Investigation of Least Square Fuzzy Identification via a Virtual Higher Resolution Fuzzy Model

K.M. Chow and A.B. Rad
The Hong Kong Polytechnic University, Department of Electrical Engineering
Email: eekmchow@ee.polyu.edu.hk; eeabrad@polyu.edu.hk

Abstract: In this paper, the memory requirement and computational burden of using recursive least square method for parameters updating of fuzzy rule table will be investigated. Conventionally, the entire fuzzy rule table is needed to update in each sampling interval which will lead the size of the covariance matrix will be very large. In order to circumvent this problem, a virtual higher resolution fuzzy model is adopted to minimize the size of the covariance matrix and hence to speed up the computation. A simulation study of a non-linear system identification is implemented to demonstrate the performance of the proposed algorithm.

1. Introduction

Recently, fuzzy modeling has gained a lot of attention for offering promising solutions to the problem of system identification. There have been various methods for tuning the fuzzy systems. For example, the popular techniques are: tuning the scaling factor by fuzzy tuner [6], tuning the consequence fuzzy set by Recursive Least-Square (RLS) method [1,9,13], genetic algorithm [12,15], tuning the TSK fuzzy model by gradient descent method [9,17]. Other solutions such as tuning various parameters (e.g. centre of fuzzy set, width of fuzzy set and output consequence’s fuzzy set of the rule base) of the fuzzy system [2,7-9,15] are also reported in literature.

It is well known that the size of covariance matrix that is used for Recursive Least Square (RLS) method is based on the number of parameters being updated. In the last decade, many researchers applied the least square method for updating the parameters of the fuzzy rule table [1,9,13]. However, if the size of the fuzzy rule table becomes large, the size of the covariance matrix will be increased exponentially and the computational burden will be very high.

In this paper, for the sake of reducing the size of covariance matrix, which will be used for RLS method, a Virtual Higher-Resolution Fuzzy Model (VHR-FM) [4,5] will be used for circumvent this situation. Each cell of the rule-base will be expanded into $2^n$ cells (where $n$ is number of input variables). Therefore, the Ordinary Fuzzy System (O-FS) is now implicitly divided into $\prod_{i=1}^{n} N_i$ Separated Local Fuzzy Systems (SLFS) (where $N_i$ is the number of fuzzy subset of input $i$). Then, the size of the covariance matrix can be reduced significantly.
The rest of this paper is organized as follows: In Section 2, fuzzy indexing method and VHR fuzzy model will be briefly discussed. Section 3 contains the formulation of fuzzy identification algorithm with RLS update. The memory requirement and computational burden by using RLS method for VHR-fuzzy model will be discussed in section 4. In Section 5, computer simulation studies demonstrate the performance of the proposed algorithm. Finally, some conclusions and further works are presented in Section 6.

2. Granulation of the VHR-Fuzzy Rule Table

The granulation of the VHR-Fuzzy Rule Table (VHR-FRT) consists of 2 parts:
1) Fuzzy indexing method [5,10]
2) VHR-fuzzy set [4,5]

2.1 Fuzzy Indexing Method

The fuzzy indexing method is used to determine which $2^n$ (the most and where $n$ is the number of input variable) rules in the fuzzy system will fired in each sampling interval. In general, the fuzzification, fuzzy inferencing and defuzzification of Ordinary Fuzzy Model (O-FM) can be written as follows:

Let,

$x_i$ be the input $i$ and $N_i$ is the number of fuzzy subset of input $i$.

$A_i^k$ be a consistent, complete, triangular fuzzy set and denote $k^{th}$ fuzzy set of input $i$.

$D_{A_i^k} = sup (A_i^k)$

$I_i = k \mid x_i \in [D_{A_i^k}, D_{A_i^{k+1}}), k = 1...N_i$ are the fuzzy index of input $i$.

$X_i = \{ \mu_{A_i^k}(x_i) \mid k = 1...N_i \}$ are the fuzzy vector of input $i$.

$X_i^{I_i} = \mu_{A_i^{I_i}}(x_i)$

$y$ be the centre of fuzzy set $B_{jk}$ and it can be indexed by fuzzy index $I_i$.

Assume to use singleton fuzzifier, product inferencing engine and centre average defuzzifier, the output $y$ of the fuzzy model can be written as: