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A new hybrid method using evolutionary algorithms to train Fuzzy Cognitive Maps

Elpiniki I. Papageorgiou*, Peter P. Groumpos

Department of Electrical and Computer Engineering, Laboratory for Automation and Robotics, Artificial Intelligence Research Center (UPAIRC), University of Patras, Rion 26500, Greece

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Abstract

A novel hybrid method based on evolutionary computation techniques is presented in this paper for training Fuzzy Cognitive Maps. Fuzzy Cognitive Maps is a soft computing technique for modeling complex systems, which combines the synergistic theories of neural networks and fuzzy logic. The methodology of developing Fuzzy Cognitive Maps relies on human expert experience and knowledge, but still exhibits weaknesses in utilization of learning methods and algorithmic background. For this purpose, we investigate a coupling of differential evolution algorithm and unsupervised Hebbian learning algorithm, using both the global search capabilities of Evolutionary strategies and the effectiveness of the nonlinear Hebbian learning rule. The use of differential evolution algorithm is related to the concept of evolution of a number of individuals from generation to generation and that of nonlinear Hebbian rule to the concept of adaptation to the environment by learning. The hybrid algorithm is introduced, presented and applied successfully in real-world problems, from chemical industry and medicine. Experimental results suggest that the hybrid strategy is capable to train FCM effectively leading the system to desired states and determining an appropriate weight matrix for each specific problem.

Keywords: Fuzzy Cognitive Maps; Learning algorithms; Nonlinear Hebbian rule; Evolutionary computation; Differential evolution algorithms; Evolutionary training

1. Introduction

Fuzzy Cognitive Maps (FCMs) were proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns [23,24]. FCMs represent knowledge in a symbolic manner and relate states, processes, events, values and inputs in an analogous manner. Compared either expert system or neural networks, it has several desirable properties, such as it is relatively easy to use for representing structured knowledge, and the inference can be computed by numeric matrix operation. FCMs are appropriate to explicit the knowledge which has

* Corresponding author. Tel.: +30 2610997293; fax: +30 26120997309.
E-mail addresses: epapageo@ee.upatras.gr (E.I. Papageorgiou), groumpos@ee.upatras.gr (P.P. Groumpos).

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been accumulated for years on the operation of a complex system.

In recent years, there is an increase of published journals and conference papers on FCMs. FCMs have already been applied in many scientific areas, such as medicine, manufacturing, organization behaviour, political science, industry [3,10,22,27,30,34,35,39, 40,48,49,55].

This research work proposes a hybrid FCM learning procedure based on the combination of an unsupervised learning rule, the nonlinear Hebbian learning (NHL) rule and an evolutionary computation (EC)-based algorithm, the differential evolution, to improve the FCM structure, to eliminate the deficiencies in the usage of FCMs and to enhance the dynamical behavior and flexibility of the FCM model. Very few research efforts have been made till today to propose an appropriate learning algorithm suitable for FCMs [1,24,33,36–38].

Artificial neural networks and evolutionary computation establish two major research and application areas in artificial intelligence. In analogy to biological neural networks, artificial neural networks (ANNs) are composed of simple processing elements that interact using weighted interconnections and are of particular interest because of their robustness, their parallelism, and their learning abilities [14,15]. Evolutionary computation is typically considered in the context of evolutionary algorithms (EAs). Evolutionary algorithms are a very rich class of multi-agent stochastic search algorithms based on the neo-Darwinian paradigm of natural evolution, which can perform exhaustive searches in complex solution spaces. These techniques start with searching a population of feasible solutions generated stochastically. Then, stochastic variations are incorporating into the parameters of the population in order to evolve the solution to a global optimum [12,18]. EAs establish a very general and powerful search, optimization and learning method that bases, in analogy to biological evolution, on the application of evolutionary operators like mutation, recombination and selection. Like no other computational method, EAs have been applied to a very broad range of problems [2,4,28,43, 44,45,47].

Recently, the idea of combining ANNs and EAs has received much attention [7,11,51], and now there is a large body of literature on this subject. Weiss [52] in his research work, provides a comprehensive and compact overview of hybrid work done in artificial intelligence, and shows the state of the art of combining artificial neural networks and evolutionary algorithms. There are two ways of synthesizing the fields of ANNs and EAs; one way is to use EAs instead of standard neural learning algorithms for training ANNs; see e.g. [7], and the other way deals with the approaches to an ''evolution-based'' design of appropriate structures of ANNs [17,42]. Furthermore, other hybrid evolutionary approaches have been proposed recently [25,29,52,53,54].

In this work, we use the differential evolution (DE) algorithms, which can be easily implemented and they are computationally inexpensive, since their memory and CPU speed requirements are low [41]. Moreover, they do not require gradient information of the objective function under consideration, but only its values, and they use only primitive mathematical operators. DE algorithms can also handle nondifferentiable, nonlinear and multimodal objective functions efficiently, and require few easily chosen control parameters. Experimental results have shown that DE algorithms have good convergence properties and outperform other evolutionary algorithms [46,47].

This paper proposes a new hybrid evolutionary algorithm (HEA) for FCM learning. The HEA could conceptually be split-up into two stages. In the first stage, nonlinear Hebbian learning is adopted using a recently proposed approach [36]. In the second stage, a differential evolution (DE) algorithm, [47], is used for FCM retraining. The usage of DE algorithm is based on the assumption that the first stage has produced a ''good'' solution that can be incorporated directly into the genes and inherited by offspring. By this manner, the initial expert knowledge (a priori), incorporated in FCMs, can be extracted and incorporated in evolutionary computation, initializing the DE population.

It is used in two termination conditions for the nonlinear Hebbian learning algorithm on the first stage of the proposed learning process and a fitness function appropriate for the specific problem in the second stage of the algorithm. If the optimization criterion (minimization of fitness function) is reached in the second stage, the algorithmic process has terminated. This two-stage learning algorithm is used to train three different FCM models with increasing complexity, two FCM models for chemical process control