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Information Sciences xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Method for Higher Order polynomial Sugeno Fuzzy Inference Systems

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A R T I C L E I N F O

Article history:
Received 25 September 2014
Revised 22 February 2016
Accepted 29 February 2016
Available online xxx

Keywords:
Higher Order
Sugeno
Polynomial
Type-1 fuzzy system

A B S T R A C T

A method for Higher Order polynomial Sugeno Fuzzy Inference Systems formation is presented. Compared to other existing Higher Order Sugeno implementations, it uses fewer parameters; and compared to Zero and 1st Order Sugeno Fuzzy Systems it has overall improved model performance. While best models are not always obtained via a Higher Order representation, in our proposed method it is possible to choose the polynomial Order which best fits the desired data. Its input is a previously established model found by a clustering algorithm (subtractive algorithm in this case). Afterward, parameters of all Higher Order polynomials are adjusted using Recursive Least Square algorithm. For experimental validation, multiple benchmark datasets are tested using Hold-Out and *K*-fold validation as well as data forecasting. Various performance measures are used, although Akaike Information Criterion is used as a primary measure to demonstrate that our proposed Higher Order polynomials have overall better model performance over Zero and 1st Order polynomials.

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1. Introduction

Ever since Zadeh introduced Fuzzy Sets (FSs) [47], an immeasurable amount of work has been done in the area, e.g. computing with words using a new linguistic model based on discrete fuzzy numbers [27], aggregation of fuzzy implications [32], qualified description of extended fuzzy logic [35], extension principle and fuzzy sets decomposition [7], fuzzy reasoning's unified full implication [30], left-continuous t-norm construction [44], multilayer fuzzy inference system with weighted average and defuzzification in layers [8]. Apart from Type-1 Fuzzy Sets (T1 FS), Interval Type-2 Fuzzy Sets (IT2 FS) [29] and General Type-2 Fuzzy Sets (GT2 FS) [28] also exist, which capture and model uncertainty in the system, yet they are more computationally intensive than T1 FS, especially GT2 FS (this being one of the reasons that T1 FS are still widely used), and although it does not directly handle uncertainty, it equally handles vagueness just like other higher types of FS. Sometimes the simplicity of T1 FS is enough for the application at hand, such examples are: automatically generating weather summaries [11], sellers decision support system in e-marketplaces [20], gravitational based clustering [36], educational activity recommender for competence acquisition [37], fuzzy control [6], group decision making [50], meat spoilage detection [19], flowshop scheduling [4], hypoglycaemia detection [21], drivers fatigue detection in real time [2], hybrid time

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http://dx.doi.org/10.1016/j.ins.2016.02.045
0020-0255/© 2016 Published by Elsevier Inc.

Please cite this article as: J.R. Castro et al., Method for Higher Order polynomial Sugeno Fuzzy Inference Systems, Information Sciences (2016), http://dx.doi.org/10.1016/j.ins.2016.02.045

series forecasting of stock price based on granular computing [10], geoid height determination [46], time series forecasting based on entropy discretization with FFT [9], offshore bar-shape profiles forecasting under high waves [17], etc.

Though a FS represents knowledge in some sense, its inference can be used to reason with information, i.e. via a Fuzzy Inference System (FIS), real valued results can be obtained and some kind of model behavior can be achieved. Two types of these Inference Systems are used: Mamdani and Assilian [24], and Sugeno [39,40]. Mamdani Inference Systems are based on Membership Functions which can be easily interpreted and manually adjusted, whereas Sugeno Inference Systems are polynomial functions which are usually adjusted by another algorithm in order to achieve a more accurate model. Some examples of these algorithms are: multi-species PSO [26], data-driven [33], systematic control design [42], genetic programming [16], hybridizing imperialist competitive algorithm and simulated annealing [48], hybrid PSO-GA [25], least square-support vector machine [13], online identification [1], Lyapunov function approach [34], genetic algorithm [34], exact analytical inversion [43], product-space fuzzy clustering [15], etc. Sugeno Fuzzy Inference Systems research has seen much interest in recent years, e.g. a strategy to estimate invariant subsets of the domain of attraction for asymptotically stable zero equilibrium points in Sugeno fuzzy systems [22], stability and stabilization conditions for Sugeno fuzzy systems with time delay [49], dynamic output feedback compensator for locally stabilizing a class of nonlinear discrete-time systems through Takagi-Sugeno models [18], evolving Sugeno fuzzy models dedicated to crane systems [31], Sugeno fuzzy model that can handle continuous input and output functions in time series forecasting [45], etc.

