Fuzzy Cognitive Maps for Modeling Complex Systems

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Abstract. This paper presents Fuzzy Cognitive Maps as an approach in modeling the behavior and operation of complex systems. This technique is the fusion of the advances of the fuzzy logic and cognitive maps theories, they are fuzzy weighted directed graphs with feedback that create models that emulate the behavior of complex decision processes using fuzzy causal relations. There are some applications in diverse domains (manage, multiagent systems, etc.) and novel works (dynamical characteristics, learning procedures, etc.) to improve the performance of these systems. First the description and the methodology that this theory suggests is examined, also some ideas for using this approach in the control process area, and then the implementation of a tool based on Fuzzy Cognitive Maps is described. The application of this theory in the field of control and systems might contribute to the progress of more intelligent and independent control systems. Fuzzy Cognitive Maps have been fruitfully used in decision making and simulation of complex situation and analysis.

Keywords: Fuzzy Cognitive Maps, Complex Systems, Casual Relations, Decision Making, Simulation.

1 Introduction

Modeling dynamic systems can be hard in a computational sense and many quantitative techniques exist. Well-understood systems may be open to any of the mathematical programming techniques of operations study. First, developing the model usually requires a big deal of effort and specialized knowledge outside the area of interest. Secondly, systems involving important feedback may be nonlinear, in which case a quantitative model may not be possible [1].

In the past years, conventional methods were used to model and control systems but their contribution is limited in the representation, analysis and solution of complex systems. In such systems, the inspection of their operation, especially from the upper level, depends on human leadership. There is a great demand for the development of autonomous complex systems that can be achieved taking advantage of human like reasoning and description of systems. Human way of thinking process for any method includes vague descriptions and can have slight variations in relation to time and space; for such situations Fuzzy Cognitive Maps (FCM) seem to be appropriate to deal with.

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FCM are a combination of Fuzzy Logic and Neural Networks; combining the heuristic and common sense rules of Fuzzy Logic with the learning heuristics of the Neural Networks. They were introduced by Kosko [2], who enhanced cognitive maps with fuzzy reasoning, that had been previously used in the field of socio-economic and political sciences to analyze social decision-making problems.

The use of FCM for many applications in different scientific fields was proposed. FCM had been apply to analyze extended graph theoretic behavior, to make decision analysis and cooperate distributed agents, were used as structures for automating human problem solving skills and as behavioral models of virtual worlds.

With the elaboration of a tool that allows the design and execution of FCM is provided to specialists of diverse knowledge areas of a means for the study and simulation of situations that characterize diverse problems. This work proposes a computational tool for the study, design and execution of FCM, tool to represent the knowledge in a graphic and comprehensible way. The maps are based on causal relationships, to try to study the systems like a whole, settling down how the entities that conform the system are affected with others, offering to users, not necessarily specialist in Computer Science, a tool that allows the creation and execution of FCM, and including experimentation facilities.

2 Overview about Fuzzy Cognitive Maps

FCM in a graphical illustration seem to be a signed directed graph with feedback, consisting of nodes and weighted arcs (see figure 1). Nodes of the graph place for the concepts that are used to express the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist connecting the concepts.

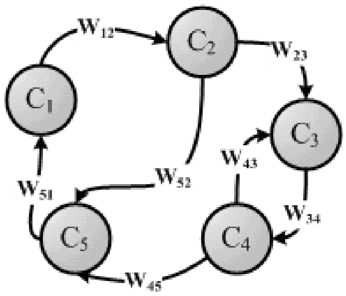

Fig. 1. Simple Fuzzy Cognitive Map

It must be mentioned that the values in the graph are fuzzy, so concepts take values in the range between [0,1] and the weights of the arcs are in the interval [-1,1]. The weights of the arcs between concept C_i and concept C_j could be positive ($W_{ij} > 0$) which means that an augment in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to a reduce of the value of concept C_j. Or there is negative causality ($W_{ij} < 0$) which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa.

Observing this graphical representation, it becomes clear which concept influences other concepts showing the interconnections between concepts and it permits updating in the construction of the graph. Each concept represents a characteristic of the system; in general it stands for events, actions, goals, values, trends of the system that is modeled as an FCM. Each concept is characterized by a number that represents its value and it results from the renovation of the real value of the system's variable [3].

Beyond the graphical representation of the FCM there is its mathematical model. It consists of a $1 \times n$ state vector A which includes the values of the n concepts and a $n \times n$ weight matrix W which gathers the weights W_{ij} of the interconnections between the n concepts.

