Mechanical Systems and Signal Processing 62-63 (2015) 254–271

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Multivariable nonlinear identification of smart buildings

Yeesock Kim [a,*], Young Hoon Kim [b], Seongsoo Lee [c]

[a] Civil and Environmental Engineering, Worcester Polytechnic Institute, Worcester, MA 01609-2280, USA
[b] Civil and Environmental Engineering, University of Louisville, Louisville, KY 40292, USA
[c] Architecture and Building Engineering, Kunsan National University, Kunsan, Republic of Korea

ARTICLE INFO

Article history:
Received 27 July 2012
Received in revised form
3 February 2014
Accepted 16 February 2015
Available online 12 March 2015

Keywords:
Wavelet transform
Multi-input–multi-output (MIMO)
Autoregressive exogenous (ARX) input models
Takagi–Sugeno (TS) fuzzy model
Smart structures
Magnetorheological (MR) damper

ABSTRACT

This paper presents a new multi-input–multi-output (MIMO) fuzzy model for nonlinear system identification (SI) of smart structures under a variety of random forces. The fuzzy SI model is developed through the integration of wavelet transform (WT), multiple MIMO linear autoregressive exogenous (ARX) input models, Takagi–Sugeno (TS) fuzzy model, weighted linear least squares, and data clustering algorithms: MIMO WARX-TS fuzzy model. To demonstrate the effectiveness of the MIMO WARX-TS fuzzy model, a three-story building equipped with a magnetorheological (MR) damper under a variety of random signals is investigated. To train the proposed model, an artificial earthquake and control forces are used as input signals while displacement and acceleration responses are used as outputs. To validate the trained model, four real recorded earthquake signals are used. It is shown from the simulation that the proposed MIMO WARX-TS fuzzy identification algorithm is effective in estimating nonlinear behavior of a building–MR damper system under a variety of seismic excitations.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

System identification (SI) is the process of developing an accurate mathematical model for a dynamic system, based on a set of input and output data [1]. The SI is used in control system design for vibration mitigation of dynamical systems because precise mathematical information related to the dynamic system is used for calculation of control forces [2–5] [61–66]. It is also used for system health monitoring through identifying severity and location of the damage within the dynamic system [67–69]. However, it is still difficult to analytically derive a mathematical model of a nonlinear dynamic system [6]. A typical example of nonlinear dynamic systems is when highly nonlinear hysteretic actuators/dampers are installed on structural systems for efficient energy dissipation, e.g., a building employing nonlinear control devices behaves nonlinearly although the building system itself is usually assumed to behavior linearly [7]. Because the building equipped with the nonlinear hysteretic control device is intrinsically nonlinear, it is challenging to develop an appropriate mathematical model for the integrated structure–control system considering the interaction effects between the structural system and the nonlinear control device which plays a key role in control system design [70] and system health monitoring [8] [71,72].

To address this issue, a number of researchers have studied a number of various SI approaches in recent years. In particular, nonlinear SI approaches can be grouped into two parts: parametric and nonparametric SI [5,9,10].

* Corresponding author.
E-mail addresses: yeesock@wpi.edu (Y. Kim), yhkim005@louisville.edu (Y.H. Kim), leess@kunsan.ac.kr (S. Lee).

http://dx.doi.org/10.1016/j.ymssp.2015.02.010
0888-3270/© 2015 Elsevier Ltd. All rights reserved.

Identification of physical quantities such as stiffness and damping of structural systems is called the parametric SI [11–13], while training the relationship between the input and output signals is called a nonparametric SI [14]. In particular, the nonparametric SI method is very effective for determining a model for large-scale complex nonlinear dynamic systems such as building and bridge structures.

