2006 IEEE International Conference on Fuzzy Systems
Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada
July 16-21, 2006

Efficient Fuzzy Cognitive Modeling for Unstructured Information

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Abstract— **This paper presents an efficient 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. This Fuzzy Cognitive Modeling will enhance the usability of fuzzy theory in modeling complex systems as well as facilitating complex decision making process based on ill structured or missing information or data.**

I. Introduction

In most real world applications today, information or data is massively available due to the popular usage of powerful and distributed computing. Among the changes of technology over the last decades, the most visible are commonly referred to as the information revolution or knowledge revolution. Closely linked to the information revolution is the intelligent systems revolution. The manifestations of this revolution are not as obvious as those of the information revolution because they involve, for the most part, not new products but higher MIQ (Machine IQ) of existing systems, products and devices. The information and intelligent systems revolutions are in a symbiotic relationship. Intelligence requires information and vice-versa. The confluence of intelligent systems and information systems has led to intelligent information systems. The nature of information has transformed to becoming more heterogeneous and complex in structure, so it is quite impossible to handle information processing in the traditional single objective semantics manner. This has brought about the increasing attention on the development of hierarchical, modular, or granular modeling in Artificial Intelligence research.

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When examining the basic concepts underlying human cognition, we can see human use the skills of granulation, organisation and causation in handling decision making and inference tasks. When dealing with massive information, humans will make use of the skill of performing information granulation. Granularity relates to clumpiness of structure while granulation refers to partitioning an object into a collection of granules, with a granule being a clump of objects (points) drawn together by indistinguishability, similarity, proximity or functionality [1]. Granulation may be crisp or fuzzy; dense or sparse; and physical or mental. All these have been the motivation for this research, which is to search for an efficient way of using fuzzy theory for cognitive modeling.

Fuzzy modeling has the ability to provide meaningful linguistic labels to the fuzzy sets [2] in the rule base [3, 4], and has been popular in many real world applications. As the size of available information or data is increasing at a very fast pace, the factors that could impede the applications of this approach are as follows. Fuzzy modeling will encounter problems when dealing with applications that require reasonably high numbers of input variables. Due to high computational cost, it is also difficult to use to deal with problems that are complex and contain many interdependent features. In most cases, when data is missing, it is difficult to generate reasonable inferences.

On the other hand, cognitive maps [5] have been used as a modeling tool for decision making for a long time. Since then, there has been much research interest in this area with the more noticeable alternative of the Fuzzy Cognitive Map (FCM) [6]. However, the FCM has some disadvantages and would not be applicable when the information is massive and ill structured. This will be discussed in section 2.

This paper examines the characteristics of cognitive maps, FCM, fuzzy theory and granulation theory to formulate an efficient Fuzzy Cognitive Modeling technique to enhance the usability of fuzzy theory in modeling complex systems. This is also used to facilitate complex decision making processes based on ill structured or missing information or data.

II. Cognitive Maps

In some cases, domain knowledge can be represented as a collection of important concepts or events with relationships between them. In [5], a mathematical model of a belief system has been developed that is expressed as a cognitive

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map. It basically collects points and nodes to represent concepts, issues or facts. To represent the causal relationships linking the nodes, directed edges are used. As for promoting or inhibitory effects, signed edges are used.

The Fuzzy Cognitive Map (FCM) [6] has been successful in modeling complex systems and handling information from a graphical representation point of view. The FCM has been successfully implemented as a modeling technique that can be used in the decision-making process. The main improvement over cognitive map is that the FCM allows the partial influence of different factors from different sources in modeling the causal relationship between them. The FCM is introduced and claimed to solve some of the limitations of the cognitive map. The FCM also allows inexact linguistic expressions of concepts and causal links. It also allows feedback with change in time. It has the ability to answer questions that have some of their concepts changed or to deal with situations when concepts are introduced or removed.

