FUZZ-IEEE 2009, Korea, August 20-24, 2009

Multi-Layer Fuzzy Cognitive Modeling Using Fuzzy Signatures

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Abstract— **This paper presents a class of fuzzy cognitive modeling which can handle granulation, organisation and causation. This cognitive modeling technique consists of multiple levels where the lowest level includes details required to make a decision or to transfer to the next stage. At the lowest level, fuzzy signatures are used to represent the concepts or knowledge.**

I. INTRODUCTION

IN most real world applications today, information or data is massively available due to the popular usage of powerful and distributed computing. Soft computing research normally used in areas of intelligent data processing and intelligent decision modelling, where the problems are very complex and often contains analytically unknown behaviours [1,2]. Most complex systems or decision models required the accurate processing of any information gathered and infer decision based on the information supplied.

Fuzzy signature [3,4] has been introduced as a technique to handle complex and sometimes interdependent features. Fuzzy signature is created with the intention to facilitate decision making based on comparisons of cases with different numbers of data components, and sometime with some components missing. One of the advantages of using fuzzy signature for complex structured decision modelling is the underlying fuzzy signature can be extracted directly from data. An illustration of the powerful features of fuzzy signature has been reported in [4], where the authors used it to construct a simple Severe Acute Respiratory Syndrome (SARs) Pre-clinical Diagnosis System. When comparing with fuzzy tree, fuzzy signature has the advantage of dealing with missing and incomplete data. In fuzzy tree, if some data are missing, it is difficult to perform the search algorithm to deduce the fuzzy inference. For fuzzy signature, as each level is aggregated by some fuzzy operators, it has the feature of dealing with missing data. In most cases, the relationship between each level of the fuzzy signatures are connected with some form of weighted fuzzy operators [5,6]. In future, fuzzy rules interpolation [7] may be implemented in the fuzzy signatures.

On the other hand, cognitive map [8] has been used as a modelling tool for decision making for a long time. Since then, there are many research interests in this area with the more noticeable alternative as Fuzzy Cognitive Map (FCM). Fuzzy Cognitive Map (FCM) [9] has been successful in modelling complex systems and handling information from a graphical representation point of view. FCM has successfully used as a modelling technique that can be used in the decision-making process. It basically allows the partial influence of different factors from different sources in modelling the causal relationship between them. However, in order to design a good and stable FCM, some research look at using genetic algorithm to assist this [10]. FCM is not fuzzy in the strictest theoretical sense; it is indeed a human controlled neural network model that allows simple causal relations between concepts. Due to this reason, there are many research efforts to extend the basic of FCM to Rule Based FCM [11,12].

When examining the basic concepts underlying the human cognition, which is granulation, organisation and causation. Fuzzy signatures can address some issues in granulation and organisation well. As for causation, an alternative or a fuzzy cognitive modeling which can used to encapsulate and enhance the functionality have been reported in [13]. The purpose of this paper is to extend [13] by introducing more granulation in the modeling using multilayer model similar to Fuzzy Knowledge Map [13].

II. EFFICIENT FUZZY COGNITIVE MODELING

Please refer to [3,4] for more details on Fuzzy signatures, it will not be discussed in this paper. We will discuss our proposed cognitive modeling published in [13]. In order to better model the human cognitive system, we have divided our cognitive modeling into two main categories. In the first category, it consists of visual representation to model decision and cognitive behavior. For ease of discussion, we will limit the discussion to one meta-level in this paper. In this category of modeling, it consists of nodes and pointers to show the concepts and relations. Within each node, it exhibits the behavior of a human cognitive system. Each node will consist of three states, the sensory input state IN_i, current state CR_i, and action state AC_i. In the second

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978-1-4244-3597-5/09/$25.00 ©2009 IEEE

category, it basically consists of the fuzzy signatures to contain the knowledge necessary for the node to take any action.

Figure 1 shows a simple Fuzzy Cognitive Modeling. For node *i*,

$$N_i = (IN_i, CR_i, AC_i)$$

The modeling of the three states can be represented by the original definition of fuzzy sets which is

$$A : X \to [0,1]$$

For some current states CR_i, if necessary, they will go down to the fuzzy signature level as

$$CR_i = A_{S_i}$$

where A_{s_i} is the fuzzy signature contributing to the knowledge of node N_i.

There are basically two modes of operation for each fuzzy cognitive node: static and dynamic mode.

Operation for static mode within each node:

- The three states within each node can be linked using fuzzy linguistic rules with antecedents and consequents.
- The antecedents of the fuzzy rules consist of either the sensory input state, current state or both the sensory input state and the current state i.e. (IN_i, CR_i).
- The consequent will be the action state (AC_i).
- The operations between the antecedent/s and consequent are the same as those of the fuzzy rules.
- Depending on how the fuzzy rules are constructed, it is possible to have missing states within each node.
- From the action state, it can either propagate to the next node or convert into dynamic mode if no reasonable inference can be produced.

