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NUMERICAL DYNAMIC MODELING AND DATA DRIVEN CONTROL VIA LEAST SQUARE TECHNIQUES AND HEBBIAN LEARNING ALGORITHM

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Abstract. The modelling and controlling for complex dynamic systems which are too complicated to establish conventionally mathematical mechanism models require new methodology that can utilize the existing knowledge, human experience and historical data. Fuzzy cognitive maps (FCMs) are a very convenient, simple, and powerful tool for simulation and analysis of dynamic systems. Since human experts are subjective and can handle only relatively simple FCMs, there is an urgent need to develop methods for automated generation of FCM models using historical data. In this paper, a novel FCM, which is automatically generated from data and can be applied to on-line control, is developed by improving its constitution, introducing Least Square methods and using Hebbian Learning techniques. As an illustrative example, the simulations results of truck backer-upper control problem quantifies the performance of the proposed constructions of FCM and emphasizes its effectiveness and advantageous characteristics of the learning techniques and control ability.

Key Words. Least Square Learning, Fuzzy cognitive map, Takagi_Sugeno model, Complex dynamic system, Hebbian learning algorithm

1. Introduction

Many conventional methods were used, successfully, to model and control systems but their contribution is often limited in the representation, analysis and solution of the systems with well established mathematically analyzable models. Unfortunately, it is impossible or costly to build the mathematical analyzable model for most of complex nonlinear systems. Currently the advanced digital technology has made the digitized data easy to capture and cheap to store. So there is a great demand for the development of intelligence and data based, autonomous systems that can be achieved taking advantage of human like reasoning and the available data from the systems and their circumstance. Human reasoning process for any procedure includes uncertain descriptions and can have subtle variations in relation to time and space. For such situations, Fuzzy Cognitive Maps(FCMs)[6] seems to be capable to deal with. Fuzzy cognitive maps (FCMs) is a soft computing technique for modeling complex systems, which follows an approach similar to human reasoning and the human decision-making process. FCMs can successfully represent knowledge and human experience, introducing concepts to represent the essential

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elements and the cause and effect relationships among the concepts to model the behavior of any system.

In [7], Kosko pointed out that it is very difficult to build FCMs for large scale intelligent systems just relying on human experts who can observe and know the operation of the systems. The large amount of temporal knowledge discovered from the database is important information which objectively and truthfully reflects the nature of dynamic complex systems. Applying this temporal knowledge to construct FCMs has two significant benefits: One is that large amount of knowledge discovered from huge databases can be integrated into a model which not only can be systematically studied by many powerful mathematical tools, but also can be very expediently understood and utilized by users. The other is that large-scale intelligent systems, which are beyond human expert's capability to observe and understand, can be represented and control via constructing large dimensional data and human knowledge based FCMs. Therefore, the investigation of constructing FCMs by the temporal data from the complex dynamic systems is very important and is one main objective of this paper.

Kosko proposed a new model by using simple Differential Hebbian Learning law (DHL) in 1994, but he used this model to learning FCMs without any applications[2]. This learning process modified weights of edges existing in a FCM in order to find the desired connection weights. In general, when the values of corresponding concept changes, the value of the related edges for that nodes will be modified too. In 2002, Vazquez introduced a new extension to DHL algorithm presented by Kosko. He used a new idea to update edge values in a new formula [22]. This method was applied only to FCMs with binary concept values, which significantly restricts its application areas. Another method of learning FCM based on the first approach(Hebbian algorithm), was introduced in 2003 by Papageorgiou et al. He developed another extension to Hebbian algorithm, called Nonlinear Hebbian Learning (NHL)[23]. The main idea behind this method is to update weights associated only with edges that are initially suggested by experts. The NHL algorithm requires human intervention before the learning process starts, which is a substantial disadvantage. Active Hebbian Algorithm (AHL) introduced by Papageorgiu et al. in 2004[13]. Nevertheless it still requires some initial human intervention. In the recent method, experts not only determined the desired set of concepts, initial structure and the interconnections of the FCM structure, but also identified the sequence of activation concepts[13]. Another category in learning connection weights of the FCM is application of genetic algorithms or evolutionary algorithms. Koulouriotis et al. applied the Genetic Strategy (GS) to learn FCM structure in 2001[24]. In mentioned model, they focused on the development of an GS-based procedure that determines the values of the cause-effect relationships (causality). Parsopoulos et al. also published other related papers in 2003. They tried to apply Particle Swarm Optimization (PSO) method, which belongs to the class of Swarm Intelligence algorithms, to learn FCM structure[11]. Khan and Chong worked on learning initial state vector of FCM in 2003. They performed a goal-oriented analysis of FCM and their learning method did not aim to compute the connection weights, and their model focused on finding initial state vector for FCMs [26]. In 2005, Stach et al. applied real-coded genetic algorithm (RCGA) to develop FCMs model from a set of historical data in 2005[25]. In most case, the performance of genetic programming depends crucially on the choice of representation and on the choice of fitness function and must search in the huge hypothesis space, hence they have the issue of the potential convergence and heavy calculation burden.