The 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. It has operations similar to a recurrent neural network. The state of S_i is determined by the sum of all its inputs modified by the causal link weights, $w_{ij.}$ However, the FCM is limited to problems which contain monotonic causal relationships. In the real world, relationships can be non-monotonic and non-symmetric. Due to these reasons, there are many research efforts aiming to extend the model of FCM to Rule Based FCM [7,8].

In rule based FCM, the fuzzy nodes are used to represent concepts and the fuzzy rule bases are used to represent the relationship between the concepts. Each rule base will consist of a number of *if..then* rules. In this case, fuzzy operations like t-norm and s-norm can be used to link the inputs together just like a normal fuzzy rule base.

However, rule based FCM is limited by the "exponential explosion" problem if the number of inputs to a node increases. In real world applications, many data mining and complex system modeling tasks contain information that is sometime incomplete or missing.

III. FUZZY SIGNATURES

The term signature as an abbreviated but unambiguously characteristic reference to data is widely used in computer based applications for data organization, retrieval, and data mining. The abbreviation, conceptual clustering feature also suggests the use of fuzzy signatures. Fuzzy signatures, as usual, create a natural bridge to verbal classifications and human estimations. Fuzzy signatures which structure data into vectors of fuzzy values, each of which can be a further vector, are introduced to handle complex structured data [9, 10, 11]. This will widen the application of fuzzy theory to many areas where objects are complex, and sometimes interdependent features are to be classified and similarities / dissimilarities evaluated. Often, human experts can and must make decisions based on comparisons of cases with different numbers of data components, with even some components missing. Fuzzy signatures were created with this objective in mind. This tree structure is a generalization of fuzzy sets and vector valued fuzzy sets in a way modeling the human approach to complex problems.

The original definition of fuzzy sets had been $A : X \to [0,1]$, and was soon extended to *L-fuzzy sets* by Goguen [12],

$$A_S : X \to [a_i]_{i=1}^{k}, a_i = \begin{cases} [0,1] \\ [a_{ij}]_{j=1}^{k_i} \end{cases}, a_{ij} = \begin{cases} [0,1] \\ [a_{ijl}]_{l=1}^{k_{ij}} \end{cases},$$

$A_L : X \to L$, L being an arbitrary algebraic lattice. A practical special case, *Vector Valued Fuzzy Sets* was introduced by Kóczy [13], where $A_{V,k} : X \to [0,1]^k$, and the range of membership values was the lattice of k-dimensional vectors with components in the unit interval. A further generalisation of this concept is the introduction of fuzzy signatures and signature sets, where each vector component is possibly another nested vector.

Fuzzy signature can be considered as special multi-dimensional fuzzy data. Some of the dimensions are inter-related in the sense that they form sub-group of variables, which jointly determine some features on a higher level. Let us consider an example. Figure 1 shows a fuzzy signature structure.

The fuzzy signature structure shown in Figure 1 can be represented in vector form as follows:

$$x = \begin{bmatrix} \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix} \\ \begin{bmatrix} x_{21} \\ \begin{bmatrix} x_{221} \\ x_{222} \\ x_{223} \end{bmatrix} \\ x_{23} \end{bmatrix} \\ \begin{bmatrix} x_{31} \\ x_{32} \end{bmatrix} \end{bmatrix}^T$$

Here $[x_{11}\ x_{12}]$ form a sub-group that corresponds to a higher level compound variable x_1. $[x_{221}\ x_{222}\ x_{223}]$ will then combine together to form x_{22} and $[x_{21}[x_{221}\ x_{222}\ x_{223}]x_{23}]$ is equivalent on a higher level with $[x_{21}\ x_{22}\ x_{23}] = x_2$. Finally, the fuzzy signature structure will become $x = [x_1\ x_2\ x_3]$ in the example.

