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Self-constructing wavelet neural network algorithm for nonlinear control of large structures

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An adaptive control algorithm is presented for nonlinear vibration control of large structures subjected to dynamic loading. It is based on integration of a self-constructing wavelet neural network (SCWNN) developed specifically for structural system identification with an adaptive fuzzy sliding mode control approach. The algorithm is particularly suitable when the physical properties such as the stiffnesses and damping ratios of the structural system are unknown or partially known which is the case when a structure is subjected to an extreme dynamic event such as an earthquake as the structural properties change during the event. SCWNN is developed for functional approximation of the nonlinear behavior of large structures using neural networks and wavelets. In contrast to earlier work, the identification and control are processed simultaneously which makes the resulting adaptive control more applicable to real life situations. A two-part growing and pruning criterion is developed to construct the hidden layer in the neural network automatically. A fuzzy compensation controller is developed to reduce the chattering phenomenon. The robustness of the proposed algorithm is achieved by deriving a set of adaptive laws for determining the unknown parameters of wavelet neural networks using two Lyapunov functions. No offline training of neural network is necessary for the system identification process. In addition, the earthquake signals are considered as unidentified. This is particularly important for on-line vibration control of large civil structures since the external dynamic loading due to earthquake is not available in advance. The model is applied to vibration control of a continuous cast-in-place prestressed concrete box-girder bridge benchmark problem seismically excited highway.

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1. Introduction

A large number of articles have been published on linear vibration control of civil structures over the past three decades (Yao, 1972; Soong, 1990; Saleh and Adeli, 1994, 1996, 1998a, b; Yang et al., 1996, 2004) using a number of different algorithms developed in the vibration control community such as LQR (for example, Adeli and Saleh, 1997, 1998; Agrawal et al., 1997), LQG (Soong, 1990; Amini et al., 2013), Proportional-Integral-Derivative (PID) type controllers (Nigdeli and Boduroğlu, 2013), and H_∞ (Chase and Smith, 1996). The great majority of these papers deal with small academic problems where the structure is modeled as a two-dimensional (2D) structure with a few degrees-of-freedom or large structures assuming the controlled structure behaves linearly.

Vibration control of large nonlinear structures remains a challenging problem because of (a) unknown time-varying properties of structural systems and (b) uncertainties existing in both structural system identification and external excitations such as those due to an earthquake. Sliding mode control (SMC) has been used as a competitive control approach in civil structures Yang et al. (1996) applied the sliding mode control to a seismically-excited 3-story building isolated by a frictional sliding-isolation system and reported its effectiveness based on experimental test results. Singh et al. (1997) applied the SMC approach to a seismically-excited 10-story two-dimensional (2D) frame. Sarbjeet and Datta (2000) applied the sliding mode control strategy to a 20-story 2D frame subjected to a narrow band ground excitation and report more reduction in displacements compared with conventional linear control strategies such as LQR. Combing the concept of fuzzy logic (Kodogiannis et al., 2013; Rigatos, 2013; Yan and Ma, 2013; Fougères and Ostrosi, 2013) with SMC, Kim and Yun (2000) proposed a fuzzy sliding mode control (FSMC) for a three-story benchmark building considering actuator–structure interaction, sensor noise, actuator time delay, precision of the analog-to-digital (A/D) and digital-to-analog (D/A) converters, control force saturation range, and order of the control model. They report improved performance for FSMC compared with other control algorithms such as $H_{2/\infty}$ control, optimal polynomial control, neural

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networks-based control, and SMC. Using a distributed parameter system equipped with active tuned mass dampers (ATMDs), Wang and Lin (2006) indicate that FSMC is more economical and practical than a variable control algorithm such as SMC (a variable high-frequently switching feedback control where the control gains in each feedback path switch between two values according to some rule) in terms of controlling force and control energy use when applied to a seismically excited three story reinforced-concrete building. Wu (2003) and Wu and Yang (2004) use a pre-filtered sliding mode control method to reduce the response of a seismically-excited three-story building and demonstrate its performance through shaking table experimental tests of a full-scale building equipped with active bracing systems. They also applied it to wind-induced vibrations of a 76-story high rising building. Lee et al. (2004) apply SMC to a 3-story frame considering controller saturation. Ning et al. (2009) apply an FSMC control to the seismically excited nonlinear benchmark bridge presented in Agrawal et al. (2009).

SMC, however, has a shortcoming for application to large civil structures rarely discussed in the literature. Controlled responses from sliding mode control are highly sensitive to the bounds of structural system uncertainties and weighing matrices of the sliding surface. A small sliding bound may cause instability in vibration control of structures, while a large sliding bound will lead to the so-called chattering effect which means the sign of the control force changes rapidly and frequently within a short time period caused by a discontinuous switching function (usually a discontinuous sign function). This chattering effect can be reduced by using a continuous approximation of the discontinuous sliding mode controller, but it may cause system instability (Leu et al., 2009). To overcome the chattering phenomena while maintaining system stability, a fuzzy compensation controller is sometimes designed to model system uncertainties and function approximation errors (Hsu et al., 2009).

