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Unsupervised learning techniques for fine-tuning fuzzy cognitive map causal links

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Abstract

Fuzzy Cognitive Maps (FCMs) constitute an attractive knowledge-based methodology, combining the robust properties of fuzzy logic and neural networks. FCMs represent causal knowledge as a signed directed graph with feedback and provide an intuitive framework which incorporates the experts' knowledge. FCMs handle available information and knowledge from an abstract point of view. They develop behavioural model of the system exploiting the experience and knowledge of experts. The construction of FCMs is based mainly on experts who determine the structure of FCM, i.e. concepts and weighted interconnections among concepts. But this methodology may not be a sufficient model of the system because the human factor is not always reliable. Thus the FCM model of the system may requires restructuring which is achieved through adjustment the weights of FCM interconnections using specific learning algorithms for FCMs. In this article, two unsupervised learning algorithms are presented and compared for training FCMs; how they define, select or fine-tuning weights of the causal interconnections among concepts. The implementation and results of these unsupervised learning techniques for an industrial process control problem are discussed. The simulations results of training the process system verify the effectiveness, validity and advantageous characteristics of those learning techniques for FCMs.

Keywords: Fuzzy cognitive maps; Learning algorithms; Hebbian learning; Process modeling and control

1. Introduction

Fuzzy Cognitive Map (FCM) is a soft computing technique capable of dealing with situations including uncertain descriptions using similar procedure such as human reasoning does. FCM is a modeling method based on knowledge and experience for describing particular domains using concepts (variables, states, inputs, outputs) and the relationships between them. The advantageous modelling features of FCMs, such as simplicity, adaptability and capability of approximating abstractive structures encourage us to enhance their structure using learning techniques, so that to broaden the FCMs functionality for complex problems.

In general, there is a great demand for modelling complex systems that can be achieved taking advantage of human like reasoning. There is also a need for advanced techniques which can take into consideration the various requirements of complex systems such as high autonomy and intelligence.

FCM was introduced by Kosko (1986), who expanded cognitive maps introducing causal algebra operating in the range of [0, 1] for propagating causality. Kosko proposed that negative influences be converted into positive ones by using the idea of *dis-concepts*. But this solution doubles the size of the concept set and increases computation time and space, particularly for large cognitive maps. In the same vein, Zhang and his colleagues proposed the POOL2 (Zhang et al., 1989), which is a generic system FCM for

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decision analysis. This system uses an approach in which both negative and positive assertions are weighted and kept separately based on the negative–positive–neutral (NPN) interval $[-1, 1]$ instead of values in $[0, 1]$. The same team went on to propose the D-POOL system (Zhang et al., 1992). The NPN causal inference was proposed to study a fuzzy time cognitive map with time lag on each arrow (Park and Kim, 1995).

FCMs have been used for representing knowledge (Taber, 1991), as artificial intelligence techniques appropriate for engineering applications, (Jain, 1997); for fault detection (Pelaez and Bowles, 1996), and modelling process control and supervision of distributed systems (Groumpos and Stylios, 2000; Stylios et al., 1999). FCMs have been used to model complex dynamical systems with chaotic characteristics, such as social and psychological processes and the organizational behaviour of a company (Craiger et al., 1996). FCMs have been also used for several tasks such as web-mining inference amplification (Lee et al., 2002), medical decision in radiotherapy, which is a complex process and is characterized by hard nonlinearities (Papageorgiou et al., 2003a), and computer-aided medical diagnosis for tumor characterization (Papageorgiou et al., 2003b).

Liu and Satur (1999) conducted extensive research on FCMs investigating their inference properties and they proposed contextual FCMs based on the object-oriented paradigm of decision support and applied contextual FCMs to geographical information systems (Liu, 2000). Other research efforts proposed FCMs to support the esthetical analysis of urban areas (Xirogiannis et al., 2004), and the management of relationships among organizational members in airline service (Kang et al., 2004). Furthermore, evaluation procedure for specifying and generating a consistent set of magnitudes for the causal relationships of a FCM, utilizing pair-wise comparison techniques have been presented (Muata and Bryson, 2004).

The development of a FCM requires that the expert provide information on both the sign and magnitude of each causal relationship. Although it is relatively easy to determine the relevant sign, experts often have difficulty in specifying the relevant magnitude. Thus, simple FCMs are often used to provide a first cut analysis of the given problem, but their value is often limited by the coarse granularity of the input information.

The methodology of developing FCMs is easily adaptable and relies on human expert experience and knowledge. However, it exhibits weaknesses in utilization of learning methods. The external intervention (typically from experts) for the determination of FCM parameters, the recalculation of the weights and causal relationships every time a new strategy is adopted, as well as the potential convergence to undesired regions for concept values are significant FCM deficiencies. It is necessary to overcome these deficiencies in order to improve efficiency and robustness of FCM. Weight adaptation methods are very promising as they can alleviate these problems by allowing the creation of less error prone FCMs where causal links are adjusted through a learning process.

FCM learning involves updating the strengths of causal links so that FCM concept values converge in a desired equilibrium region. A learning strategy is to modify FCM by fine-tuning its initial causal links based on ideas coming from the field of artificial neural networks (ANNs) training.

Learning methodologies for FCMs need to be developed in order to update the initial knowledge of human experts and to enhance the human experts' structural knowledge using training. So far there have been attempts to investigate and propose learning technique suitable for FCMs (Kosko, 1986; Koulouriotis et al., 2001; Aguilar, 2002; Papageorgiou et al., 2003c, d, 2004a; Papageorgiou and Groumpos, 2004; Khan et al., 2004; Stach et al., 2005).

Here two learning techniques have been proposed to adapt the cause–effect relationships of the FCM model improving the efficiency and robustness of FCMs. The introduction of FCM weight adaptation technique eliminates the deficiencies in the usage of FCM, enhances the dynamical behaviour and flexibility of the FCM model and enables it to learn nonlinear mappings. The aim of this paper is to present and compare the two proposed unsupervised learning algorithms for fine-tuning FCM causal links.

In this paper Section 2 describes the theoretical aspects of FCMs, while Section 3 presents a literature review on the learning algorithms for FCMs. Section 4 proposes the two learning algorithms, the Active Hebbian Learning (AHL) and Nonlinear Hebbian Learning (NHL) for FCM and how these learning techniques are implemented in general problems/case-studies. In Section 5, an industrial process control problem is described; the simulation results on modelling and controlling the process problem, using the proposed weight adaptation methods are presented in Section 6. Section 7 compares the two proposed learning techniques with each other as well as with other learning techniques for the same problem and concludes the paper.

2. Theoretical aspects of fuzzy cognitive maps

FCM is a soft computing technique used for causal knowledge acquisition and supporting causal knowledge reasoning process. FCM permits the necessary cycles for knowledge expression within their feedback framework of systems. FCMs are useful methods for exploring and evaluating the impact of inputs on dynamical systems that involve a set of objects such as processes, policies, events and value as well as the causal relationships between those objects.

More specifically, a FCM illustrates the whole system by a graph showing the effect and the cause among concepts. FCM is a simple way to describe the system's model and behaviour in a symbolic manner, exploiting the accumulated knowledge for the system. A FCM integrates the knowledge and experience with the operation of the