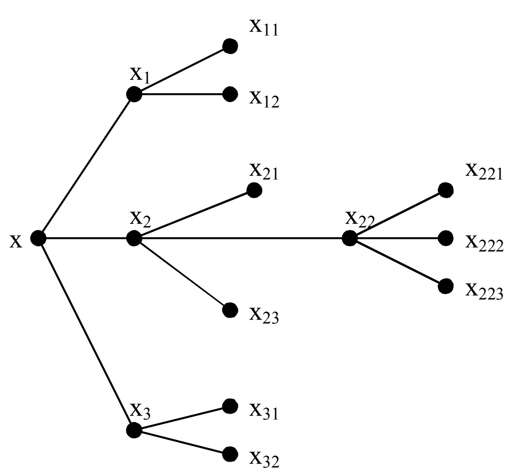

Figure 1: A Fuzzy Signature Structure

The relationship between higher and lower levels is governed by a set of fuzzy aggregations. The results of the parent signature at each level are computed from their branches with appropriate aggregation of their child signatures. Let a_1 be the aggregation associating x_{11} and x_{12} used to derive x_1, thus $x_1 = x_{11}\ a_1\ x_{12}$. By referring to Figure 1, the aggregations for the whole signature structure would be a_1, a_2, a_{22}, and a_3. The aggregations a_1, a_2, a_{22}, and a_3 are not necessarily identical or different. The simplest case for a_{22} might be the *min* operation, the most well known t-norm. Let all aggregations be *min* except a_{22} be the averaging aggregation. We will show the operations based on the following fuzzy signature values for the structure in the example.

$$x = \begin{bmatrix} \begin{bmatrix} 0.3 \\ 0.4 \end{bmatrix} \\ \begin{bmatrix} 0.2 \\ \begin{bmatrix} 0.6 \\ 0.8 \\ 0.1 \end{bmatrix} \\ 0.9 \end{bmatrix} \\ \begin{bmatrix} 0.1 \\ 0.7 \end{bmatrix} \end{bmatrix}^T$$

After the aggregation operation is performed to the lowest branch of the structure, it will be described on the next higher level as:

$$x = \begin{bmatrix} 0.3 \\ \begin{bmatrix} 0.2 \\ 0.5 \\ 0.9 \end{bmatrix} \\ 0.1 \end{bmatrix}^T$$

Finally, the fuzzy signature structure will be:

$$x = \begin{bmatrix} 0.3 \\ 0.2 \\ 0.1 \end{bmatrix}^T$$

Each of these signatures contains information relevant to the particular data point x_0; by going higher in the signature structure, less information will be kept. In some operations it is necessary to reduce and aggregate information to become compatible with information obtained from another source (some detail variables missing or simply being locally omitted). Such is when interpolation within a fuzzy signature rule base is done, where the fuzzy signatures flanking an observation are not exactly of the same structure. In this case the maximal common sub-tree must be determined and all signatures must be reduced to that level in order to be able to interpolate between the corresponding branches or roots in some cases.

Let S_{S_0} denote the set of all fuzzy signatures whose structure graphs are sub-trees of the structural ("stretching") tree of a given signature S_0. Then the signature sets introduced on S_{S_0} are defined by

$$A_{S_0} : X \to S_{S_0}$$

In this case, the prototype structure S_0 describes the "maximal" signature type that can be assumed by any element of X in the sense that any structural graph obtained by a set of repeated omissions of leaves from the original tree of S_0 might be the tree stretching the signature of some A_{S_0}.

They are two ways to determine the sub-trees of the fuzzy signature structure S_0. One way is to predetermine by a human expert of the field. Alternatively, the structure of the fuzzy signature can be determined by finding the separability in the data [10].

