Behavioral Analysis of Fuzzy Cognitive Maps

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Abstract <To be prepared>

1 Introduction

Decision support systems and methods are at the center of researcher's attention for a long time [1], because prudent decision making can be really hard in practice, especially if the effect of many related factors with continuously changing states have to be taken into account, and a wrong intervention may cause serious personal injury or damage to property.

Fuzzy Cognitive Maps (FCMs) [7] can be one of the possible tools of a decision maker [10]. They are bipolar fuzzy graphs that are made of nodes interconnected by directed, weighted edges. The various factors, variables of a complex system can be described by the nodes (also called *concepts*) and the strength of causal relations among them can be expressed by edges. Even if an FCM model can characterize the studied system only qualitatively [11], this method is easy to use and provides a transparent, clear description of it. Modeling capabilities and simulations that reveal the dynamic behavior of the system made FCM an inevitable opportunity in decision support.

There are two main ways of model creation [9]:

1. an expert, or a group of experts can give the description of the system, or
2. based on a long time-series database a suitable machine learning technique may generate the model with more or less support of experts.

In the first case the expert who makes the model unavoidably includes his/her beliefs and subjectivity in the map. This can be decreased if a group of experts works

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out the model instead of a sole expert [8, 2], but the result will contain some uncertainty for sure. They can agree relatively quickly and easily on the number of concepts, the existence and sign of relationships, but the magnitude of those relationships are much harder to define, especially if an order of importance or strength exists among them. The number of relationships is a quadratic function of the number of concepts, therefore even if the modelers follow Kosko's advice and they do not include self-loops in the FCM, in case of a small model containing only 10 concepts the number of relationships can be up to 90. It will be really hard to define so many weights properly and worse is that the steepness parameter λ of the threshold function does not have any connection with real objects, but its value may strongly influence the results of simulations (number and values of fixed points, limit cycles, chaotic behavior).

That is why the second method, based on machine learning is preferred in most cases. In those cases it can be applied the concepts are still defined by experts, however, and/or the nature of time series data. Sometimes such data is not available and only the first method remains.

No matter how the model is made, it worth investigating the effect of small modifications of connection weights or steepness parameter on model behavior. The sensitive points of the model can be revealed and experts can discuss about the possibilities on making the model more stable and reliable. Unfortunately it cannot be made by hand, following a trial and error approach. In an FCM the connection weights are specified by real numbers, thus the number of possible modified weights are practically infinite. With a reasonable compromise we can say that the weights to try can be limited to the number of used linguistic variables, eg. 5: -1, -0.5, 0, 0.5 and 1. In the already mentioned model containing only 10 concepts, where even 90 relationships may exist, the number of model versions may up to $5^{90} = 8,078 \times 10^{62}$. Obviously the experts are primarily interested only in the effect of slight modifications, thus they would be satisfied with the check of one less and one greater values (or keeping the current one), but it could still mean $3^{90} = 8,728 \times 10^{42}$ model versions. That can be even worse if they want to take the effect of different λ values into account and of course, one simulation is not enough to characterize the behavioral effect of a modification, many simulations (depending on the model size to cover all interesting parts of the search space) are needed and these simulations are rather time consuming on their own. There is a clear need for an automated, consistent method for such investigations, and the work on that started in [3, 4] and further developed in [6, 5]. This task is too big even for a computer: an exhaustive search cannot be performed, but an evolutionary search technique, eg. the Bacterial Evolutionary Algorithm is able to guide the directions of search for a slightly modified model that behaves significantly different.

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