System Identification Using Hierarchical Fuzzy CMAC Neural Networks

Floriberto Ortiz Rodriguez[1], Wen Yu[1], and Marco A. Moreno-Armendariz[2]

[1] Departamento de Control Automático, CINVESTAV-IPN
A.P. 14-740, Av.IPN 2508, México D.F., 07360, México
yuw@ctrl.cinvestav.mx
[2] Centro de Investigación en Computación-IPN
AV. Juan de Dios Bátiz S/N,
Unidad Profesional "Adolfo López Mateos"
México, D.F.C.P. 07738, México

Abstract. The conventional fuzzy CMAC can be viewed as a basis function network with supervised learning, and performs well in terms of its fast learning speed and local generalization capability for approximating nonlinear functions. However,it requires an enormous memory and the dimension increase exponentially with the input number. Hierarchical fuzzy CMAC (HFCMAC) can use less memory to model nonlinear system with high accuracy. But the structure is very complex, the normal training for hierarchical fuzzy CMAC is difficult to realize. In this paper a new learning scheme is employed to HFCMAC. A time-varying learning rate assures the learning algorithm is stable. The calculation of the learning rate does not need any prior information such as estimation of the modeling error bounds. The new algorithms are very simple, we can even train each sub-block of the hierarchical fuzzy neural networks independently.

1 Introduction

The Cerebellar Model Articulation Controller (CMAC) presented by Albus [1] is an auto-associative memory feedforward neural network, which is a simple mathematics mode of the cerebellar based on the neurophysiological theory. Because of the simple structure and fast learning speed of CMAC, it has been successfully used in many areas especially in control and robot where the real-time capabilities of the network are of the particular importance. In CMAC the data for a quantized state are constant and the derivative information is not preserved. To overcome this problem a new structure of CMAC called Fuzzy CMAC (FCMAC) [3], [7], uses fuzzy set (fuzzy label) as the input clusters instead of crisp set. Compared to normal CMAC which associates with numeric values, FCMAC can model a problem using linguistic variables based a set of If-Then fuzzy rules which are determined by fuzzy membership functions. Thus, the FCMAC network becomes more robust, highly intuitive and easily comprehended.

In the design of the fuzzy CMAC is common to use a table look-up approach, which is a time-consuming task. Especially when the number of inputs is huge,

D.-S. Huang, K. Li, and G.W. Irwin (Eds.): ICIC 2006, LNAI 4114, pp. 230–235, 2006.

the memory of fuzzy CMAC increase exponentially. This would be overload the memory and make the fuzzy system very hard to implement. Generally n input variables with m quantization, has $n-$dimension space and m^n memory. This phenomenon is called "curse of dimensionality". In order to deal with the memory explosion problem. A number of low-dimensional fuzzy CMAC in a hierarchical form are consisted, instead of a single high-dimensional fuzzy CMAC. This is main idea of hierarchical fuzzy CMAC (HFCMAC) [2] [5]. But they did not give learning algorithms.

Both neural networks and fuzzy logic are universal estimators. Resent results show that the fusion procedure of these two different technologies seems to be very effective for nonlinear systems identification. Gradient descent and backpropagation are always used to adjust the parameters of membership functions (fuzzy sets) and the weights of defuzzification (neural networks) for fuzzy neural networks.

The stability problem of fuzzy neural identification is very important in applications. It is well known that normal identification algorithms (for example, gradient descent and least square) are stable in ideal conditions. In the presence of unmodeled dynamics, they might become unstable. Some robust modifications must be applied to assure stability with respect to uncertainties. Projection operator is an effective tool to guarantee fuzzy modeling bounded . It was also used by many fuzzy-neural systems [7]. Another general approach is to use robust adaptive techniques [4] in fuzzy neural modeling. For example, [9] applied a switch $\sigma-$modification to prevent parameters drift. By using passivity theory, we successfully proved that for continuous-time recurrent neural networks, gradient descent algorithms without robust modification were stable and robust to any bounded uncertainties [10], and for continuous-time identification they were also robustly stable [11]. Nevertheless, do hierarchical fuzzy CMAC has the similar characteristics?

In this paper backpropagation-like approach is applied to system identification via hierarchical fuzzy CMAC neural networks (FCMAC), which is capable of resolving high-dimensional classification problems well. The new algorithms are very simple, we can even train the parameters of each sub-block independently. Time-varying learning rates is used to hierarchical FCMAC neural networks. One example is given to illustrate the effectiveness of the suggested algorithms.

2 Hierarchical Fuzzy CMAC for System Identification

Consider following discrete-time nonlinear system to be identified

$$\begin{array}{l} y(t) = h\left[x\left(t\right)\right] = \Psi\left[X\left(t\right)\right] \\ = \Psi\left[y\left(t-1\right), y\left(t-2\right), \cdots u\left(t-1\right), u\left(t-2\right), \cdots\right] \end{array}. \tag{1}$$

where $X\left(t\right) = \left[y\left(t-1\right), y\left(t-2\right), \cdots u\left(t\right), u\left(t-1\right), \cdots\right]^T$.

This network can be divided into five layers: Input Layer (L_1), Fuzzified Layer (L_2), Fuzzy Association Layer (L_3), Fuzzy Post-association Layer (L_4) and Output Layer (L_5). The input Layer transfers input $x = (x_1, x_2..x_n)^T$ to the next