Neural network (NN) has been widely used as a nonparametric nonlinear SI methodology. When compared to the parametric SI, the NN typically yields robust solutions even with incomplete and incoherent measurements. This advantage can be amplified in the SI of large-scale structural systems [15–17], although there are some disadvantages, including the slow rate of convergence, the potential to local minima in conventional NN models, and the characteristics of the black-box modeling [17]. Fuzzy logic theory is also a common nonparametric SI method. When compared to the NN method, it provides an effective framework for modeling complex nonlinearities and uncertainties of dynamic systems in a more transparent way [18]. Since 1965 Zadeh's research [19], many researchers adopted the fuzzy theory to solve complex nonlinear SI problems using fuzzy sets, fuzzy rules, and linear system theory [20–28] [73–79]. Fuzzy models have been mainly used to develop the design procedures to identify nonlinear control systems for large-scale civil infrastructures [29–49]. However, the research on nonlinear fuzzy SI for building structures subject to seismic excitations is limited. For instance, a multi-input, single-output (MISO) fuzzy wavelet neural network (FWNN) model is proposed by Jiang and Adeli [50]. The MISO FWNN model is used to identify nonlinear behavior of tall building structures. Note that the Jiang and Adeli model is not a fuzzy input–output mapping model, but it adopts a fuzzy C-mean algorithm as a data clustering approach for use in a NN model. Therefore, the MISO FWNN model cannot be applied to a model-based fuzzy control system design framework. The reason is that a parallel distributed compensation (PDC)-based fuzzy control design framework needs the same premise parameters of a Takagi–Sugeno fuzzy model [51,52]. This is a motivation of this research.

With this in mind, Kim et al. [52,53] proposed a multi-input, multi-output (MIMO) TS fuzzy identification model for use with building structures equipped with highly nonlinear hysteretic MR dampers. They trained the proposed model using a random zero-mean Gaussian white noise signal and then demonstrated its effectiveness in estimating nonlinear behavior of smart structures under a sum of sinusoids and other random zero-means Gaussian white signals. However, the model has drawbacks: (1) the modeling procedure is computationally expensive so it is difficult to apply the model to real time applications such as real-time health monitoring and adaptive control system design and (2) it is not effective in predicting nonlinear behavior to a non-zero mean non-Gaussian random signals such as earthquake disturbance signals. Therefore, the aim of this paper is to provide an alternative SI framework for smart structures under a variety of earthquake excitations in order to improve the SI performance with less computational loads. It is developed through the integration of a wavelet transform, TS fuzzy model, data clustering algorithms, and weighted linear least squares estimation with a set of MIMO autoregressive exogenous (ARX) input models.

This paper is organized as follows: the wavelet-based nonlinear MIMO ARX input–TS fuzzy identification framework is described in Section 2. Next, the governing equations and the properties of a smart building–MR damper system are briefly described, followed by simulation results involving the time histories of the excitation input signals and the associated system output responses in Section 3. Concluding remarks are given in Section 4.

2. Nonlinear system identification

In this section, wavelet-based multiple multi-input, multi-output (MIMO) ARX input models integrated with a fuzzy logic-based interpolation method are introduced: wavelet transform is discussed first; then, the MIMO ARX-based TS fuzzy model is described; finally, the MIMO ARX-TS fuzzy model is combined with the wavelet transform framework.

2.1. Wavelet transform

Wavelet analysis began during the 1980s by Morlet, who discovered the use of wavelet analysis in signal processing [54]. It was created by modifying previous mathematical concepts such as Fourier analyses, where the time window is fixed to include the entirety of the signal. Wavelet theory began by bypassing this drawback of the Fourier analysis so that wavelet analysis used a variable time-window, allowing scientists and engineers to look at a specific time frame of the signal for signal analysis. Mathematicians working with filter theory were able to use this concept of wavelet analysis and apply it to their field, and reconstruction filters were developed. This meant that signals were able to be divided into sampled signals and then reconstructed into a signal that is equivalent to the original signal. Mallat [82] created a fast wavelet decomposition algorithm to compute the wavelet coefficients using the wavelet filters, with one algorithm for decomposition of the signal and another algorithm for the reconstruction to the equivalent signal. Being able to reconstruct a signal using these algorithms provides the ability for data compression and noise reduction.

Fourier transforms and its modifications, such as short-time Fourier transforms and fast Fourier transforms, use a fixed time–frequency resolution, causing an issue in many engineering applications, mainly an inability to see low or high frequency portions of the window when viewing the entire window. A continuous wavelet transform of a function $y_g(t)$ with respect to some analyzing wavelet ψ is given by

$$W_\psi(b_w, a_w) := \frac{1}{\sqrt{a_w}} \int_{-\infty}^{\infty} y_g(t) \cdot \overline{\psi\left(\frac{t-b_w}{a_w}\right)} dt, \tag{1}$$

Download English Version:

https://daneshyari.com/en/article/560149

Download Persian Version:

https://daneshyari.com/article/560149

Daneshyari.com