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Nonlinear observer-based recurrent wavelet neuro-controller in disturbance rejection control of flexible structures

Atta Oveisi *, Mateus Bagetti Jeronimo, Tamara Nestorović

Ruhr-Universität Bochum, Mechanics of Adaptive Systems (MAS), Bochum, Germany

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ABSTRACT

In this paper, a model-based output feedback recurrent wavelet neural network (RWNN) controller is proposed for a class of nonlinear MIMO systems with time-varying matched/mismatched uncertainties. The proposed RWNN emulator adaptively trains to follow an ideal state-feedback controller which is designed on the underlying linear model (ULM) of the plant. Simultaneously, the control system employs an adaptive neural network (NN) mechanism to estimate the mismatch between the RWNN controller and this ideal control law. As a result, the conservatism associated with the classical robust control methods where the controller is synthesized based on worst-case bounds is addressed. Moreover, in order to generalize the subjected class of the investigatable plants, the echo-state feature of adaptive RWNN is used to contribute to the performance of nonminimum phase systems. Accordingly, in the context of flexible smart structures with non-collocated sensor/actuator configuration, a delayed feedback is added in the network which brings about a better match between the model output and the measured output. As a result, even for systems with an unknown Lipschitz constant of lumped uncertainty, the controller can be trained online to compensate with an additional revision of the control law following some Lyapunov-based adaptive stabilizing rules. Additionally, the current approach is proposed as an alternative to the hot topic of nonlinear system identification-based control synthesis where the exact structure of the nonlinearity is required.

1. Introduction

Neural networks (NN) are structures of massively interconnected cells which as a whole can model complex dynamical systems. These structures function by imitating the composition and capacity of the human brain. Each of the simplistic processing unit cells receives weighted input signals, passes the weighted summation of these signals through a nonlinear operator, and emits an output to be transmitted to the next level processing elements along the outgoing pathways. The application of NN as a controller (neuro-controllers) in active vibration control has been studied in the last two decades as the practical implementation of disturbance rejection control (DRC). However, only a handful of real-time implementations of nonlinear neuro-active vibration control systems is reported in the literature (Bouchard et al., 1999). For instance, Li et al. proposed a new filtered-error back-propagation NN (FEBPNN) algorithm for vibration control of flexible piezolaminated structures (Li et al., 2005). They implemented their FEBPNN algorithm on a digital signal processor (DSP), and it was shown that the proposed active vibration/noise control method (AVC/ANC) is effective for the system in the presence of modeling nonlinearities.

The conventional controllers are often synthesized to deliver only a specific control performance. In contrast, the neuro-controllers adapt online to satisfy the time-varying performance objectives in a supervised/unsupervised fashion depending on the available computational power. This distinguishing factor enables the NN to detect and learn extremely involved and nonlinear mappings (Ghaboussi and Joghataie, 1995). Moreover, various sources of nonlinearities in elastic light-weight mechanical structures make it impossible to use simplistic feedforward neural network excluding the tapped delay (Snyder and Tanaka, 1995). In other words, especially in any ANC scheme and AVC of non-collocated input/output (IO) configuration, where the measurement delay is the natural feature of the plant, an adaptive mechanism should be employed in synthesizing the control input signal associated with nonlinear output measurements. Two practical realizations of these nonlinearities in smart structures are the geometrical nonlinearities due to high vibration amplitudes where the linear models are not

* Corresponding author.
E-mail address: atta.oveisi@rub.de (A. Oveisi).
URL: http://www.ruhr-uni-bochum.de/mas/ (T. Nestorović).

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valid anymore (Oveisi and Nestorović, 2017) and the non-collocated sensor/actuators configurations where an inherent delay is an inevitable feature of the IO relation (Lee and Elliott, 2001). Providing technical details of the nonlinearities mentioned earlier is out of the scope of this paper. However, it is worth mentioning that the authors are interested in dealing with model-based output feedback nonlinear control design where the effects of these nonlinearities are treated directly subjected to the fact that the quantifications of these nonlinear terms are available in the nominal model of the plant. Recently, methods such as *Reverse Path* method (Richards and Singh, 1998; Muhamad et al., 2012) and *Nonlinear Normal Model* method (Shaw and Pierre, 1993; Peeters et al., 2011) gained many attentions for analyzing and quantifying these geometrical nonlinearities. The interested reader is highly recommended to refer to Noël and Kerschen (2017) for in-depth technical details. An alternative to such modeling approaches is the combination of semi-analytical techniques, e.g. Oveisi et al. (2016), in structural modeling of nonlinear systems and parameter optimization techniques in *Gray-box System Identification* framework (Astroza et al., 2016). Accordingly, adaption of the black-box polynomial nonlinear state space (PNLSS) identification approach i.e. Paduart et al. (2010) to the geometrically nonlinear system is an ongoing research. For AVC purposes, the control design process for such an elaborate nonlinear model is a complicated task. In contrast, the proposed controller in this paper relies on the underlying linear model (ULM) and treats the nonlinearities in an online framework. Consequently, the comparison of the proposed neuro-controller in this paper and the nonlinear ones developed based on Gray-box system identification approaches can be used to determine if the latter approach is justifiable. This reasonable comparison not only assesses the justifiability of going through complex modeling procedure in AVC but also can be used as an alternative solution in the case-studies where the uncertainty/nonlinearity detection, characterization, and quantification of the three-step paradigm in Kerschen et al. (2006) is not possible for technical reasons e.g. experimental costs and accessibility issues.

On the other hand, the nonlinear model-free robust control schemes based on the upper-bounds of the norm of the disturbance signals and matched-/mismatched-uncertainties such as high-gain, variable-structure, and fuzzy methods can be used in combination with NN to address nonlinearities in system dynamics (Khalil and Praly, 2014; Oveisi and Nestorović, 2016c). For instance, Jnifene and Andrews proposed a combination of a fuzzy logic controller and neural networks to regulate the end-effector vibration in a flexible smart beam positioned on a two DoF platform (Jnifene and Andrews, 2005). He et al. employed a neural network for modeling the dynamics of a flexible robot manipulator subjected to input deadzone. They have used radial basis function NN to capture the deadzone and designed a high-gain observer-based NN controller (He et al., 2017). Moreover, it is reported that one of the major deficiencies of standard control systems based on linear time-invariant (LTI) nominal models are the evolution of plant dynamics w.r.t. time and the actuator windup problem both of which add to the nonlinearity of the system (Lin et al., 1996). Accordingly, Li et al. introduced a genetic algorithm (GA) based back-propagation neural network suboptimal controller to address the vibration attenuation of a nine DoF modular robot (Li et al., 2005).

The nonminimum phase vibrating systems with non-collocated actuator/sensor placements with centralized control configuration may have right-half plane (RHP) zeros which can significantly restrict the closed-loop performance as reported in Lee and Elliott (2001). A detailed analysis on the tradeoff imposed on the performance of these nonminimum phase systems at different frequencies (in *linear control theory*) is previously reported by Freudenberg and Looze (1985). Alternatively, the echo-state feature of adaptive RWNN is investigated in this paper to contribute to the performance of nonminimum phase systems.

To put in a nutshell, the following contributions are reported. Instead of worst-case analysis based on the classical robust control methods and on the grounds of following adaptive nonlinear (non-conservative) control synthesis in AVC framework, a network is assigned to identify any dynamics that cannot be fit into the LTI framework, or the identified system fails to capture (see Section 2.1). This feature together with *generalization* and *information storing capabilities* of NN opens the possibility of further investigations based on the nonlinear disturbance observer based control (DOBC) as a hot topic in modern DRC (Chen et al., 2016). An ideal controller is derived in terms of the tracking error of the estimated system state, and an adaptive recurrent wavelet neural network (RWNN) is configured in Section 2.2.2 to imitate the perfect controller. An advantage of such configuration compared to the asymptotic stabilizing techniques is that the mismatch between the ideal and the realized control law is not left alone. In other words, although the network parameters of RWNN are adaptively tuned following Lyapunov stabilizing scheme, an additional observer is assigned to identify the error bounds and reject them in the tracking error dynamics. This feature may significantly contribute to the transient performance of the neural controller especially for the application of smart structures where the frequency range of interest may encompass up to hundreds of states which cannot be all considered in the nominal model of the system for obvious reasons. Note that the WNN-control systems benefit simultaneously from the learning capabilities of the artificial NN as well as the identification strength of the wavelet decomposition (Sousa et al., 2002; Hsu et al., 2006). Two contributions in terms of applicability of the proposed NN-based control system in real implementations are reported as: (a) Unlike the state-feedback schemes suggested in the literature (i.e. Lin et al., 2012, 2014), and similar to the output feedback neural control in Ge et al. (1999) and Dierks and Jagannathan (2010), the proposed technique is practical for smart structures where the continuous real system has infinite dynamics (represented with states) which cannot be measured individually. However, following the actuator/sensor placement criteria proposed in the literature (e.g. Nestorović and Trajkov, 2013; Hashem-inejad and Oveisi, 2016) that reserve the observability conditions in smart structures, the neural network-based state-observer may provide an accurate measure of system states in real-time. The nonlinear-in-parameters neural network (NLPNN) used in observer design is capable of handling the nonlinearities without *a priori* known dynamics. The modified backpropagation (BP) algorithm is therefore implemented to realize the learning process. For this purpose, the idea in Abdollahi et al. (2006) is followed. (b) The stabilization of the nominal model of the plant as pointed in D'haene et al. (2006) encompasses a delay which if separated from the transfer function of IO results in minimum phase model. This indicates that similar to echo-state NN (e.g. Mahmoud and Elshenawy, 2016), the network can capture the delay and the problem of stabilizing a minimum phase system (as an alternative to Hua et al., 2007) is a much easier task. Accordingly, the performance of the proposed control system in damping the effects of disturbance signal at frequencies close to those of right half plane (RHP) zeros is investigated for non-collocated configuration. It should be noted that the NN-based control methods that include the input nonlinearities such as actuation saturation, deadzone, and output constraints such as He et al. (2016a, b) are out of the scope of this paper.

In the experimental implementation of the proposed technique of this paper, a comparison with a standard approach (LQG) is performed. The interested reader may also compare the results of this paper with the robust observer-based adaptive fuzzy sliding mode controller and non-fragile H_2/H_∞ observer-based control system published respectively in Oveisi and Nestorović (2016c) and Oveisi and Nestorovic (2016b) on the same benchmark problem. Meanwhile, for some AVC applications (even with complex geometries), systematical methods are available in the literature for providing the measure of IO delay e.g. Bossi et al. (2011).