Operations for dynamic mode within each node:

- In this mode, the time factor (*t*) is considered.
- The fuzzy signature will be formulated as $A_{s_i}(t)$.
- For (*t+1*), cross check with the fuzzy rules in the Fuzzy Cognitive Meta-level to see if the present node can propagate to the next node. If not, it will enter into (*t+2*). This is continued until an action can be propagated to the next connecting node/s, or when there exists a fuzzy rule to resolve the outcome.

For cases where there are more than one input arrows coming into the node, i.e. IN_i consists of more than one input,

$$IN_i = \{IN_{i1}, IN_{i2}, ..., IN_{in}\}$$

In order to avoid the rule explosion problem, the relationship between $IN_{i1}, IN_{i2}, ..., IN_{in}$ is governed by a set of fuzzy aggregations. The aggregations between them are not necessarily identical or different. It can be a mixture of t-norm, s-norm, averaging aggregations and so on. Thus,

$$IN_i = IN_{i1} a_{1,2} IN_{i2} a_{2,3} ... a_{n-1,n} IN_{in}$$

Therefore, regardless of how many inputs are fed into the node, it will be resolved into one fuzzy set before being used by the node. With this flexibility, it allows missing information when performing modeling. For applications where computing power is crucial or when the available information or data is massive, the nodes can be arranged in a distributed computing architecture, with each node is being taken care of by separate nodes in the distributed computing cluster.

In those nodes where there is no input state, for example the node N_1 in Figure 1, the input state could be:

$$IN_1 = \varnothing$$

An example of the use of this Fuzzy Cognitive Signature Modelling is given as follows. Let assume the decision model used to decide whether a patient has SARs. Figure 2 shows the Fuzzy Cognitive Modelling of the problem. For node N_1, the three states are:

$$N_1 = (IN_1, CR_1, AC_1)$$

where $IN_1 = \varnothing$,
$CR_1 = A_{S_1}$, for A_{S_1} see Figure 3
and $AC_1 = \{N_2, N_3\}$

Some examples of the fuzzy rules are shown in Figure 4.

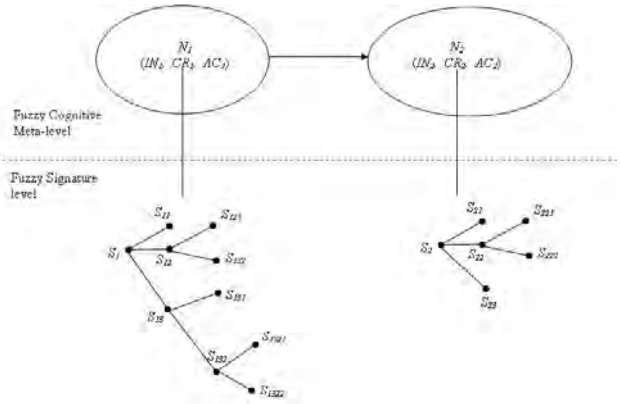

Figure 1: The basic Efficient Fuzzy Cognitive Model

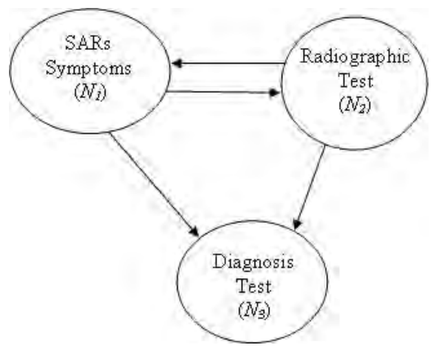

Figure 2: The Fuzzy Cognitive Meta-Level

$$A_{S_1} = \begin{bmatrix} \text{Fever} \begin{bmatrix} \text{1sthour} \\ \text{6thhour} \\ \text{12thhour} \\ \text{18thhour} \\ \text{24thhour} \end{bmatrix} \\ \text{Cough} \\ \text{Sputum} \\ \text{Dyspnea} \\ \text{Pleurisy} \\ \text{Sorethroat} \\ \text{Rhinorrhea} \\ \text{Malaise} \\ \text{Myalgia} \\ \text{Rigor} \\ \text{Headache} \end{bmatrix}$$

Figure 3: The Fuzzy Signature within N_1

If A_{S_1} is *very positive*, then N_2 is *definitely require*
If A_{S_1} is *very positive*, then N_3 is *definitely require*
If A_{S_1} is *moderate*, then *enter dynamic mode*
If A_{S_1} is *quite positive*, then N_3 is *may require*

