Applied Soft Computing 25 (2014) 309–321

Contents lists available at ScienceDirect

Applied Soft Computing

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

A fuzzy-based spatio-temporal multi-modeling for nonlinear distributed parameter processes

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ARTICLE INFO

Article history:
Received 16 June 2013
Received in revised form 30 June 2014
Accepted 5 September 2014
Available online 16 September 2014

Keywords:
Distributed parameter system
Spatio-temporal modeling
Multi-modeling
Kernel model
Space/time separation
Fuzzy clustering

ABSTRACT

Many industrial processes belong to nonlinear distributed parameter systems (DPS) with significant spatio-temporal dynamics. They often work at multiple operating points due to different production and working conditions. To obtain a global model, the direct modeling and experiments in a large operating range are often very difficult. Motivated by the multi-modeling, a fuzzy-based spatio-temporal multi-modeling approach is proposed for nonlinear DPS. To obtain a reasonable operating space division, a priori information and the fuzzy clustering are used to decompose the operating space from coarse scale to fine scale gradually. To reduce the dimension in the local spatio-temporal modeling, the Karhunen–Loève method is used for the space/time separation. Both multi-modeling and space/time separation can reduce the modeling complexity. Finally, to get a smooth global model, a three-domain (3D) fuzzy integration method is proposed. Using the proposed method, the model accuracy will be improved and the experiments become easier. The effectiveness is verified by simulations.

1. Introduction

Many industrial processes are distributed parameter systems (DPSs), e.g., convection–diffusion–reaction process in the chemical industry [1], spray deposition process in the material industry [2] and snap curing process in the integrated circuit (IC) packaging industry [3]. Different from lumped parameter system (LPSs), the inputs and outputs of DPSs are distributed in space [1,4]. Sometimes, the spatial nature is ignored in the modeling and control. However, the control performance will deteriorate if the system dynamics significantly vary with space. In this case, the spatial nature must be considered in the modeling and control. The feedback control depends on high-dimensional spatial measurements or an accurate model. In practice, only some locations are measured due to a limited number of sensors. To estimate for unmeasured locations, an accurate model is very desirable.

Unknown dynamics often exist due to incomplete process knowledge. In this case, system identification from experimental data is required. However, it is not easy due to spatio-temporal coupled, nonlinear and infinite-dimensional dynamics. Due to different production and working conditions, the system often works at a large operating range with multiple operating points. The model obtained at one operating point may not work well for another operating point. All these considerations motivate the global modeling over multiple operating points.

If the models of partial differential equations (PDEs) are known, lumping techniques can be used to reduce infinite-dimensional PDEs into finite-dimensional ordinary differential equations (ODEs) for implementation. *Spectral method* and *approximate inertial manifold* [1] are popularly used to derive control models for parabolic PDE systems because it may result in lower-order ODEs than *finite difference* and *finite element methods*. For nonlinear parabolic PDEs with nonlinear spatial operators, the Karhunen–Loève (KL) method can obtain empirical eigenfunctions from the process data for dimension reduction [5,6]. However, these lumping methods require the PDEs accurately known.

If the PDEs are unknown, system identification will be used. When the PDE structure is known, it often becomes a parameter estimation problem (e.g., [7–9]). If the DPS structure is unknown, the black-box identification has to be used.

- For a linear DPS, the transfer function or Green's function model can be estimated from the input–output data [10]. For example, the concept of residence time distribution is used to get

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http://dx.doi.org/10.1016/j.asoc.2014.09.003
1568-4946/

an input–output model [11]. A time-invariant Green's function model can be estimated using singular value decomposition (SVD) method [12]. For linear time-varying DPS, a time-varying Green's function model can be obtained from the singular function and Karhunen–Loève (KL) basis function expansion using SVD–KL method [13–15]. The least-squares method can also be used [16]. For nonlinear DPS, traditional Green's function model is only an approximation at an operating point. Though the linear time-varying Green's function model can approximate the nonlinear DPS, the identification of the time-varying kernel is not easy because the parameterization of the time-varying kernel on the time variable is difficult to be proper for an unknown system.
- For nonlinear DPS, an infinite-dimensional PDE model can be estimated [17–19]. A high-dimensional ODE model can also be obtained based on *finite difference* [20] and *finite element* [21]. *Neural networks* can model unknown nonlinearities based on *spectral method* [3] for a partially unknown DPS. *Neural networks* can also model completely unknown nonlinear DPS based on *KL method* [22]. It can result in low-order ODEs and handle complex boundary conditions. However, the model is a general nonlinear model that could lead to difficult control design. Recently, *spatio-temporal Volterra*, *Hammerstein* and *Wiener* models [23–27] with simple structures are proposed that could lead to simple control design.

