FUCOMA: Fuzzy Cognitive Maps

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Abstract - **The information abstracted by humans and quite complex processes, are usually imprecise or approximate. The adopted modelling strategy is usually imprecise in nature, with no or partial knowledge of the problem, and generally expressed in linguistic terms. Thus, the use of Fuzzy Logic can help solving the ambiguities and vagueness usually faced in this kind of problems. Soft computing techniques like Fuzzy Cognitive Maps (FCMs) can help modeling the behavior of complex problems with feedback. FCMs can be built using knowledge collected from domain experts or can be built by extracting knowledge from historical data.**

Keywords- Fuzzy Cognitive Maps; Intelligent Systems

I. Introduction

.In recent years, the Fuzzy Cognitive Maps (FCM) based on FCM Theory has become a proper tool for designing knowledge-based systems with interpretable features. Essentially, a FCM is an information a graph whose nodes represent objects, states, concepts or entities of the investigated system and comprise a precise meaning for the problem domain. Such concepts are equivalent to neurons in connectionist models and are connected by causal relationships that normally take values in the range [−1, 1] [1].

FCMs are an extension of Cognitive Maps (CM) that were initially proposed by Axelrod [2] to represent words, thoughts, tasks, or other items linked to a central concept and willing radially around this concept. Axelrod developed also a mathematical treatment for these maps, based on graph theory, and operations with matrices. These maps can thus be considered as a mathematical model of "belief structure" of a person or group, allowing you to infer or predicting the consequences that this mental ideas represented in the universe. However, despite the similarity between mental maps and cognitive maps, there is a remarkable difference. In the cognitive maps do not have the need to be a central concept.

Kosko proposed Fuzzy Cognitive Maps as an extension to Cognitive Maps by using Fuzzy Logic to describe causal relationships between concepts [1]. Like CMs, FCMs are directional graphs that use numerical descriptions or fuzzy weights instead of positive or negative edges in CMs. In some implementations, even the "graph nodes", can be associated to linguistic concepts, and represented by fuzzy sets and each "node" is linked with others through connections.

On the other hand, the Fuzzy Cognitive Map is a tool for modeling human knowledge, obtained through linguistic terms, inherent to Fuzzy systems [4], but with a graphical structure like that of Artificial Neural Networks (ANN) [5], which facilitates data processing and has training and adaptation capacity. In this context, a FCM can be considered a hybrid model (fusion of two approaches in intelligent systems) with a strong degree of iteration, in which it is not possible to identify and separate the structures of the areas of origins, only the construction semantics. In this context,

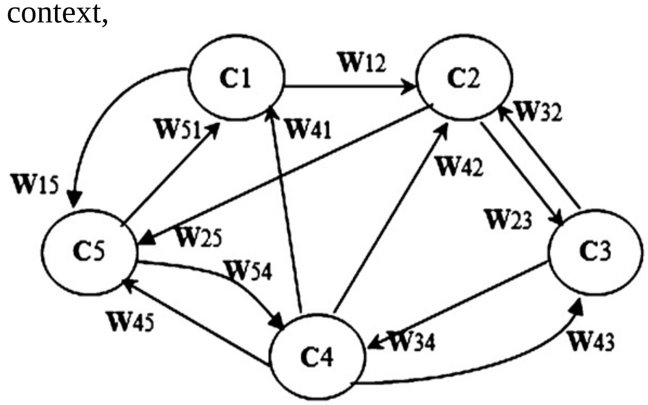

Figure 1 – Classic FCM

Fuzzy cognitive maps are gaining popularity and have been applied in a wide range of areas such as social studies, emotion modeling, artificial live, commerce temporal prediction, Multi-Agents

Systems. Autonomous robotics, and pedagogical area. As compared with many classic knowledge models, fuzzy cognitive map has several advantages. A Classic FCM example (Figure 1) is a graph and which can be found in [6].

The FCM concepts can be updated through iteration with the other concepts and their own value. This is given by graph with the causal relations weights, and is represented by the sum's weight.

The concepts values evolve after several iterations, as shown in equation (1), until they stabilize at a fixed point or limit cycle [7].

$$A_i = f(\sum_{\substack{j=1 \\ j \neq i}}^{n} (A_j \times W_{ji}) + A_i^{previous} \qquad (1)$$

Since k is the iteration counter, n is the number of graph nodes, Wij are the weight of the arc which connects concept Cj to concept Ci. Aiprevious are the concept value Ci in the actual iteration (previous), and f function (equation 2) is a sigmoid:

$$f(x) = \frac{1}{1 + e^{-\lambda x}}$$

(2)

In some cases, the FCM may not stabilize and oscillate, or even show chaotic behavior [6]. Generally, for well-behaved systems, it is observed that after a finite number of iterations, the concepts values reach an equilibrium point or a limit cycle. This can be observed in Fig. 4, in which after 4 iterations the previously modelled concept final values stay fixed. Recently, the FCM convergence is investigated by [7].