Figure 4: Abstract of some example fuzzy rules

III. Multi-layer Design

The concept of developing the mutli-layer cognitive modeling is based on the concept used in modular design and granulation computation. Each node used to model the concepts or knowledge can be encapsulated in a node to provide a higher level of abstraction. In order to simplify the design and the computation of complex multi-layer cognitive modeling, we use basic fuzzy operators to relate the nodes in the higher layer to the lower. In other words, it can be imagine that the encapsulation as a lower layer of nodes linked to the higher layer via fuzzy operators or even Boolean operators if it is not complicated. In this case, the node in the upper layer in an abstraction level will encapsulates the nodes at the lower layer. With this simple computational model, there could be no limit of the number of layers. The only limitation could be the complexity of dividing them. With this architecture, it is also easier to distribute the different nodes at the higher layer for distributing computing or multi-core processing environment. However, this is out of the scope of this paper, it will not be discussed in details here.

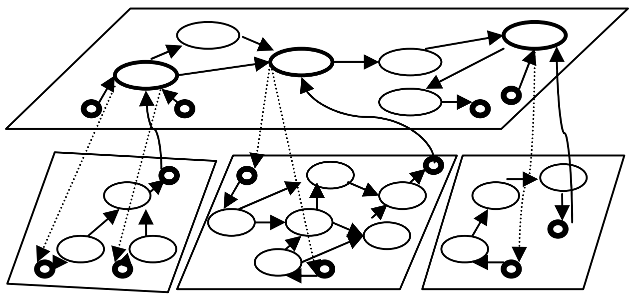

Figure 5: An example Multi layer Fuzzy Cognitive Model comprise of 2-layered configuration.

Figure 5 shows an example of a Multi layer Fuzzy Cognitive Model consisting of two layers configuration. The top layer contains one module or decision model; bottom layer contains three different modules, which are the components required in contributing to the decision of the highest level. The small round circles are the input and output terminals that encapsulate the fuzzy operators or fuzzy aggregations which enable the operation to go up to the higher level or going down to the lower level.

Encapsulation of lower level modules is useful because it allows reuse of modules. Figure 6 shows an example of the multi layer modules using Fuzzy OR. Other fuzzy operators and fuzzy aggregations can also be implemented in similar manner. The concept is similar to those presented in [14]. We demonstrate the explanation using simple logic, other fuzzy operations and fuzzy rules can also be used in the arcs with some modification to the following. The following illustrated the concept with Fuzzy OR.

Fuzzy OR can be defined as:

$$\tilde{}OR = \max(y_1, y_2) = \frac{1}{2}(y_1 + y_2 + | y_1 - y_2 |)$$

where y_1 and y_2 are two fuzzy values.

Hence we can construct our fuzzy rules for fuzzy OR multi layer fuzzy cognitive modeling (see Figure 6) as follows:

R_{AC}: If x_A is positive then $y_{AC} = x_A$

R_{BC}: If x_B is positive then $y_{BC} = -x_A$

R_{AD}: If x_A is positive then $y_{AD} = -x_A$

R_{BD}: If x_B is positive then $y_{BD} = x_A$

R_{AE}: If x_A is positive then $y_{AE} = x_A$

R_{BE}: If x_B is positive then $y_{BE} = x_B$

R_{CF}: If x_C is positive then $y_{CF} = x_C$

R_{DF}: If x_d is positive then $y_{DF} = x_d$

R_{EF}: If x_E is positive then $y_{EF} = x_E$

R_{FG}: If x_F is positive then $y_{FG} = 0.5 * x_F$

The notation R_{ij} denotes the fuzzy rule for the arc from node i to node j; y_{ij} denotes output for the rule R_{ij}; and x_i is the input to the node i. The links between A to D and B to C are labeled as negative to denote that the fuzzy rules in these arcs negate the outputs to node D and C.

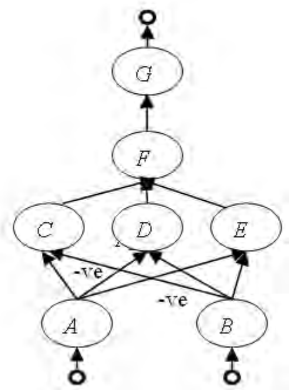

Figure 6: Multi layer configuration for OR

This section has presented the initial idea of how the multi layer cognitive model can be implemented, with fuzzy signatures as the lowest level in the granulation to provide a more powerful usage of fuzzy theories.

IV. Conclusions

This paper has extended the initial work in the efficient fuzzy cognitive modeling approach by incorporating more granulation by introducing multi-layer cognitive modeling. With this new extension, it can be used for more complex decision problems. It is also formulated with the possibility to be easily extended for a distributed computing environment or even multi-core processing environment. The paper shows an example illustrated by fuzzy OR. The same concept can be extended to other fuzzy operators and fuzzy aggregations. In future, the design criteria and the automated multi-layer construction algorithms will be investigated to build the different layers in the multi-layer cognitive modeling.

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