In [11], the authors have presented an example of the fuzzy signature for a SARs patient in Hong Kong as:

$$A_{S(HK1)} = \begin{bmatrix} Fever \begin{bmatrix} 1st hour \\ 6th hour \\ 12th hour \\ 18th hour \\ 24th hour \end{bmatrix} \\ Sex \\ Age \\ Smoking \\ Cough \\ Dyspnea \\ Pleurisy \\ Malaise \\ Myalgia \\ Rigor \\ Headache \\ \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \end{bmatrix} \\ 1 \\ 0.6 \\ 0.1 \\ 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \\ 0.9 \\ \end{bmatrix}$$

The fuzzy signature has the flexibility to accommodate any missing information, and it is easy to accommodate any future information into the structure. The structure of the fuzzy signature contains some information by the association of vector components. The use of aggregation operators allows us to compare components regardless of the different numbers of sub-components. Such aggregation operators would in general be designed for each vectorial component with the assistance of a domain expert. This hierarchically structured access to the information is a key benefit of fuzzy signatures.

IV. EFFICIENT FUZZY COGNITIVE MODELING

Fuzzy signatures as has been described in the previous section, can address some issues in granulation and organisation well. In [10] and [11], the authors have shown that fuzzy signatures can extend the application of fuzzy theory to many areas where objects are complex. It is also useful for interdependent features that are structured badly and need to be classified.

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 meta-levels 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 category, it basically consists of the fuzzy signatures as describe in the previous section to contain the knowledge necessary for the node to take any action.

Figure 2 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

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 2, the input state could be:

$$IN_1 = \varnothing$$

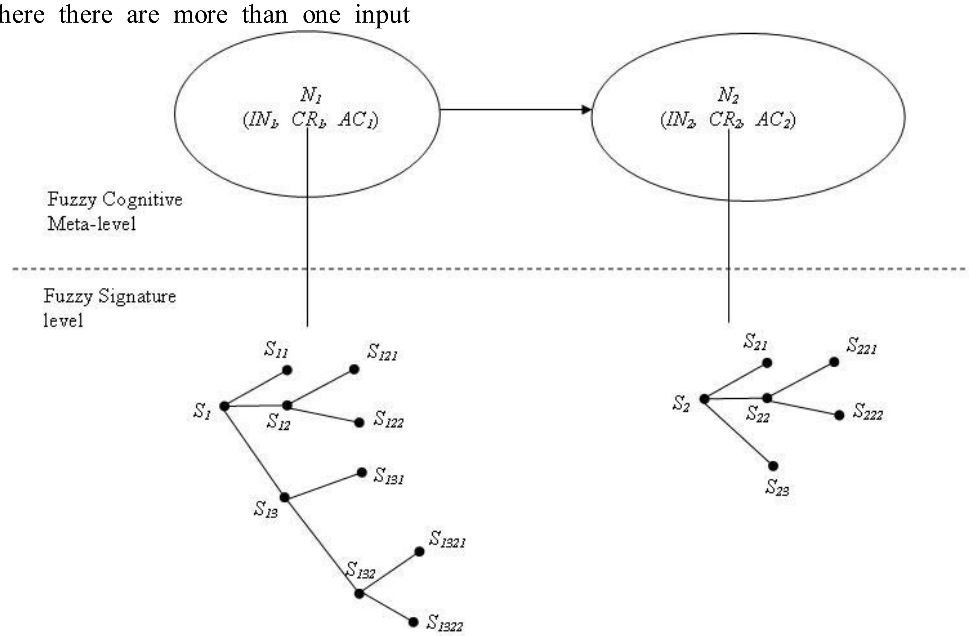

Figure 2: The basic Efficient Fuzzy Cognitive Model

V. CONCLUSIONS

This paper has examined the problems of some existing cognitive modeling systems. As the available information or data are growing at a very fast pace for all real world applications, with many containing ill structured and missing data, there is a need to look for new modeling tools to handle these kinds of problems. This paper has introduced an efficient fuzzy cognitive modeling approach which is suitable to deal with these information or data. This efficient fuzzy cognitive modeling is formulated with the possibility to be easily extended for a distributed computing environment. This will improve the handling of the increasing amount of information today. Future work will focus on developing the modeling further, examining applicability conditions and illustration using a real world application.

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