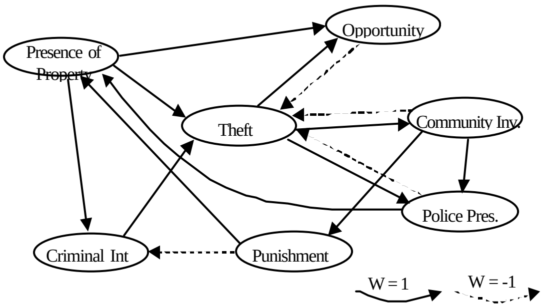

Figure 7 – Crime and Punishment Causal Map

Iteration	Opportunity	Community Involvement	Police Presence	Punishment	Criminal Intent	Presence of Property	Theft
t0	0	0	81	0	0	81	0
t1	81	0	0	0	81	81	0
t2	81	0	0	0	81	0	81
t3	-82	81	81	0	0	0	81
t4	-82	81	81	81	0	81	-81
t5	81	-82	0	81	0	81	-41
t6	81	-82	-81	-82	0	81	81
t7	0	81	0	-82	81	-81	81
t8	-81	81	81	81	0	-82	-27
t9	-5	-76	3	81	-81	81	-81
t10	81	-82	-81	-82	0	81	7
…							
t32	81	-82	0	81	0	81	-49
t33	81	-82	-81	-82	0	81	81
t34	0	81	0	-82	81	-81	81
t35	-81	81	81	81	0	-82	-27
t36	-5	-76	3	81	-81	81	-81
t37	81	-82	-81	-82	0	81	7
t38	36	34	-38	-82	81	-81	81
t39	-81	81	81	81	0	-81	15
t40	-80	55	81	81	-81	81	-81
t41	81	-82	0	81	0	81	-49

We used the mbf represented in Figure 5. 81 and –82 are values corresponding to the largest positive and negative variation. Each causal relation was modelled using 10 rules, for a total of 150 rules in the system. Two different macros (sets of rules) were used: one corresponding to a weight 1 in the FCM, and the other to the weight –1.

7. Conclusion

RBFCM can be a valid alternative to FCM when trying to model qualitative complex real world systems. One might argue that RBFCM implementation is complex and intensive, needing lots of rules, which is true when compared to the simplicity and elegance of FCM. However, as we have seen, RBFCM potential is far superior to FCM capabilities. RBFCM are still being developed in collaboration with Social Sciences scientists. We are trying to find and implement a standard set of relations (other than causal) that would allow us to model the cognitive maps involved in negotiation processes.

8. References

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

[2] Laukkanen, M., *Comparative Cause Mapping of Management Cognition: A computer Database For Natural Data* , Helsinki School of Economics and Business Publications, 1992

[3] Decision Explorer, Banxia Software

[4] Laukkanen, M. *Conducting Causal Mapping Research: Opportunities and Challenges*, in *Managerial and Organisational Cognition*, edited by Eden, C. and Spender, Sage, 1998

[5] Vensim., *The complete toolkit for building and using high quality dynamic feedback models*, Vensim

[6] Kosko, B., *Fuzzy Thinking*, Hyperion, 1993

[7] Zadeh, L., *Fuzzy Sets and Applications: Selected Papers*, Wiley-Interscience, 87

[8] Kaufmann, A., *Introduction à la Théorie des Ensembles Floues, Aplications à la Linguistique, à la logique et à la sémantique*, Masson, 1975

[9] Carvalho, J.P. and Tomé J.A.B., *Rule Based Fuzzy Cognitive Maps – Fuzzy Causal Relations*, Computational Intelligence for Modelling, Control and Automation: Evolutionary Computation & Fuzzy Logic for Intelligent Control, Knowledge Acquisition & Information Retrieval, edited by M. Mohammadian, IOS Press, 1999

[10] Carvalho, J.P. and Tomé J.A.B., *Fuzzy Mechanisms for causal Relations*, Proceedings of the IFSA99, 8th International Fuzzy systems Association World Congress, Taiwan 1999

[11] Huff, A., *Mapping Strategic Thought*, John Wiley and Sons, 1990

[12] Guimelli, C., *Transformation des Représentations sociales, Pratiques Nouvelles et Schèmes Cognitifs de Base*, Textes de Base en Sciences Sociales, Ch. Guimelli, ed. TDB Delachaux et Niestlé

[13] Rouquette, M., *Une Classe de Modèles pout L'Analyse des Relations entre Cognème*, Textes de

Base en Sciences Sociales, Ch. Guimelli, ed. TDB Delachaux et Niestlé

[14] Mohr, S. T., *The Use and Interpretation of Fuzzy Cognitive Maps*, Master Project, Rensselaer Polytechnic Institute, 1997 (http://www.voicenet.com/~smohr/fcm _white.html)