The global modeling for nonlinear DPS over multiple operating points is very challenging due to complex nonlinear or time-varying dynamics. The persistently exciting experiment over a large operating range is also difficult. In the modeling of LPS, to overcome similar difficulties, the multi-modeling [28–30] is often a choice from a view of cost and performance. The complex nonlinear dynamics are decomposed into several local operating regions where the local modeling and experiment can be easily performed. By integrating multiple local models, it can obtain a global model at a large operating range. One advantage is that the complexity of modeling and experiment can be largely reduced. Many multi-modeling methods, e.g., local model networks [31], Takagi–Sugeno fuzzy model [32,33] and multiple neural network models [34] all involve the same underlying ideas. Though the multi-modeling has been developed with many industrial applications, most of them are only utilized for lumped processes.

Recently, a kernel-based spatio-temporal multi-modeling approach is proposed [35] for nonlinear DPS. Note that the operating space division is mainly based on the experiment data and no process knowledge is utilized. Considering the performance and cost, using both process knowledge and data analysis could be a good choice. To model the local dynamics, a linear spatio-temporal kernel model is used. After that a global model is obtained by integrating multiple local models using a scheduling (weight) function. However, the scheduling function only depends on system states (temporal variables). Actually, the local model may have different weights at different spatial locations. To enhance the modeling capability, a spatial integration could be required.

In this study, a fuzzy-based spatio-temporal multi-modeling for nonlinear distributed parameter processes with multiple operating points is proposed. The whole operating space of the nonlinear DPS is first divided into multiple local operating regions. Complex nonlinear spatio-temporal dynamics are decomposed into multiple simple spatio-temporal dynamics. To obtain a reasonable operating space division, a hybrid approach that integrates process knowledge and data analysis is proposed. The operating space is decomposed from coarse scale to fine scale gradually. In the local spatio-temporal modeling, the Karhunen–Loève method is performed for the space/time separation and dimension reduction. The multi-model decomposition and space/time separation will gradually reduce the complexity of global nonlinear spatio-temporal modeling. Next, unknown parameters of each model are estimated using the linear optimization method. Finally, to guarantee a smooth transition between local spatio-temporal models, a three-domain (3D) fuzzy integration method is used to provide a global spatio-temporal model. The experiment and modeling for each local region become easier than direct global modeling. The modeling accuracy is better than one local modeling. The dimension reduction in the modeling actually utilizes the time-scale properties, thus this modeling approach is particularly suitable for dissipative PDEs (e.g., parabolic PDEs).

Compared with the previous paper [35], the main contributions of this study are that a fuzzy-based spatio-temporal multi-modeling approach is proposed for the nonlinear distributed parameter system (DPS).

- In this study, a hybrid approach that integrates a priori process knowledge and data based fuzzy clustering is proposed for the operating space decomposition. The operating space is decomposed from coarse scale to fine scale gradually. In the previous paper, the proposed iterative approach is only based on the process data, and the operating space division and local modeling are performed iteratively.
- In this study, a three-domain (3D) fuzzy integration method is proposed to integrate multiple local models, where the weights depends on both system states (temporal variables) and spatial locations. In the previous paper, the scheduling function only depends on system states (temporal variables), and different weights of the local model at different spatial locations are not considered.

The rest of the paper is organized as follows. The fuzzy-based spatio-temporal multi-modeling is presented in Section 2. Section 2.1 gives the multi-modeling methodology. In the Section 2.2, the fuzzy-based operating space division is presented. The kernel-based construction of local spatio-temporal models and the 3D-fuzzy aggregation of local spatio-temporal models are given in Sections 2.3 and 2.4 respectively. Section 3 contains one application example. Finally, a few conclusions are presented in Section 4.

2. Fuzzy-based spatio-temporal multi-modeling

2.1. Multi-modeling methodology

The methodology of the proposed fuzzy-based spatio-temporal multi-modeling for nonlinear DPS is shown in Fig. 1. There are three main parts:

- Fuzzy-based operating space division. As shown in Fig. 1a, to handle complex nonlinearity, the whole operating space is decomposed into multiple local operating regions using a priori information and fuzzy clustering. Correspondingly the original nonlinear spatio-temporal dynamics are divided into multiple simple spatio-temporal dynamics.
- Kernel-based local spatio-temporal modeling. As shown in Fig. 1b, for each local region, the local spatio-temporal modeling is easily performed using a kernel-based method. Here a linear kernel modeling is used because the modeling complexity can be reduced significantly. If a nonlinear model is used in the local modeling, the modeling complexity cannot be reduced significantly. To handle the spatio-temporal coupling, the Karhunen–Loève (KL) method is used for the space/time separation.
- 3D-fuzzy aggregation. As shown in Fig. 1c, to provide a global spatio-temporal model, the local spatio-temporal models are