Neural networks (NNs) can be used for universal approximation of both linear and nonlinear functions (Hung and Adeli, 1993; Senouci and Adeli, 2001; Zhang and Ge, 2013; Vlahogianni and Karlaftis, 2013; Boutalis et al., 2013; Cona and Ursino, 2013; Story and Fry, 2014; Butcher et al., 2014; Khalid et al., 2014). Traditional NNs consist of multiple layers with a sufficient number of nodes in each hidden layer and adjustable weights (Cen et al., 2013; Cabessa and Siegelmann, 2014). They suffer from some common drawbacks such as lack of an efficient constructive model resulting in an arbitrary selection of the number of hidden nodes, slow convergence rate, and entrapment in a local minimum. Control algorithms based on this type of NN require extensive off-line training.

To overcome the aforementioned drawbacks of classical NNs used for system control and/or identifications, radial basis function (RBF) neural networks (Alexandridis, 2013; Zhou et al., 2013) have been used to simplify the network structure and reduce computational burden where Gaussian functions are generally used as the basis functions (Chen et al., 1990). These offline RBF-based NNs are further improved by using a resource allocating network (RAN) algorithm (Platt, 1991), which adds new hidden neurons depending on the input characteristics and output errors, where the weights connecting hidden layer and output layer are updated based on a least mean square (LMS) criterion. Two modifications of RAN are: (1) the replacement of the LMS criterion with extended Kalman Filter (EKF) (Kadirkamanathan and Niranjan, 1993) which improves the network compactness, and (2) using a pruning criterion which is able to remove hidden neurons that are less influential to the output in order to make the network more compact (Lu et al., 1997, 1998). A network based on these two improvements is generally referred to as minimal resource allocation network (MRAN).

As an extension of MRAN, the extended MRAN (EMRAN) was introduced subsequently (Irwin et al., 1995; Li et al., 2000; Wang et al., 2002). Rather than updating the parameters of all hidden neurons in each time step in MRAN, EMRAN allocates new hidden nodes (called Gaussian nodes) using a growing/pruning criterion, which means the number of nodes is reduced if the network can accurately approximate the unknown system given an allowed error range, and is increased if the error is outside the range. Gaussian nodes are able to store characteristic information of the unknown system. Each Gaussian node responds only to the local region of the input space. Only those parameters of a given node closest to the selected *winner node* are updated. As such, the learning patterns are not fully repeated as a result of the local updating process. The EMRAN algorithm reduces the computational time compared with MRAN (Li et al., 2000) and therefore is more suitable for online adaptation of high order unknown nonlinear systems. However, the EMRAN algorithm cannot ensure the stability of control models. A learning algorithm based on the Lyapunov function may be used to guarantee system stability (Gao and Er, 2003; Hsu, 2007).

Adeli and Kim (2004) introduced the concept of wavelet (Perez et al., 2014; Katicha et al., 2014) in structural control. They present a wavelet-hybrid feedback Least Mean Squared (LMS) algorithm (Kim and Adeli, 2004) for robust control of civil structures and demonstrate its effectiveness to vibration control of large irregular building structures subjected to seismic loading in an arbitrary direction (Kim and Adeli, 2005a), wind-excited motion of a 76-story building benchmark example (Kim and Adeli, 2005b), and a cable-stayed bridge subjected to seismic loading (Kim and Adeli, 2005c).

Compared with the Gaussian radial basis functions, wavelet basis functions yield more compact and efficient system representations while preserving global closed-loop stability if a proper adaptive law is used to train the neural network (Cannon and Slotine, 1995). A wavelet neural network (WNN) model was proposed by Zhang and Benveniste (1992) for signal processing. Hung et al. (2003) applied WNN to system identification of civil structures. Adeli and Jiang (2006) modified WNN using fuzzy logic to achieve a more efficient constructive model and higher identification accuracy. Their modified fuzzy WNN model is based on adroit integration of four different computing concepts: dynamic time delay neural network, wavelet as the basis function, fuzzy logic, and the state space reconstruction based on the chaos theory (Jiang and Adeli, 2003). They used a Mexican hat wavelet in their WNN model because (a) its analytical expression makes it amenable for both differentiation of multiple dimensional time series, and (b) it provides computational efficiency (Zhou and Adeli, 2003). They employ chaos theory to model the complicated and unknown nonlinear dynamics of structure-earthquake system which requires determining an appropriate embedding dimension for which they use the false nearest neighbor method. The input dimension of a time series can be obtained using Takens' embedding theorem for structural identification (Adeli and Jiang, 2006). The number of wavelet neurons in the hidden layer of their WNN model is determined by a self-constructing method using the Akaike's final prediction error (AFPE) criterion. Their model works well when the time series for training data is available. Amini and Zabihi-Samani (2014) discuss a wavelet-based time varying pole assignment method to control seismic vibrations of a multi-degree of freedom frame structure.

The selection of the number of nodes in the hidden layer is crucial for obtaining consistently accurate approximations with a reasonable computational cost. A trial-and-error method was generally used in earlier approaches to obtain the most suitable value for the number of nodes in the hidden layer using the NARMAX approach (Hung et al., 2003). That approach is time-consuming, does not provide a rational basis for the selection of the number of nodes in the hidden layer, and cannot guarantee accurate approximations. In order to determine the number of nodes in a neural network model for real-time control of nonlinear dynamic systems, a self-constructing method without *a priori* knowledge may be used. Researchers have introduced self-organizing/self-constructing algorithms to dynamically adapt the

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