ARTICLE IN PRESS
JID: NEUCOM [m5G;December 15, 2017;13:29]

Neurocomputing 000 (2017) 1–8

Contents lists available at ScienceDirect

Neurocomputing

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

Integration of weighted LS-SVM and manifold learning for fuzzy modeling

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ARTICLE INFO

Article history:
Received 25 August 2016
Revised 5 December 2017
Accepted 8 December 2017
Available online xxx

Communicated by Wei Chiang Hong

Keywords:
Fuzzy model
Weighted LS-SVM
Manifold learning
Robustness
Hydraulic actuator
Noise

ABSTRACT

In this paper, a robust fuzzy modeling method is proposed for strongly nonlinear systems in the presence of noise and/or outliers. The proposed method integrates the advantages of the fuzzy structure, the manifold learning, and the weighted least squares support vector machine (LS-SVM). First, the Gustafson–Kessel clustering algorithm (GKCA) is applied to split the training data set into several subsets to determine the fuzzy rules and premise parameters. Then, a new objective function is constructed based on the fuzzy structure, the weighted LS-SVM, and the manifold regularization, which takes into account robustness and the intrinsic geometry of the data. A solving method is further developed, from which the fuzzy model is achieved and can effectively approximate a nonlinear system with various types of random noise. The proposed method is applied to an artificial case as well as a practical hydraulic actuator, demonstrating its effectiveness in modeling of a nonlinear system even under noise.

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1. Introduction

In industry, many processes or systems are complex and strongly nonlinear, and are typically contaminated by noise from many sources [1], including environment noise, sampling errors, measurement errors, human errors, etc. Often, outliers also exist in process data. In general, modeling this kind of process or system is very difficult.

In the past decades, much progress has been made in modelling complex nonlinear systems using the so-called Takagi–Sugeno (T–S) fuzzy model [2,3]. The T–S model provides a simple and straightforward way to decompose the complex task into a group of simple tasks [4,5]. It has also been proven to have uniform approximation ability for any nonlinear system [6].

In general, there are two approaches to T–S fuzzy modelling. One is to determine the fuzzy rules and premise parameters by methods such as K-mean clustering, fuzzy C-means (FCM) [7], kernel FCM [8], Gustafson–Kessel clustering algorithm (GKCA) [9], or the fuzzy system with rule generation and iterative linear support vector regression (FS-RGLSVR) [10].

The other approach is to identify the consequent parameters. Many studies have contributed methods for determining consequent parameters, such as recursive least squares (RLS) [4], weighted recursive least squares (WRLS) [11], and the Kalman filter [12]. However, these methods do not take into account the complexity of the model in ambient space, and thus have poor generalization and are often over-fitting for models of complex nonlinear systems. In order to guarantee the generalization without significantly increasing computational costs, the least squares support vector machine (LS-SVM) has been employed [13]. Although this method can maintain generality and avoid over-fitting, it is ineffective when dealing with non-Gaussian noise or data with outliers. Moreover, the aforementioned identification methods do not consider the intrinsic nature of data. This makes them less accurate for strongly nonlinear systems in the presence of noise. Thus, an effective fuzzy modeling method is still needed for strongly nonlinear systems in the presence of non-Gaussian noise and/or outliers.

It is well-known that manifold learning can effectively maintain the intrinsic geometry of high dimensional data. Manifold learning has been widely applied to dimensionality reduction [14], such as locally linear embedding (LLE) [15], Isomap [16], locality preserving projection (LPP) [17], and linear local tangent space alignment (LTSA) [18]. Manifold learning has also been extended to regression and classification in order to improve modeling ability [19], such as least-squares classification [20], support vector machine (SVM) [21–25], and extreme learning machine (ELM) [26–28]. It spans the range from unsupervised to fully supervised learning [29–32]. However, manifold learning has never been applied to the fuzzy modeling to date.

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https://doi.org/10.1016/j.neucom.2017.12.019
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Please cite this article as: G. Qin, X. Lu, Integration of weighted LS-SVM and manifold learning for fuzzy modeling, Neurocomputing (2017), https://doi.org/10.1016/j.neucom.2017.12.019

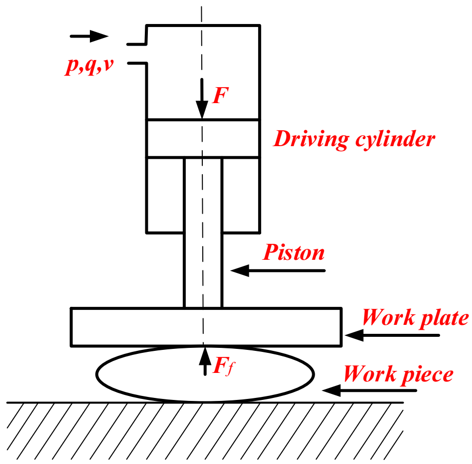

Fig. 1. A hydraulic actuator system.

