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Fuzzy stochastic neural network model for structural system identification

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ABSTRACT

This paper presents a dynamic fuzzy stochastic neural network model for nonparametric system identification using ambient vibration data. The model is developed to handle two types of imprecision in the sensed data: fuzzy information and measurement uncertainties. The dimension of the input vector is determined by using the false nearest neighbor approach. A Bayesian information criterion is applied to obtain the optimum number of stochastic neurons in the model. A fuzzy C-means clustering algorithm is employed as a data mining tool to divide the sensed data into clusters with common features. The fuzzy stochastic model is created by combining the fuzzy clusters of input vectors with the radial basis activation functions in the stochastic neural network. A natural gradient method is developed based on the Kullback–Leibler distance criterion for quick convergence of the model training. The model is validated using a power density pseudospectrum approach and a Bayesian hypothesis testing-based metric. The proposed methodology is investigated with numerically simulated data from a Markov Chain model and a two-story planar frame, and experimentally sensed data from ambient vibration data of a benchmark structure.

1. Introduction

Nonparametric system identification has been widely pursued in health monitoring and damage detection (e.g., [2,20,21–23,31,44,45,49,56], and [41]) and active control (e.g., [19,56,6,7], and [3]) of structural systems under natural hazards such as earthquake and winds. Unlike parametric methods, the identification model in the nonparametric approach does not represent any physical quantity directly, but it is trained to approximate a physical structure and predict its response. In addition, the nonlinear autoregressive moving average with exogenous inputs (NARMAX) approach [11] is commonly used in the nonparametric methods for mapping the input–output relationship. The approach has flexibility in effectively representing structural nonlinearity. Despite the substantial research, accurate system identification is still a challenging

Abbreviations: ; ASCE, American Society of Civil Engineers; BIC, Bayesian Information Criterion; BP, Backpropagation; CPU, Central Processing Unit; DOF, Degree of Freedom; FCM, Fuzzy C-means; FFT, Fast Fourier Transform; FNN, False Nearest Neighbor; IASC, International Association for Structural Control; iid, independent and identically-distributed; KL, Kullback-Leibler; MSE, Mean Squared Error; MUSIC, MUltiple SIgnal Classification; NARMAX, Nonlinear AutoRegressive Moving Average with eXogenous inputs; RAM, Random-Access Memory; RBFNN, Radial Basis Function Neural Network; RRMS, Relative Root Mean Square; SNN, Stochastic Neural Network; SHM, Structural Health Monitoring; SSE, Sum of Squared Errors

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problem due to (1) the complicated stochastic behavior of the structural system, (2) the imprecise nature of sensed data, (3) uncertainties in both sensed data and model prediction, and (4) quantitative assessment of the system identification model under uncertainty. This paper proposes a new probabilistic methodology for nonparametric system identification that addresses the abovementioned four challenges.

During the past decade a good number of research papers have been published on the use of neural networks for nonparametric system identification (e.g., [53,44,45,49,42,57], and [58]). Loh et al. [42] use the Levenberg–Marquardt backpropagation (BP) neural network for nonparametric identification of a five story test frame [44] investigated the use of the BP neural network method for structural system identification and health monitoring. Their study shows that the neural network method is a practical tool in detecting changes in nonlinear structures with unknown constitutive properties and topologies.

It should be pointed out, however, that BP neural network methods suffer from some common drawbacks such as lack of an efficient constructive model, slow convergence rate, and entrapment in a local minimum [1]. Also, neural network-based models lose their effectiveness when the patterns are very complicated and data are imperfectly sensed. In particular, the neural network is a deterministic model with the approximation error as an additive noise to the output. This approach cannot effectively capture the complicated behavior of structural systems under stochastic loading environments such as ambient effects or natural hazards. An alternative approach, *stochastic neural network* (SNN), has been shown to be a powerful tool for effective approximation of complex nonlinear stochastic systems in financial engineering [34,40] and mechanical engineering [51]. The SNN model is a type of artificial neural network where stochastic activation functions are used as neurons or stochastic weights are used in the links. To the best knowledge of the authors, however, no research has been reported on developing this model to identify a complicated structural system under uncertainty, which is the focus of this paper.

The motivation of developing the SNN model for structural system identification lies in two aspects. First, sensed data from real structures is nondeterministic, due to natural variability (described through stochastic or random processes) and uncertainties (due to lack of knowledge) in the inspection setup, measurement conditions, and different measured quantities of interest. Ignoring the uncertainties in the sensed data may result in erroneous decision making in the structural condition assessment after the data is collected. Second, ambient vibration testing (e.g., winds and traffic) of existing structures is much easier and more frequently conducted for structural health monitoring (SHM) than other vibration tests such as free-induced and forced vibration tests. However, the exact structural inputs such as winds or ground acceleration due to traffic are actually immeasurable. In addition, ambient vibration data is random because excitations are generated from a random source. As a result, structural system identification approaches need to account for both uncertainty and randomness of the measured data subject to unknown input excitations.

Note that, during the past decade a good number of researchers have developed various parametric methods for system identification using ambient vibration data (e.g., [16,17,24,9,18,59]). Modal analysis is used to extract structural dynamic parameters such as natural frequency and modal damping for structural damage detection [26,32]. However, they do not consider the uncertainty and randomness in the measurements, which may make the identification results inaccurate. Currently little research has been reported on developing nonparametric neural network-based methods for system identification using the ambient vibration data.

In this paper, a dynamic fuzzy SNN model is explored to effectively capture random characteristics in a complicated structural system. The proposed methodology is able to handle two types of imprecision in the sensed data: fuzzy information and measurement uncertainties. The former is handled by fuzzy logic theory integrated in the dynamic SNN model. The latter is explicitly considered in Bayesian hypothesis testing, which will be implemented to validate the identification model. The randomness of the ambient vibration data is represented by the stochastic neural network model. A fuzzy C-means clustering algorithm presented in Jiang and Adeli [25] is employed as a data mining tool to divide the sensed data into clusters with common features. A fuzzy-SNN model is created by combining the fuzzy clusters of reconstructed state space vectors with the activation functions in the SNN model. Any nonlinearity in the structural behavior will be captured by the NARMAX approach, which is incorporated in the developed model.

Because of the introduction of stochastic variables to the model, the traditional error backpropagation learning algorithm will have slow convergence [50]. In this study, a log-likelihood function is defined as a loss function based on the model prediction and the vibration response data. A natural gradient method based on Kullback–Leibler (KL) [39] distance criterion is explored to maximize the loss function, which measures the similarity between two probability density functions. Refer to Kapur and Kesavan [36] and Jiang and Mahadevan [28] for details regarding the KL distance.

In addition to the nonparametric system identification model, a proper validation metric is needed as the quantitative measure of agreement between model prediction and measurement data in the system identification. Currently the widely used metric in practice is the relative root mean square (RRMS) error between the sensed structural responses and the responses predicted by the nonparametric model (e.g., [44,57,22]). It is customary to assume that structural system is identified when the RRMS error is less than a pre-defined threshold level obtained by trial and error (for example, 0.5). However, the RRMS error method is not always accurate because two other sources also contribute to this error: (1) training of the nonparametric model (e.g., neural network) to approximate the structural properties, and (2) sensor data which are imperfect and contain measurement noise.

The above two types of errors are addressed in this paper using a Bayesian hypothesis testing-based methodology for quantitative validation of the system identification model. In recent years, Mahadevan and co-workers have developed