The value of each concept is influenced by the values of the connected concepts with the appropriate weights and by its previous value. So the value A_i for each concept C_i is calculated by the following rule expressed in (1).

$$\mathrm{A_i} = f\left(\sum_{\substack{\mathrm{j=1} \\ \mathrm{j \neq i}}}^{\mathrm{n}} \mathrm{A_j W_{ji}}\right) \tag{1}$$

A_i is the activation level of concept C_i, A_j is the activation level of concept C_j and W_{ij} is the weight of the interconnection between C_j and C_i, and f is a threshold function.

So the new state vector A_{new} is computed by multiplying the previous state vector A_{old} by the weight matrix W, see equation (2). The new vector shows the effect of the change in the value of one concept in the whole FCM [4].

$$A_{new} = f(A_{old} \times W) \tag{2}$$

In order to build an FCM, the knowledge and experience of one expert on the system's operation must be used. The expert determines the concepts that best illustrate the system; a concept can be a feature of the system, a state or a variable or an input or an output of the system; indentifying which factors are central for the modeling of the system and representing a concept for each one.

Moreover the expert has observed which elements of the system influence others elements; and for the corresponding concepts the expert determines the negative or positive effect of one concept on the others, with a fuzzy value for each interconnection, since it has been considered that there is a fuzzy degree of causation between concepts.

It is possible to have better results in the drawing of the FCM, if more than one expert is used. In that case, all experts are polled together and they determine the relevant factors and thus the concepts that should be presented in the map. Then, experts are individually asked to express the relationship among concepts; during the assigning of weights three parameters must be considered: how strongly concepts influence each other, what is the sign of the weight and whether concepts cause.

This is one advantage over other approaches like Bayesian Networks (BN) or Petri Nets (PN). PN is another graphical and mathematical modeling tool consisting of places, transitions, and arcs that connect them that can be used as a visual-communication aid similar to flow charts, block diagrams, and networks. As a mathematical instrument, it is possible to set up state equations, algebraic equations, and other mathematical models governing the performance of systems. It is well known that the use of PN has as a disadvantage the drawing process by a non-expert in this technique, that's way there is a limited numbers of tools usable for this purpose, and it is not well established how to combine different PN that describe the same system [5].

If there will be a collection of individual FCM that must be combined into a collective map (see figure 2) and if there are experts of different credibility, for them, then their proposed maps must be multiplied with a nonnegative "credibility" weight.

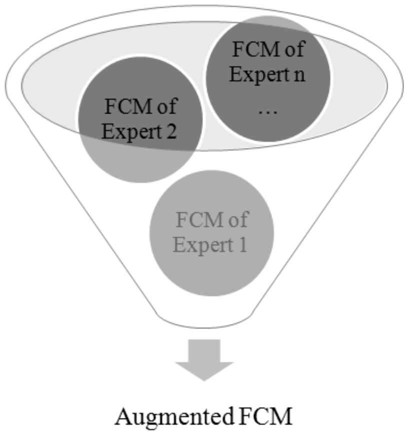

Fig. 2. Combining some FCM into a collective map

As over PN, this is an advantage over BN [6]. BN is a powerful tool for graphically representing the relationships among a set of variables and for dealing with uncertainties in expert systems, but demanding effort caused by specification of the net (structure and parameters) and difficulty to implement the algorithms of propagation of probabilities, which besides being more or less complex are very expensive computationally. Also is not evident for a non-expert in this field how to construct a BN, and even more difficult how to combine different BN that describe the same system.

So the combination of these different FCM will produce an augmented FCM. When a FCM has been constructed, it can be used to model and simulate the behavior of the system. Firstly, the FCM should be initialized, the activation level of each of the nodes of the map takes a value based on expert's opinion for the current state and then the concepts are free to interact.

This interaction between concepts continues until:

- A fixed equilibrium is reached
- A limited cycle is reached
- Chaotic behavior is exhibited

FCM are a powerful tool that can be used for modeling systems exploiting the knowledge on the operation of the system. It can avoid many of the knowledge extraction problems which are usually present in by rule based systems and moreover it must be mentioned that cycles are allowed in the graph [7].

The threshold function serves to decrease unbounded inputs to a severe range. This destroys the possibility of quantitative results, but it gives us a basis for comparing nodes (on or off, active or inactive, etc.). This mapping is a variation of the "fuzzification" process in fuzzy logic, giving us a qualitative model and frees us from strict quantification of edge weights [8].