In Sugeno Inference Systems the polynomial's Order is important, being Zero Order most common due to its simplicity. The next common polynomial type is 1st Order Sugeno polynomial, although it has more parameters than Zero Order, it typically obtains better models due to improved fitting of 1st Order when compared to Zero Order. Higher Order Sugeno polynomials are typically avoided due to combinatorial growth of operations between increasing number of parameters on each Order level. Higher Order Polynomial Sugeno FIS eliminates the need of combinatorial operations between parameters, thus greatly reducing the final amount of parameters and also improving FIS performance. With Higher Order polynomials it is expected that some, but not all, models could achieve better performance due to improved fitting characteristics. Where Zero Order uses points as a behavioral pattern for data modeling, and 1st Order uses lines, whereas Higher Order polynomials use different types of curves, depending on the Order, which can in some cases improve the fitting.

This paper is organized in five sections. Section 1 reviews other Higher Order Sugeno implementations. Section 2 describes our proposed Higher Order polynomial Sugeno FIS. Section 3 shows experiments, and Section 4 discusses the results. Finally, the last section conclusions and future work is discussed.

2. A review of existing Higher Order Sugeno implementations

The best known proposal for Higher Order Sugeno Fuzzy Systems [5] is shown in Eq. (1), where y^k is kth non-linear function in a Sugeno Fuzzy System, m stands for polynomial Order, $\tilde{b}_0^k$ is a Zero Order coefficient, $\tilde{\vec{b}}_1^k$ is a 1st Order coefficient vector, $\tilde{b}_2^k$ is a 2nd Order coefficient triangular matrix, $\tilde{b}_m^k$ are coefficients in a triangular m-dimensional matrix, $\vec{x} = [x_1, x_2, \ldots, x_n]$ is a vector of all inputs in the Fuzzy System, and $\otimes$ is the tensor product. As an alternate, Eq. (1) can also be rewritten as Eq. (2), where $b^k_{ji\ldots q}$ are ith Order coefficients in the kth fuzzy rule, and $j,i,\ldots,q$ are the variable's Order. This implementation's strong feature is also its weakest point: it has good fitting characteristics which can adapt to very complex data behavior, due to its combinatorial nature with Order increase, the drawback being that as the number of inputs and/or Order increases, so does the number of required parameters. This ultimately is the reason why it is not widely used.

$$y^k = \tilde{b}_0^k + \tilde{\vec{b}}_1^k \vec{x} + \vec{x}^T \tilde{b}_2^k \vec{x} + \cdots + \left\langle \tilde{b}_m^k * (\vec{x} \otimes \cdots \otimes \vec{x}) \right\rangle \tag{1}$$

$$y^k = \sum_{j=0}^{m} \sum_{i=0}^{m} \cdots \sum_{q=0}^{m} b^k_{ji\ldots q} x_1^j x_2^i \cdots x_n^q \tag{2}$$

Another approach for Higher Order Sugeno [38] modeling is shown in Eq. (3), where y^k is the non-linear function on the kth Fuzzy rule, b_0 is a constant, b_p is the pth parameter, p is the number of inputs, and x_p is the pth input on the Fuzzy System. Its alternate form is seen in Eq. (4). This Higher Order Sugeno implementation has very poor general fitting characteristics, as it was specifically designed for evaluating a Modification of Diet in Renal Disease formula used for calculating glomerular filtration rate.

$$y^k = b_0 x_1^{b_1} x_2^{b_2} \cdots x_p^{b_p} \tag{3}$$

$$y^k = b_0 \prod_{i=1}^{p} x_i^{p_i} \tag{4}$$

There is also a Higher Order Sugeno approximator based on Taylor polynomials [3], shown in Eq. (5), where y^k is the kth output function in a Sugeno Fuzzy System, A_i is a continuous membership function, x_i and $f(x_i)$ are the input and output values of the function's sample data, $i = 0, 1, \ldots, n$ is the ith data pair of n data pairs, and m is the amount of times the function representing all data pairs can be continuously differentiable. This approach has many points which must be

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