FCMs have been applied successfully in many scientific fields, a recent review on FCMs research during the last decade can be found in [8, 9]. Whenever, due to the difficulty of the temporal treatment of the information in classic FCM (all the relations of cause and effect occur at the same time), there were evolutions of the FCM, such as in autonomous mobile robotics and process control, respectively ED-FCM (Event Driven-Fuzzy Cognitive Maps) [10] and DCN (Dynamic Cognitive Networks) [11]. The rare some formal adaptation so the original FCM is via a new tool called TAFCM (Timed Automata Fuzzy Cognitive Maps) [12] that can be used in intelligent environments.

The concepts of a cognitive map can be updated through the iteration with other concepts and with its own value. In this context, a FCM uses a structured knowledge representation through causal relationships being calculated mathematically from matrix operations, unlike much of intelligent systems whose knowledge representation is based on rules if-then type. However, due to this "rigid" knowledge representation by means of graph and matrix operation, the FCM based inference models lack robustness in presence of dynamic modifications not a priori modeled [3]. To circumvent this problem, this ARRUDA article develops a new type of FCM in which concepts and causal relationships are dynamically inserted into the graph from the occurrence of events. In this way, the dynamic fuzzy cognitive map model is able to dynamically acquire and use the heuristic knowledge.

In resume, this special track presents four works. One classical work using classic FCM applied in diagnoses about satisfaction level of the University´s students [13]. And, three extensions named sDFCM, DFCM and Dynamic Rule Based Fuzzy Cognitive Maps (DRBFCM). Respectively, sDFCM is simplified Dinamic Cognitive Maps applied in industry, diagnosis and process control, the third extension uses Dynamic Rule Based Fuzzy Cognitive Maps (DRBFCM) in application of cotton yield in precision farming by building on the work [8].

In detail, the work [13] aims to develop a FCM (Fuzzy Cognitive Map) and Weighted Fuzzy Classic (WFC) for the satisfaction level of students at Federal Technological University of Parana, Campus Cornélio Procópio (UTFPR-CP). This tool has inference capacity through concepts and causal relations among them (the influence level among the variables of the model). Its development begins with the determination of the possible areas that would affect or fit as indicators for satisfaction level in UTFPR-CP. Through online forms, it was possible to quantify the influence of the following initially detected areas: professor training, structures of laboratories and classrooms, habitation, library and cleaning, for example. In general, educational institutions do not have tools to provide a critical analysis of its quality. This work proposes a tool for improving the institution in a medium/long time, three years or more. Thus, with the development of the FCM model, it was possible to identify the positive and negative points that affect the satisfaction level in UTFPR-CP. To validate the results WFC used with same structure and heuristic for comparison with FCM.

The industry has systems and machines that need to operate within appropriate parameters to ensure quality in production. In this context it is necessary to maintain, through maintenance, the conditions necessary for proper operation. Thus, through the Reliability Centered Maintenance with quantitative feedback by Fuzzy Cognitive Maps applied to electric motors, can suggest a better reliability, proposal of this research. This paper discusses the Reliability Centered Maintenance (RCM) with reference to a generic Check list of electric motors' maintenance. Through the maintenance actions for correction of faults and/or defects, it can be modeled a critical and qualitative FCM that will present a quantitative diagnosis aimed at a proposal for a computational tool to assist in the maintenance management, adding improvements to the system. This approach industrial application using initial extension of FCM applied to the Maintenance Management of Electric Motors [14].

The complete extended proposal is Dynamic Fuzzy Cognitive Maps Embedded Controllers Applied in Industrial Process. [15], this research presents the application of intelligent techniques to control an industrial mixer. The controller design is based on Hebbian learning for evolution of Fuzzy Cognitive Maps. A Fuzzy Classic Controller and Artificial Neural Network was used to validate the simulation results. Experimental simulations and analysis in this control problem was made. In addition, the results were embedded using algorithms into the Arduino platform.

And, finally, the cotton yield model shows the relationships between soil properties like pH, K, P, Mg, N, Ca, Na and cotton yield. DRBFCM was evaluated for 360 cases measured for three years (2001, 2003 and 2006) in a 5 ha experimental cotton field. The results revealed an accuracy of predictions of 85.55%, 87.22% and 73.33% for the years 2001, 2003 and 2006 respectively. DRBFCM also proved, in this case study, to be more faithful to the real world model [16].

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