3 Use of FCM in Control Process

After the presentation of FCM, their illustration and their methodology with which they are constructed; their application is examined in control aspects. There are two distinct uses of a knowledgeable based model like the FCM in the upper level of a process [9]. When an FCM is used for direct control and FCM influences directly the process.

FCM can replace the conventional control element and it performs every function that a conventional controller could implement. It is similar to the closed loop control approach because FCM is dependent directly on the real behavior of the process. Another important use of FCM is for supervisory control of a conventional controller, so complementing rather than replacing a conventional controller. The role of FCM is to extend the range of application of a conventional controller by using more abstract representation of process, general control knowledge and adaptation heuristics and enhance the performance of the overall system.

Thus, FCM may replicate some of the knowledge and skills of the control engineer and it is built by using a combination of the knowledge representation techniques as causal models, production rules and object hierarchies. At the conventional controller level or at the process it may exist more than one controller for different parts of the process and only local information is available to each controller who communicates with the supervisor at the higher level [10].

The role of the supervisor is to elaborate information of the controllers and to allocate actions to controllers taking into account their effect on the global system. The supervisor indicates undesired or unpermitted process states and takes actions such as fail safe or reconfiguration schemes. Supervisory FCM is used to perform more demanding procedure as failure detection, diagnose abnormalities, decision making; also planning tasks and to intervene when a certain task or state is reached and take control in abnormal or unsafe situations [11].

A human supervisor of the controlled process usually performs these tasks. If the nature of the process under control is such that appropriate analytic models do not exist or are inadequate, but human operation at the process can manually control the process to a satisfactory degree, then the need to use an abstract methodology as FCMs is motivated.

The meaning of the whole model of the system can be described beginning in the lower level to the upper one. In the lower level sensors measure some defined variables of the process and these measurements must pass to the higher level where information of the process is organized and categorized [12]. After that, available information on process is clustering and grouping, because some measured variables could cause changes in the value of one or more concepts of the FCM.

4 Tool Based on Fuzzy Cognitive Maps

The scientific literature shows some software developed with the intention of drawing FCM by non-expert in computer science, as FCM Modeler [13] and FCM Designer [14]. The first one is a very rustic and superficial incursion, while the second one is a better implementation, but still hard to interact with and with insufficient experimental facilities. Figure 3 shows the general architecture of our proposing tool to model and simulate FCM, the organization and structuring of the components are presented.

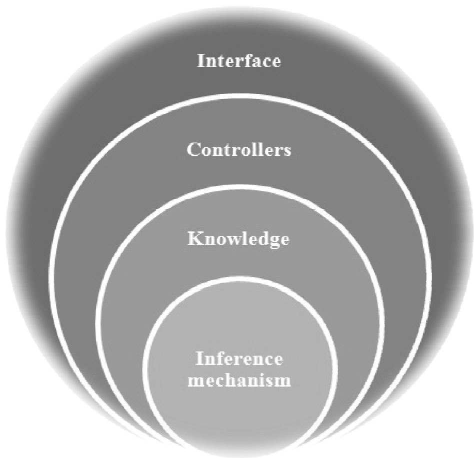

Fig. 3. General architecture of the tool

Brief description of the components of the tool:

- **Interface:** Allows the user-tool interaction through the options to create FCM and the definition of parameters. Makes the input data for a formalization of the information into a knowledge base.
- **Controllers:** Makes a link between the Interface and the algorithms and data, it is a connectivity layer that guarantees a right manipulation of the information.
- **Knowledge:** Generates the computational representation of the created FCM from an Artificial Intelligence point of view. Processes the input and output data of algorithms in the variables modeling.
- **Inference Mechanism:** Makes the inference process through the mathematical calculus for the prediction of the variable values.

In figure 4 is possible to observe the main window of the tool, and a modeled example, in the interface appear some facilities to create concepts, make relations, define parameters, etc. Also the option to initialize the execution of the inference process, and the visualization options for a better understanding of the simulation process.

There were defined some facilities and options in the tool, to create, open or save an FCM, and options to other properties of nodes and arrows. Through these amenities a non-expert in computer science is able to elaborate his own FCM describing a system; we had paid attention to these facilities guarantying a usable tool, specifically for simulation purposes.