In this paper, a robust fuzzy modeling method is proposed for strongly nonlinear systems in the presence of noise and/or outliers. It integrates the advantages of the fuzzy structure with manifold learning and the weighted LS-SVM [33]. Unlike traditional fuzzy modeling, the proposed method takes the intrinsic nature of the data into account and can achieve a robust model even under noise or outliers. Firstly, the GKCA is applied to divide a training data set into several subsets in order to determine the fuzzy rules and premise parameters. Then, a new objective function is constructed based on the fuzzy structure, the weighted LS-SVM and the manifold regularization. A solving method is then developed, from which the fuzzy model is achieved and can effectively approximate an unknown nonlinear system with various types of random noise.

2. Problem description and T–S fuzzy model

2.1. Problem description

In industry, many processes or systems have strongly nonlinear characteristics and are contaminated by noise or outliers. A hydraulic actuator used for forging, shown in Fig. 1, is a typical example of such systems [34,35]. In order to forge the work piece to the desired shape, the velocity and position of the piston must be accurately controlled, which depends on the accurate driving model. However, the irregular shape and varied deformation of the work piece, nonlinear hydraulic driving system and the compressibility of the hydraulic oil contribute to strong nonlinearity of the system. Together with the external disturbances including random noise and outliers render the system difficult to model.

The aforementioned nonlinear system can be described as follows:

$$y = f(x, \varepsilon) \tag{1}$$

where x and y are the input and output of the system, respectively, f is an unknown nonlinear function, and ε represents random noise including Gaussian noise, non-Gaussian noise and outliers.

2.2. T–S fuzzy model

It is well-known that the T–S fuzzy model can approximate a large class of complex nonlinear systems. This model is described as follows [36]

R_k: If $x^{(1)}$ is A_{k1} and…and $x^{(n)}$ is A_{kn}

Then $y = a_k^T x + b_k, k = 1, 2, \ldots, R$,

where R_k is the kth rule, $x^{(j)}$ and A_{kj} are the premise variables of the system and its fuzzy set respectively, y represents the output of kth rule, a_k and b_k are consequent parameters of the kth rule, and R is the number of rules. The final T–S fuzzy model can be written as follows:

$$\hat{f}(x) = \sum_{k=1}^{R} \phi_k(x)(a_k^T x + b_k) \tag{2}$$

With

$$\phi_k(x) = \frac{\beta_k(x)}{\sum_{j=1}^{R} \beta_j(x)} \tag{3}$$

$$\beta_k(x) = \prod_{j=1}^{n} G_{kj}(x), k = 1, 2, \ldots, R \tag{4}$$

Here, $G_{kj}(x)$ is the membership function of the fuzzy set A_{kj}.

In general there are many options to identify the consequent parameters a_k and b_k from data including RLS, Kalman filter, and W-RLS. Recently the LS-SVM has been used to improve generalization and avoid over-fitting during consequent parameter identification. This method only requires solving the following optimization problem using the least squares method:

$$J = \frac{1}{2}(a_1^T a_1 + \cdots + a_R^T a_R) + \frac{1}{2}\gamma \sum_{i=1}^{N} e_i^2 \tag{5}$$

Subject to:

$$y_i = \sum_{k=1}^{R} \phi_k(x_i)(a_k^T x_i + b_k) + e_i, (i = 1, 2, \ldots, N)$$

Although the LS-SVM based identification method is effective in many cases, it still has a few disadvantages:

- ☐ It is ineffective when non-Gaussian noise or noise distributions with heavy tails are present;
- ☐ It is sensitive to outliers and gives equal weight to all data points, including outliers, which can decrease model performance.

Thus, the development of a robust T–S fuzzy method for modeling nonlinear systems with noise is needed.

3. Novel fuzzy modeling method

It is well-known that manifold learning can effectively preserve data sequence spatial structure or geometry of the data distribution. In addition, outliers and/or noise samples should have a lower frequency than the number of elements found in the main body of data collected. In this sense, samples acquired at the lower frequency should be more likely contaminated with outliers or noise. Thus, statistical distribution inherently reflects the degree to which a dataset is contaminated by outliers and/or noise.

Based on these concepts, a robust fuzzy modeling method, as presented in Fig. 2, is proposed to describe a dataset with noise and outliers. The proposed method integrates the advantages of the T–S fuzzy structure constructed by the GKCA, manifold learning, and the weighted LS-SVM that weights modeling error according to the distribution of modeling error in order to improve the robustness of modeling. By constructing the statistical distribution of errors, Weighted LS-SVM can deal with outliers. The T–S fuzzy model can effectively model a nonlinear system due to its uniform approximation ability and the manifold regularization can preserve the intrinsic nature of the system. This model is also robust to outliers and/or noise based on incorporation of the weighted LS-SVM strategy. Thus, it can effectively model strongly nonlinear systems with outliers and/or noise.

Please cite this article as: G. Qin, X. Lu, Integration of weighted LS-SVM and manifold learning for fuzzy modeling, Neurocomputing (2017), https://doi.org/10.1016/j.neucom.2017.12.019

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