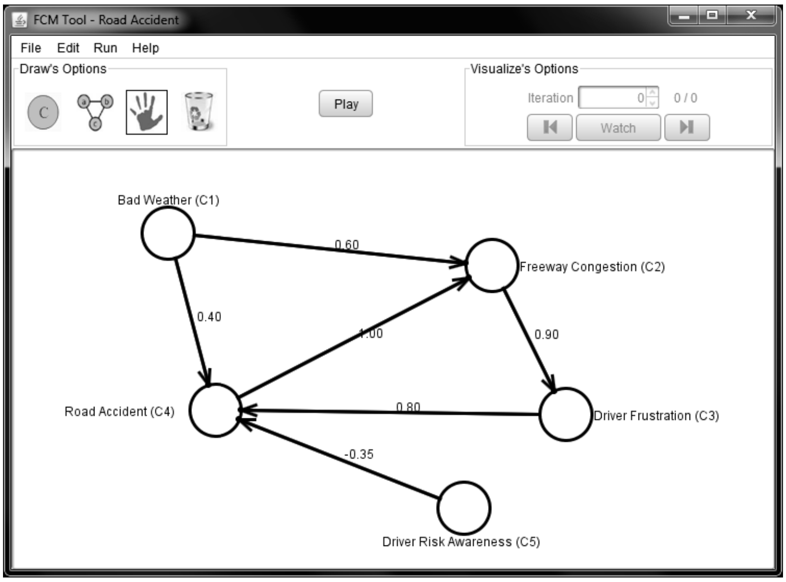

Fig. 4. Main view of the FCM Tool

In figure 5 we can appreciate some important options, where is possible to define the assignment of a delay time in the execution for a better understanding of the running of the FCM in the inference process, also it is possible to define the normalization function that the FCM will use in the running [15].

This is a very important option because in simulation experiments the user can compare results using these different functions or just can select the appropriate function depending of the problem to model:

- Binary FCM are suitable for highly qualitative problems where only representation of increase or stability of a concept is required.
- Trivalent FCM are suitable for qualitative problems where representation of increase, decrease or stability of a concept is required.
- Sigmoid FCMs are suitable for qualitative and quantitative problems where representation of a degree of increase, a degree of decrease or stability of a concept is required and strategic planning scenarios are going to be introduced.

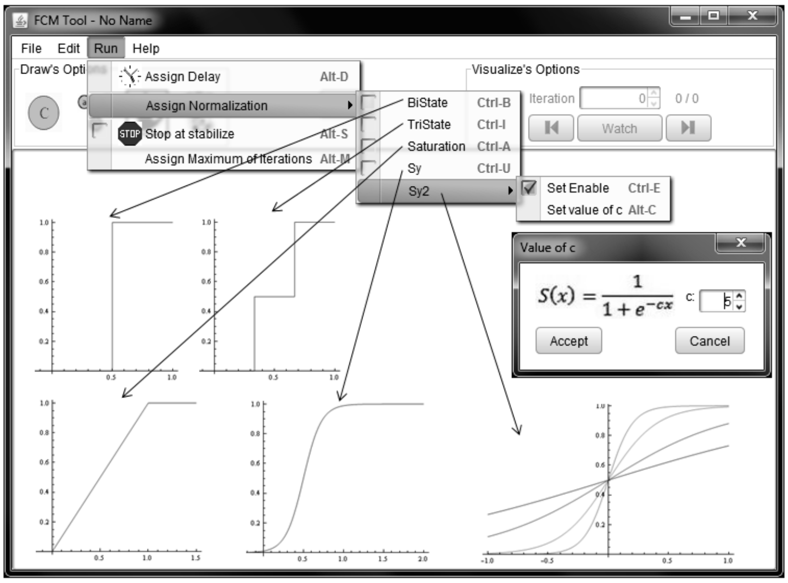

Fig. 5. Run options of the FCM Tool

5 Conclusions

It has been examined Fuzzy Cognitive Maps as a theory used to model the behavior of complex systems, where is extremely difficult to describe the entire system by a precise mathematical model.

Consequently, it is more attractive and practical to represent it in a graphical way showing the causal relationships between concepts. Since this symbolic method of modeling and control of a system is easily adaptable and relies on human expert experience and knowledge, it can be considered intelligent.

FCM appear to be positive method in modeling and control of complex systems which will help the designer of a system in choice analysis and tactical planning. FCM appear to be an appealing tool in the description of the supervisor of complex control systems, which can be complemented with other techniques and will lead to more sophisticated control systems.

The development of a tool based on FCM for the modeling of complex systems was presented, showing the facilities for the creation of FCM, the definition of parameters and options to make the inference process more comprehensible, understanding and used for simulations experiments.

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